An Intelligent Cyber Physical System of Machining Operation for Industry 4.0

Md Shihab Shakur, Maishat Lubaba, Mir Wahidul Islam, Md. Saniat Kamal, M. Azizur Rahman, Md. Shahnawaz Bhuiyan
Department of Mechanical and Production Engineering
Ahsanullah University of Science and Technology (AUST)
Dhaka, Bangladesh
maishatvnc35@gmail.com, shihabshakur2016@gmail.com, mirwahid4978@gmail.com, sani.sjs09@gmail.com, aziz.mpe@aust.edu, newaz.mpe@aust.edu

Md. Abdul Gaffur
Principal Scientific Officer, Pilot Plant and Process Development Centre
Bangladesh Council of Scientific and Industrial Research (BCSIR)
Dhaka, Bangladesh
d_r_magafur@yahoo.com

Abstract
Smart machining has brought revolutionary change in the manufacturing field turning the physical world into an intelligent one with the decision-making approach and sustainability. In this era of fourth industrial revolution (4IR), intelligent machining has become an essential and reliable part with the help of machine learning, Internet of things (IoT), Cyber physical System (CPS), Cloud Computing etc. In this work, an intelligent cyber physical system has been developed for live monitoring the milling operation. The machining vibration may result in poor quality products. As a result, part rejection and customer dissatisfaction may occur. A combination of real time sensor data, microcontroller, IoT, cloud computing, has been used to monitor vibration so that the milling machine can act more smartly. The Aluminum Alloy 1100 used to cut slots by tungsten coated carbide end mill cutter in 3-axis CNC milling. While machining vibration data have been monitored over Thingspeak Cloud Platform sending the data through an IoT device. The data have been analyzed with the integration of Artificial Neural Network for decision making approach. To avoid excess vibration, an optimum set of parameters have been picked from this model, which enable decision making in process parameter selection.

Keywords
Machining Monitoring System, Data driven machining, Intelligent machining, Cyber Physical System, Vibration

1. Introduction
Industry 4.0, or the Fourth Industrial Revolution (4IR), is a manufacturing paradigm in which intelligent machining is recognized as a new technique of accurate machining. Intelligent machining is given relevance and priority over the automation of traditional machining processes as a result of its acknowledgment. In Industry 4.0, automated complicated machining is accomplished through the development of a sophisticated cyber-physical system; it is a key component in the development of a cyber-physical system. The Internet of Things (IoT), big data, cloud computing, artificial intelligence are just a few examples of rapidly growing technology. These technologies are infiltrating the manufacturing system, making it smarter and more capable of dealing with current difficulties like increasingly customized requirements, enhanced quality, and shorter time to market. Moreover, a growing number of sensors are being used in the equipment to communicate with one another. Real-time data of machining or any production system may be gathered and shared using these technologies to allow for quick and precise decision-making in any manufacturing system. In the manufacturing sector, Industry 4.0 has changed the dimension of the manufacturing industry by improving and recognizing the intelligent machining systems (Rittinghouse and Ransome, 2010). Smart manufacturing or intelligent manufacturing have become a popular concept with 4IR as information and data-driven manufacturing process optimize the production, part interaction to a new level. Intelligent manufacturing has influenced people's livelihood and can play a game changing impact on

manufacturing models. IoT enabled manufacturing, cloud-based manufacturing, Cyber physical system in manufacturing, Artificial intelligence in machining is most advanced intelligent manufacturing (Forcina, Introna and Silvestri, 2021). Cyber-physical systems (CPS) is integrated with physical and computational capabilities which makes human effort easy in various ways. The capacity to interact with the physical world and enhance its capabilities through computing, communication, and control is a critical enabler for future technological advancements. The purpose is to create new systems science and engineering methodologies for creating high-confidence systems that are compatible, synergistic, and linked at all scales. Identifying requirements, difficulties, and possibilities in a variety of industrial sectors, as well as supporting transdisciplinary collaborative research between academia and industry, can help expedite CPS research (Xu, Xu and Li, 2018). Moreover, unwanted vibrations are common during machining operations, and the primary sources are the machine tools, environment, process, among others. Intelligent machining can be used to monitor the vibration that has been generated during machining operations. Vibration appears to have a significant impact on surface quality, as evidenced by various studies. Material and energy waste, tool breakage and tool waste, poor quality surface, noise, etc. are some of the effects of chatter vibration. Because of such issues the topic of noise avoidance has sparked a lot of curiosity (Quintana and Ciurana, 2011). This machining vibration is harmful to both workpiece and tool. Because both of them can lead to early tool failure and low-quality surface finish (Sivasakthivel, Velmurugan and Sudhakaran, 2010). Monitoring vibrations is one of the most important ways to preserve the CNC machine throughout the manufacturing process. When warning conditions are discovered actual observation such as vibration can be used to take prompt action (Rastegari, Archenti and Mobin, 2017). Data acquisition is a process where the sensorial signals from the physical conditions while machining is gathered and sampling them and converting the samples into digital numeric values that a computer can manipulate and optimize the parameters. Data acquisition and feature extraction are used in monitoring processes and it plays an important role in the whole industrial production procedure (Li *et al.*, 2009). One of the major advantages of using data acquisition techniques is that it creates a real-time overview of the current situation on production facilities and it creates a detailed and efficient base for the problem-solving process (Li *et al.*, 2009). Data acquisition can be done in both automated and non-automated production systems and automated production gives the acquisition of the data continuously for technical process control and thus automated gives fewer difficulties than non-automated production system (Ćwikła, 2014). Therefore, machining system needs automated data accusing process to make the manufacturing process more flexible, robust, scalable with respect to industry 4.0 trend.

1.1 Objectives

The main aim of this research is to develop an IoT and Cloud based real time data monitoring for machining operation using vibration sensor to make intelligent and smart manufacturing process. ANN have been employed in the cloud platform to make decision making approach in the machining process. The whole process is combined with IoT, Machine learning, Cloud computing to make a Cyber physical System for machining process.

2. Literature Review

With the 4IR, quality and mass customization of products have become a prime factor to meet the intensified global competition by lowering production cost and time. To achieve the goal, manufacturers are opting to data driven, intelligent, automated process to lower the dependence over operator rather than data. The successfulness of a data driven manufacturing system depends on the automatic data acquiring, data storing, data analysis which is reliable, robust system to make the manufacturing process intelligent (Liang, Hecker and Landers, 2004). Several approaches have been proposed to integrate intelligent system to monitor computer numerical control (CNC) machining operation increasingly in this study. Based on the industrial application, tool condition monitoring system have already been adapted (Mohanraj *et al.*, 2020). Various sensor for measuring sound, cutting force, temperature, displacement, spindle power and current, torque, vibration, acoustic Emissions etc. have been used to know the industrial field environment (Kuntoğlu *et al.*, 2021). Usually, a wireless sensor sense data from the environment and sends the data using communicating components. However, the process nature needs to be self-organized, flexible, scalable, rapid deployable and inherent intelligence capability (Åkerberg, Gidlund and Bjorkman, 2011). Internet of things (IoT) is a scalable infrastructure can be used to send the machining environment data around the world through Internet (Fujishima *et al.*, 2019). The data gathered from the sensor can be used for cloud manufacturing to use on line machining process monitoring in the cloud to utilize a cyber-physical system (Caggiano, Segreto and Teti, 2016). To meet the challenges caused by fourth industrial revolution, a new combination of IoT and cloud-based approach for real time monitoring of machining process, related to the CNC machines, can pave the way towards intelligent manufacturing (Tapoglou *et al.*, 2015). The variation in CNC machining parameters significantly affect the product quality and thus and intelligent manufacturing system being developed by using ANFIS predictor and PSO algorithm. The intelligent process shows suitable manufacturing parameters for different machining parameters (Surface smoothness, accuracy and speed). The process and result show the verification of effectiveness and performance for intelligent manufacturing process (Chiu and Lee, 2020). Machine learning, deep learning-based model can help to take decision making where multiple variables are involved in machining. Complex input-output and in-process parameters relationship of machining control problems may be handled by Artificial Neural Network (ANN). ANN is a dynamic, non-linear, multi-variable estimator to solve problems by self-organization and self-learning. By using the ANN a dynamic surface roughness monitoring system for milling operation is developed (Khorasani and Yazdi, 2015). Most common operations done in the machining process are milling, turning, facing, drilling, boring, grinding etc. where vibration occurs when machine is started and increased by the machining process. Machining vibration is an unbalanced state can happen during the machining process when the workpiece material is deformed as a form of chip due to cutting tool to workpiece interface. The machining vibrations play an important role in surface roughness as the higher the vibration, that much rough the surface of the product. Vibration during machining may affect surface roughness which results in faulty product rejection by influencing product quality. Therefore, smart machining can be a used to monitor the vibration during the machining process (Sun, Luo and Zhang, 2020). Induced vibration can be measured by triple-axis accelerometers by attaching with workpiece, tool holder, spindle etc (Devillez and Dudzinski, 2007). The vibration data can be analyzed using machine learning, deep learning, wavelet to diagnose the machine conditions during the machining operations (Krishnakumar, Rameshkumar and Ramachandran, 2018). Therefore, it can be summarized that IoT and Cloud based data monitoring system in the machining process can be a potential enabler of data driven smart monitoring system.

3. Methods

3.1 Material:

In this work, Aluminum alloy 1100 have been used, which is a soft, low-strength aluminum alloy that is one of numerous popular aluminum alloys. Chemical equipment, name plates, reflectors, railroad tank cars, dials, culinary utensils, rivets, fin stock, and sheet metal are all examples of objects made from aluminum alloy1100. It is also used in the plumbing and lighting sectors, as well as a range of other industries. The most prevalent method of forming aluminum 1100 is cold-working. This material can be hot-worked as well as cold-worked, but it is more commonly formed via spinning, stamping, and drawing methods, none of which need the use of high heat. The Chemical composition analysis was performed using the Portable XRF Spectrometer, is shown in Table 1.

Table 1: The composition analysis of Al 1100

Element	Al	Si	Fe	Cu	V	Co	Ni	Sn	W
Percentage	98.26	0.24	0.49	0.62	0.02	0.06	0.03	0.14	0.14

3.2 Cutting tool

For the milling operation, a tungsten coated carbide end mill cutter (MTS Tools) has been used. As carbide tools have superior abrasion resistance and ability to perform a high-speed cutting, it is recommended for cutting aluminum alloy. The cutter specifications are shown in the table 2.

Table 2: Cutting tool specifications

Material	Diameter	Flute	Length	Type
Carbide	6 mm	4	60 mm	Flat

The End mill cutter is illustrated in figure 1

Figure 1: 4 flute coated carbide end mill cutter

3.3 Machining Operation

In this study, a slot milling operation has been done on the workpiece in the dry condition. The Aluminum alloy workpiece was a rectangular block with a dimension of 43mm* 37mm* 16 mm. The machining were performed in the VF-5 vertical CNC milling machine,as specified in the Table 2.

Table 2: Specifications of VF-5

Specification Name	Value
Number of axis	4
Spindle orientation	Vertical
Power	Maximum: 22.4 kW (30.46hp)
Spindle Speed	10,000 RPM
Spindle Motor	30 hp
Maximum Table Load	4,000 LBS
Tool Changer	30 ATC
Drive System	2 Speed Gearbox

3.4 Experimental Setup

For this study, an electrical circuit has been developped to sense the data from the workpiece. The circuit connection is shown in the figure 2 below.

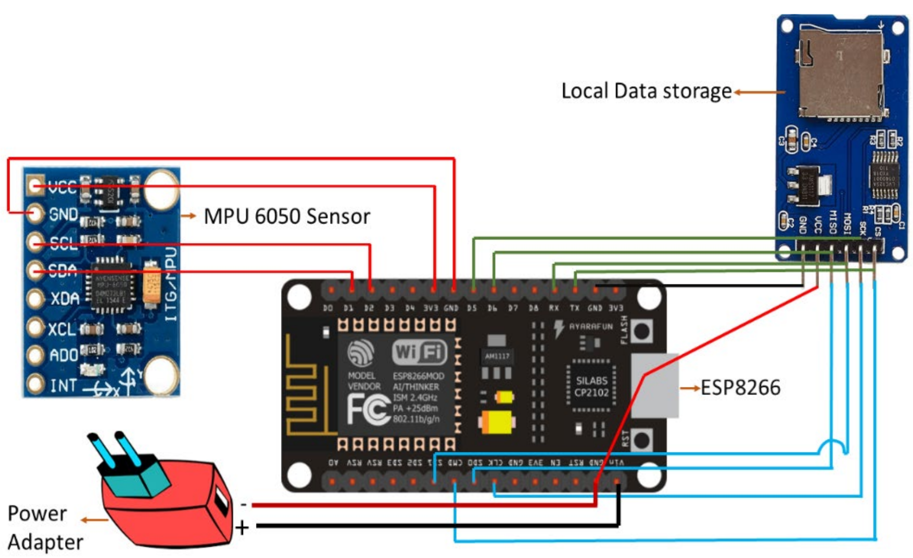


Figure 2: Electrical Connection for live monitoring

The circuit of figure 2, consists of a Vibration sensor MPU 6050, microcontroller ESP 8266, power adapter and local data storage adapter. Variable power adapter has been used to supply a 5V current to the ESP 8266, MPU6050 is powered using the 3.3V line from the ESP 8266. MPU6050 is a three-axis accelerometer and three-axis gyroscope Micro Electro-mechanical system (MEMS). It allows anyone for orientation, displacement, acceleration, calculating velocity, and other motion-related characteristics. It can be used widely for various applications (*What Is MPU6050? - Arduino Project Hub*, 18 December, 2021). However, ESP 8266 microcontroller is an inexpensive Wi-Fi microchip with integrated TCP/IP networking software and a microprocessor. Because of its improved performance and flexibility, easy application development, it has become popular to use. The MPU-6050 sensor has been attached to the workpiece connected to the ESP 8266 microcontroller. While machining, the sensor sense the vibration data and send to the micro controller ESP 8266. The Experimental setup is shown in the figure 3.

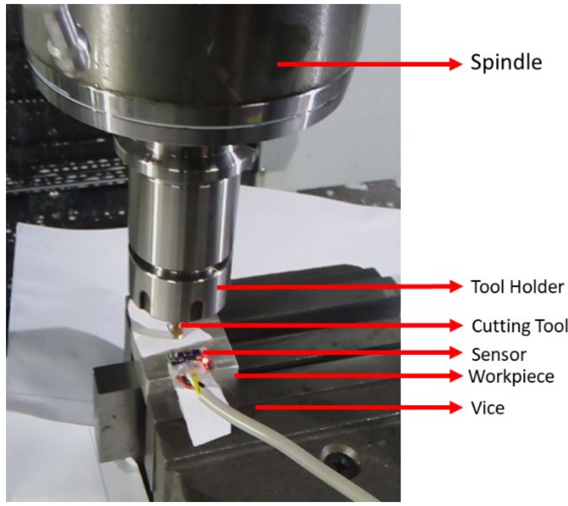


Figure 3: Experimental Setup

In this experiment a 6mm slot has been cut on the workpiece vibration sensor perimeter and 25 runs have been conducted with the combination of process parameters given in the table 3.

Table 3: Process paramters for slot cutting

Parameters Name	Parameters Value
Feed Rate (mm/s)	200, 300,400,500,600
Cutting Speed (RPM)	1000, 2000, 3000, 4000, 5000
Depth of Cut (mm)	0.4, 0.6, 0.8, 1, 1.2

4. Data Collection

The workpiece being set up on the vice of the VF-5 and home position was defined. The sensorial setup has been attached with the workpiece consisting sensor and microcontroller mainly. A 6mm width slot is cut on the workpiece and vibration has been occurred while the cutting tool penetrating the workpiece. MPU 6050 sensor senses the vibrations during the operation and transfer the data as electrical signal to the microcontroller ESP 8266. The ESP 8266 microcontroller is connected to internet via Wi-Fi connection. The ESP 8266 microcontroller sends data to the cloud platform and directed to “Thingspeak”. In the modern world of technology and recognition of Industry 4.0 it became a must necessity to manage large numbers of data through various devices such that sensors and actuators; the existing traditional analysis models are mostly complex and expensive. Thus, IoT based platforms are created and ThingSpeak is a commonly used IoT based platform for monitoring data and provides processing of data that is integrated with various applications (Salami and Yari, 2018). ThingSpeak users can store and retrieve numeric and alphanumeric networks of things; it supports data entries with API up to 8 data fields, latitude, longitude, elevation, and status updates. It provides persistent storage of data with queries, sorting, and transactions and besides, automatic scaling also (Doukas and Maglogiannis, 2011). The data can be visualized in the Thingspeak platform with different type of widgets. Different machine learning algorithm can be employed in the platform with MATLAB storming. Artificial neural network has been applied for this study to make decision making approach. The data collection process has been automated in this work. The data flow and whole process has been illustrated in figure 4.

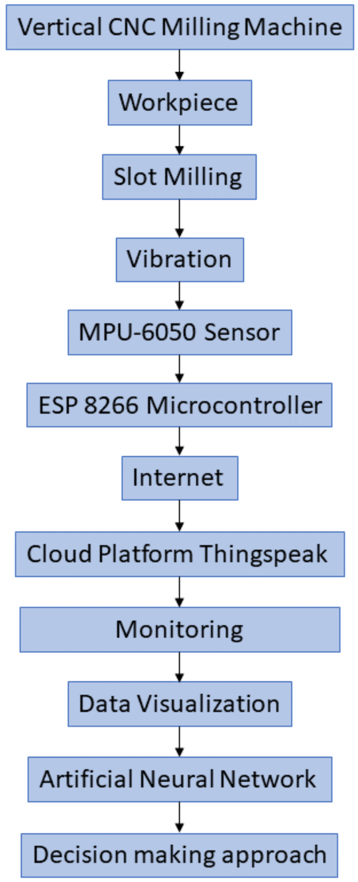


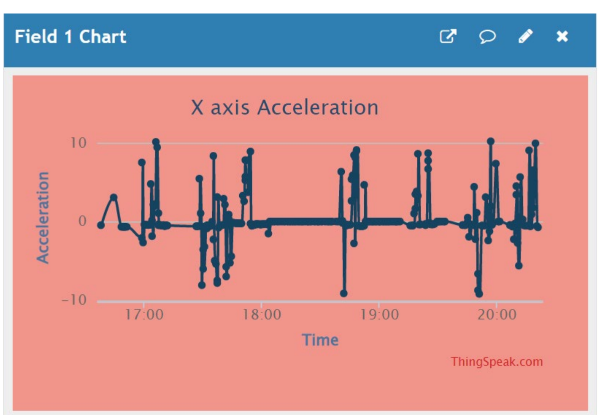
Figure 4: Data collection flowchart

5. Results and Discussion

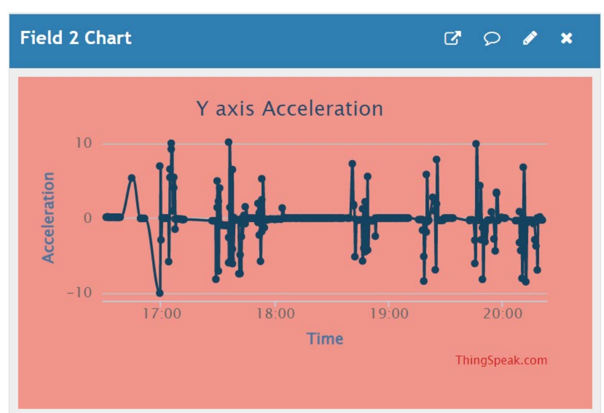
In the Thingspeak platform vibration data has been stored in every 1s and about 600 data have got entry. The data have been analyzed in the following portion.

5.1 Graphical Results

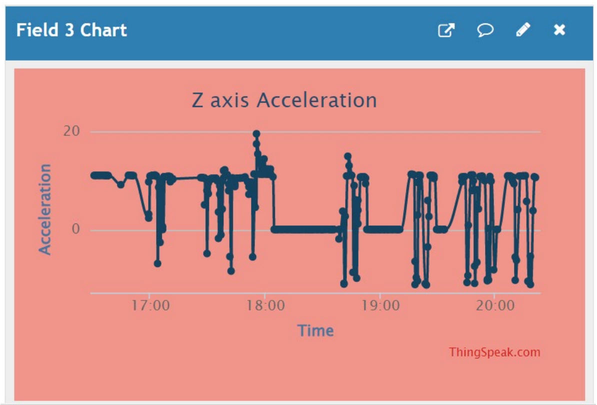
The data can be seen in the Thingspeak platform. The data of acceleration on X axis, Y axis, Z axis and Rotation data of X axis, Y axis, Z axis have been seen in the Thingspeak platform live. It also shows the last update time and number of entities of the acquired data. The live data have been illustrated below.



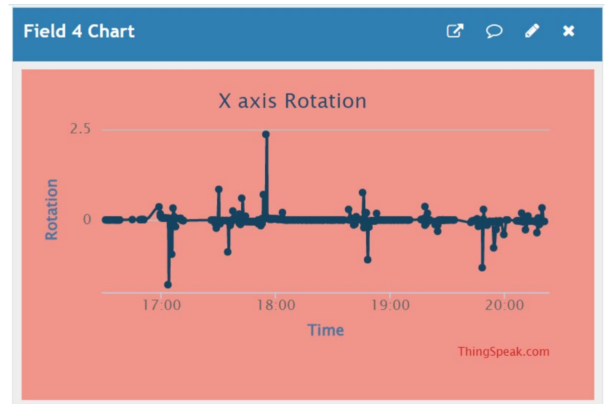
(a)



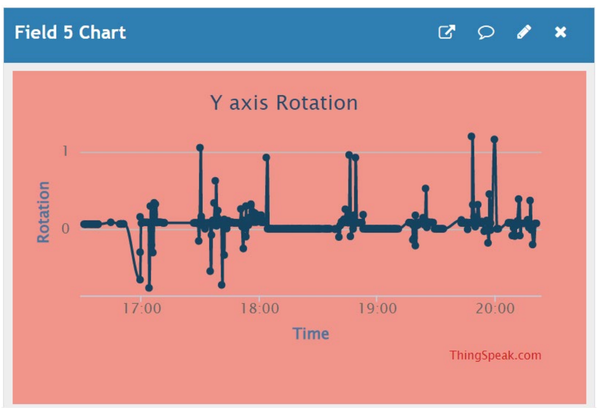
(b)



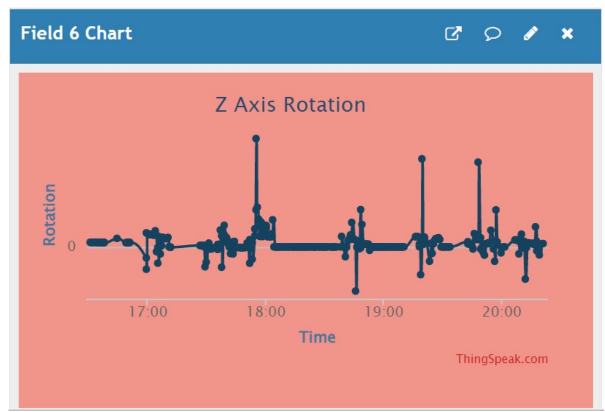
(c)



(d)



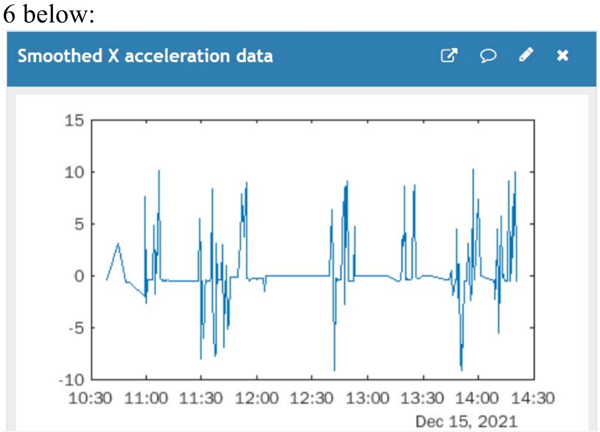
(e)



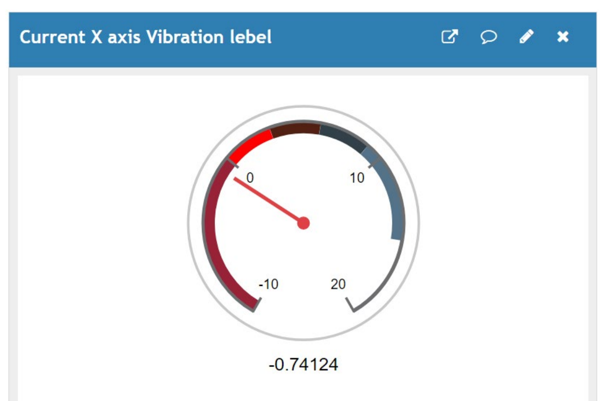
(f)

Figure 5: Live sensor data with respect to local time in thingspeak (a) X acceleration (b) Y acceleration (c) Z acceleration (d) X rotation (e) Y rotation (f) Z rotation

The data can be smoothed and live monitored with different type of widget as per requirement with Matlab command, integrated in Thingspeak Platform. The X axis smoothed data and live monitoring is illustrated in Figure 6 below:



(a)



(b)

Figure 6: Data visualization in Thingspeak (a) Smothed X axis Plot (b) live visualization of X axis data

5.3 Artificial Neural Network for Prediction

The Vibration level have been smoothed and are merged to set vibration level by dividing highest by the highest value. The highest value has been sorted for each vibration level. Then Artificial neural network has been used to predict the vibration data for different process parameters. The experimental and predicted value is presented in Table 4.

Table 4: Experimental value vs Predicted value using ANN

Sample No	Feed rate (mm/min)	Depth of Cut (mm)	Cutting Speed (RPM)	Vibration level (m/s2)	Predicted vibration	Error Percentage
1	200	0.4	1000	0.08	0.0719	10.125
2	200	0.6	2000	0.07	0.066	5.714
3	200	0.8	3000	0.08	0.0625	21.875
4	200	1	4000	0.09	0.0784	12.889
5	200	1.2	5000	0.11	0.0963	12.455
6	300	0.4	2000	0.08	0.0749	6.375
7	300	0.6	3000	0.05	0.0371	25.800
8	300	0.8	4000	0.06	0.0635	-5.833
9	300	1	5000	0.09	0.1011	-12.333
10	300	1.2	1000	0.08	0.0773	3.375
11	400	0.4	3000	0.09	0.0799	11.222
12	400	0.6	4000	0.05	0.056	-12.000
13	400	0.8	5000	0.11	0.1064	3.273
14	400	1	1000	0.06	0.0686	-14.333
15	400	1.2	2000	0.07	0.0878	-25.429
16	500	0.4	4000	0.08	0.086	-7.500
17	500	0.6	5000	0.08	0.072	10.000
18	500	0.8	1000	0.1	0.0907	9.300
19	500	1	2000	0.12	0.1047	12.750
20	500	1.2	3000	0.1	0.0944	5.600
21	600	0.4	5000	0.1	0.0932	6.800
22	600	0.6	1000	0.06	0.0677	-12.833
23	600	0.8	2000	0.06	0.068	-13.333
24	600	1	3000	0.07	0.0678	3.143
25	600	1.2	4000	0.13	0.1128	13.231

In the neural network for prediction, 75% data were used for training, 15% data were sued for validation and 10% data were used for testing. The Levenberg-Marquardt have been used for training. From the Model, a performance curve has been generated showed in figure 7.

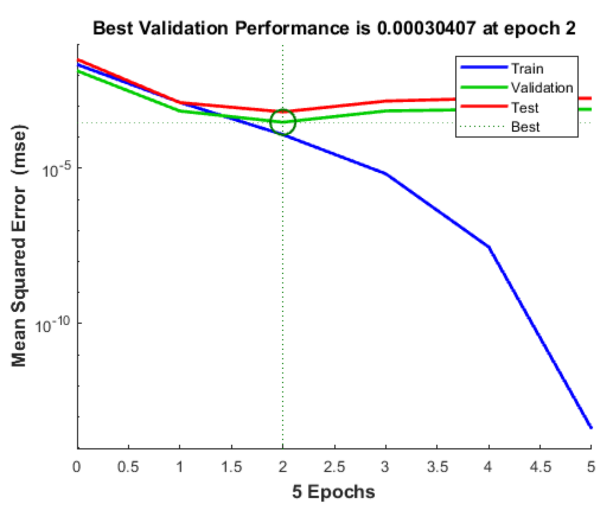


Figure 7: Performance curve of ANN model

From the curve, it can be said that the model is running well as loss (MSE) is decreasing with respect to epoch number. The best performance of the model is seen at Epoch 2. But it also shows overfitting problem after crossing the 2 epochs. The problem can be solved by increasing the data set.

5.4 Validation

The ANN model can predict the vibration data with a good R^2 value about 99%, which proofs good fit of the model. The regression plot for training. Testing and validation is shown in the Figure 8.

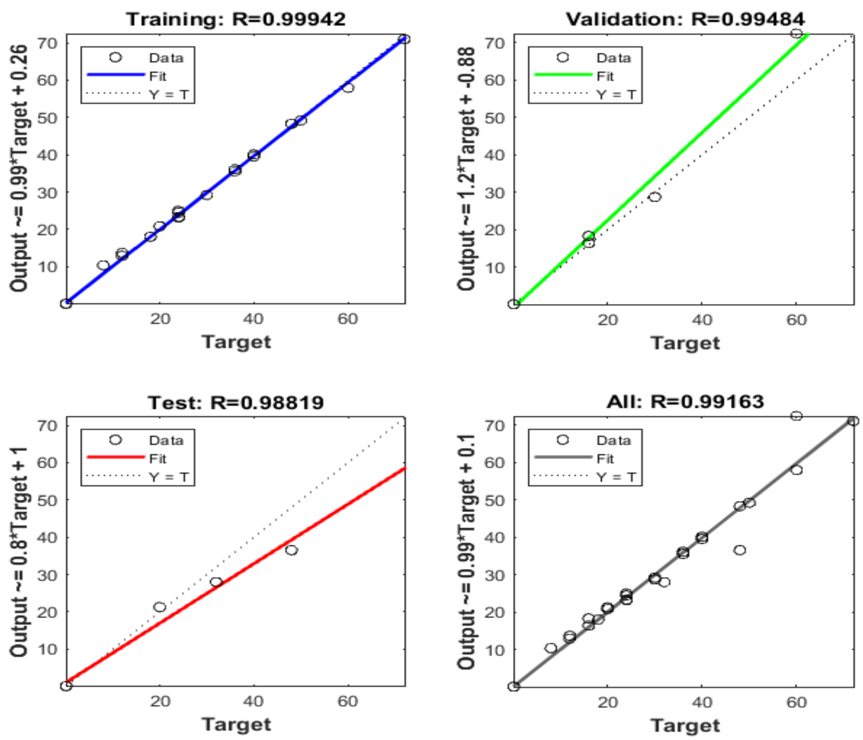


Figure 8: Regression plot for training, validation and testing of ANN model

The findings show that the vibration level prediction done by ANN shows very good correlation with significant R^2 value 99%. The experimental vibration data and predicted data can be illustrated in the graph, shown in figure 9.

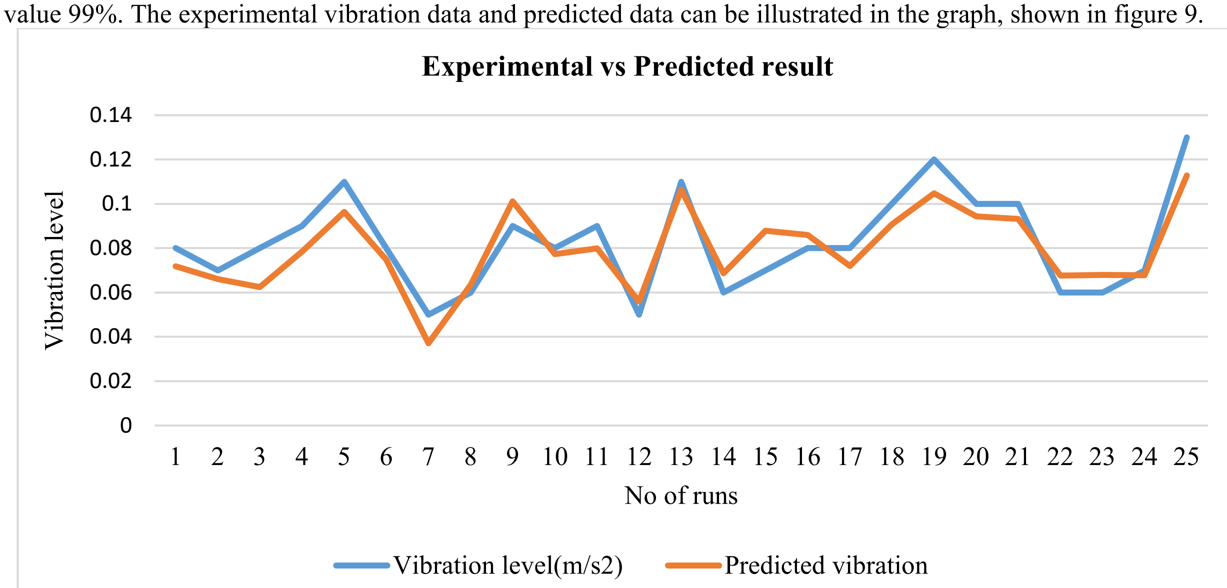


Figure 9: Experimental vs predicted Vibration levels

6. Conclusion

In this study, slot milling operation have been performed on Aluminum 1100 to enable intelligent. An IoT based sensorial system has been developed to collect the vibration data while machining and send to cloud monitoring platform Thinkspeak. The data have been monitored to build the cyber physical system with artificial intelligence algorithm named ANN. The ANN, has been used to predict the vibration level with respect to machining parameters. The ANN model accuracy was found to be significant (99%). The findings show that the vibration level prediction done by ANN shows very good correlation with experimental vibration data. The study concludes an emerging way to do further research on IoT based monitoring under industry 4.0 perspective to do further development in the field of smart and intelligent machining.

References

Åkerberg, J., Gidlund, M. and Bjorkman, M. (2011) 'Future research challenges in wireless sensor and actuator networks targeting industrial automation', *IEEE International Conference on Industrial Informatics (INDIN)*, pp. 410–415. doi: 10.1109/INDIN.2011.6034912.

Caggiano, A., Segreto, T. and Teti, R. (2016) 'Cloud Manufacturing Framework for Smart Monitoring of Machining', *Procedia CIRP*, 55, pp. 248–253. doi: 10.1016/j.procir.2016.08.049.

Chiu, H. W. and Lee, C. H. (2020) 'Intelligent Machining System Based on CNC Controller Parameter Selection and Optimization', *IEEE Access*, 8, pp. 51062–51070. doi: 10.1109/ACCESS.2020.2980286.

Ćwikła, G. (2014) 'Methods of Manufacturing Data Acquisition for Production Management - A Review', *Advanced Materials Research*, 837, pp. 618–623. doi: 10.4028/WWW.SCIENTIFIC.NET/AMR.837.618.

Devillez, A. and Dudzinski, D. (2007) 'Tool vibration detection with eddy current sensors in machining process and computation of stability lobes using fuzzy classifiers', *Mechanical Systems and Signal Processing*, 21(1), pp. 441–456. doi: 10.1016/J.YMSSP.2005.11.007.

Fujishima, M. *et al.* (2019) 'UTILISATION OF IOT AND SENSING FOR MACHINE TOOLS', *Journal of Machine Engineering*, 19(1), pp. 38–47. doi: 10.5604/01.3001.0013.0447.

Khorasani, A. M. and Yazdi, M. R. S. (2015) 'Development of a dynamic surface roughness monitoring system based on artificial neural networks (ANN) in milling operation', *The International Journal of Advanced Manufacturing Technology 2015 93:1*, 93(1), pp. 141–151. doi: 10.1007/S00170-015-7922-4.

Krishnakumar, P., Rameshkumar, K. and Ramachandran, K. I. (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), pp. 265–282. doi: 10.3233/IDT-180332.

Kuntoğlu, M. *et al.* (2021) 'A state-of-the-art review on sensors and signal processing systems in mechanical machining processes', *The International Journal of Advanced Manufacturing Technology 2021 116:9*, 116(9), pp. 2711–2735. doi: 10.1007/S00170-021-07425-4.

Li, H. *et al.* (2009) 'Research on data acquisition system based on FlexRay', *ICEMI 2009 - Proceedings of 9th International Conference on Electronic Measurement and Instruments*, pp. 4386–4389. doi: 10.1109/ICEMI.2009.5274030.

Liang, S. Y., Hecker, R. L. and Landers, R. G. (2004) 'Machining Process Monitoring and Control: The State-of-the-Art', *Journal of Manufacturing Science and Engineering*, 126(2), pp. 297–310. doi: 10.1115/1.1707035.

Mohanraj, T. *et al.* (2020) 'Tool condition monitoring techniques in milling process — a review', *Journal of Materials Research and Technology*, 9(1), pp. 1032–1042. doi: 10.1016/J.JMRT.2019.10.031.

Quintana, G. and Ciurana, J. (2011) 'Chatter in machining processes: A review', *International Journal of Machine Tools and Manufacture*, 51(5), pp. 363–376. doi: 10.1016/J.IJMACHTOOLS.2011.01.001.

Rastegari, A., Archenti, A. and Mobin, M. (2017) 'Condition based maintenance of machine tools: Vibration monitoring of spindle units', *Proceedings - Annual Reliability and Maintainability Symposium*. doi: 10.1109/RAM.2017.7889683.

Rittinghouse, J. W. and Ransome, J. F. (2010) 'Cloud computing : implementation, management, and security', p. 301.

Sivasakthivel, P. S., Velmurugan, V. and Sudhakaran, R. (2010) 'Prediction of vibration amplitude from machining parameters by response surface methodology in end milling', *The International Journal of Advanced Manufacturing Technology 2010 53:5*, 53(5), pp. 453–461. doi: 10.1007/S00170-010-2872-3.

Sun, W., Luo, M. and Zhang, D. (2020) 'Machining vibration monitoring based on dynamic clamping force measuring in thin-walled components milling', *International Journal of Advanced Manufacturing Technology*, 107(5–6), pp. 2211–2226. doi: 10.1007/S00170-020-05153-9/FIGURES/14.

Tapoglou, N. *et al.* (2015) 'Cloud-based platform for optimal machining parameter selection based on function blocks and real-time monitoring', *Journal of Manufacturing Science and Engineering, Transactions of the ASME*, 137(4). doi: 10.1115/1.4029806/375251.

Xu, L. Da, Xu, E. L. and Li, L. (2018) 'Industry 4.0: state of the art and future trends', *https://doi.org/10.1080/00207543.2018.1444806*, 56(8), pp. 2941–2962. doi: 10.1080/00207543.2018.1444806.

Acknowledgements
Bangladesh Industrial Technical Assistance Center (BITAC) and Pilot Plant and Process Development Center of Bangladesh Council of Scientific and Industrial Research (BCSIR) helped by providing technical assistance.

Biographies

Md Shihab Shakur is an undergraduate student of Industrial and Production Engineering (IPE) under the Department of Mechanical and Production Engineering (MPE) at the Ahsanullah University of Science and Technology (AUST). His research interest includes the area of Manufacturing process, Additive manufacturing, Advanced material processing, Metal cutting, Industry 4.0, Sustainable Product Design. He has achieved prizes in different tech-based competitions in Bangladesh like Innoventure'19, IN + !, CODWARE'18, TECHNOCAD, etc. He has been the semifinalist in the national Television reality show "Esho Robot Banai". He has also achieved prizes in international event named "Mindspark'20" and participated in Techkriti'19 at IIT, Kanpur, India. He has completed his internship program at Hatil Furniture under the research and development department. He has good command over Solidworks, keyshot, Mastercam, Abaqus, Matlab, Minitab, Cura and knows the C, C ++, python programming languages. He is ambitious to do extensive research work in manufacturing process design, Industry 4.0, intelligent manufacturing, non-conventional manufacturing process etc. Shihab is a general member of IEOM AUST Chapter.

Maishat Lubaba is an undergraduate student of the Industrial and Production Engineering of Mechanical and Production Engineering department at the Ahsanullah University of Science and Technology (AUST). Her research interests include the area of Industry 4.0, Smart machining, Intelligent milling, Machining Parameter Optimization, Product Design, and development. She achieved a prize in an international event named Mindspark'20. She also takes part in different tech-based competitions. She has experience short time industrial exposure training at Bangladesh Industrial Technical Assistance Center (BITAC).

Mir Wahidul Islam is an undergraduate student of Industrial and Production Engineering (IPE) at Ahsanullah University of Science and Technology. He has a great research interest in the field of manufacturing. His research interest includes Smart Machining, Smart Monitoring, Optimization of Machining Parameters, Industry 4.0, etc. He has experienced short-term industrial exposure training at Bangladesh Industrial Technical Assistance Center (BITAC). He has taken part in different tech-based competitions.

Md. Saniat Kamal is an undergraduate student of Ahsanullah University of Science & Technology from the Industrial & Production Engineering (IPE Program) of the Mechanical & Production Engineering Department. His research interests include the area of Industry 4.0, Smart machining, Intelligent milling, Machining Parameter Optimization, Product Design, and development. He has experience short time industrial exposure training at Bangladesh Industrial Technical Assistance Center (BITAC).

Dr. M. Azizur Rahman is an Assistant Professor in Industrial and Production Engineering (IPE) under the department of Mechanical and Production Engineering (MPE) at Ahsanullah University of Science and Technology (AUST), Dhaka, Bangladesh. He is a member of IEB (Bangladesh), OCIEBS (Singapore) and IMechE (UK). Dr. Azizur is a registered Chartered Engineer (CEng, UK). He earned B.Sc. in Mechanical Engineering from Bangladesh University of Engineering and Technology (BUET), Masters in Mechanical Engineering from National University of Singapore (NUS), Master of Science (Logistics) from Nanyang Technological University (NTU), Singapore and Ph.D. in Mechanical Engineering from National University of Singapore (NUS), Singapore. Dr. Azizur is currently serving as a Guest Editor for Special Issue "Intelligent Additive/Subtractive Manufacturing" in Journal Micromachines. He also serves in Editorial, Advisory, and Review Board of IJAMP (International Journal of Advanced Manufacturing Processes), JPSME (Journal of Production System and Manufacturing engineering), AOE (Annals of Engineering). Dr. Azizur has extensive working experience in various manufacturing industries in Singapore. His research interests include Additive manufacturing (3D printing), Metal cutting and Ultra-precision machining, Electrical discharge and Laser beam machining, Micro/nanofabrication, Logistics and Supply chain management, Intelligent manufacturing process for Industry 4.0.

Dr. Md Shahnewaz Bhuiyan is an Associate professor in Mechanical Engineering (ME) program under the Department of Mechanical and Production Engineering at Ahsanullah University of Science and Technology (AUST). He is a member of IMechE (UK). He is a registered Chartered Engineer (C Eng, UK). He received his D. Eng. and Masters in Mechanical Engineering from Nagaoka University of Technology (Japan), B.Sc. in Mechanical Engineering from Bangladesh University of Engineering and Technology (BUET). His research activities include the area of fatigue and fracture of light alloys, fracture of composite materials, microstructural studies of SME products in Bangladesh, environmental assisted cracking, additive manufacturing. He has published many journal papers and conference articles in these areas.

Dr. Md. Abdur Gafur is the principal scientific officer of Pilot Plant & Process Development Centre (PP & PDC) at Bangladesh Council of Scientific and Industrial Research (BCSIR), Dhaka. He completed his BSc and MSc in Metallurgical Engineering. He also completed his Ph.D. in Metallurgical Engineering. He is a member of IEB, BSME, and BAAS. His working areas are 4IR, Composite materials, Ceramics, Metals, and many more. He has about 187 articles published in many international journals. He is also engaged as a Part-Time Teacher coordinating different courses of Materials and Metallurgical Engineering.