DEVELOPMENT OF CYBER-PHYSICAL SYSTEM FOR ADVANCED MICRO-MACHINING SETUP

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DEVELOPMENT OF CYBER-PHYSICAL SYSTEM FOR ADVANCED MICRO-MACHINING SETUP

by

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Department of Mechanical Engineering

Submitted
in fulfilment of the requirements of the degree of *Doctor Of Philosophy*
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CERTIFICATE

This is to certify that the thesis entitled, **“Development of Cyber-Physical System for Advanced Micro-Machining Setup”** submitted by **Mr Jitin Malhotra** to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy**, in the Department of Mechanical Engineering, is a record of bonafide original research work carried out by him under my guidance and supervision.

The results contained in it have not been submitted in part or full to any other institute or university for the award of any degree/diploma.

Prof. Sunil Jha
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Place: New Delhi

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(Jitin Malhotra)

ABSTRACT

Emerging miniaturisation technologies are potential vital technologies of the future that will bring completely different ways people and machines interact with the physical world. This miniaturisation of devices demands mechanical components manufactured with complex features ranging from a few microns to a few hundred microns with high accuracy and surface finish requirements. To address these demands, micro-milling, a widely used micro-machining process similar to conventional milling in terms of kinematics and material removal mechanism, can come in handy. It has tool diameters ranging from 50 μm to 1 mm with the capability to machine hard and soft materials.

Further, the advances in digital electronics have led to a significant increase in the number of systems that couple the digital (cyber) components with the physical world, popularly known as the Cyber-Physical Systems (CPS). Current research work exploits the implementation of CPS in the manufacturing context, focusing on the micro-milling process. It starts with developing a machine tool of micro-machining techniques having customised kinematics and is named Advanced Micro-Machining System (AMMS). This machine tool is a five-axis CNC machine capable of performing five different machining processes, with multiple measurement facilities, all integrated into a single setup. The mechatronic design of this machine tool actively considers the requirements of a CPS system.

Once the physical component is ready, a CPS framework for transitioning this machine tool to an intelligent machine tool is presented. This framework is named the Intelligent Cyber-Physical Production System (i-CPPS) and has a four-layer structure. The first level is the unit level. It covers all the smart physical systems that produce data, captures them, pre-processes them, and share them with upper levels. The second level is the shop-floor level, which constitutes a group of unit-level entities working in collaboration and has a FOG cluster

network for data processing and analyses. The third level is the factory level, which combines various shop floors and acts as a complete service and management platform inside a manufacturing unit. The topmost level is the cyber level, which provides a platform to serve the needs of various enterprises and customers. It acts as a bridge between the enterprises and customers. A step-by-step use-case implementation of this framework on AMMS follows this framework with a brief discussion on a few application areas possible under the hat of this framework.

Among various application areas, process monitoring applications for micro-tools and workpieces are selected for demonstration. First, a three-step algorithm for tool wear segmentation and quantisation is presented for the tool side. This algorithm uses intensity-based multi-modal image registration and image subtraction methods on micro-milling tool colour images followed by a fuzzy c-means clustering technique for wear segmentation. In the end, the wear is quantified and presented to the user. Once the wear is quantified, an ML model for tool wear prediction is presented. Acceleration and spindle current consumption data is acquired during machining, pre-processed, and used for Gaussian Process Regression (GPR) modelling. From a combination of mean and covariance functions and an optimal GPR model is selected based on evaluation indices: mean-absolute error, root-mean-square error, mean-absolute percentage error, and Pearson-correlation coefficient. Lastly, a comparison between the optimal model and popular ML models is made, where the GPR outperforms all of them.

While looking at the process monitoring application on the workpiece side, a surface roughness (Ra) prediction model for a micro-milling process is developed. It is trained similar to the tool wear prediction application but with an additional input of tool wear values. On all four indices, the model is evaluated, and the optimal GPR model is selected. Finally, a comparison is made between optimal and other data models where GPR outperforms all in the prediction task.

सार

उभरती हुई लघुकरण प्रौद्योगिकियां भविष्य की संभावित महत्वपूर्ण प्रौद्योगिकियां हैं जो लोगों और मशीनों को भौतिक दुनिया के साथ पूरी तरह से अलग तरीके से पेश करेंगी। उपकरणों का यह लघुकरण उच्च सटीकता और सरफेस फिनिशआवश्यकताओं के साथ कुछ माइक्रोन से लेकर कुछ सौ माइक्रोन तक की जटिल विशेषताओं के साथ निर्मित यांत्रिक घटकों की मांग करता है। इन मांगों को पूरा करने के लिए, माइक्रो-मिलिंग, एक व्यापक रूप से इस्तेमाल की जाने वाली माइक्रो-मशीनिंग प्रक्रिया, जो किनेमेटिक्स और सामग्री हटाने की व्यवस्था के संदर्भ में पारंपरिक मिलिंग के समान है, काम आ सकती है। इसमें हार्ड और सॉफ्ट सामग्री को मशीन करने की क्षमता के साथ 50 माइक्रोन से 1 मिमी तक के टूल डायमीटर हैं।

इसके अलावा, डिजिटल इलेक्ट्रॉनिक्स में प्रगति ने उन प्रणालियों की संख्या में उल्लेखनीय वृद्धि की है जो भौतिक दुनिया के साथ डिजिटल (साइबर) घटकों को जोड़ते हैं, जिन्हें साइबर-भौतिक सिस्टम (सीपीएस) के रूप में जाना जाता है। माइक्रो-मिलिंग प्रक्रिया पर ध्यान केंद्रित करते हुए, वर्तमान शोध कार्य विनिर्माण संदर्भ में सीपीएस के कार्यान्वयन का फायदा उठाता है। यह अनुकूलित किनेमेटिक्स वाले माइक्रो-मशीनिंग तकनीकों का एक मशीन टूल विकसित करने के साथ शुरू होता है और इसे उन्नत माइक्रो-मशीनिंग सिस्टम (एएमएमएस) नाम दिया गया है। यह मशीन टूल एक पांच-अक्ष वाली सीएनसी मशीन है जो पांच अलग-अलग मशीनिंग प्रक्रियाओं को करने में सक्षम है, जिसमें कई माप सुविधाएं हैं, सभी एक ही सेटअप में एकीकृत हैं। इस मशीन टूल का मेक्ट्रोनिक डिज़ाइन सीपीएस सिस्टम की आवश्यकताओं पर सक्रिय रूप से विचार करता है।

एक बार भौतिक घटक तैयार हो जाने के बाद, इस मशीन उपकरण को एक इंटेलिजेंट मशीन उपकरण में बदलने के लिए एक सीपीएस ढांचा प्रस्तुत किया जाता है। इस ढांचे को इंटेलिजेंट साइबर-

फिजिकल प्रोडक्शन सिस्टम (i-CPPS) नाम दिया गया है और इसमें चार-परत संरचना है। पहला स्तर इकाई स्तर है। यह सभी स्मार्ट भौतिक प्रणालियों को कवर करता है जो डेटा का उत्पादन करते हैं, उन्हें कैप्चर करते हैं, उन्हें पूर्व-संसाधित करते हैं, और उन्हें ऊपरी स्तरों के साथ साझा करते हैं। दूसरा स्तर शॉप-फ्लोर स्तर है, जो सहयोग में काम कर रहे यूनिट-स्तरीय संस्थाओं के एक समूह का गठन करता है और डेटा प्रोसेसिंग और विश्लेषण के लिए एक एफओजी क्लस्टर नेटवर्क है। तीसरा स्तर कारखाना स्तर है, जो विभिन्न दुकान के फर्श को जोड़ता है और एक निर्माण इकाई के अंदर एक पूर्ण सेवा और प्रबंधन मंच के रूप में कार्य करता है। शीर्षतम स्तर साइबर स्तर है, जो विभिन्न उद्यमों और ग्राहकों की जरूरतों को पूरा करने के लिए एक मंच प्रदान करता है। यह उद्यमों और ग्राहकों के बीच एक सेतु का काम करता है। AMMS पर इस ढांचे का चरण-दर-चरण उपयोग-मामला कार्यान्वयन इस ढांचे का अनुसरण करता है और इस ढांचे की हैट के तहत संभव कुछ अनुप्रयोग क्षेत्रों पर एक संक्षिप्त चर्चा करता है।

विभिन्न अनुप्रयोग क्षेत्रों में, प्रदर्शन के लिए सूक्ष्म उपकरणों और वर्कपीस के लिए प्रक्रिया निगरानी अनुप्रयोगों का चयन किया जाता है। सबसे पहले, टूल वियर सेगमेंटेशन और क्वांटिज़ेशन के लिए टूल साइड के लिए तीन-चरण एल्गोरिदम प्रस्तुत किया गया है। यह एल्गोरिथम माइक्रो-मिलिंग टूल कलर इमेज पर तीव्रता-आधारित मल्टी-मोडल इमेज रजिस्ट्रेशन और इमेज घटाव विधियों का उपयोग करता है, इसके बाद वियर सेगमेंटेशन के लिए फजी सी-मीन्स क्लस्टरिंग तकनीक का उपयोग करता है। अंत में, पहनने की मात्रा निर्धारित की जाती है और उपयोगकर्ता को प्रस्तुत की जाती है। एक बार पहनने की मात्रा निर्धारित हो जाने के बाद, उपकरण पहनने की भविष्यवाणी के लिए एक एमएल मॉडल प्रस्तुत किया जाता है। त्वरण और स्पिंडल वर्तमान खपत डेटा मशीनिंग के दौरान प्राप्त किया जाता है, पूर्व-संसाधित, और गाऊसी प्रक्रिया प्रतिगमन (जीपीआर) मॉडलिंग के लिए उपयोग किया जाता है। माध्य और सहप्रसरण कार्यों के संयोजन से और मूल्यांकन सूचकांकों के आधार पर एक इष्टतम जीपीआर मॉडल का चयन किया जाता है: माध्य-पूर्ण त्रुटि, मूल-माध्य-वर्ग त्रुटि, माध्य-पूर्ण प्रतिशत त्रुटि, और

पियर्सन-सहसंबंध गुणांक। अंत में, इष्टतम मॉडल और लोकप्रिय एमएल मॉडल के बीच तुलना की जाती है, जहां जीपीआर उन सभी से बेहतर प्रदर्शन करता है।

वर्कपीस पक्ष पर प्रक्रिया निगरानी अनुप्रयोग को देखते हुए, सूक्ष्म-मिलिंग प्रक्रिया के लिए एक सतह खुरदरापन (आरए) भविष्यवाणी मॉडल विकसित किया गया है। इसे टूल वियर प्रेडिक्शन एप्लिकेशन के समान प्रशिक्षित किया जाता है लेकिन टूल वियर वैल्यू के अतिरिक्त इनपुट के साथ। सभी चार सूचकांकों पर, मॉडल का मूल्यांकन किया जाता है, और इष्टतम जीपीआर मॉडल का चयन किया जाता है। अंत में, इष्टतम और अन्य डेटा मॉडल के बीच एक तुलना की जाती है जहां जीपीआर भविष्यवाणी कार्य में सभी से बेहतर प्रदर्शन करता है।

PUBLICATIONS AND AWARDS

International Journals

1. **J. Malhotra**, and S. Jha, *Fuzzy c-means clustering based colour image segmentation for tool wear monitoring in micro-milling*, Precision Engineering, 72 (2021), 690-705. DOI:10.1016/j.precisioneng.2021.07.013.
2. **J. Malhotra**, and S. Jha, *Intelligent Cyber-Physical Production System Framework for Industry 4.0 Realization*, in T. Semwal, F. Iqbal (eds.) Cyber-Physical Systems: Solutions to Pandemic Challenges. Boca Rotan: CRC Press, Chapter-11 (2021), 209-248.
3. F. Iqbal, **J. Malhotra**, S. Jha and T. Semwal, *Introduction to Cyber-Physical systems and challenges faced due to COVID19 pandemic,* in T. Semwal, F. Iqbal (eds.) Cyber-Physical Systems: Solutions to Pandemic Challenges. Boca Rotan: CRC Press, Chapter-1 (2021), 1-23.
4. F. Iqbal, Z. Alam, M. Shukla*,* **J. Malhotra**, and S. Jha, *Transforming standalone machine tool to cyber-physical system: A use case of BEMRF machine tool to tackle COVID-19 restrictions,* in T. Semwal, F. Iqbal (eds.) Cyber-Physical Systems: Solutions to Pandemic Challenges. Boca Rotan: CRC Press, Chapter-14(2021), 330-344.
5. A.K. Sahu, **J. Malhotra**, and S. Jha. *Laser-based hybrid micromachining processes: A review.* Optics and Laser Technology 146 (2022): 107554.
   DOI:10.1016/j.optlastec.2021.107554

Communicated to International Journals

1. **J. Malhotra**, and S. Jha, *Machine learning-based prediction modelling of micro-milling tool wear using multi-sensor data*.
2. **J. Malhotra**, and S. Jha, *Gaussian Process Regression Model for Roughness Prediction of Micro-Milled Surface Using Multi-Sensor Data and Tool Wear*.

International Conferences

1. **J. Malhotra**, F. Iqbal, A.K. Sahu, and S. Jha, *A Cyber-Physical System Architecture for Smart Manufacturing, Advances in Forming*, In Machining and Automation, Springer Singapore, AIMTDR 2018, 637-647.
2. A. K. Sahu, H. A. Patel, **J. Malhotra**, and S. Jha. *Experimental Study of Nanosecond Fiber Laser Micromilling of Ti6Al4V Alloy.,* In Advances in Micro and Nano Manufacturing and Surface Engineering, Springer, Singapore, AIMTDR 2018, pp. 371-380.

National Level Awards

1. Winner of the "Gandhian Young Technological Innovation Appreciation Award, 2020" for Design and Development of Advanced CNC Micro-machining System.

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