INDIRECT MONITORING OF SURFACE QUALITY BASED ON THE INTEGRATION OF SUPPORT VECTOR MACHINE AND 3D I-KAZ TECHNIQUES IN THE MACHINING PROCESS

NORLIDA BINTI JAMIL

DOCTOR OF PHILOSOPHY

UNIVERSITI MALAYSIA PAHANG

SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis, and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy.

(Supervisor's Signature)

Full Name : PROF. IR. DR. AHMAD RAZLAN BIN YUSOFF

Position : PROFESSOR

Date : 08 SEPTEMBER 2023

STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

____

(Student's Signature)

Full Name : NORLIDA BINTI JAMIL

ID Number : PMF16001

Date : 08 SEPTEMBER 2023

INDIRECT MONITORING OF SURFACE QUALITY BASED ON THE INTEGRATION OF SUPPORT VECTOR MACHINE AND 3D I-KAZ TECHNIQUES IN THE MACHINING PROCESS

NORLIDA BINTI JAMIL

The thesis submitted in fulfillment of the requirements
for the award of the degree of
Doctor of Philosophy

Faculty of Manufacturing and Mechatronic Engineering Technology

UNIVERSITI MALAYSIA PAHANG

SEPTEMBER 2023

ACKNOWLEDGEMENTS

In the name of Allah, the Most Gracious and the Most Merciful

All praises to Allah and His blessing for the completion of this thesis. I am deeply grateful for the opportunities, challenges, and strength that were bestowed upon me throughout this journey. My humblest gratitude to the holy Prophet Muhammad (Peace be upon him) whose way of life has been continuous guidance for me.

I would like to express my heartfelt appreciation to my supervisor, Professor Ir. Dr. Ahmad Razlan Bin Yusoff, for his invaluable guidance, understanding, patience, and positive encouragement throughout the course of my research. It has been an honour and a privilege to have him as my supervisor.

I would also like to extend my profound gratitude to my family for their unwavering support and love throughout this endeavour. I cannot express enough appreciation for my parents and siblings for their love, prayers, care, and support.

I am also greatly indebted to the lecturers and staff of the Manufacturing and Mechatronic Engineering Faculty at UMP, who have provided me with invaluable assistance and support throughout my studies. I would also like to express my sincere gratitude to my research group for their excellent motivation, inspiration, and assistance.

I would sincerely like to thank all my beloved friends who were with me and support me through thick and thin. Many people contributed and supported me, and I would love to list them all but forgive me, whoever you are you know I would if I could.

May God shower the above-cited personalities with success and honour in their life.

ABSTRAK

Kualiti proses pemesinan yang lebih baik boleh menyumbang kepada pembuatan mampan dari segi kelestarian ekonomi, alam sekitar, dan sosial. Pengurangan pembaziran, peningkatan kecekapan, dan kualiti produk yang lebih baik juga dapat membantu pengeluar mengurangkan kos dan meningkatkan kadar produktiviti. Pemesinan adalah salah satu kaedah yang biasa digunakan dalam industri dan memainkan peranan utama dalam pembuatan moden. Selama bertahun-tahun, penyelidik telah mengkaji kaedah pemantauan untuk menghasilkan kualiti permukaan terbaik. Pengukuran melibatkan tiga teknik yang berbeza, yang dikategorikan kepada kaedah kuantitatif dan visualisasi. Kaedah pemantauan umumnya boleh diklasifikasikan kepada langsung atau tidak langsung. Kaedah umum yang digunakan untuk mengukur kualiti pemesinan mengalami cerutan pembuatan kerana ia dikekang oleh pemeriksaan manusia dan peralatan mahal. Kaedah umum untuk mengukur kualiti pemesinan adalah tidak praktikal kerana memerlukan pemeriksaan manusia dan peralatan yang mahal. Proses yang perlahan menyebabkan kepada kos buruh yang lebih tinggi dan risiko kerosakan peralatan yang tinggi pada bahan kerja. Kajian ini bertujuan untuk mengisi kesenjangan ini dengan memanfaatkan keupayaan model 3D I-kaz dan Gaussian SVM sederhana (MG-SVM) untuk meningkatkan ketepatan dan kadar klasifikasi dalam menentukan kualiti permukaan. Objektif khusus adalah untuk menganalisis kesan parameter pemesinan pada analisis statistik, mengklasifikasikan isyarat pecutan untuk pengenalan kasar permukaan menggunakan SVM, dan mengintegrasikan SVM dengan 3D I-kaz untuk meningkatkan pengenalan kualiti permukaan dan mengesahkan keberkesanannya melalui eksperimen. Pengukuran pemprosesan isyarat untuk bahan besi tahan lentur, FCD450 pada parameter pemotongan: kelajuan putaran dengan 1000–3026 rev/mm, kadar pengumpanan 120–720 mm/min, aksial 0.75–3.5 mm, dan kedalaman pemotongan jejari (RDOC) telah dikaji dan disahkan melalui eksperimen dalam keadaan kering dan pelinciran kuantiti minimum (MQL). Kekasar permukaan diukur untuk mengesahkan isyarat pecutan. Pekali Korelasi Pearson (PCC) digunakan untuk menilai kekuatan korelasi antara isyarat pecutan dan kekasaran permukaan. Pembezaan Pearson, nilai r didapati menjadi 0.6543, yang menunjukkan korelasi positif tetapi bukan linear antara isyarat pecutan dan kekasaran permukaan. Nilai kurtosis yang diukur daripada maklumat isyarat pecutan dan kekasaran permukaan kemudian digunakan untuk mengklasifikasikan keadaan pemesinan dan pengenalpastian kualiti permukaan. Dalam eksperimen pertama, model menunjukkan ketepatan 84.87% dan nilai F1 84.57%. Didapati bahawa pelarasan hyperparameter boleh meningkatkan ketepatan model menjadi 85.53% dan skor F1-nya menjadi 84.93%. Sebelum pengelasan keadaan permukaan mesin, keadaan tersebut dikenal pasti melalui teknik *support vector machine* (SVM), dan ia menunjukkan bahawa keadaan itu boleh dibahagikan kepada lima tahap kualiti permukaan yang berbeza. Daripada data ujian eksperimen, penunjuk pecutan dan Ra diiktiraf untuk analisis korelasi. Satu hubungan dibangunkan yang membolehkan ramalan atau pengenalpastian kualiti permukaan secara langsung berdasarkan penunjuk terpilih (pepejal 3D I-kaz) tanpa perlu menginspeksi proses kisar untuk kasar permukaan. Telah ditunjukkan bahawa integrasi model 3D I-kaz dan SVM mampu menghasilkan ketepatan dan skor F1 masing-masing sebanyak 96.0% dan 96.3%, menunjukkan bahawa data kuantifikasi adalah berdaya maju untuk pengenalpastian kualiti permukaan. Eksperimen pemantauan digunakan untuk mengesahkan pengenalpastian kualiti permukaan melalui tahap kasar permukaan segera yang diperolehi daripada eksperimen. Kesimpulannya, pemantauan tidak langsung kualiti permukaan menggunakan isyarat getaran dapat mengenal pasti

kualiti permukaan dengan cepat menggunakan analisis SVM dan 3D I-kaz, justeru, mengurangkan masa dan kos yang berkaitan dengan pemeriksaan manual yang membolehkan ia digunakan dalam pelbagai proses pengisaran lain.

ABSTRACT

Improved machining process quality can contribute to sustainable manufacturing in terms of economic, environmental, and social sustainability. Reducing waste, increasing efficiency, and improving product quality can also help manufacturers to reduce costs and increase productivity rate. Machining is one of the common methods in industry and plays a central role in modern manufacturing. For many years, researchers have been studying monitoring methods to produce the best surface quality. The measurement involves three distinct techniques, which are categorised into quantitative and visualisation methods. Monitoring methods can be classified as either direct or indirect methods. The common method of measuring machining quality undergoes manufacturing bottlenecks, as it is constrained by human inspection and expensive equipment. A slow process leads to higher labour costs and a high risk of equipment damage to the workpiece. The present study aims to bridge this gap by leveraging the capabilities of 3D I-kaz and medium Gaussian SVM models to improve accuracy and classification rates for determining surface quality. The specific objectives are to analyse the impact of machining parameters on statistical analysis, classify acceleration signals for surface roughness identification using SVM, integrate SVM with 3D I-kaz to improve surface quality identification and validate its effectiveness through experiments. The quantification of signal processing for ductile iron, FCD450 material on cutting parameters: rotation speed with 1000–3026 rev/mm, feed rate of 120–720 mm/min, axial of 0.75–3.5 mm, and radial depth of cut (RDOC) is studied and validated through experiments under dry and minimum quantity lubrication (MQL) conditions. Surface roughness was measured to verify the acceleration signal, while Pearson's correlation coefficient was used to evaluate the correlation strength between the acceleration signal and surface roughness. The calculated coefficient, r-value, was found to be 0.6543, which indicates a positive but nonlinear correlation between the acceleration signal and surface roughness. The kurtosis value measured from acceleration signals and surface roughness information was then used to classify the machining condition and identification of the surface quality. In the first experiment, the model displayed an accuracy of 84.87% and 84.57% in terms of F1 values. It was observed that by adjusting the hyperparameter, the model's accuracy was augmented to 85.53% and its F1 score was enhanced to 84.93%. Additionally, the model was applied in the second experiment, resulting in an accuracy of 84.0%. Before the classification of machined surface condition, the condition is identified through the support vector machine (SVM) technique, and it was demonstrated that the condition could be demarcated into five different levels of surface quality. From the experimental test data, acceleration and average roughness (Ra)-based indicators are identified for correlation analysis. A relation is developed, which enables the prediction or identification of surface quality directly based on the selected based indicators (3D I-kaz coefficient) without having to inspect the milling process for surface roughness. It was demonstrated that the integration of the 3D I-kaz and SVM model resulted in an accuracy and F1 score of 96.0% and 96.3% respectively, suggesting that the quantification data is viable for surface quality identification. A monitoring experiment was conducted in this study to validate the identification of surface quality through the instantaneous surface roughness level obtained from the experiment. In conclusion, indirect monitoring of surface quality using vibration signals can quickly identify the surface quality using SVM and 3D I-kaz analyses, thus reducing the time and cost associated with manual inspection and allowing for its use in many other machining processes.

TABLE OF CONTENT

REFERENCES

Abainia, S., & Ouelaa, N. (2021). Predicting the dynamic behaviour of the turning tool vibrations using an experimental measurement, numerical simulation and analytical modelling for comparative study. *The International Journal of Advanced Manufacturing Technology*, 115(7), 2533-2552. https://doi.org/https://doi.org/10.1007/s00170-021-07275-0

Abdeltawab, A., Zhang, X., Zhang, L., & Li, C. (2021). Tool Wear Inspection and Classification by Artificial Neural Network Based on Vision System and Cutting Force Signal. https://doi.org/https://doi.org/10.21203/rs.3.rs-229749/v1

Abellan-Nebot, J. V., & Romero Subirón, F. (2010). A review of machining monitoring systems based on artificial intelligence process models. *The International Journal of Advanced Manufacturing Technology*, 47(1), 237-257. https://doi.org/https://doi.org/10.1007/s00170-009-2191-8

Abu-Mahfouz, I., El Ariss, O., Esfakur Rahman, A., & Banerjee, A. (2017a). Surface roughness prediction as a classification problem using support vector machine. *The International Journal of Advanced Manufacturing Technology*, 92, 803-815. https://doi.org/https://doi.org/10.1007/s00170-017-0165-9

Abu-Mahfouz, I., Rahman, A. E., & Banerjee, A. (2018). Surface roughness prediction in turning using three artificial intelligence techniques; a comparative study. *Procedia Computer Science*, 140, 258-267. https://doi.org/https://doi.org/10.1016/j.procs.2018.10.322

Abubakr, M., Abbas, A. T., Tomaz, I., Soliman, M. S., Luqman, M., & Hegab, H. (2020). Sustainable and smart manufacturing: an integrated approach. *Sustainability*, 12(6), 2280. https://doi.org/https://doi.org/10.3390/su12062280

Abubakr, M., Hassan, M. A., Krolczyk, G. M., Khanna, N., & Hegab, H. (2021). Sensors selection for tool failure detection during machining processes: A simple accurate classification model. *CIRP Journal of Manufacturing Science and Technology*, 32, 108-119. https://doi.org/https://doi.org/10.1016/j.cirpj.2020.12.002

Aburomman, A. A., & Reaz, M. B. I. (2016). Ensemble of binary SVM classifiers based on PCA and LDA feature extraction for intrusion detection. 2016 IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC).

Adamczak, S., & Zmarzły, P. (2019). Research of the influence of the 2D and 3D surface roughness parameters of bearing raceways on the vibration level. Journal of Physics: Conference Series.

Ahmad, M., Nuawi, M., Abdullah, S., Wahid, Z., Karim, Z., & Dirhamsyah, M. (2015). Development of tool wear machining monitoring using novel statistical analysis method, I-kaz™. *Procedia engineering*, 101, 355-362. https://doi.org/https://doi.org/10.1016/j.proeng.2015.02.043

Ahmad, M. A. F., Nuawi, M. Z., Ghani, J. A., Abdullah, S., & Ramli, M. I. (2018). An investigation on tool wear monitoring using MFC and PVDF sensors via I-kazTM statistical signal analysis. *Proceedings of Mechanical Engineering Research Day 2018*, 2018, 301-302.

Aich, U., & Banerjee, S. (2014). Modeling of EDM responses by support vector machine regression with parameters selected by particle swarm optimization. *Applied Mathematical Modelling*, 38(11-12), 2800-2818. https://doi.org/https://doi.org/10.1016/j.apm.2013.10.073

Alajmi, M. S., & Almeshal, A. M. (2021). Estimation and optimization of tool wear in conventional turning of 709M40 alloy steel using support vector machine (SVM) with Bayesian optimization. *Materials*, 14(14), 3773. https://doi.org/https://doi.org/10.3390/ma14143773

Albertelli, P., Braghieri, L., Torta, M., & Monno, M. (2019). Development of a generalized chatter detection methodology for variable speed machining. *Mechanical systems and signal processing*, 123, 26-42. https://doi.org/https://doi.org/10.1016/j.ymssp.2019.01.002

Aramesh, M., Attia, M., Kishawy, H., & Balazinski, M. (2016). Estimating the remaining useful tool life of worn tools under different cutting parameters: A survival life analysis during turning of titanium metal matrix composites (Ti-MMCs). *CIRP Journal of Manufacturing Science and Technology*, 12, 35-43. https://doi.org/https://doi.org/10.1016/j.cirpj.2015.10.001

Aulestia Viera, M. A., Aguiar, P. R., Oliveira Junior, P., Alexandre, F. A., Lopes, W. N., Bianchi, E. C., da Silva, R. B., D'addona, D., & Andreoli, A. (2019). A time–frequency acoustic emission-based technique to assess workpiece surface quality in ceramic grinding with PZT transducer. *Sensors*, 19(18), 3913. https://doi.org/https://doi.org/10.3390/s19183913

Ba, E. C. T., Dumont, M. R., Martins, P. S., Drumond, R. M., Martins da Cruz, M. P., & Vieira, V. F. (2021). Investigation of the effects of skewness R sk and kurtosis R ku on tribological behavior in a pin-on-disc test of surfaces machined by conventional milling and turning processes. *Materials Research*, 24. https://doi.org/https://doi.org/10.1590/1980-5373-mr-2020-0435

Babu, A. K., Raj, V. A., & Kumaresan, G. (2016). Misfire detection in a multi-cylinder diesel engine: A machine learning approach. *J. Eng. Sci. Technol*, 11(2), 278-295. https://doi.org/https://doi.org/10.1504/pie.2018.10016965

Bai, X., Li, C., Dong, L., & Yin, Q. (2019). Experimental evaluation of the lubrication performances of different nanofluids for minimum quantity lubrication (MQL) in milling Ti-6Al-4V. *The International Journal of Advanced Manufacturing Technology*, 101(9), 2621-2632. https://doi.org/https://doi.org/10.1007/s00170-018-3100-9

Balestriero, R., Glotin, H., & Baranuik, R. (2022). Interpretable and learnable super-resolution time-frequency representation. Mathematical and Scientific Machine Learning

Barreiro, J., Fernández-Abia, A., González-Laguna, A., & Pereira, O. (2017). TCM system in contour milling of very thick-very large steel plates based on vibration and AE signals. *Journal of Materials Processing Technology*, 246, 144-157. https://doi.org/https://doi.org/10.1016/j.jmatprotec.2017.03.016

Barton, D., Federhen, J., & Fleischer, J. (2021). Retrofittable vibration-based monitoring of milling processes using wavelet packet transform. *Procedia Cirp*, 96, 353-358. https://doi.org/https://doi.org/10.1016/j.procir.2021.01.099

Benardos, P., & Vosniakos, G.-C. (2003). Predicting surface roughness in machining: a review. *International Journal of Machine Tools and Manufacture*, 43(8), 833-844. https://doi.org/https://doi.org/10.1016/s0890-6955(03)00059-2

Benjamin, D. M., Sabarish, V. N., Hariharan, M., & Raj, D. S. (2018). On the benefits of sub-zero air supplemented minimum quantity lubrication systems: An experimental and mechanistic investigation on end milling of Ti-6-Al-4-V alloy. *Tribology International*, 119, 464-473. https://doi.org/https://doi.org/10.1016/j.triboint.2017.11.021

Bhagat, S. N., & Nalbalwar, S. (2016). LabVIEW based tool condition monitoring and control for CNC lathe based on parameter analysis. 2016 IEEE international conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT).

Bhandari, B., & Park, G. (2022). Non-contact surface roughness evaluation of milling surface using CNN-deep learning models. *International Journal of Computer Integrated Manufacturing*, 1-15. https://doi.org/https://doi.org/10.21203/rs.3.rs-246947/v1

Bort, C. M. G., Leonesio, M., & Bosetti, P. (2016). A model-based adaptive controller for chatter mitigation and productivity enhancement in CNC milling machines. *Robotics and Computer-Integrated Manufacturing*, 40, 34-43. https://doi.org/https://doi.org/10.1016/j.rcim.2016.01.006

Boswell, B., Islam, M. N., Davies, I. J., Ginting, Y., & Ong, A. K. (2017). A review identifying the effectiveness of minimum quantity lubrication (MQL) during conventional machining. *The International Journal of Advanced Manufacturing Technology*, 92(1), 321-340. https://doi.org/https://doi.org/10.1007/s00170-017-0142-3

Brito, L. C., da Silva, M. B., & Duarte, M. A. V. (2021). Identification of cutting tool wear condition in turning using self-organizing map trained with imbalanced data. *Journal of Intelligent Manufacturing*, 32, 127-140. https://doi.org/https://doi.org/10.1007/s10845-020-01564-3

Burges, C. J. (1998). A tutorial on support vector machines for pattern recognition. *Data mining and knowledge discovery*, 2(2), 121-167.

Bustillo, A., Pimenov, D. Y., Mia, M., & Kapłonek, W. (2021). Machine-learning for automatic prediction of flatness deviation considering the wear of the face mill teeth. *Journal of Intelligent Manufacturing*, 32(3), 895-912. https://doi.org/https://doi.org/10.1007/s10845-020-01645-3

Byrne, G., Dornfeld, D., Inasaki, I., Ketteler, G., König, W., & Teti, R. (1995). Tool condition monitoring (TCM)—the status of research and industrial application. *CIRP annals*, 44(2), 541-567. https://doi.org/https://doi.org/10.1016/s0007-8506(07)60503-4

Caggiano, A. (2018). Tool wear prediction in Ti-6Al-4V machining through multiple sensor monitoring and PCA features pattern recognition. *Sensors*, 18(3), 823. https://doi.org/https://doi.org/10.3390/s18030823

Caixu, Y., Zhenlong, X., Xianli, L., & Mingwei, Z. (2022). Chatter prediction of milling process for titanium alloy thin-walled workpiece based on EMD-SVM. *Journal of Advanced Manufacturing Science and Technology*, 2(2), 2022010-2022010. https://doi.org/https://doi.org/10.51393/j.jamst.2022010

Cao, H., Yue, Y., Chen, X., & Zhang, X. (2018). Chatter detection based on synchrosqueezing transform and statistical indicators in milling process. *The International Journal of Advanced Manufacturing Technology*, 95(1), 961-972. https://doi.org/https://doi.org/10.1007/s00170-017-1283-0

Cao, X.-C., Chen, B.-Q., Yao, B., & He, W.-P. (2019). Combining translation-invariant wavelet frames and convolutional neural network for intelligent tool wear state identification. *Computers in Industry*, 106, 71-84. https://doi.org/https://doi.org/10.1016/j.compind.2018.12.018

Carmichael, I., & Marron, J. (2021). Geometric insights into support vector machine behavior using the KKT conditions. *Electronic Journal of Statistics*, 15(2), 6311-6343. https://doi.org/https://doi.org/10.1214/21-ejs1902

Catalán, N., Ramos-Moore, E., Boccardo, A., & Celentano, D. (2022). Surface Laser Treatment of Cast Irons: A Review. *Metals*, 12(4), 562. https://doi.org/https://doi.org/10.3390/met12040562

Cavaleri, L., Chatzarakis, G. E., Di Trapani, F., Douvika, M. G., Roinos, K., Vaxevanidis, N. M., & Asteris, P. G. (2017). Modeling of surface roughness in electro-discharge machining using artificial neural networks. *Advances in materials Research*, 6(2), 169.

Çaydaş, U., & Ekici, S. (2012). Support vector machines models for surface roughness prediction in CNC turning of AISI 304 austenitic stainless steel. *Journal of Intelligent Manufacturing*, 23(3), 639-650. https://doi.org/https://doi.org/10.1007/s10845-010-0415-2

Chang, M.-K., & Chang, W.-J. (2016). Surface Roughness Prediction in CNC End Milling Machining Using Artificial Neural Networks. *ICIC express letters. Part B, Applications: an international journal of research and surveys*, 7(4), 759-764.

Chen, G., & Zheng, Q. (2018). Online chatter detection of the end milling based on wavelet packet transform and support vector machine recursive feature elimination. *The International Journal of Advanced Manufacturing Technology*, 95(1), 775-784. https://doi.org/https://doi.org/10.1007/s00170-017-1242-9

Chen, H., Huang, S., Li, D., & Fu, P. (2010). Turning tool wear monitoring based on fuzzy cluster analysis. In *Advances in neural network research and applications* (pp. 739-745). Springer. https://doi.org/https://doi.org/10.1007/978-3-642-12990-2_86

Chen, N., Li, H. N., Wu, J., Li, Z., Li, L., Liu, G., & He, N. (2021). Advances in micro milling: From tool fabrication to process outcomes. *International Journal of Machine Tools and Manufacture*, 160, 103670. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2020.103670

Chen, Y., Li, H., Hou, L., & Bu, X. (2019a). Feature extraction using dominant frequency bands and time-frequency image analysis for chatter detection in milling. *Precision Engineering*, 56, 235-245. https://doi.org/https://doi.org/10.1016/j.precisioneng.2018.12.004

Chen, Y., Li, H., Jing, X., Hou, L., & Bu, X. (2019b). Intelligent chatter detection using image features and support vector machine. *The International Journal of Advanced Manufacturing Technology*, 102(5), 1433-1442. https://doi.org/https://doi.org/10.1007/s00170-018-3190-4

Cheng, M., Jiao, L., Yan, P., Li, S., Dai, Z., Qiu, T., & Wang, X. (2022). Prediction and evaluation of surface roughness with hybrid kernel extreme learning machine and monitored tool wear. *Journal of manufacturing processes*, 84, 1541-1556. https://doi.org/https://doi.org/10.1016/j.jmapro.2022.10.072

Cherkassky, V., & Ma, Y. (2004). Practical selection of SVM parameters and noise estimation for SVM regression. *Neural networks*, 17(1), 113-126. https://doi.org/https://doi.org/10.1016/s0893-6080(03)00169-2

Chinchanikar, S., & Choudhury, S. (2015). Machining of hardened steel—experimental investigations, performance modeling and cooling techniques: a review. *International Journal of Machine Tools and Manufacture*, 89, 95-109. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2014.11.002

Chinnasamy, M., Rathanasamy, R., Kaliyannan, G. V., Paramasivam, P., & Jaganathan, S. K. (2021). A frontier statistical approach towards online tool condition monitoring and optimization for dry turning operation of SAE 1015 steel. *Archives of Metallurgy and Materials*, 901-909-901-909. https://doi.org/https://doi.org/10.24425/amm.2021.136396

Chiu, Y.-C., Wang, P.-H., & Hu, Y.-C. (2021). The thermal error estimation of the machine tool spindle based on machine learning. *Machines*, 9(9), 184. https://doi.org/https://doi.org/10.3390/machines9090184

Cuka, B., & Kim, D.-W. (2017). Fuzzy logic based tool condition monitoring for end-milling. *Robotics and Computer-Integrated Manufacturing*, 47(C), 22-36. https://doi.org/https://doi.org/10.1016/j.rcim.2016.12.009

Dai, W., Sun, J., Chi, Y., Lu, Z., Xu, D., & Jiang, N. (2019). Review of machining equipment reliability analysis methods based on condition monitoring technology. *Applied Sciences*, 9(14), 2786. https://doi.org/https://doi.org/10.3390/app9142786

Denkena, B., Dittrich, M.-A., Lindauer, M., Mainka, J., & Stürenburg, L. (2020). Using automl to optimize shape error prediction in milling processes. Proceedings of the machining innovations conference (MIC).

Dimla, D. E. (2000). Sensor signals for tool-wear monitoring in metal cutting operations—a review of methods. *International Journal of Machine Tools and Manufacture*, 40(8), 1073-1098. https://doi.org/https://doi.org/10.1016/s0890-6955(99)00122-4

Drouillet, C., Karandikar, J., Nath, C., Journeaux, A.-C., El Mansori, M., & Kurfess, T. (2016). Tool life predictions in milling using spindle power with the neural network technique. *Journal of manufacturing processes*, 22, 161-168. https://doi.org/https://doi.org/10.1016/j.jmapro.2016.03.010

Dun, Y., Zhu, L., Yan, B., & Wang, S. (2021). A chatter detection method in milling of thin-walled TC4 alloy workpiece based on auto-encoding and hybrid clustering. *Mechanical systems and signal processing*, 158, 107755. https://doi.org/https://doi.org/10.1016/j.ymssp.2021.107755

Dureja, J., Singh, R., Singh, T., Singh, P., Dogra, M., & Bhatti, M. S. (2015). Performance evaluation of coated carbide tool in machining of stainless steel (AISI 202) under minimum quantity lubrication (MQL). *International Journal of Precision Engineering and Manufacturing-Green Technology*, 2(2), 123-129. https://doi.org/https://doi.org/10.1007/s40684-015-0016-9

Elangovan, M., Ramachandran, K., & Sugumaran, V. (2010). Studies on Bayes classifier for condition monitoring of single point carbide tipped tool based on statistical and histogram features. *Expert Systems with Applications*, 37(3), 2059-2065. https://doi.org/https://doi.org/10.1016/j.eswa.2009.06.103

Elangovan, M., Sakthivel, N., Saravanamurugan, S., Nair, B. B., & Sugumaran, V. (2015). Machine learning approach to the prediction of surface roughness using statistical features of vibration signal acquired in turning. *Procedia Computer Science*, 50, 282-288. https://doi.org/https://doi.org/10.1016/j.procs.2015.04.047

Fang, N., Pai, P. S., & Edwards, N. (2014). A method of using Hoelder exponents to monitor tool-edge wear in high-speed finish machining. *The International Journal of Advanced Manufacturing Technology*, 72(9), 1593-1601. https://doi.org/https://doi.org/10.1007/s00170-014-5764-0

Farkas, G., & Drégelyi-Kiss, Á. (2018). Measurement uncertainty of surface roughness measurement. IOP Conference Series: Materials Science and Engineering.

Fatima, A., Kamal, A., & Wasif, M. (2022). Use of Taguchi experimental design in an offline optimization estimation of surface finish in machining.

Feng, C.-X. J., Yu, Z.-G. S., Kingi, U., & Baig, M. P. (2005). Threefold vs. fivefold cross validation in one-hidden-layer and two-hidden-layer predictive neural network modeling of machining surface roughness data. *Journal of Manufacturing Systems*, 24(2), 93-107. https://doi.org/https://doi.org/10.1016/s0278-6125(05)80010-x

Feng, K., Smith, W. A., Borghesani, P., Randall, R. B., & Peng, Z. (2021). Use of cyclostationary properties of vibration signals to identify gear wear mechanisms and track wear evolution. *Mechanical systems and signal processing*, 150, 107258. https://doi.org/https://doi.org/10.1016/j.ymssp.2020.107258

Furushima, T., Sato, H., Manabe, K.-i., & Alexandrov, S. (2018). Identification of an empirical equation for predicting free surface roughness evolution in thin sheets of aluminum alloy and pure copper. *Journal of Manufacturing Science and Engineering*, 140(3). https://doi.org/https://doi.org/10.1115/1.4038822

Gadelmawla, E., Koura, M. M., Maksoud, T. M., Elewa, I. M., & Soliman, H. (2002). Roughness parameters. *Journal of Materials Processing Technology*, 123(1), 133-145. https://doi.org/https://doi.org/10.1016/s0924-0136(02)00060-2

Gao, H., Ma, B., Singh, R. P., & Yang, H. (2020). Areal surface roughness of AZ31B magnesium alloy processed by dry face turning: An experimental framework combined with regression analysis. *Materials*, 13(10), 2303. https://doi.org/https://doi.org/10.3390/ma13102303

Gao, R., Wang, L., Teti, R., Dornfeld, D., Kumara, S., Mori, M., & Helu, M. (2015). Cloud-enabled prognosis for manufacturing. *CIRP annals*, 64(2), 749-772. https://doi.org/https://doi.org/10.1016/j.cirp.2015.05.011

Gopaluni, R. B., Tulsyan, A., Chachuat, B., Huang, B., Lee, J. M., Amjad, F., Damarla, S. K., Kim, J. W., & Lawrence, N. P. (2020). Modern machine learning tools for monitoring and control of industrial processes: A survey. *IFAC-PapersOnLine*, 53(2), 218-229. https://doi.org/https://doi.org/10.1016/j.ifacol.2020.12.126

Guleria, V., Kumar, V., & Singh, P. K. (2022). Classification of surface roughness during turning of forged EN8 steel using vibration signal processing and support vector machine. *Engineering Research Express*, 4(1), 015029. https://doi.org/https://doi.org/10.1088/2631-8695/ac57fa

Guo, K., & Sun, J. (2021). Sound singularity analysis for milling tool condition monitoring towards sustainable manufacturing. *Mechanical systems and signal processing*, 157, 107738. https://doi.org/https://doi.org/10.1016/j.ymssp.2021.107738

Guo, K., Yang, B., Wang, H., Sun, J., & Lu, L. (2019). Singularity analysis of cutting force and vibration for tool condition monitoring in milling. *IEEE access*, 7, 134113-134124. https://doi.org/https://doi.org/10.1109/access.2019.2941287

Han, S., Mannan, N., Stein, D. C., Pattipati, K. R., & Bollas, G. M. (2021). Classification and regression models of audio and vibration signals for machine state monitoring in precision machining systems. *Journal of Manufacturing Systems*, 61, 45-53. https://doi.org/https://doi.org/10.1016/j.jmsy.2021.08.004

Hatefi, S., & Abou-El-Hossein, K. (2020). Review of single-point diamond turning process in terms of ultra-precision optical surface roughness. *The International Journal of Advanced Manufacturing Technology*, 106, 2167-2187. https://doi.org/https://doi.org/10.1007/s00170-019-04700-3

He, C., & Zong, W. (2019). Influencing factors and theoretical models for the surface topography in diamond turning process: A review. *Micromachines*, 10(5), 288. https://doi.org/https://doi.org/10.3390/mi10050288

He, C., Zong, W., & Zhang, J. (2018). Influencing factors and theoretical modeling methods of surface roughness in turning process: State-of-the-art. *International Journal of Machine Tools and Manufacture*, 129, 15-26. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2018.02.001

He, K., Xu, Q., & Jia, M. (2015). Modeling and predicting surface roughness in hard turning using a Bayesian inference-based HMM-SVM model. *IEEE Transactions on Automation Science and Engineering*, 12(3), 1092-1103. https://doi.org/https://doi.org/10.1109/tase.2014.2369478

Hegab, H., Hassan, M., Rawat, S., Sadek, A., & Attia, H. (2020). A smart tool wear prediction model in drilling of woven composites. *The International Journal of Advanced Manufacturing Technology*, 110(11), 2881-2892. https://doi.org/https://doi.org/10.1007/s00170-020-06049-4

Hessainia, Z., Belbah, A., Yallese, M. A., Mabrouki, T., & Rigal, J.-F. (2013). On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations. *Measurement*, 46(5), 1671-1681. https://doi.org/https://doi.org/10.1016/j.measurement.2012.12.016

Hsieh, W.-H., Lu, M.-C., & Chiou, S.-J. (2012). Application of backpropagation neural network for spindle vibration-based tool wear monitoring in micro-milling. *The International Journal of Advanced Manufacturing Technology*, 61(1), 53-61. https://doi.org/https://doi.org/10.1007/s00170-011-3703-x

Huang, P. B., Ma, C.-C., & Kuo, C.-H. (2015). A PNN self-learning tool breakage detection system in end milling operations. *Applied Soft Computing*, 37, 114-124.

Huang, Z., Zhu, J., Lei, J., Li, X., & Tian, F. (2021). Tool wear monitoring with vibration signals based on short-time fourier transform and deep convolutional neural network in milling. *Mathematical Problems in Engineering*, 2021. https://doi.org/https://doi.org/10.1155/2021/9976939

Iliyas, M., Yusof, Y., Daud, M. E., Latiff, K., Abdul Kadir, A. Z., & Saif, Y. (2020). Machine monitoring system: a decade in review. *The International Journal of Advanced Manufacturing Technology*, 108(11), 3645-3659. https://doi.org/https://doi.org/10.1007/s00170-020-05620-3

Iso, E. (1997). 4287–Geometrical product specifications (GPS)–Surface texture: profile method–terms, definitions and surface texture parameters. *International Organization for Standardization: Geneva, Switzerland*. https://doi.org/https://doi.org/10.3403/01161286

Jaini, S. N. B., Lee, D., Lee, S., Kim, M., & Kwon, Y. (2021). Tool monitoring of end milling based on gap sensor and machine learning. *Journal of Ambient*

Intelligence and Humanized Computing, 12(12), 10615-10627. https://doi.org/https://doi.org/10.1007/s12652-020-02875-2

Jamil, N., & Yusoff, A. (2018). Kurtosis quantification of different minimal quantity lubrication effects in machining cast iron with coated and uncoated tool. Proceedings of Asia International Conference on Tribology 2018.

Jáuregui, J. C., Reséndiz, J. R., Thenozhi, S., Szalay, T., Jacsó, Á., & Takács, M. (2018). Frequency and time-frequency analysis of cutting force and vibration signals for tool condition monitoring. *IEEE access*, 6, 6400-6410. https://doi.org/https://doi.org/10.1109/access.2018.2797003

Jeon, B., Yoon, J.-S., Um, J., & Suh, S.-H. (2020). The architecture development of Industry 4.0 compliant smart machine tool system (SMTS). *Journal of Intelligent Manufacturing*, 31(8), 1837-1859. https://doi.org/https://doi.org/10.1007/s10845-020-01539-4

Ji, X., Li, B., Zhang, X., & Liang, S. Y. (2014). The effects of minimum quantity lubrication (MQL) on machining force, temperature, and residual stress. *International journal of precision engineering and manufacturing*, 15(11), 2443-2451. https://doi.org/https://doi.org/10.1007/s12541-014-0612-6

Ji, Y., Wang, X., Liu, Z., Wang, H., Jiao, L., Wang, D., & Leng, S. (2018). Early milling chatter identification by improved empirical mode decomposition and multi-indicator synthetic evaluation. *Journal of Sound and Vibration*, 433, 138-159. https://doi.org/https://doi.org/10.1016/j.jsv.2018.07.019

Jiang, F., Li, J., Yan, L., Sun, J., & Zhang, S. (2010). Optimizing end-milling parameters for surface roughness under different cooling/lubrication conditions. *The International Journal of Advanced Manufacturing Technology*, 51(9), 841-851. https://doi.org/https://doi.org/10.1007/s00170-010-2680-9

Jimenez-Cortadi, A., Irigoien, I., Boto, F., Sierra, B., & Rodriguez, G. (2019). Predictive maintenance on the machining process and machine tool. *Applied Sciences*, 10(1), 224. https://doi.org/https://doi.org/10.3390/app10010224

Kalidass, S., & Palanisamy, P. (2014). Prediction of surface roughness for AISI 304 steel with solid carbide tools in end milling process using regression and ANN models. *Arabian Journal for Science and Engineering*, 39, 8065-8075. https://doi.org/https://doi.org/10.1007/s13369-014-1346-6

Kang, M., & Jameson, N. J. (2018). Machine learning: fundamentals. *Prognostics and Health Management of Electronics: Fundamentals, Machine Learning, and the Internet of Things*, 85-109. https://doi.org/https://doi.org/10.1002/9781119515326.ch4

Karandikar, J. (2019). Machine learning classification for tool life modeling using production shop-floor tool wear data. *Procedia Manufacturing*, 34, 446-454. https://doi.org/https://doi.org/10.1016/j.promfg.2019.06.192

Karandikar, J., McLeay, T., Turner, S., & Schmitz, T. (2015). Tool wear monitoring using naive Bayes classifiers. *The International Journal of Advanced Manufacturing Technology*, 77(9), 1613-1626. https://doi.org/https://doi.org/10.1007/s00170-014-6560-6

Karim, Z., Nuawi, M., Ghani, J., & Said, A. (2016). Preliminary Study on Machining Condition Monitoring System Using 3-Channel Force Sensor Analyzed by I-kaz Multilevel Method. *International Journal on Advanced Science, Engineering and Information Technology*, 6(4), 508-511. https://doi.org/https://doi.org/10.18517/ijaseit.6.4.896

Karkalos, N. E., Karmiris-Obratański, P., Kurpiel, S., Zagórski, K., & Markopoulos, A. P. (2021). Investigation on the surface quality obtained during trochoidal milling of 6082 aluminum alloy. *Machines*, 9(4), 75. https://doi.org/https://doi.org/10.3390/machines9040075

Kechagias, J. D., Aslani, K.-E., Fountas, N. A., Vaxevanidis, N. M., & Manolakos, D. E. (2020). A comparative investigation of Taguchi and full factorial design for machinability prediction in turning of a titanium alloy. *Measurement*, 151, 107213. https://doi.org/https://doi.org/10.1016/j.measurement.2019.107213

Khan, S., & Yairi, T. (2018). A review on the application of deep learning in system health management. *Mechanical systems and signal processing*, 107, 241-265. https://doi.org/https://doi.org/10.1016/j.ymssp.2017.11.024

Kim, D.-H., Kim, T. J., Wang, X., Kim, M., Quan, Y.-J., Oh, J. W., Min, S.-H., Kim, H., Bhandari, B., & Yang, I. (2018). Smart machining process using machine learning: A review and perspective on machining industry. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 5(4), 555-568. https://doi.org/https://doi.org/10.1007/s40684-018-0057-y

Kirby, E. D., & Chen, J. C. (2007). Development of a fuzzy-nets-based surface roughness prediction system in turning operations. *Computers & Industrial*

Engineering, 53(1), 30-42. https://doi.org/https://doi.org/10.1016/j.cie.2006.06.018

Kong, D., Chen, Y., & Li, N. (2018). Gaussian process regression for tool wear prediction. *Mechanical systems and signal processing*, 104, 556-574. https://doi.org/https://doi.org/10.1016/j.ymssp.2017.11.021

Kong, D., Chen, Y., Li, N., Duan, C., Lu, L., & Chen, D. (2019a). Relevance vector machine for tool wear prediction. *Mechanical systems and signal processing*, 127, 573-594. https://doi.org/https://doi.org/10.1016/j.ymssp.2019.03.023

Kong, D., Chen, Y., Li, N., Duan, C., Lu, L., & Chen, D. (2019b). Tool wear estimation in end milling of titanium alloy using NPE and a novel WOA-SVM model. *IEEE Transactions on Instrumentation and Measurement*, 69(7), 5219-5232. https://doi.org/https://doi.org/10.1109/tim.2019.2952476

Kong, D., Zhu, J., Duan, C., Lu, L., & Chen, D. (2021). Surface roughness prediction using kernel locality preserving projection and Bayesian linear regression. *Mechanical systems and signal processing*, 152, 107474. https://doi.org/https://doi.org/10.1016/j.ymssp.2020.107474

Kopczewska, K. (2020). *Applied spatial statistics and econometrics: data analysis in R*. Routledge. https://doi.org/https://doi.org/10.4324/9781003033219-5

Kothuru, A., Nooka, S. P., & Liu, R. (2018). Application of audible sound signals for tool wear monitoring using machine learning techniques in end milling. *The International Journal of Advanced Manufacturing Technology*, 95(9), 3797-3808. https://doi.org/https://doi.org/10.1007/s00170-017-1460-1

Krishnakumar, P., Rameshkumar, K., & Ramachandran, K. (2018). Machine learning based tool condition classification using acoustic emission and vibration data in high speed milling process using wavelet features. *Intelligent Decision Technologies*, 12(2), 265-282. https://doi.org/https://doi.org/10.3233/idt-180332

Krishnan, B. R. (2020). Review of surface roughness prediction in machining process by using various parameters. *International Journal of Recent Trends in Engineering & Research (IJRTER)*, 6(1), 7-12. https://doi.org/https://doi.org/10.23883/ijrter.2020.6002.vulm3

Kryzhanivskyy, V., M'Saoubi, R., Bhallamudi, M., & Cekal, M. (2022). Machine Learning based Approach for the Prediction of Surface Integrity in Machining.

Procedia Cirp, 108, 537-542. https://doi.org/https://doi.org/10.1016/j.procir.2022.03.084

Kuljanic, E., Totis, G., & Sortino, M. (2009). Development of an intelligent multisensor chatter detection system in milling. *Mechanical systems and signal processing*, 23(5), 1704-1718. https://doi.org/https://doi.org/10.1016/j.ymssp.2009.01.003

Kumar, A. S., Deb, S., & Paul, S. (2018). A study on micro-milling of aluminium 6061 and copper with respect to cutting forces, surface roughness and burr formation. International Manufacturing Science and Engineering Conference.

Kumar, G., Kumar, M., & Tomer, A. (2021). Optimization of end milling machining parameters of SS 304 by Taguchi technique. In *Recent Advances in Mechanical Engineering* (pp. 683-689). Springer. https://doi.org/https://doi.org/10.1007/978-981-15-8704-7_84

Kumar, S. L. (2019). Measurement and uncertainty analysis of surface roughness and material removal rate in micro turning operation and process parameters optimization. *Measurement*, 140, 538-547. https://doi.org/https://doi.org/10.1016/j.measurement.2019.04.029

Kuntoğlu, M., Salur, E., Gupta, M. K., Sarıkaya, M., & Pimenov, D. Y. (2021). A state-of-the-art review on sensors and signal processing systems in mechanical machining processes. *The International Journal of Advanced Manufacturing Technology*, 116(9), 2711-2735. https://doi.org/https://doi.org/10.1007/s00170-021-07425-4

La Fé-Perdomo, I., Ramos-Grez, J. A., Jeria, I., Guerra, C., & Barrionuevo, G. O. (2022). Comparative analysis and experimental validation of statistical and machine learning-based regressors for modeling the surface roughness and mechanical properties of 316L stainless steel specimens produced by selective laser melting. *Journal of manufacturing processes*, 80, 666-682. https://doi.org/https://doi.org/10.1016/j.jmapro.2022.06.021

Lamraoui, M., El Badaoui, M., & Guillet, F. (2015). Chatter detection in CNC milling processes based on Wiener-SVM approach and using only motor current signals. In *Vibration engineering and technology of machinery* (pp. 567-578). Springer. https://doi.org/https://doi.org/10.1007/978-3-319-09918-7_50

Lamraoui, M., Thomas, M., & El Badaoui, M. (2014). Cyclostationarity approach for monitoring chatter and tool wear in high speed milling. *Mechanical systems and* *signal processing*, 44(1-2), 177-198. https://doi.org/https://doi.org/10.1016/j.ymssp.2013.05.001

Lauro, C., Brandão, L., Baldo, D., Reis, R., & Davim, J. (2014). Monitoring and processing signal applied in machining processes–A review. *Measurement*, 58, 73-86. https://doi.org/https://doi.org/10.1016/j.measurement.2014.08.035

Leal-Muñoz, E., Diez, E., Perez, H., & Vizan, A. (2018). Accuracy of a new online method for measuring machining parameters in milling. *Measurement*, 128, 170-179. https://doi.org/https://doi.org/10.1016/j.measurement.2018.06.018

Lee, D.-E., Hwang, I., Valente, C. M., Oliveira, J., & Dornfeld, D. A. (2006). Precision manufacturing process monitoring with acoustic emission. In *Condition monitoring and control for intelligent manufacturing* (pp. 33-54). Springer. https://doi.org/https://doi.org/10.1007/1-84628-269-1_2

Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manufacturing letters*, 18, 20-23. https://doi.org/https://doi.org/10.1016/j.mfglet.2018.09.002

Lee, S. (2010). Tool condition monitoring system in turning operation utilizing wavelet signal processing and multi-learning ANNs algorithm methodology. *Int J Eng Res Innov*, 49.

Li, L., Wong, H. C., & Lee, R. B. (2020). Evaluation of a Novel Nanodroplet Cutting Fluid for Diamond Turning of Optical Polymers. *Polymers*, 12(10), 2213. https://doi.org/https://doi.org/10.3390/polym12102213

Li, P., Zhai, Y., Huang, S., Wang, Q., Fu, W., & Yang, H. (2017). Investigation of the contact performance of machined surface morphology. *Tribology International*, 107, 125-134. https://doi.org/https://doi.org/10.1016/j.triboint.2016.07.007

Li, X., Liu, X., Yue, C., Liang, S. Y., & Wang, L. (2022). Systematic review on tool breakage monitoring techniques in machining operations. *International Journal of Machine Tools and Manufacture*, 103882. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2022.103882

Li, Z., Wang, G., & He, G. (2018a). Surface quality monitoring based on time-frequency features of acoustic emission signals in end milling Inconel-718. *The International Journal of Advanced Manufacturing Technology*, 96, 2725-2733. https://doi.org/https://doi.org/10.1007/s00170-018-1773-8

Li, Z., Wang, G., & He, G. (2018b). Surface quality monitoring based on time-frequency features of acoustic emission signals in end milling Inconel-718. *The International Journal of Advanced Manufacturing Technology*, 96(5), 2725-2733. https://doi.org/https://doi.org/10.1007/s00170-018-1773-8

Li, Z., Zhang, Z., Shi, J., & Wu, D. (2019). Prediction of surface roughness in extrusion-based additive manufacturing with machine learning. *Robotics and Computer-Integrated Manufacturing*, 57, 488-495. https://doi.org/https://doi.org/10.1016/j.rcim.2019.01.004

Lin, W.-J., Lo, S.-H., Young, H.-T., & Hung, C.-L. (2019). Evaluation of deep learning neural networks for surface roughness prediction using vibration signal analysis. *Applied Sciences*, 9(7), 1462. https://doi.org/https://doi.org/10.3390/app9071462

Lin, Y.-C., Wu, K.-D., Shih, W.-C., Hsu, P.-K., & Hung, J.-P. (2020). Prediction of surface roughness based on cutting parameters and machining vibration in end milling using regression method and artificial neural network. *Applied Sciences*, 10(11), 3941. https://doi.org/https://doi.org/10.3390/app10113941

Liu, C., Gao, L., Wang, G., Xu, W., Jiang, X., & Yang, T. (2020). Online reconstruction of surface topography along the entire cutting path in peripheral milling. *International Journal of Mechanical Sciences*, 185, 105885. https://doi.org/https://doi.org/10.1016/j.ijmecsci.2020.105885

Liu, C., Wang, G., & Li, Z. (2015). Incremental learning for online tool condition monitoring using Ellipsoid ARTMAP network model. *Applied Soft Computing*, 35, 186-198. https://doi.org/https://doi.org/10.1016/j.asoc.2015.06.023

Liu, Z., Ai, X., Zhang, H., Wang, Z., & Wan, Y. (2002). Wear patterns and mechanisms of cutting tools in high-speed face milling. *Journal of Materials Processing Technology*, 129(1-3), 222-226. https://doi.org/https://doi.org/10.1016/s0924-0136(02)00605-2

Lu, J., Liao, X., Li, S., Ouyang, H., Chen, K., & Huang, B. (2019). An effective ABC-SVM approach for surface roughness prediction in manufacturing processes. *Complexity*, 2019.

Lu, J., Zhang, Z., Yuan, X., Ma, J., Hu, S., Xue, B., & Liao, X. (2020). Effect of machining parameters on surface roughness for compacted graphite cast iron by analyzing covariance function of Gaussian process regression. *Measurement*, 157, 107578. https://doi.org/https://doi.org/10.1016/j.measurement.2020.107578

Lu, Z., Wang, M., & Dai, W. (2020). A condition monitoring approach for machining process based on control chart pattern recognition with dynamically-sized observation windows. *Computers & Industrial Engineering*, 142, 106360. https://doi.org/https://doi.org/10.1016/j.cie.2020.106360

Ma, K., Wang, G., Yang, K., Hu, M., & Li, J. (2022). Tool wear monitoring for cavity milling based on vibration singularity analysis and stacked LSTM. *The International Journal of Advanced Manufacturing Technology*, 120(5-6), 4023-4039. https://doi.org/https://doi.org/10.1007/s00170-022-08861-6

Madhusudana, C., Gangadhar, N., Kumar, H., & Narendranath, S. (2018). Use of discrete wavelet features and support vector machine for fault diagnosis of face milling tool. *Structural Durability & Health Monitoring*, 12(2), 111. https://doi.org/https://doi.org/10.1016/j.matpr.2018.02.178

Madhusudana, C., Kumar, H., & Narendranath, S. (2016). Condition monitoring of face milling tool using K-star algorithm and histogram features of vibration signal. *Engineering science and technology, an international journal*, 19(3), 1543-1551. https://doi.org/https://doi.org/10.1016/j.jestch.2016.05.009

Madhusudana, C., Kumar, H., & Narendranath, S. (2017). Face milling tool condition monitoring using sound signal. *International Journal of System Assurance Engineering and Management*, 8(2), 1643-1653.

Mahesh, G., Muthu, S., & Devadasan, S. (2015). Prediction of surface roughness of end milling operation using genetic algorithm. *The International Journal of Advanced Manufacturing Technology*, 77, 369-381. https://doi.org/https://doi.org/10.1007/s00170-014-6425-z

Manjunath, K., Tewary, S., Khatri, N., & Cheng, K. (2021). Monitoring and Predicting the Surface Generation and Surface Roughness in Ultraprecision Machining: A Critical Review. *Machines*, 9(12), 369. https://doi.org/https://doi.org/10.3390/machines9120369

Marinescu, I., & Axinte, D. A. (2008). A critical analysis of effectiveness of acoustic emission signals to detect tool and workpiece malfunctions in milling operations. *International Journal of Machine Tools and Manufacture*, 48(10), 1148-1160. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2008.01.011

Mia, M., Gupta, M. K., Singh, G., Królczyk, G., & Pimenov, D. Y. (2018). An approach to cleaner production for machining hardened steel using different cooling-lubrication conditions. *Journal of Cleaner Production*, 187, 1069-1081. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.03.279

Michalik, P., Zajac, J., Hatala, M., Mital, D., & Nowakovski, Ł. (2019). Evaluation of the Transverse Roughness of the Outer and Inner Surfaces of the Thin-Walled Components Produced by Milling. In *Smart Technology Trends in Industrial and Business Management* (pp. 353-364). Springer.

Miller, E., Borysenko, V., Heusinger, M., Niedner, N., Engelmann, B., & Schmitt, J. (2021). Enhanced Changeover Detection in Industry 4.0 Environments with Machine Learning. *Sensors*, 21(17), 5896. https://doi.org/https://doi.org/10.3390/s21175896

Mishra, V., Khan, G. S., Chattopadhyay, K., Nand, K., & Sarepaka, R. V. (2014). Effects of tool overhang on selection of machining parameters and surface finish during diamond turning. *Measurement*, 55, 353-361. https://doi.org/https://doi.org/10.1016/j.measurement.2014.05.019

Mohanraj, T., Shankar, S., Rajasekar, R., Sakthivel, N., & Pramanik, A. (2020). Tool condition monitoring techniques in milling process—a review. *Journal of Materials Research and Technology*, 9(1), 1032-1042. https://doi.org/https://doi.org/10.1016/j.jmrt.2019.10.031

Mohanraj, T., & Shanmugam, A. (2021a). Prediction of tool wear in milling of Inconel 625 using and integrated kurtosis-based algorithm with vibration signals. Journal of Physics: Conference Series,

Mohanraj, T., Yerchuru, J., Krishnan, H., Aravind, R. N., & Yameni, R. (2021b). Development of tool condition monitoring system in end milling process using wavelet features and Hoelder’s exponent with machine learning algorithms. *Measurement*, 173, 108671. https://doi.org/https://doi.org/10.1016/j.measurement.2020.108671

Mu, X., Sun, Q., Xu, J., Chai, Z., Sun, W., & Zhao, B. (2019). Feasibility analysis of the replacement of the actual machining surface by a 3D numerical simulation rough surface. *International Journal of Mechanical Sciences*, 150, 135-144.

Muñoz-Escalona, P., & Maropoulos, P. G. (2010). Artificial neural networks for surface roughness prediction when face milling Al 7075-T7351. *Journal of Materials Engineering and Performance*, 19, 185-193. https://doi.org/https://doi.org/10.1007/s11665-009-9452-4

Nam, S., Eren, B., Hayasaka, T., Sencer, B., & Shamoto, E. (2021). Analytical prediction of chatter stability for modulated turning. *International Journal of Machine Tools and Manufacture*, 165, 103739. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2021.103739

Nasir, V., & Sassani, F. (2021). A review on deep learning in machining and tool monitoring: methods, opportunities, and challenges. *The International Journal of Advanced Manufacturing Technology*, 115(9), 2683-2709. https://doi.org/https://doi.org/10.1007/s00170-021-07325-7

Natarajan, C., Muthu, S., & Karuppuswamy, P. (2011). Prediction and analysis of surface roughness characteristics of a non-ferrous material using ANN in CNC turning. *The International Journal of Advanced Manufacturing Technology*, 57(9), 1043-1051. https://doi.org/https://doi.org/10.1007/s00170-011-3343-1

Nath, C. (2020). Integrated tool condition monitoring systems and their applications: a comprehensive review. *Procedia Manufacturing*, 48, 852-863. https://doi.org/https://doi.org/10.1016/j.promfg.2020.05.123

Ngatiman, N. A., Nuawi, M. Z., Putra, A., Qamber, I. S., Sutikno, T., & Jopri, M. H. (2021). Spark plug failure detection using Z-freq and machine learning. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, 19(6), 2020-2029. https://doi.org/https://doi.org/10.12928/telkomnika.v19i6.22027

Nguyen, D., Yin, S., Tang, Q., & Son, P. X. (2019). Online monitoring of surface roughness and grinding wheel wear when grinding Ti-6Al-4V titanium alloy using ANFIS-GPR hybrid algorithm and Taguchi analysis. *Precision Engineering*, 55, 275-292.

Niemczewska-Wójcik, M., & Piekoszewski, W. (2017). The surface texture and its influence on the tribological characteristics of a friction pair: Metal-polymer. *Archives of civil and mechanical engineering*, 17(2), 344-353. https://doi.org/https://doi.org/10.1016/j.acme.2016.10.011

Ntemi, M., Paraschos, S., Karakostas, A., Gialampoukidis, I., Vrochidis, S., & Kompatsiaris, I. (2022). Infrastructure monitoring and quality diagnosis in CNC machining: A review. *CIRP Journal of Manufacturing Science and Technology*, 38, 631-649. https://doi.org/https://doi.org/10.1016/j.cirpj.2022.06.001

Nuawi, M., Lamin, F., Ismail, A., Abdullah, S., & Wahid, Z. (2009). A Novel Machining Signal Filtering Technique: Z-notch Filter. *International Journal of Electronics and Communication Engineering*, 3(6), 1252-1257.

Nuawi, M., Lamin, F., Nor, M., Jamaluddin, N., & Abdullah, S. (2008). The noise cancelling technique using Z-filter on machining signal. Proceedings of the 7th WSEAS International Conference on Signal Processing, Robotics and Automation.

Nuawi, M., Nor, M., Lamin, F., Abdullah, S., & Nizwan, C. (2007). Tool life monitoring using coefficient of integrated Kurtosis-based algorithm for Z-filter (I-kaz) technique. Proceedings of the 7th WSEAS international conference on Wavelet analysis & multirate systems.

Olejárová, Š., Dobránsky, J., Svetlík, J., & Pituk, M. (2017). Measurements and evaluation of measurements of vibrations in steel milling process. *Measurement*, 106, 18-25. https://doi.org/https://doi.org/10.1016/j.measurement.2017.04.023

Orra, K., & Choudhury, S. K. (2016). Development of flank wear model of cutting tool by using adaptive feedback linear control system on machining AISI D2 steel and AISI 4340 steel. *Mechanical systems and signal processing*, 81, 475-492. https://doi.org/https://doi.org/10.1016/j.ymssp.2016.03.011

Padzi, M., Abdullah, S., Nuawi, M., Beden, S., & Nopiah, Z. (2014). Evaluating ultrasound signals of carbon steel fatigue testing using signal analysis approaches. *Journal of Central South University*, 21, 232-241. https://doi.org/https://doi.org/10.1007/s11771-014-1934-3

Pahuja, R., & Ramulu, M. (2019). Surface quality monitoring in abrasive water jet machining of Ti6Al4V–CFRP stacks through wavelet packet analysis of acoustic emission signals. *The International Journal of Advanced Manufacturing Technology*, 104, 4091-4104. https://doi.org/https://doi.org/10.1007/s00170-019-04177-0

Palpandian, P., Prabhu, R. V., & Babu, S. S. (2013). Stability Lobe Diagram for High Speed Machining Processes: Comparison of Experimental and Analytical Methods–A Review. *International Journal of Innovative Research in Science, Engineering and Technology*, 2(3), 747-752.

Papandrea, P. J., Frigieri, E. P., Maia, P. R., Oliveira, L. G., & Paiva, A. P. (2020). Surface roughness diagnosis in hard turning using acoustic signals and support vector machine: A PCA-based approach. *Applied Acoustics*, 159, 107102. https://doi.org/https://doi.org/10.1016/j.apacoust.2019.107102

Patange, A., Jegadeeshwaran, R., & Dhobale, N. (2019). Milling cutter condition monitoring using machine learning approach. IOP Conference Series: Materials Science and Engineering.

Patel, V. D., & Gandhi, A. H. (2019). Analysis and modeling of surface roughness based on cutting parameters and tool nose radius in turning of AISI D2 steel using CBN tool. *Measurement*, 138, 34-38. https://doi.org/https://doi.org/10.1016/j.measurement.2019.01.077

Pham, T.-H., Nguyen, D.-T., Banh, T.-L., & Tong, V.-C. (2020). Experimental study on the chip morphology, tool–chip contact length, workpiece vibration, and surface roughness during high-speed face milling of A6061 aluminum alloy. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 234(3), 610-620. https://doi.org/https://doi.org/10.1177/0954405419863221

Pimenov, D. Y., Bustillo, A., & Mikolajczyk, T. (2018b). Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. *Journal of Intelligent Manufacturing*, 29(5), 1045-1061. https://doi.org/https://doi.org/10.1007/s10845-017-1381-8

Pimenov, D. Y., Bustillo, A., Wojciechowski, S., Sharma, V. S., Gupta, M. K., & Kuntoğlu, M. (2022). Artificial intelligence systems for tool condition monitoring in machining: Analysis and critical review. *Journal of Intelligent Manufacturing*, 1-43. https://doi.org/https://doi.org/10.1007/s10845-022-01923-2

Plaza, E. G., López, P. N., & González, E. B. (2019). Efficiency of vibration signal feature extraction for surface finish monitoring in CNC machining. *Journal of manufacturing processes*, 44, 145-157. https://doi.org/https://doi.org/10.1016/j.jmapro.2019.05.046

Prabhakar, D., Kumar, M. S., & Krishna, A. G. (2020). A Novel Hybrid Transform approach with integration of Fast Fourier, Discrete Wavelet and Discrete Shearlet Transforms for prediction of surface roughness on machined surfaces. *Measurement*, 164, 108011. https://doi.org/https://doi.org/10.1016/j.measurement.2020.108011

Premachandran, V., & Kakarala, R. (2010). Measuring the effectiveness of bad pixel detection algorithms using the ROC curve. *IEEE Transactions on Consumer Electronics*, 56(4), 2511-2519. https://doi.org/https://doi.org/10.1109/tce.2010.5681135

Rafal, R., Pawel, L., Krzysztof, K., Bogdan, K., & Jerzy, W. (2015). Chatter identification methods on the basis of time series measured during titanium superalloy milling. *International Journal of Mechanical Sciences*, 99, 196-207. https://doi.org/https://doi.org/10.1016/j.ijmecsci.2015.05.013

Ramesh, R., Ravi Kumar, K., & Anil, G. (2009). Automated intelligent manufacturing system for surface finish control in CNC milling using support vector machines. *The International Journal of Advanced Manufacturing Technology*, 42, 1103-1117. https://doi.org/https://doi.org/10.1007/s00170-008-1676-1

Ranga, C., & Chandel, A. K. (2015). Advanced tool based condition monitoring of induction machines by using LabVIEW—A review. 2015 IEEE UP Section Conference on electrical computer and electronics (UPCON).

Rao, K. V., Murthy, B., & Rao, N. M. (2013). Cutting tool condition monitoring by analyzing surface roughness, work piece vibration and volume of metal removed for AISI 1040 steel in boring. *Measurement*, 46(10), 4075-4084. https://doi.org/https://doi.org/10.1016/j.measurement.2013.07.021

Rao, K. V., Murthy, B., & Rao, N. M. (2014). Prediction of cutting tool wear, surface roughness and vibration of work piece in boring of AISI 316 steel with artificial neural network. *Measurement*, 51, 63-70. https://doi.org/https://doi.org/10.1016/j.measurement.2014.01.024

Ratnam, C., Vikram, K. A., Ben, B., & Murthy, B. (2016). Process monitoring and effects of process parameters on responses in turn-milling operations based on SN ratio and ANOVA. *Measurement*, 94, 221-232. https://doi.org/https://doi.org/10.1016/j.measurement.2016.07.090

Reddy, T., & Reddy, C. (2010). Real Time Monitoring of Surface Roughness by Acoustic Emissions in CNC Turning. *Journal of Engineering Science & Technology Review*, 3(1). https://doi.org/https://doi.org/10.25103/jestr.031.19

Ribeiro, J., Lopes, H., Queijo, L., & Figueiredo, D. (2017). Optimization of cutting parameters to minimize the surface roughness in the end milling process using the Taguchi method. *Periodica Polytechnica Mechanical Engineering*, 61(1), 30-35. https://doi.org/https://doi.org/10.3311/ppme.9114

Ritter, D. J. (2001). *LabVIEW GUI: essential techniques*. McGraw-Hill Professional.

Rizal, M., Ghani, J. A., Nuawi, M. Z., & Che Haron, C. H. (2014a). I-kazTM-Based Analysis of Cutting Force Signals for Tool Condition Monitoring in Turning Process. Applied Mechanics and Materials.

Rizal, M., Ghani, J. A., Nuawi, M. Z., & Haron, C. H. C. (2013). The application of I-kazTM-based method for tool wear monitoring using cutting force signal. *Procedia engineering*, 68, 461-468. https://doi.org/https://doi.org/10.1016/j.proeng.2013.12.207

Rizal, M., Ghani, J. A., Nuawi, M. Z., & Haron, C. H. C. (2014b). A comparative study of I-kaz based signal analysis techniques: application to detect tool wear during turning process. *Jurnal Teknologi*, 66(3). https://doi.org/https://doi.org/10.11113/jt.v66.2704

Rizal, M., Ghani, J. A., Nuawi, M. Z., & Haron, C. H. C. (2018). An embedded multi-sensor system on the rotating dynamometer for real-time condition monitoring in milling. *The International Journal of Advanced Manufacturing Technology*, 95(1), 811-823. https://doi.org/https://doi.org/10.1007/s00170-017-1251-8

Rodríguez, J. J., Quintana, G., Bustillo, A., & Ciurana, J. (2017). A decision-making tool based on decision trees for roughness prediction in face milling. *International Journal of Computer Integrated Manufacturing*, 30(9), 943-957. https://doi.org/https://doi.org/10.1080/0951192x.2016.1247991

Roth, J. T., Djurdjanovic, D., Yang, X., Mears, L., & Kurfess, T. (2010). Quality and inspection of machining operations: tool condition monitoring. *Journal of Manufacturing Science and Engineering*, 132(4). https://doi.org/https://doi.org/10.1115/1.4002022

Roy, R., Stark, R., Tracht, K., Takata, S., & Mori, M. (2016). Continuous maintenance and the future–Foundations and technological challenges. *CIRP annals*, 65(2), 667-688. https://doi.org/https://doi.org/10.1016/j.cirp.2016.06.006

Sakib, N., & Wuest, T. (2018). Challenges and opportunities of condition-based predictive maintenance: a review. *Procedia Cirp*, 78, 267-272. https://doi.org/https://doi.org/10.1016/j.procir.2018.08.318

Sakthivel, N., Nair, B. B., Elangovan, M., Sugumaran, V., & Saravanmurugan, S. (2014). Comparison of dimensionality reduction techniques for the fault diagnosis of mono block centrifugal pump using vibration signals. *Engineering science and technology, an international journal*, 17(1), 30-38. https://doi.org/https://doi.org/10.1016/j.jestch.2014.02.005

Sakthivel, R. K., Nagasubramanian, G., Al-Turjman, F., & Sankayya, M. (2022). Core-level cybersecurity assurance using cloud-based adaptive machine learning techniques for manufacturing industry. *Transactions on Emerging Telecommunications Technologies*, 33(4), e3947. https://doi.org/https://doi.org/10.1002/ett.3947

Salonitis, K., & Kolios, A. (2014). Reliability assessment of cutting tool life based on surrogate approximation methods. *The International Journal of Advanced Manufacturing Technology*, 71(5), 1197-1208. https://doi.org/https://doi.org/10.1007/s00170-013-5560-2

Samin, R., Nuawi, M., Haris, S., & Ghani, J. (2019). Stability analysis of regenerative vibration in turning operation using I-kaz3DTM signal processing approach. Journal of Physics: Conference Series.

Samin, R., Nuawi, M., Haris, S., & Ghani, J. (2020). Statistical investigation for cutting force and surface roughness of S45C steel in turning processes by I-kazTM method. Journal of Physics: Conference Series.

Sayyad, S., Kumar, S., Bongale, A., Kamat, P., Patil, S., & Kotecha, K. (2021). Data-driven remaining useful life estimation for milling process: sensors, algorithms, datasets, and future directions. *IEEE access*, 9, 110255-110286. https://doi.org/https://doi.org/10.1109/access.2021.3101284

Scacco, F., Campagnolo, A., Franceschi, M., & Meneghetti, G. (2022). Strain-Controlled Fatigue Behavior of a Nodular Cast Iron in Real Off-Highway Axles: Effects of Casting Skin and Strain Ratio. *Metals*, 12(3), 426. https://doi.org/https://doi.org/10.3390/met12030426

Schmidt, B., & Wang, L. (2018). Predictive maintenance of machine tool linear axes: A case from manufacturing industry. *Procedia Manufacturing*, 17, 118-125. https://doi.org/https://doi.org/10.1016/j.promfg.2018.10.022

Schorr, S., Möller, M., Heib, J., & Bähre, D. (2020). Quality prediction of drilled and reamed bores based on torque measurements and the machine learning method of random forest. *Procedia Manufacturing*, 48, 894-901. https://doi.org/https://doi.org/10.1016/j.promfg.2020.05.127

Segreto, T., Simeone, A., & Teti, R. (2011). Principal Component Analysis of Multiple Sensor Signals for Tool Wear Identification during Composite Materials Machining. *10th AI Te. M-Enhancing the Science of Manufacturing, Naples, Italy*, 87.

Sehgal, A. K. (2018). Grey relational analysis coupled with principal component analysis to optimize the machining process of ductile iron. *Materials Today: Proceedings*, 5(1), 1518-1529. https://doi.org/https://doi.org/10.1016/j.matpr.2017.11.241

Sen, B., Mia, M., Krolczyk, G., Mandal, U. K., & Mondal, S. P. (2021). Eco-friendly cutting fluids in minimum quantity lubrication assisted machining: a review on the perception of sustainable manufacturing. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 8(1), 249-280. https://doi.org/https://doi.org/10.1007/s40684-019-00158-6

Sevilla-Camacho, P., Robles-Ocampo, J., Muñiz-Soria, J., & Lee-Orantes, F. (2015). Tool failure detection method for high-speed milling using vibration signal and reconfigurable bandpass digital filtering. *The International Journal of Advanced Manufacturing Technology*, 81(5), 1187-1194. https://doi.org/https://doi.org/10.1007/s00170-015-7302-0

Shankar, S., Mohanraj, T., & Rajasekar, R. (2019). Prediction of cutting tool wear during milling process using artificial intelligence techniques. *International Journal of Computer Integrated Manufacturing*, 32(2), 174-182. https://doi.org/https://doi.org/10.1080/0951192x.2018.1550681

Shi, F., Cao, H., Zhang, X., & Chen, X. (2020). A reinforced k-nearest neighbors method with application to chatter identification in high-speed milling. *IEEE Transactions on Industrial Electronics*, 67(12), 10844-10855. https://doi.org/https://doi.org/10.1109/tie.2019.2962465

Shokrani, A., Al-Samarrai, I., & Newman, S. T. (2019). Hybrid cryogenic MQL for improving tool life in machining of Ti-6Al-4V titanium alloy. *Journal of manufacturing processes*, 43, 229-243. https://doi.org/https://doi.org/10.1016/j.jmapro.2019.05.006

Shurrab, S., Almshnanah, A., & Duwairi, R. (2021). Tool wear prediction in computer numerical control milling operations via machine learning. 2021 12th International Conference on Information and Communication Systems (ICICS).

Siddhpura, A., & Paurobally, R. (2013). A review of flank wear prediction methods for tool condition monitoring in a turning process. *The International Journal of Advanced Manufacturing Technology*, 65(1), 371-393. https://doi.org/https://doi.org/10.1007/s00170-012-4177-1

Simon, G. D., & Deivanathan, R. (2019). Early detection of drilling tool wear by vibration data acquisition and classification. *Manufacturing letters*, 21, 60-65. https://doi.org/https://doi.org/10.1016/j.mfglet.2019.08.006

Singh, B., & Misra, J. (2019). Surface finish analysis of wire electric discharge machined specimens by RSM and ANN modeling. *Measurement*, 137, 225-237. https://doi.org/https://doi.org/10.1016/j.measurement.2019.01.044

Smola, A. J., & Schölkopf, B. (2004). A tutorial on support vector regression. *Statistics and computing*, 14(3), 199-222. https://doi.org/https://doi.org/10.1023/b:stco.0000035301.49549.88

Sofuoğlu, M. A., Çakır, F. H., Kuşhan, M. C., & Orak, S. (2019). Optimization of different non-traditional turning processes using soft computing methods. *Soft Computing*, 23, 5213-5231. https://doi.org/https://doi.org/10.1007/s00500-018-3471-8

Srinivasa Rohit, V., Venu Gopal, A., & Rama Krishna, L. (2020). A new approach in establishing stable machining parameters using frame statistics and kurtosis. In *Advances in Applied Mechanical Engineering* (pp. 1159-1167). Springer. https://doi.org/https://doi.org/10.1007/978-981-15-1201-8_122

Stachurski, W., Sawicki, J., Januszewicz, B., & Rosik, R. (2022). The Influence of the Depth of Grinding on the Condition of the Surface Layer of 20MnCr5 Steel Ground with the Minimum Quantity Lubrication (MQL) Method. *Materials*, 15(4), 1336. https://doi.org/https://doi.org/10.3390/ma15041336

Stewart, A. (2018). *Basic statistics and epidemiology: a practical guide*. CRC Press. https://doi.org/https://doi.org/10.1201/9781315383286

Sugihara, T., Kobayashi, R., & Enomoto, T. (2021). Direct observations of tribological behavior in cutting with textured cutting tools. *International Journal of Machine Tools and Manufacture*, 168, 103726. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2021.103726

Sun, H., Zhang, J., Mo, R., & Zhang, X. (2020). In-process tool condition forecasting based on a deep learning method. *Robotics and Computer-Integrated Manufacturing*, 64, 101924. https://doi.org/https://doi.org/10.1016/j.rcim.2019.101924

Suparmaniam, M. V., & Yusoff, A. R. (2019). Suppression of Chatter in High Speed Milling Machine Using Spindle Speed Variation Method with Acoustic Feedback PID Controller. *MEKATRONIKA*, 1(1), 21-26. https://doi.org/https://doi.org/10.15282/mekatronika.v1i1.156

Tahir, M., Ghani, J., Nuawi, M., Rizal, M., & Haron, C. (2015). Flank wear and I-kaz 3D correlation in ball end milling process of Inconel 718. *Journal of Mechanical Engineering and Sciences*, 9, 1595-1603. https://doi.org/https://doi.org/10.15282/jmes.9.2015.7.0155

Tai, B. L., Stephenson, D. A., Furness, R. J., & Shih, A. J. (2014). Minimum quantity lubrication (MQL) in automotive powertrain machining. *Procedia CIRP*, 14, 523-528.

Tamiloli, N., Venkatesan, J., Raja Raghu Vamsi Krishna, P., & Sampath Kumar, T. (2022). Time domain and frequency domain of coated milling inserts using FFT spectrum. *Materials and Manufacturing processes*, 1-11. https://doi.org/https://doi.org/10.1080/10426914.2022.2065012

Taufik, M., & Jain, P. K. (2022). Part surface quality improvement studies in fused deposition modelling process: A review. *Australian Journal of Mechanical Engineering*, 20(2), 527-551. https://doi.org/https://doi.org/10.1080/14484846.2020.1723342

Tepe, C., & Demir, M. C. (2021). The effects of the number of channels and gyroscopic data on the classification performance in EMG data acquired by Myo armband. *Journal of Computational Science*, 51, 101348. https://doi.org/https://doi.org/10.1016/j.jocs.2021.101348

Teti, R. (2015). Advanced IT methods of signal processing and decision making for zero defect manufacturing in machining. *Procedia Cirp*, 28, 3-15. https://doi.org/https://doi.org/10.1016/j.procir.2015.04.003

Tharwat, A. (2016). Principal component analysis-a tutorial. *International Journal of Applied Pattern Recognition*, 3(3), 197-240. https://doi.org/https://doi.org/10.1504/ijapr.2016.10000630

Thomazella, R., Lopes, W. N., Aguiar, P. R., Alexandre, F. A., Fiocchi, A. A., & Bianchi, E. C. (2019). Digital signal processing for self-vibration monitoring in grinding: A new approach based on the time-frequency analysis of vibration signals. *Measurement*, 145, 71-83. https://doi.org/https://doi.org/10.1016/j.measurement.2019.05.079

Tschätsch, H., & Reichelt, A. (2009). Cutting fluids (coolants and lubricants). In *Applied Machining Technology* (pp. 349-352). Springer.

Upadhyay, V., Jain, P., & Mehta, N. (2013). In-process prediction of surface roughness in turning of Ti–6Al–4V alloy using cutting parameters and vibration signals. *Measurement*, 46(1), 154-160. https://doi.org/https://doi.org/10.1016/j.measurement.2012.06.002

Vakharia, V., Sanghvi, J., & Thakker, H. (2022). Material Removal Rate and Surface Roughness Prediction in Turning and Milling Operations Using Taguchi Analysis, Support Vector Machine and Gaussian Process Regression. In *Advances in Mechanical and Materials Technology* (pp. 515-524). Springer. https://doi.org/https://doi.org/10.1007/978-981-16-2794-1_46

Vapnik, V. N. (1995). The Nature of Statistical Learning Theory. https://doi.org/https://doi.org/10.1007/978-1-4757-2440-0

Vapnik, V. N. (2000). Introduction: Four periods in the research of the learning problem. In *The nature of statistical learning theory* (pp. 1-15). Springer. https://doi.org/https://doi.org/10.1007/978-1-4757-3264-1_1

Vasiloni, A. M., & Drăgoi, M. V. (2014). Smart Adaptive CNC Machining-State of the Art. *Applied Mechanics and Materials*, 657, 859-863. https://doi.org/https://doi.org/10.4028/www.scientific.net/amm.657.859

Vichare, P., Nassehi, A., Kumar, S., & Newman, S. T. (2009). A Unified Manufacturing Resource Model for representing CNC machining systems. *Robotics and Computer-Integrated Manufacturing*, 25(6), 999-1007. https://doi.org/https://doi.org/10.1016/j.rcim.2009.04.014

Viera, M. A., Alexandre, F., Lopes, W., Aguiar, P. d., Silva, R. B. d., D'addona, D., Andreoli, A., & Bianchi, E. (2018). A contribution to the monitoring of ceramic surface quality using a low-cost piezoelectric transducer in the grinding operation. *Multidisciplinary Digital Publishing Institute Proceedings*, 4(1), 16. https://doi.org/https://doi.org/10.3390/ecsa-5-05733

Wan Mansor, W. N., Md Tahir, N. H., Abd Ghani, J., Che Haron, C. H., Nuawi, M. Z., & Rizal, M. (2017). Tool wear condition monitoring using slip ring and accelerometer system in milling AISI P20 tool steel. *Journal of Mechanical Engineering (JMechE)*(2), 63-72.

Wang, G., Yang, Y., Zhang, Y., & Xie, Q. (2014). Vibration sensor based tool condition monitoring using ν support vector machine and locality preserving projection. *Sensors and Actuators A: Physical*, 209, 24-32. https://doi.org/https://doi.org/10.1016/j.sna.2014.01.004

Wang, G. F., Xie, Q. L., & Zhang, Y. C. (2017). Tool condition monitoring system based on support vector machine and differential evolution optimization. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 231(5), 805-813. https://doi.org/https://doi.org/10.1177/0954405415619871

Wang, L., Pan, J., Shao, Y., Zeng, Q., & Ding, X. (2021). Two new kurtosis-based similarity evaluation indicators for grinding chatter diagnosis under non-stationary working conditions. *Measurement*, 176, 109215. https://doi.org/https://doi.org/10.1016/j.measurement.2021.109215

Wang, R., Song, Q., Liu, Z., Ma, H., Gupta, M. K., & Liu, Z. (2021). A novel unsupervised machine learning-based method for chatter detection in the milling of thin-walled parts. *Sensors*, 21(17), 5779. https://doi.org/https://doi.org/10.3390/s21175779

Wang, W.-K., Wan, M., Zhang, W.-H., & Yang, Y. (2022). Chatter detection methods in the machining processes: A review. *Journal of manufacturing processes*, 77, 240-259. https://doi.org/https://doi.org/10.1016/j.jmapro.2022.03.018

Wang, X., He, L., & Wang, P. (2020). Milling cutter breakage detection based on VMD. *J Vib Shock*, 39(16), 135.

Wang, X., Ying, T., & Tian, W. (2020). Spectrum Representation Based on STFT. 2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI).

Wang, Y., Zhang, M., Tang, X., Peng, F., & Yan, R. (2022). A kMap optimized VMD-SVM model for milling chatter detection with an industrial robot. *Journal of Intelligent Manufacturing*, 33(5), 1483-1502. https://doi.org/https://doi.org/10.1007/s10845-021-01736-9

Wong, S. Y., Chuah, J. H., & Yap, H. J. (2020). Technical data-driven tool condition monitoring challenges for CNC milling: a review. *The International Journal of Advanced Manufacturing Technology*, 107(11), 4837-4857. https://doi.org/https://doi.org/10.1007/s00170-020-05303-z

Wu, T., & Lei, K. (2019a). Correction to: Prediction of surface roughness in milling process using vibration signal analysis and artificial neural network. *The International Journal of Advanced Manufacturing Technology*, 102(1-4), 315-315.

Wu, T., & Lei, K. (2019b). Prediction of surface roughness in milling process using vibration signal analysis and artificial neural network. *The International Journal of Advanced Manufacturing Technology*, 102(1-4), 305-314. https://doi.org/https://doi.org/10.1007/s00170-018-3176-2

Wu, Z., & Huang, N. E. (2009). Ensemble empirical mode decomposition: a noise-assisted data analysis method. *Advances in adaptive data analysis*, 1(01), 1-41.

Wuyang, S., ZHANG, D., & Ming, L. (2021). Machining process monitoring and application: a review. *Journal of Advanced Manufacturing Science and Technology*, 1(2), 2021001-2021001-2021001-2021002. https://doi.org/https://doi.org/10.1016/j.cirpj.2013.07.001

Xiao, Z., Liao, X., Long, Z., & Li, M. (2017). Effect of cutting parameters on surface roughness using orthogonal array in hard turning of AISI 1045 steel with YT5 tool. *The International Journal of Advanced Manufacturing Technology*, 93(1), 273-282. https://doi.org/https://doi.org/10.1007/s00170-016-8933-5

Xu, G., Zhou, H., & Chen, J. (2018). CNC internal data based incremental cost-sensitive support vector machine method for tool breakage monitoring in end milling. *Engineering Applications of Artificial Intelligence*, 74, 90-103. https://doi.org/https://doi.org/10.1016/j.engappai.2018.05.007

Xu, L., Huang, C., Niu, J., Li, C., Wang, J., Liu, H., & Wang, X. (2021). An improved case-based reasoning method and its application to predict machining performance. *Soft Computing*, 25, 5683-5697. https://doi.org/https://doi.org/10.1007/s00500-020-05564-6

Xu, X., Feng, B., Huang, S., Luan, Z., Niu, C., Lin, J., & Hu, X. (2019). Capillary penetration mechanism and machining characteristics of lubricant droplets in electrostatic minimum quantity lubrication (EMQL) grinding. *Journal of* *manufacturing processes*, 45, 571-578. https://doi.org/https://doi.org/10.1016/j.jmapro.2019.07.036

Yadav, S., & Shukla, S. (2016). Analysis of k-fold cross-validation over hold-out validation on colossal datasets for quality classification. 2016 IEEE 6th International conference on advanced computing (IACC).

Yang, B., Guo, K., & Sun, J. (2022). Chatter Detection in Robotic Milling Using Entropy Features. *Applied Sciences*, 12(16), 8276. https://doi.org/https://doi.org/10.3390/app12168276

Yang, Y., Guo, Y., Huang, Z., Chen, N., Li, L., Jiang, Y., & He, N. (2019). Research on the milling tool wear and life prediction by establishing an integrated predictive model. *Measurement*, 145, 178-189. https://doi.org/https://doi.org/10.1016/j.measurement.2019.05.009

Yang, Y., Hao, B., Hao, X., Li, L., Chen, N., Xu, T., Aqib, K. M., & He, N. (2020). A novel tool (single-flute) condition monitoring method for end milling process based on intelligent processing of milling force data by machine learning algorithms. *International journal of precision engineering and manufacturing*, 21, 2159-2171. https://doi.org/https://doi.org/10.1007/s12541-020-00388-8

Yao, Z., Fan, C., Zhang, Z., Zhang, D., & Luo, M. (2021a). Position-varying surface roughness prediction method considering compensated acceleration in milling of thin-walled workpiece. *Frontiers of Mechanical Engineering*, 1-13.

Yao, Z., Fan, C., Zhang, Z., Zhang, D., & Luo, M. (2021b). Position-varying surface roughness prediction method considering compensated acceleration in milling of thin-walled workpiece. *Frontiers of Mechanical Engineering*, 16(4), 855-867. https://doi.org/https://doi.org/10.1007/s11465-021-0649-z

Yeganefar, A., Niknam, S. A., & Asadi, R. (2019). The use of support vector machine, neural network, and regression analysis to predict and optimize surface roughness and cutting forces in milling. *The International Journal of Advanced Manufacturing Technology*, 105, 951-965. https://doi.org/https://doi.org/10.1007/s00170-019-04227-7

Yunoh, M., Abdullah, S., Saad, M., Nopiah, Z., & Nuawi, M. (2017). K-means clustering analysis and artificial neural network classification of fatigue strain signals. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 39(3), 757-764. https://doi.org/https://doi.org/10.1007/s40430-016-0559-x

Zahoor, S., Mufti, N. A., Saleem, M. Q., Mughal, M. P., & Qureshi, M. A. M. (2017). Effect of machine tool's spindle forced vibrations on surface roughness, dimensional accuracy, and tool wear in vertical milling of AISI P20. *The International Journal of Advanced Manufacturing Technology*, 89(9), 3671-3679. https://doi.org/https://doi.org/10.1007/s00170-016-9346-1

Zain, A. M., Haron, H., & Sharif, S. (2010). Prediction of surface roughness in the end milling machining using Artificial Neural Network. *Expert Systems with Applications*, 37(2), 1755-1768. https://doi.org/https://doi.org/10.1016/j.eswa.2009.07.033

Zaretalab, A., Haghighi, H. S., Mansour, S., & Sajadieh, M. S. (2019). Optimisation of tool replacement time in the machining process based on tool condition monitoring using the stochastic approach. *International Journal of Computer Integrated Manufacturing*, 32(2), 159-173. https://doi.org/https://doi.org/10.1080/0951192x.2018.1550677

Zhang, C., Yao, X., Zhang, J., & Jin, H. (2016). Tool condition monitoring and remaining useful life prognostic based on a wireless sensor in dry milling operations. *Sensors*, 16(6), 795. https://doi.org/https://doi.org/10.3390/s16060795

Zhang, C., Zhang, S., Yan, X., & Zhang, Q. (2016). Effects of internal cooling channel structures on cutting forces and tool life in side milling of H13 steel under cryogenic minimum quantity lubrication condition. *The International Journal of Advanced Manufacturing Technology*, 83(5-8), 975-984. https://doi.org/https://doi.org/10.1007/s00170-015-7644-7

Zhang, G., Li, J., Chen, Y., Huang, Y., Shao, X., & Li, M. (2014). Prediction of surface roughness in end face milling based on Gaussian process regression and cause analysis considering tool vibration. *The International Journal of Advanced Manufacturing Technology*, 75, 1357-1370. https://doi.org/https://doi.org/10.1007/s00170-014-6232-6

Zhang, K.-f., Yuan, H.-q., & Nie, P. (2015). A method for tool condition monitoring based on sensor fusion. *Journal of Intelligent Manufacturing*, 26(5), 1011-1026. https://doi.org/https://doi.org/10.1007/s10845-015-1112-y

Zhang, X., Yu, T., & Zhao, J. (2020). Surface generation modeling of micro milling process with stochastic tool wear. *Precision Engineering*, 61, 170-181. https://doi.org/https://doi.org/10.1016/j.precisioneng.2019.10.015

Zhao, X., Cui, X., Hu, Z., Zhang, Q., & Sun, T. (2021). Development of an End-Toothed Disc-Based Quick-Change Fixture for Ultra-Precision Diamond Cutting. *Machines*, 9(11), 257. https://doi.org/https://doi.org/10.3390/machines9110257

Zhao, Y., Adjallah, K. H., Sava, A., & Wang, Z. (2021). MaxEnt feature-based reliability model method for real-time detection of early chatter in high-speed milling. *ISA transactions*, 113, 39-51. https://doi.org/https://doi.org/10.1016/j.isatra.2020.07.022

Zhou, M., Zhang, H., Huang, S., Chen, S., & Cheng, K. (2011). Experimental study on the effects of feed rate and tool geometries on tool wear in diamond cutting of sinusoidal microstructured surfaces. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 225(2), 172-183. https://doi.org/https://doi.org/10.1177/09544054jem1933

Zhou, Y., & Sun, W. (2020). Tool wear condition monitoring in milling process based on current sensors. *IEEE access*, 8, 95491-95502. https://doi.org/https://doi.org/10.1109/access.2020.2995586

Zhou, Y., & Xue, W. (2018a). A multisensor fusion method for tool condition monitoring in milling. *Sensors*, 18(11), 3866. https://doi.org/https://doi.org/10.3390/s18113866

Zhou, Y., & Xue, W. (2018b). Review of tool condition monitoring methods in milling processes. *The International Journal of Advanced Manufacturing Technology*, 1-15.

Zhou, Y., & Xue, W. (2018c). Review of tool condition monitoring methods in milling processes. *The International Journal of Advanced Manufacturing Technology*, 96(5), 2509-2523.

Zong, W., Huang, Y., Zhang, Y., & Sun, T. (2014). Conservation law of surface roughness in single point diamond turning. *International Journal of Machine Tools and Manufacture*, 84, 58-63. https://doi.org/https://doi.org/10.1016/j.ijmachtools.2014.04.006

Zuperl, U., & Cus, F. (2016). Surface roughness fuzzy inference system within the control simulation of end milling. *Precision Engineering*, 43, 530-543. https://doi.org/https://doi.org/10.1016/j.precisioneng.2015.09.019