Tran, Minh Quang; Elsisi, Mahmoud; Liu, Meng Kun; Vu, Viet Q.; Mahmoud, Karar; Darwish, Mohamed M.F.; Abdelaziz, Almoataz Y.; Lehtonen, Matti

Reliable Deep Learning and IoT-based Monitoring System for Secure Computer Numerical Control Machines Against Cyber-Attacks with Experimental Verification

Reliable Deep Learning and IoT-Based Monitoring System for Secure Computer Numerical Control Machines Against Cyber-Attacks With Experimental Verification

MINH-QUANG TRAN[1,2], **MAHMOUD ELSISI**[1,3], **MENG-KUN LIU**[1,4], **VIET Q. VU**[2],
KARAR MAHMOUD[5,6], **(Senior Member, IEEE), MOHAMED M. F. DARWISH**[3,5],
ALMOATAZ Y. ABDELAZIZ[7], **(Senior Member, IEEE), AND MATTI LEHTONEN**[5]

[1]Industry 4.0 Implementation Center, Center for Cyber-Physical System Innovation, National Taiwan University of Science and Technology, Taipei 10607, Taiwan
[2]Department of Mechanical Engineering, Faculty of International Training, Thai Nguyen University of Technology, Thai Nguyen 250000, Vietnam
[3]Department of Electrical Engineering, Faculty of Engineering at Shoubra, Benha University, Cairo 11629, Egypt
[4]Department of Mechanical Engineering, National Taiwan University of Science and Technology, Taipei 10607, Taiwan
[5]Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, 02150 Espoo, Finland
[6]Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan 81542, Egypt
[7]Faculty of Engineering and Technology, Future University in Egypt, Cairo 11835, Egypt

Corresponding authors: Karar Mahmoud (karar.mostafa@aalto.fi), Mohamed M. F. Darwish (mohamed.m.darwish@aalto.fi; mohamed.darwish@feng.bu.edu.eg), and Minh-Quang Tran (minhquang.tran@mail.ntust.edu.tw)

ABSTRACT This paper introduces a new intelligent integration between an IoT platform and deep learning neural network (DNN) algorithm for the online monitoring of computer numerical control (CNC) machines. The proposed infrastructure is utilized for monitoring the cutting process while maintaining the cutting stability of CNC machines in order to ensure effective cutting processes that can help to increase the quality of products. For this purpose, a force sensor is installed in the milling CNC machine center to measure the vibration conditions. Accordingly, an IoT architecture is designed to connect the sensor node and the cloud server to capture the real-time machine's status via message queue telemetry transport (MQTT) protocol. To classify the different cutting conditions (i.e., stable cutting and unstable cuttings), an improved model of DNN is designed in order to maintain the healthy state of the CNC machine. As a result, the developed deep learning can accurately investigate if the transmitted data of the smart sensor via the internet is real cutting data or fake data caused by cyber-attacks or the inefficient reading of the sensor due to the environment temperature, humidity, and noise signals. The outstanding results are obtained from the proposed approach indicating that deep learning can outperform other traditional machine learning methods for vibration control. The Contact elements for IoT are utilized to display the cutting information on a graphical dashboard and monitor the cutting process in real-time. Experimental verifications are performed to conduct different cutting conditions of slot milling while implementing the proposed deep machine learning and IoT-based monitoring system. Diverse scenarios are presented to verify the effectiveness of the developed system, where it can disconnect immediately to secure the system automatically when detecting the cyber-attack and switch to the backup broker to continue the runtime operation.

INDEX TERMS Deep learning, industry 4.0, Internet of Things, smart machines, milling process.

I. INTRODUCTION

Nowadays, the internet of things (IoT), artificial intelligence (AI), and big data analysis are three exciting technology

The associate editor coordinating the review of this manuscript and approving it for publication was Kan Liu.

innovations that play a core role and drive the industry 4.0 implementation. Typically, those technologies accelerate the global manufacturing industry to transform it into intelligence factories by integrating smart sensors, data analysis, and information security [1]. Manufacturers can implement the industrial IoT topology using smart automated

equipment, cloud techniques, data analytics, and management to make promptly respond to market demands [2]–[4]. Meanwhile, obtaining precision parts using metal cutting processes as well as raising awareness about cyber-attack are the motivations of decision-makers and manufacture planners to develop new efficient strategies to ensure stable and secure computer numerical control (CNC) operation in almost all industries. Improving the productivity of CNC machine tools with high precision and good surface quality takes great attention from many manufacturers and it is the current trend in the modern cutting industry. Interestingly, a promising IoT technology could play a key role to monitor and control CNC status [5]. The development of cutting productivity is considered the most important issue of manufacturing technology, where the usage of traditional and manual cutting is unlikely [6]. The improvement of cutting productivity is important to increase the material depth of cutting, feed, and spindle speed. However, undesired cutting vibrations may be caused at high metal cutting speeds and high cutting depth [7]. The tool will be excited by itself and vibrate at a certain frequency called chatter frequency. This phenomenon was introduced by Budak, and Altintas [8]. When the chatter vibration appears during the cutting, it will destroy the finished surface of the part, affect dimensional accuracy, and reduce the tool life, particularly with the small tool [9]. Therefore, detection of chatter vibration and control is very important to maintain stable cutting and improve productivity and product quality.

Many monitoring and diagnostic systems for the cutting process have been developed to deal with this problem, in which the cutting signals have been used for chatter identification, but most of them are offline systems [10]–[12]. Traditionally, the chatter monitoring process consists of data collection, processing of cutting signals, and applying statistical methods and model training for chatter detection [13], [14]. Recently, machine learning approaches have been recognized to be an effective method for classification and recognition problems [15]–[17]. Many studies also applied these techniques for monitoring machining stability successfully. Traditionally, machine learning-based chatter detection consists of signal collection, data acquisition, feature extraction, feature selection, and classification [18]. This approach usually relies on how to determine the set of features that are relevant to cutting stability. Feature extraction and feature selection are therefore required to find out the most important features within the dataset. The irrelevant and redundant features will reduce classification accuracy and increase the computation time, it is expected to remove those features from the data set. Besides that, traditional feature learning required deep expertise and knowledge for signal processing to design and select the best features within the dataset. Those drawbacks can be overcome by applying the deep learning method because it can learn the pattern and extract representative features automatically within the dataset without defining the feature extraction and selection [19]. Deep learning is a special type of machine learning; it is able to discover features from a large volume of data using a neural network with multiple layers. Artificial intelligence approaches were shown promising results to automate optimization, detection, and classification [20]–[25]. However, those methods usually involve signal processing that may require a deep understanding and knowledge of signal processing. Important chatter indicators need to be defined to build an accurate chatter detection model [26], [27]. With the development of technology innovation, recently, deep learning is considered to be a powerful approach for classification problems. The deep learning approach can learn the representative features automatically within the input signals instead of manually extracting and selecting the significant features as the limitations of the conventional machine learning methods previously [28]. The approach shows a promising tool for chatter detection with high accuracy of classification [18]. An architecture of a deep learning-based chatter detection approach has been developed based on a convolutional neural network (CNN) and time-frequency images [14]. The long short-term memory (LSTM) method has been applied for online chatter detection based on the current signal without additional sensors [29]. This can well distinguish the unstable state from stable cutting conditions and deep learning outperformed other traditional approaches.

The development of Industry 4.0 leads to automation in cutting processes that are required with online condition monitoring systems for improving the quality of products. The industrial IoT architecture consists of smart machine tool attached sensors, connectivity system, cloud management, and application layer [30]. In which, sensor data management and big data analytics are the main issues, especially for real-time monitoring of the IoT system [31], [32]. The IoT systems can help to accelerate manufacturing efficiency. It enables the manufacturers to see the cutting condition in real-time and give a quick response to the machine tool with proper adjustments [33]. An IoT platform for intelligent chatter suppression was conducted by Chang et. al. [34]. The system could collect the cutting data, analyze the vibration, and upload it to the cloud for remote monitoring with reference to the stability lobe diagram. However, Impact testing always takes a lot of time to measure frequency response function because it has to be conducted for each tool-holder-spindle combination [35], [36]. A real-time chatter monitoring was successfully conducted by the cloud-based monitoring system and an intelligent algorithm for selecting the proper action according to the collected signal [37]. However, the proposed system was developed to deal with a specific industrial problem of chatter suppression in train wheel repair.

As clear aforementioned, the effective monitoring and controlling of the vibration issues are recognized as the key challenges of the modern intelligence infrastructures to increase the operational efficiency of the smart machines. Regarding the development of IoT and deep learning techniques that drive the smart machine tool in manufacturing, this research

aims to propose an IoT platform integrating a developed deep learning method to monitor the cutting process to maintain cutting stability. Besides, the powerful learning ability of deep learning allows the suggested system to identify malicious attacks with fake data accurately. Accordingly, the proposed IoT topology with deep learning can provide a reliable and effective infrastructure that enhances industrial decision-making and improves investments in industry 4.0. The main contributions of this study are listed as follows:

- A new intelligent integration is performed between the IoT platform and the DNN algorithm for online monitoring of the CNC machines in order to detect the status of the vibrations due to the cutting process.
- The developed system can identify the stable and unstable cutting status in order to ensure effective cutting processes, keep the cutting process in stable cutting that can help to increase the quality of products.
- The introduced deep learning method is able to recognize the cyber-attack and the IoT platform can show it in the main dashboard. Moreover, the suggested infrastructure can switch the IoT system to the backup broker in case of a cyber-attack to keep reliable and secure cutting processes.
- The major contribution of this research from an industry 4.0 perspective is that the applying of deep learning algorithms to replace the feature-generation and feature-selection procedures, which are usually done by experienced engineers using trial-and-error. The fact that the proposed system has higher accuracy than the conventional machine-learning techniques indicates it could make an objective judgment of machining status.

II. INDUSTRIAL IOT ARCHITECTURE AND METHODOLOGY
A. INDUSTRIAL IOT OVERVIEW
The industrial internet of things (IIoT) is an extension of the IoT in industrial areas. The IIoT relates to the machine-to-machine (M2M) concept, signal processing, and artificial intelligence towards smart machine tools and smart factories to have better reliability and efficiency of their applications [38]. Because the data and status of each manufacturing device can be collected and then managed by software processes, the manufacturing processes will be able to move faster, be more flexible, meet higher work safety standards, and fulfill higher quality standards [39]. Figure 1 illustrates a complete architecture of Industrial IoT, in which the hardware part is the machine tool equipped with sensors to sense the machining process and perform actions in real-time. Then the connectivity layer allows the hardware to pass the sensor data on the cloud layer. An IoT gateway is usually used as a step in the middle of the hardware and the connection to the cloud layer. The IIoT software part is also needed for data management that has functions for storing and processing large volumes of sensor data, and for making decisions. Artificial Intelligence capabilities in cloud and machine learning thrive on large volumes of data and become a powerful tool of new cloud computing generation [40].

A user interface allows users to communicate with the IIoT system, dashboards are designed for visualizing data and monitoring the data in real-time. However, the cyber-attack represents a critical issue against the collection of real data for the right decision-making. In this paper, the developed IIoT is integrated with a deep learning technique in order to classify the fake data. Furthermore, the new infrastructure can switch to the backup broker in case of cyber-attack enabling the user to work with real data that provide reliable decision-making and keep the cutting process of the smart machine in normal condition with stable cutting.

B. PROPOSED METHODOLOGY
The purpose of this work is to introduce an intelligence IoT infrastructure integrating a deep neural network algorithm to monitor the cutting process regarding maintaining the cutting stability. Besides that, the powerful learning ability of deep learning allows the developed system to identify malicious attacks with fake data accurately. An IoT architecture for smart CNC machines on the shop floor is proposed in Fig. 2. A high accuracy 5-Axis trunnion table machining center has equipped a dynamometer between the workpiece and the workbench to measure cutting forces under various cutting conditions. Then, the chatter in the cutting process can be detected using the measurement of the cutting force as a popular way for chatter recognition. Typically, it characterizes the cutting dynamic behavior and provides the cutting conditions including the tooth passing frequency and harmonics. Moreover, the measuring of the cutting force can detect the chatter frequency of the unstable cutting process [35], [36]. The cutting force is responding quickly to the variations of cutting processes. Therefore, it is suitable for early chatter detection in real-time behavior. The dynamometer captures the force signal in three directions. Then, the collected signal is transmitted through a charge amplifier and module type 5167×1 for data acquisition with 2.5 mN accuracy. The data is sampled with a sampling rate of 70 kHz. The collected raw signals are processed by a LabVIEW program and transmitted to the cloud server of Microsoft SQL (Ms SQL). The sensor data stored in the cloud will act as input for a deep learning algorithm which is developed for monitoring the status of the cutting in real-time. In this scheme, a complete platform from edge connectivity to business applications via the web using a Digital Twin named CONTACT Elements for IoT @ [41] is deployed to quickly evaluate the collected data and monitor the machine tool intelligently. The CONTACT Elements for IoT is utilized with the standard MQTT protocol to display such information on the main dashboard after further operation of signal processing and deep learning technique.

III. EXPERIMENTAL DESIGN
In this section, experiments are designed to conduct different cutting conditions of slot milling. The details of the experimental design are shown in Fig. 2. The workpiece of Al6061-T6 with a size of $30 \times 30 \times 40$ mm was used in
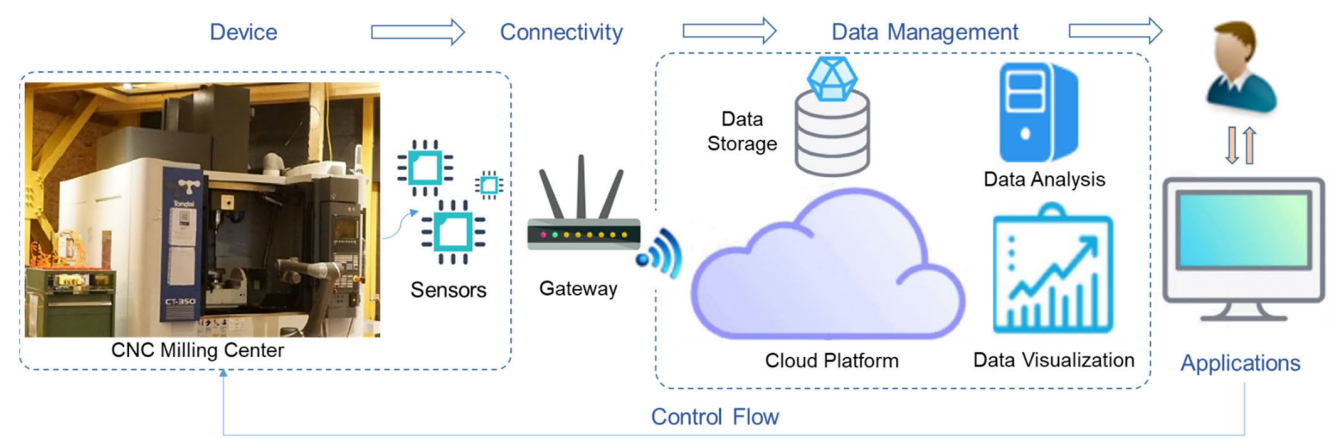
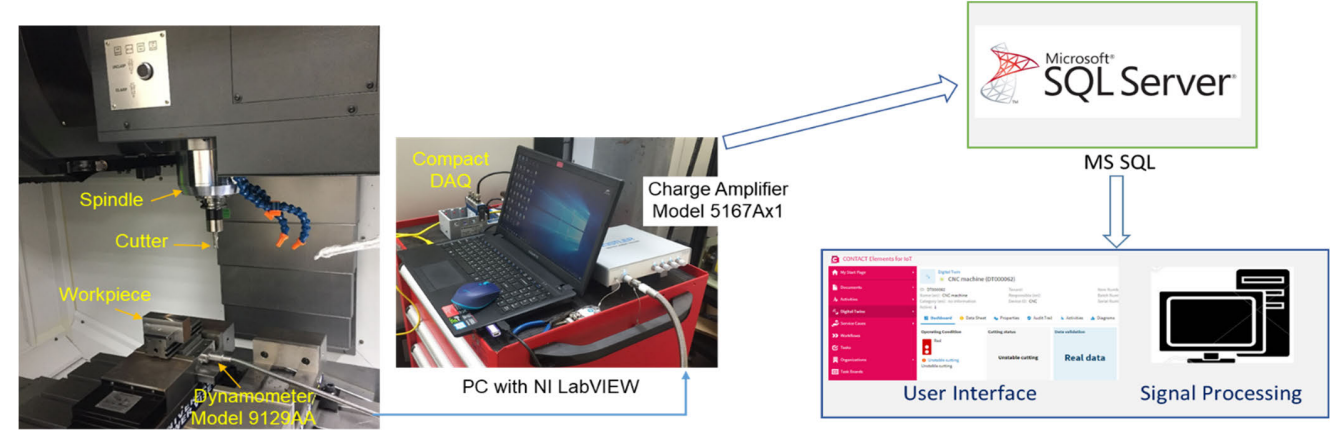**FIGURE 1.** Industrial IoT architecture on the shop floor.

FIGURE 2. Intelligence industrial IoT architecture for smart CNC machines on the shop floor.

TABLE 1. Composition of aluminum alloy type of 6061 by weight %.

Al	Mg	Si	Cu	Cr	Fe	Zn	Ti
95.85 - 98.56	0.8 - 1.2	0.4 - 0.8	0.15 - 0.40	0.04 - 0.35	0.0 - 0.7	0.0 - 0.25	0.0 - 0.25

TABLE 2. Chemical composition by weight % of uncoated carbide cutting tool.

Tungsten Carbide, WC	VC + Cr3C2	Cobalt, Co
88.4 – 90.0	9.5 – 10.5	0.5 – 1.1

TABLE 3. Cutting parameters.

Spindle speed (rpm)	2250	3000	3750	4500	5250	6000
Range of DOC (mm)	0.4	0.6	0.8	1.0	1.2	1.4
Feed rate (mm/min)	150					

all cutting experiments. The chemical composition of the workpiece is recorded in Table 1. The mill cutter is an uncoated carbide that has two flutes with a 12 mm diameter. The tool geometry has a helix angle of 26° and a relief angle of 6°. The geometrical properties and the chemical composition of the cutting tool are shown in Table 2 [42]. The cutting force signals were collected from various cutting conditions with the cutting parameters described in Table 3. In this study, three groups of experiments were conducted to collect the cutting force signals under different machining states, including stable cutting, unstable cutting, and fake data. The dynamometer was used to capture the cutting force signals. The collected signal is then transmitted through a charge amplifier and module type 5167×1 for data acquisition with 2.5 mN accuracy. The data is sampled with a sampling rate of 70 kHz. The collected raw signals are

processed by a LabVIEW program and transmitted to the cloud server of Microsoft SQL (Ms SQL). We collected the cutting data from 36 cutting conditions, in which 24 cutting conditions are stable cuttings and 12 cutting conditions are unstable cuttings. While the fake data which stands for the cyber-attack is generated using randomly distributed function within the range of the cutting force signals. All the experiments were performed with dry cutting conditions.
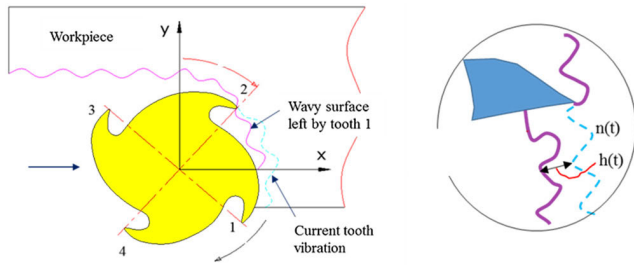
FIGURE 3. Milling regenerative chatter.

In order to detect chatter using in-process techniques with the cutting signal, an understanding of the dynamics of the regenerative chatter is very important. Figure 3 shows the milling regenerative chatter, in which the current tooth will remove the previous wavy surface left by tooth 1 and so on. It shows that the instantaneous chip thickness $h(t)$ relies on the previous and current wavy surface $n(t)$ and it will make the tool gain a response. If the vibration from the current cutting edge to the next wavy is out of phase that causes the chip thickness variation to be more significant, then the tool vibrates and imprints on the work surface that is the signature of chatter vibration [43]. The cutting force characterizes the cutting dynamics and swiftly reflects the tooth passing frequency and especially chatter frequency. Therefore, cutting force is commonly used to identify the cutting behavior, especially in the laboratory. In this research, we used the tabletop dynamometer with a sampling rate of 70 kHz in order to measure the chatter frequency. Although both tabletop and spindle-based dynamometers have difficulties to be applied to the shop floor due to their high cost, the chatter detection method proposed in this study could still be applied to the signals measured from other sensors such as accelerometers and microphones. Those sensors are more affordable and suitable for the shop floor compared to the dynamometer.

An analysis for the measurement of force signals is described in Fig. 4, indicating vibrations of the tool under different cutting conditions in the time domain (see Fig. 4.a) and in the frequency domain (see Figs. 4.b and 4.c). During stable cutting, the Fourier spectrum presents the tooth passing frequency of 150 Hz and its harmonics (cutting at the spindle speed of 4500 rpm) as shown in Fig. 4.b. Whereas high peaks of frequency around 4000 Hz beyond the tooth passing frequencies and their harmonics can be seen in Fig. 4.c, which signifies unstable cutting conditions thereby indicating the presence of chatter.

IV. DEEP LEARNING FOR MONITORING MACHINING STABILITY

The deep learning architecture for monitoring cutting stability includes an input layer, multiple hidden layers, and an output layer as shown in Figure 5. Deep learning processes the input data of the force signal through multiple hidden layers to recognize the status of machining. Each layer in the network is made of artificial neurons that are interconnected.

Artificial neuron in layer l_i takes the input from the previous output of layer l_{i-1} with the weight and runs it through a non-linear activation function to compute its output. Then this result will be passed to the next layer l_{i+1}, and finally, the nodes of the last layer represent the targets of the model. The network is, therefore, able to learn very complex functions if it is provided enough computational power.

The nonlinear relationship between two adjacent layers in the deep neural network is described in Eq. (1). It shows the transformation of the $(l-1)^{th}$ layer into the neuron j in l^{th} layer, in which a^l and a^{l-1} are the hidden representations of the $(l-1)^{th}$ layer and the lth layer, respectively.

$$a_j^l = \sigma \left(\sum_k w_{jk}^l a_k^{l-1} + b_j^l \right), \tag{1}$$

where w_{jk}^l is the weight matrix that connects to the lth layer of neurons from node k in layer $(l\text{-}1)$ to node j in layer l Also, b_j^l is the bias vector for each layer l. Further, σ represents the activation function, in this work the rectified linear unit (ReLU) is used as the activation function which is defined in Eq. (2).

$$\sigma(x) = \max(0, x), \tag{2}$$

In the output layer, we used the softmax function as an activation function to calculate a probability for each possible class. The softmax function is formulated as in Eq. (3),

$$y_c = \frac{\exp(a_c)}{\sum_{i=1}^{K} \exp(a_i)} \tag{3}$$

where a_c is the values of the input vector to the softmax function, the term of $\sum_{i=1}^{K} \exp(a_i)$ is the normalization term which makes the summation of all the output values of the function equal to 1. $K = 3$ presents the number of classes. Therefore, a predicted label is determined with the largest value of the output.

In order to build the neural network architecture properly, the determination of hidden layers' numbers and the choosing of suitable neurons number in each layer represent the most important issues. Generally, more hidden layers will cause an increase in computation time and may result in overfitting that leads to reducing prediction performance of the model. In this work, the deep neural network architecture is structured using a network with one input layer, four hidden layers, and one output layer. In which, the first hidden layer has 128 nodes, the second hidden layer has 512 nodes, the third layer has hidden 256 nodes, and the fourth hidden layer has 128 nodes. The details of the proposed network architecture are described in Table 4. The proposed deep neural network model is trained using a back-propagation strategy to update all the weights of the network. The gradient of the error function is calculated and proceeded backward through the network with reference to the weights of the network. In the training model, an efficient Adam optimization algorithm is
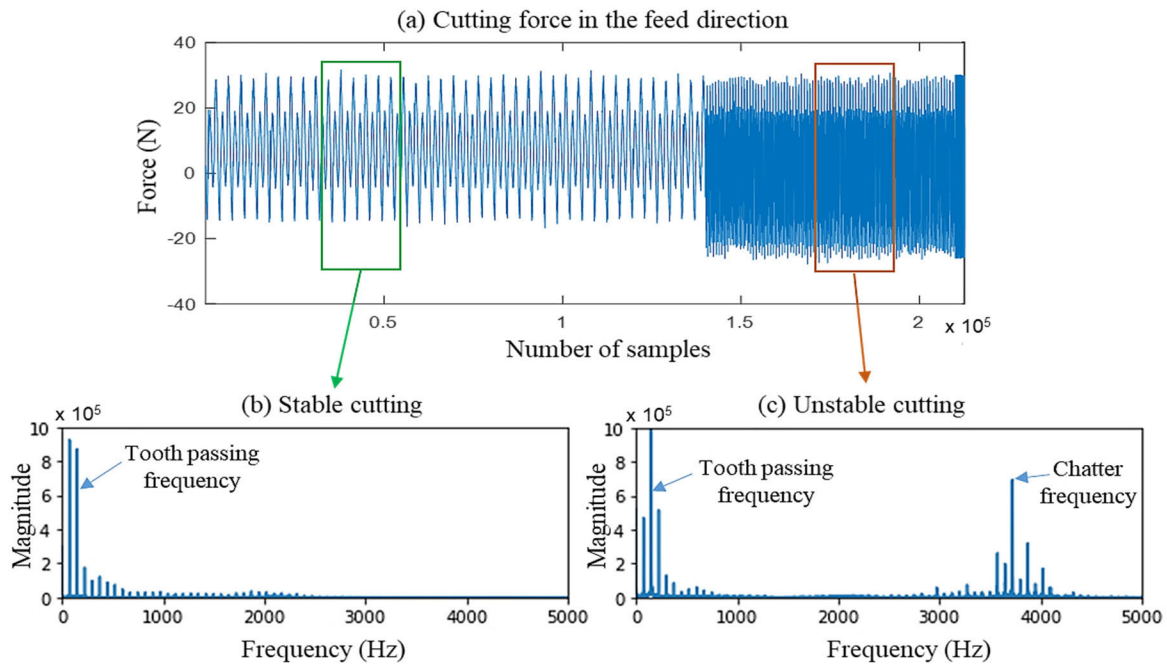
FIGURE 4. Force signals under different cutting conditions in the following cases: (a) time domain, (b) Frequency spectrum of stable cutting, and (c) Frequency spectrum of unstable cutting.
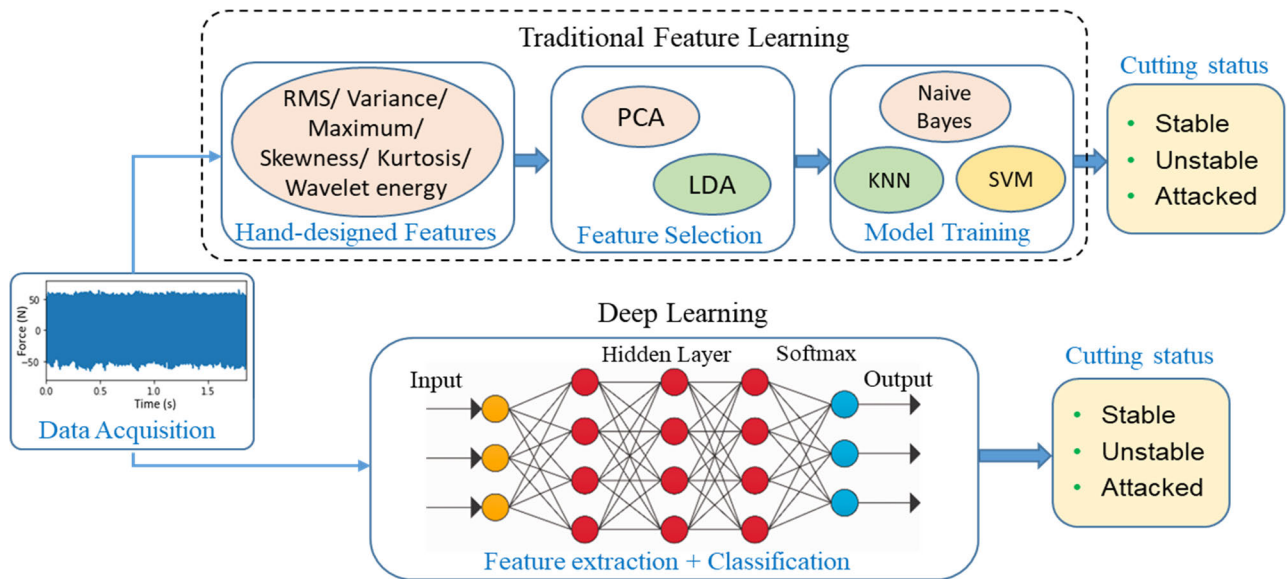

FIGURE 5. Traditional feature learning and deep learning architecture for cutting stability monitoring.

used for stochastic gradient descent, and the category cross-entropy is utilized as the loss function. The number of epochs for training is set to 100 epochs, and the best parameters of training are saved to evaluate the test data.

V. RESULTS AND DISCUSSIONS

The developed deep learning algorithm is devoted to classi-fying different statues of machining including stable cutting, unstable cutting, and attacked signal. Then, the developed model by deep learning is combined with an IoT system to support the online validation of cutting processes of the smart

CNC machine in order to overcome the vibration problem of the unstable cutting. Furthermore, it can detect cyber-attack, provide a reliable and effective cutting process, keep the smart machine in a healthy state. In order to create an effective deep learning model, a real-time dataset is selected from the smart CNC machine at different cases of cutting processes in order to train and test the proposed deep learning technique. A fake dataset is created randomly to represent the cyber-attack and it is added to the real-time dataset of the smart CNC machine. Figs. 6a, 6b, and 6c show different real-time states of stable, unstable, and fake signals that it
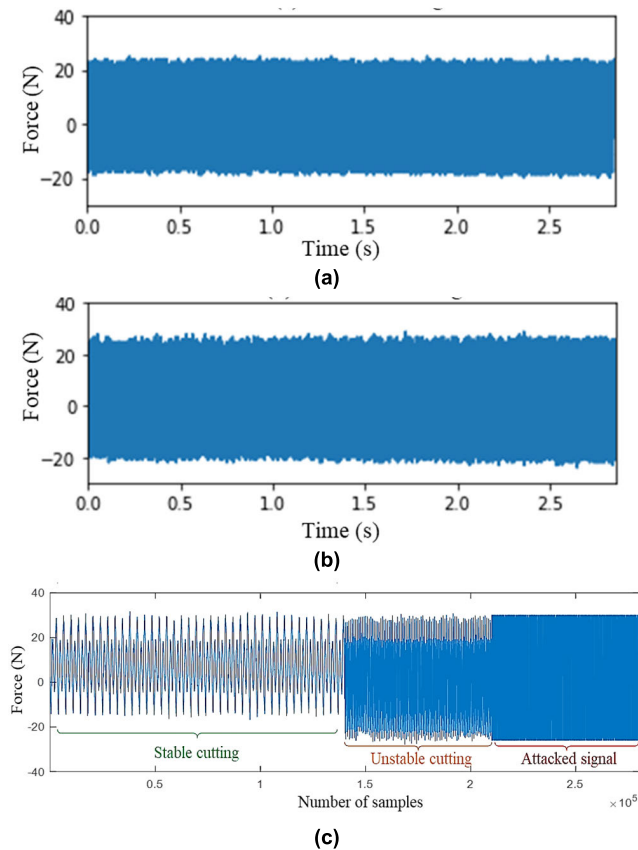
FIGURE 6. (a) Stable cutting at the cutting speed of 5250 rpm and 0.6 mm and (b) Unstable cutting at the cutting speed of 5250 rpm and 1.2 mm (c) Cutting signal under different states.

TABLE 4. Network architecture.

Layer	Output shape	Number of Parameters
Hidden layer 1	128	8960128
Hidden layer 2	512	66048
Hidden layer 3	256	131328
Hidden layer 4	128	32382
Output layer	3	381

Total parameters: 9,190,267

Trainable parameters: 9,190,267

Non-trainable parameters: 0
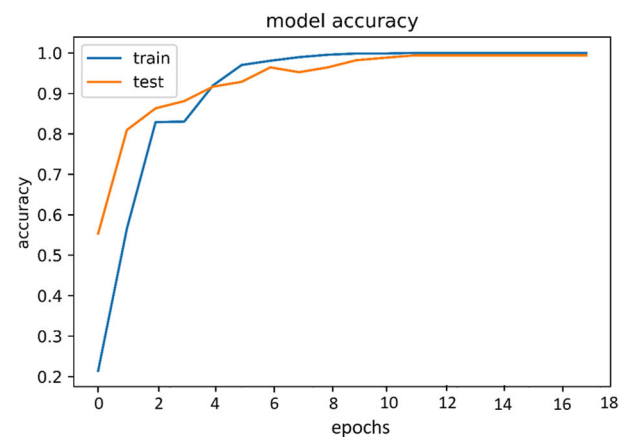
FIGURE 7. Classification accuracy of the training dataset.

**TABLE 5.** Classification report by the deep learning model.

Modes	Precision	Recall	F1-score
Stable	0.99	1.0	0.99
Unstable	1.0	0.95	0.98
Fake data	1.0	1.0	1.0

is utilized for the training and testing of the proposed deep learning algorithm. In this case, the stable cutting is very obvious at a low cutting speed of 3000 rpm and a small cutting depth of 0.6 mm, and the unstable cutting form is also clear at a high cutting speed of 5250 rpm and the cutting depth of 1.4 mm. Though, the difference between stable and unstable cuttings cannot be easy to be known in the time domain for other cases. For example, when considering the same cutting speed of 5250 rpm, the chatter occurs at a cutting depth of 1.2 mm while remaining stable cutting at 0.6 mm cutting depth.

Various cutting signals under various cutting conditions are labeled into three classes. Totally, 840 samples were split for the training and testing process. Of which 80% is used for the training dataset and the rest of it is used for testing dataset. Figure 7 describes the classification results of the improved model of the deep learning approach. The classification rate improves when increasing the number of training epochs. It shows that both training and validation progress can reach the accuracy of 90% after 5 epochs and the highest accuracy is up to 99.47% after 17 training epochs. Moreover, the performance of the proposed model on the testing dataset is also evaluated via precision, recall, and f1-score, which are detailed in Table 5. It shows that both precision and recall values for each cutting class are quite close to one. As a result,

the f1-score, which measures the average of the precision and recall, is also close to 1 for every class, as shown in Table 5.

Figure 8 shows the receiver operating characteristic (ROC) curves of three classes from the deep learning model. Overall, the performance is around 0.99 for all cases that indicating the balanced distribution between the performances of three different classes within the dataset. It shows that the model can detect the fake signals well when the system is attacked with the highest performance at 1.0, followed by the stable case at 0.99. The unstable cutting has the lowest performance at 0.98.

Traditional feature learning techniques are conducted to compare with the proposed model. Initially, several conventional chatter indicators have been applied to identify cutting chatter vibration [44], [45]. In this work, eight statistical indexes are adopted to generate cutting features from the measured force signal in real-time. The determinations of these indicators are formulated in the following
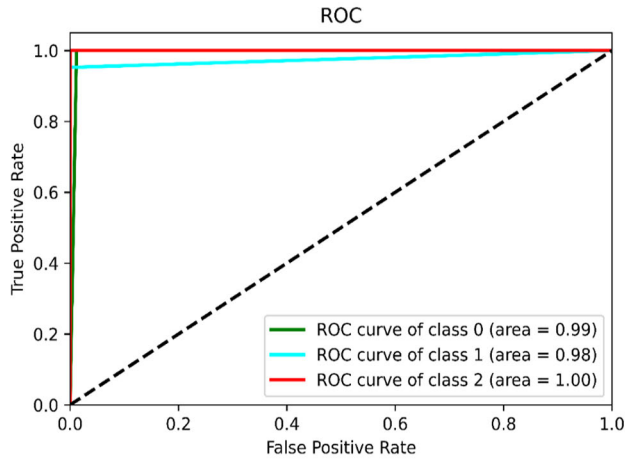
FIGURE 8. ROC of three different classes, means (0: stable cutting, 1: unstable cutting, and 2: attacked signal).

FIGURE 9. Classification accuracy of different methods.

Algorithm 1 The Pseudo-Code of Data Acquisition, Validation, and Visualization for Smart Machine

---
1: *Read* data from the dynamometer
2: *Input* the data to the deep learning model
3: *Classify* the machining status by the deep learning model
4: **if** the output of the deep learning model == 0
5:    *Publish* that the data is 'Stable cutting' and 'Real data'
6: **elseif** the output of the deep learning model == 1
7:    *Publish* that the data is 'Unstable cutting' and 'Real data'
8:    **Adjust** the cutting parameter to reach a stable condition
9: **else** the output of the deep learning model == 2
10:    *Publish* that the data is 'Fake cutting' and 'Attacked data'
11:    **Switch** the broker to the backup IoT broker
12: **end if**

---

equations (4)-(11):

$$\text{Average (AVG)} \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{4}$$

$$\text{Standard Deviation (STD)} s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{5}$$

$$\text{Root Mean Square (RMS)} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \tag{6}$$

$$\text{Variance (VAR)} = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \tag{7}$$
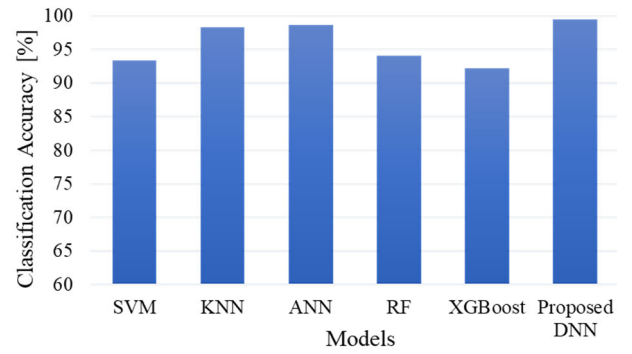
$$\text{Max Value (MAX)} = (x_{max}) \tag{8}$$

$$\text{Kurtosis (KUR)} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{s} \right)^4 \tag{9}$$

$$\text{Skewness (SKE)} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{S} \right)^3 \tag{10}$$

$$\text{Crest Value (CRE)} = \frac{x_{max}}{\sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}} \tag{11}$$

in which n represents sample numbers and x_i represents the magnitude of the ith cutting force signal value.

Once all the features were extracted, different traditional machine learning classifiers such as k-nearest neighbours (KNN), artificial neural network (ANN) [46]–[49], and supported vector machine (SVM) were implemented for the classification. The details of those classifiers were introduced in [50], [51]. In addition, the effectiveness of the proposed DNN model is also evaluated by comparing to ensemble learning approaches such as random forest (RF) and eXtreme Gradient Boosting (XGBoost) [52], [53]. The classification accuracy of different approaches is listed in Fig. 9, in which the classification accuracies of different approaches are shown in a vertical bar plot as an effective clarified way for comparison. The results demonstrate that the lowest accuracy comes from the linear SVM classifier with a classification accuracy of 93.33%. The KNN structure uses the nearest neighbours' number equal to 3 that improving the classification with 98.3% accuracy. While, by applying a signal

hidden layer of 10 neurons for the ANN model heuristically, the classification accuracy can reach 98.6%. The ensemble learning approaches have lower classification accuracies, in which the accuracy of the RF model is 94.05%, and 92.26% accuracy is obtained by the XGBoost model. The improved proposed deep neural network (DNN) provides classification with 99.47% accuracy that outperforms the other traditional machine learning methods to recognize different statuses of the milling process successfully as clear in Fig. 9. This demonstrates that the deep learning network is able to learn the pattern and extract representative features automatically within the dataset. Moreover, traditional feature learning required deep expertise and knowledge for signal processing to design and select the best features within the dataset.

Once the status of the machine was captured by the proposed deep learning approach, the result is sent to the IoT platform through the MQTT protocol. The IoT system will read the cutting conditions online and publish them on the dashboard. An IoT dashboard was designed on the Contact element for IoT. Thus, the current cutting status including stable cutting, cutting chatter, and fake cutting can be visualized, then the cutting process is monitored in real-time. The operations of the data acquisition, validation, and visualization are illustrated by following pseudo-code in Algorithm 1. Besides, Figure 10 shows the flowchart of the proposed IoT architecture based on DNN for CNC machines. As shown, the main goal of this experiment is to introduce a new intelligent integration between an IoT platform and the DNN algorithm for the online monitoring of CNC machines.
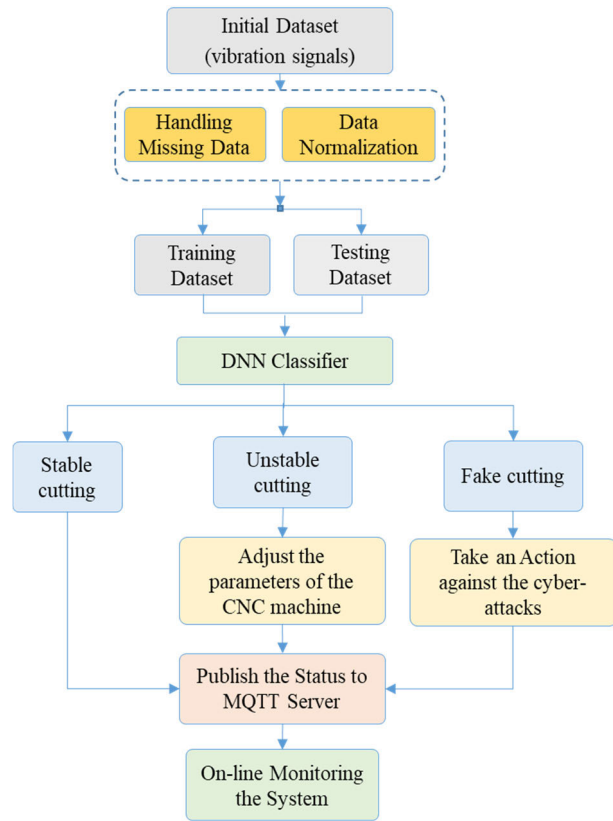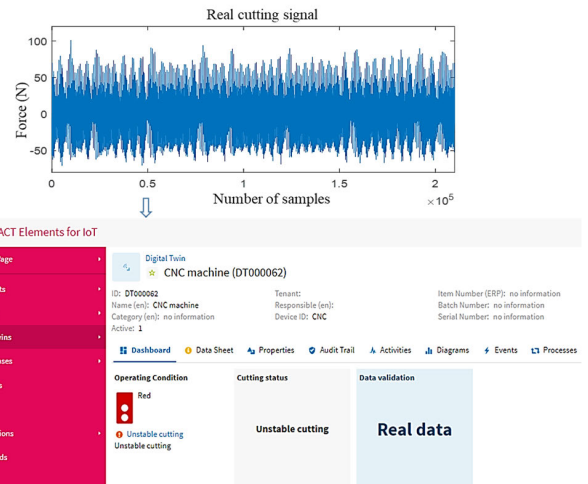
FIGURE 10. Flowchart of the proposed IoT architecture based on DNN for CNC machine.
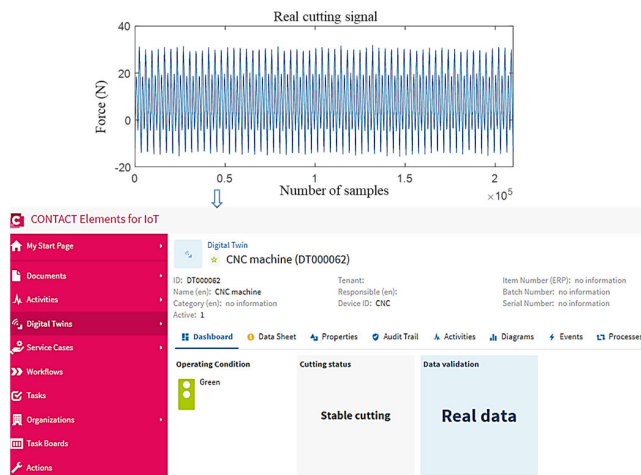
FIGURE 11. IoT dashboard in case of stable cutting.

FIGURE 12. IoT dashboard in case of unstable cutting chatter.

A. SCENARIO 1: STABLE CUTTING

In this scenario, the proposed IoT system is examined when the data of the cutting force is real and the cutting under stable conditions. Figure 11 represents the output of the proposed system for this test that is shown in the dashboard of the IoT platform. The status now is showing the real data with stable cutting which means the cutting process and the data measurement are working properly. Therefore, the green in the traffic light is assigned to describe the operation without

any notice of the event and/or alarms. This demonstrates that the proposed system works well without any errors.

B. SCENARIO 2: CUTTING CHATTER

In this case, the proposed system is examined when the data of the cutting force is real and the cutting under unstable conditions. Figure 12 illustrates the output of the test on the dashboard of the IoT platform, in which the real data of cutting is displayed but the cutting condition is now changed to the unstable cutting. This indicates that the tool is vibrating with the chatter frequency. Thus, the red in the traffic light is assigned to make the alarm warnings to the manufacturers. Then they need to take further actions to modify the cutting parameter, in which they can play first with the spindle speed, increase it and reduce it gradually to disturb the wave regeneration mechanism in dynamic milling in order to seek stable machining [54]. If it does not work, then they can reduce the depth of the cut. Furthermore, a chatter suppression strategy based on the stability lobe diagram introduced in [55], [56] can be used to find the best cutting conditions to obtain stable cutting but maintain the machining efficiency simultaneously. Additionally, increasing the stiffness and damping of the machine tool system and choosing the optimal tool geometry are the other strategies to suppress chatter vibration.

C. SCENARIO 3: TESTING FAKE CUTTING DUE TO CYBER-ATTACKS

In this scenario, the proposed IoT system is examined when the force signal is fake due to the cyber-attack. The output of this test on the IoT dashboard is shown in Fig. 13. The proposed deep learning technique can successfully detect the fake cutting condition. The traffic light is changed to red color to make an alarm to the user about the abnormal case of fake data. This scenario is a serious case, and the system has to automatically disconnect immediately to secure the system from the cyber-attack [57].

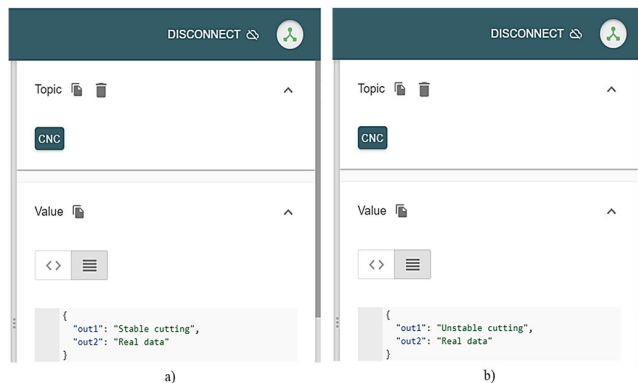**FIGURE 13.** IoT dashboard in case of fake cutting.

FIGURE 14. Switching the broker to the backup IoT broker; (a) the case of stable cutting, and (b) the case of unstable cutting.

D. SCENARIO 4: SWITCHING TO THE BACKUP IoT BROKER

From scenario 3, the proposed system may be damaged by the cyber-attack or the inefficient reading of the sensor due to the environment temperature, humidity, and noise signals. This makes the system get a fake signal. A solution has been developed to deal with the attack case to secure the system, in which the broker is switched to the backup IoT broker to stop the attack. Figure 14 describes the results after switching the broker to the backup IoT broker. This demonstrates that the proposed IoT system can automatically hook up with the real cutting and continue to monitor the cutting operation in real-time.

VI. CONCLUSION

This research was inspired by the concept of the cyber-physic system in the Industry 4.0 era where deep learning and the IoT play a core role. A newly developed intelligent IoT architecture for vibrations control and monitoring of smart machines, in which an improved deep learning algorithm has been applied to monitor the cutting process regarding maintaining the cutting stability of CNC machines. In the IoT platform, the milling CNC machine center was equipped with a force sensor to capture the cutting vibrations. The

IoT architecture using the MQTT protocol was designed to connect the sensor node and the cloud server to capture the cutting conditions. Different cutting statuses including stable cutting, unstable cutting, and fake cutting were successfully classified by the improved model of deep learning neural network. An IoT dashboard was designed on the Contact element for IoT to online visualize the cutting condition in order to ensure that the CNC machine works efficiently in a healthy state. Furthermore, the proposed system can automatically switch the IoT system to the backup broker in case of a cyber-attack to keep reliable and secure cutting processes. The excellent performance was achieved from the proposed approach indicating that deep learning can outperform other traditional machine learning methods for vibration control. Furthermore, the proposed IoT structure with deep learning can be applied to other smart systems in future work.

REFERENCES

[1] P. O'Donovan, K. Leahy, K. Bruton, and D. T. J. O'Sullivan, "An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities," *J. Big Data*, vol. 2, no. 1, p. 25, 2015.

[2] J. Davis, T. Edgar, J. Porter, J. Bernaden, and M. Sarli, "Smart manufacturing, manufacturing intelligence and demand-dynamic performance," *Comput. Chem. Eng.*, vol. 47, pp. 145–156, Dec. 2012.

[3] P. Saqlain and L. Shim, "Framework of an IoT-based industrial data management for smart manufacturing," *J. Sensor Actuator Netw.*, vol. 8, no. 2, p. 25, Apr. 2019.

[4] D. S. Gupta, S. H. Islam, M. S. Obaidat, P. Vijayakumar, N. Kumar, and Y. Park, "A provably secure and lightweight identity-based two-party authenticated key agreement protocol for IIoT environments," *IEEE Syst. J.*, vol. 15, no. 2, pp. 1732–1741, Jun. 2021.

[5] H. Kim, W.-K. Jung, I.-G. Choi, and S.-H. Ahn, "A low-cost vision-based monitoring of computer numerical control (CNC) machine tools for small and medium-sized enterprises (SMEs)," *Sensors*, vol. 19, no. 20, p. 4506, 2019.

[6] B. Wang, F. Tao, X. Fang, C. Liu, Y. Liu, and T. Freiheit, "Smart manufacturing and intelligent manufacturing: A comparative review," *Engineering*, vol. 7, no. 6, pp. 738–757, 2020.

[7] C. Yue, H. Gao, X. Liu, S. Y. Liang, and L. Wang, "A review of chatter vibration research in milling," *Chin. J. Aeronaut.*, vol. 32, no. 2, pp. 215–242, Feb. 2019.

[8] E. Budak and Y. Altintasá, "Analytical prediction of chatter stability in milling—Part I: General formulation," *J. Dyn. Syst., Meas., Control*, vol. 120, no. 1, pp. 22–30, Mar. 1998.

[9] J. Munoa, X. Beudaert, Z. Dombovari, Y. Altintas, and E. Buda, "Chatter suppression techniques in metal cutting," *CIRP Ann.*, vol. 65, no. 2, pp. 785–808, 2016.

[10] Y. Chen, H. Li, X. Jing, L. Hou, and X. Bu, "Intelligent chatter detection using image features and support vector machine," *Int. J. Adv. Manuf. Technol.*, vol. 102, nos. 5–8, pp. 1433–1442, 2019.

[11] E. Kuljanic, M. Sortino, and G. Totis, "Multisensor approaches for chatter detection in milling," *J. Sound Vibrat.*, vol. 312, nos. 4–5, pp. 672–693, May 2008.

[12] S. S. M. Ghoneim, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Enhancing diagnostic accuracy of transformer faults using teaching-learning-based optimization," *IEEE Access*, vol. 9, pp. 30817–30832, 2021.

[13] M.-K. Liu, M.-Q. Tran, C. Chung, and Y.-W. Qui, "Hybrid model- and signal-based chatter detection in the milling process," *J. Mech. Sci. Technol.*, vol. 34, no. 1, pp. 1–10, Jan. 2020.

[14] M.-Q. Tran, M.-K. Liu, and Q.-V. Tran, "Milling chatter detection using scalogram and deep convolutional neural network," *Int. J. Adv. Manuf. Technol.*, vol. 107, nos. 3–4, pp. 1505–1516, Mar. 2020.

[15] M. Tran, M. Liu, and M. Elsisi, "Effective multi-sensor data fusion for chatter detection in milling process," *ISA Trans.*, Jul. 2021, doi: 10.1016/j.isatra.2021.07.005.

[16] M. Tran, M. Elsisi, and M. Liu, "Effective feature selection with fuzzy entropy and similarity classifier for chatter vibration diagnosis," *Measurement*, vol. 184, Oct. 2021, Art. no. 109962.

[17] M. Elsisi, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Reliable industry 4.0 based on machine learning and IoT for analyzing, monitoring, and securing smart meters," *Sensors*, vol. 21, no. 2, pp. 487–503, 2021.

[18] G. Seràna, M. U. Gudeleka, B. Senera, A. M. Ozbayoglua, and H. O. Unvera, "Chatter detection in milling with acoustic emissions and deep learning," presented at the 10th Int. Congr. Machining, 2019.

[19] M. Elsisi, M.-Q. Tran, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Deep learning-based industry 4.0 and Internet of Things towards effective energy management for smart buildings," *Sensors*, vol. 21, no. 4, pp. 1038–1057, 2021.

[20] M. Elsisi, "Future search algorithm for optimization," *Evol. Intell.*, vol. 12, no. 1, pp. 21–31, 2019.

[21] D. Emara, M. Ezzat, A. Y. Abdelaziz, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Novel control strategy for enhancing microgrid operation connected to photovoltaic generation and energy storage systems," *Electronics*, vol. 10, no. 11, p. 1261, May 2021.

[22] E. S. Ali, R. A. El-Sehiemy, A. A. Abou El-Ela, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "An effective bi-stage method for renewable energy sources integration into unbalanced distribution systems considering uncertainty," *Processes*, vol. 9, no. 3, p. 471, Mar. 2021.

[23] M. N. Ali, M. Soliman, K. Mahmoud, J. M. Guerrero, M. Lehtonen, and M. M. F. Darwish, "Resilient design of robust multi-objectives PID controllers for automatic voltage regulators: D-decomposition approach," *IEEE Access*, vol. 9, pp. 106589–106605, 2021.

[24] M. Elsisi, "New variable structure control based on different meta-heuristics algorithms for frequency regulation considering nonlinearities effects," *Int. Trans. Elect. Energy Syst.*, vol. 30, no. 7, 2020, Art. no. e12428.

[25] M. Al-Gabalawy, K. Mahmoud, M. M. F. Darwish, J. A. Dawson, M. Lehtonen, and N. S. Hosny, "Reliable and robust observer for simultaneously estimating state-of-charge and state-of-health of LiFePO$_4$ batteries," *Appl. Sci.*, vol. 11, no. 8, p. 3609, Apr. 2021.

[26] M. Lamraoui, M. Thomas, and M. E. Badaoui, "Cyclostationarity approach for monitoring chatter and tool wear in high speed milling," *Mech. Syst. Signal Process.*, vol. 44, nos. 1–2, pp. 177–198, 2014.

[27] Z. H. Yao, D. Q. Mei, and Z. C. Chen, "On-line chatter detection and identification based on wavelet and support vector machine," *J. Mater. Process. Technol.*, vol. 210, no. 5, pp. 713–719, Mar. 2010.

[28] S. Zhang, S. Zhang, B. Wang, and T. G. Habetler, "Deep learning algorithms for bearing fault diagnostics—A review," in *Proc. IEEE 12th Int. Symp. Diag. for Electr. Mach., Power Electron. Drives (SDEMPED)*, Aug. 2019, pp. 257–263.

[29] R. K. Vashisht and Q. Peng, "Online chatter detection for milling operations using LSTM neural networks assisted by motor current signals of ball screw drives," *J. Manuf. Sci. Eng.*, vol. 143, no. 1, Jan. 2021, Art. no. 011008.

[30] R. Y. Zhong, L. Wang, and X. Xu, "An IoT-enabled real-time machine status monitoring approach for cloud manufacturing," *Proc. CIRP*, vol. 63, pp. 709–714, Jul. 2017.

[31] Q. Cao, F. Giustozzi, C. Zanni-Merk, F. de Bertrand, and C. Reich, "Smart condition monitoring for industry 4.0 manufacturing processes: An ontology-based approach," *Cybern. Syst.*, vol. 50, no. 2, pp. 82–96, Feb. 2019.

[32] M. Elsisi, M.-Q. Tran, K. Mahmoud, D.-E. A. Mansour, M. Lehtonen, and M. M. F. Darwish, "Towards secured online monitoring for digitalized GIS against cyber-attacks based on IoT and machine learning," *IEEE Access*, vol. 9, pp. 78415–78427, 2021.

[33] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, "Intelligent manufacturing in the context of industry 4.0: A review," *Engineering*, vol. 3, no. 5, pp. 616–630, 2017.

[34] W. Chang, W. Sheng-Jhih, and L. Po-Hua, "Real-time chatter suppression and on-line IoT cloud platform for intelligent manufacturing," in *Proc. 8th Int. Congr. Adv. Appl. Inform. (IIAI-AAI)*, vol. 2019, pp. 472–476.

[35] T. L. Schmitz and K. S. Smith, *Machining Dynamics: Frequency Response to Improved Productivity*. New York, NY, USA: Springer, 2009.

[36] K. Cheng, *Machining Dynamics: Fundamentals, Applications and Practices*. London, U.K.: Springer-Verlag, 2009.

[37] R. Merino, I. Bediaga, A. Iglesias, and J. Munoa, "Hybrid edge-cloud-based smart system for chatter suppression in train wheel repair," *Appl. Sci.*, vol. 9, no. 20, p. 4283, Oct. 2019.

[38] M. Weyrich, J.-P. Schmidt, and C. Ebert, "Machine-to-machine communication," *IEEE Softw.*, vol. 31, no. 4, pp. 19–23, Jul./Aug. 2014.

[39] S. Phuyal, D. Bista, and R. Bista, "Challenges, opportunities and future directions of smart manufacturing: A state of art review," *Sustain. Futures*, vol. 2, Jan. 2020, Art. no. 100023.

[40] J. Chen, P. Hu, H. Zhou, J. Yang, J. Xie, Y. Jiang, Z. Gao, and C. Zhang, "Toward intelligent machine tool," *Engineering*, vol. 5, no. 4, pp. 679–690, Aug. 2019.

[41] *IoT Platform for Digital Bus. Models|CONTACT Software*. Accessed: Dec. 22, 2020. [Online]. Available: https://www.contact-software.com/en/ N.

[42] N. K. Muhamad Khairussaleh, A. K. Aqella, and I. S. S. Sharifah, "Optimization of milling carbon fibre reinforced plastic using RSM," *Proc. Eng.*, vol. 184, pp. 518–528, Jan. 2017.

[43] Y. Altintas and A. Ber, "Manufacturing automation: Metal cutting mechanics, machine tool vibrations, and CNC design," *Appl. Mech. Rev.*, vol. 54, no. 5, p. B84, Sep. 2001.

[44] M. Lamraoui, M. Barakat, M. Thomas, and M. E. Badaoui, "Chatter detection in milling machines by neural network classification and feature selection," *J. Vibrat. Control*, vol. 21, no. 7, pp. 1251–1266, May 2015.

[45] G. S. Chen and Q. Z. Zheng, "Online chatter detection of the end milling based on wavelet packet transform and support vector machine recursive feature elimination," *Int. J. Adv. Manuf. Technol.*, vol. 95, nos. 1–4, pp. 775–784, Mar. 2018.

[46] M. Elsisi, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "An improved neural network algorithm to efficiently track various trajectories of robot manipulator arms," *IEEE Access*, vol. 9, pp. 11911–11920, 2021.

[47] M. Elsisi, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Effective nonlinear model predictive control scheme tuned by improved NN for robotic manipulators," *IEEE Access*, vol. 9, pp. 64278–64290, 2021.

[48] M. Elsisi, M.-Q. Tran, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Robust design of ANFIS-based blade pitch controller for wind energy conversion systems against wind speed fluctuations," *IEEE Access*, vol. 9, pp. 37894–37904, 2021.

[49] A. F. Bendary, A. Y. Abdelaziz, M. M. Ismail, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "Proposed ANFIS based approach for fault tracking, detection, clearing and rearrangement for photovoltaic system," *Sensors*, vol. 21, no. 7, p. 2269, 2021.

[50] A. Moosavian, H. Ahmadi, A. Tabatabaeefar, and M. Khazaee, "Comparison of two classifiers; K-nearest neighbor and artificial neural network, for fault diagnosis on a main engine journal-bearing," *Shock Vib.*, vol. 20, no. 2, pp. 263–272, 2013.

[51] A. Ben-Hur, D. Horn, H. T. Siegelmann, and V. Vapnik, "Support vector clustering," *J. Mach. Learn. Res.*, vol. 2, pp. 125–137, Dec. 2001.

[52] M.-Q. Tran, M. Elsisi, K. Mahmoud, M.-K. Liu, M. Lehtonen, and M. M. F. Darwish, "Experimental setup for online fault diagnosis of induction machines via promising IoT and machine learning: Towards industry 4.0 empowerment," *IEEE Access*, vol. 9, pp. 115429–115441, 2021.

[53] M. Elsisi, M.-Q. Tran, K. Mahmoud, D.-E. A. Mansour, M. Lehtonen, and M. M. F. Darwish, "Effective IoT-based deep learning platform for online fault diagnosis of power transformers against cyberattack and data uncertainties," *Measurement*, vol. 190, Jan. 2022, Art. no. 110686.

[54] Y. Altintas and P. Chan, "In-process detection and suppression of chatter in milling," *Int. J. Mach. Tools Manuf.*, vol. 32, no. 3, pp. 329–347, 1992.

[55] M.-K. Liu, Q. M. Tran, Y.-W. Qui, and C.-H. Chung, "Chatter detection in milling process based on time-frequency analysis," in *Proc. Int. Manuf. Sci. Eng. Conf., Collocated*, Jun. 2017, pp. 1–7.

[56] Y. Yung-Chen, Y. Chen, L. Chien-Hao, and S. Wen-Pin, "Real-time chatter detection and automatic suppression for intelligent spindles based on wavelet packet energy entropy and local outlier factor algorithm," *Int. J. Adv. Manuf. Technol.*, vol. 103, nos. 1–4, pp. 297–309, 2019.

[57] D. Gumusbas, T. Yldrm, A. Genovese, and F. Scotti, "A comprehensive survey of databases and deep learning methods for cybersecurity and intrusion detection systems," *IEEE Syst. J.*, vol. 15, no. 2, pp. 1717–1731, Jun. 2021.

MINH-QUANG TRAN received the B.Sc. degree in mechanical engineering from the Thai Nguyen University of Technology, Vietnam, in 2011, and the M.Sc. and Ph.D. degrees in mechanical engineering from the National Taiwan University of Science and Technology, Taiwan, in 2017 and 2020, respectively. Since 2011, he has been working as a Lecturer with the Department of Mechanical Engineering, Thai Nguyen University of Technology. He is currently a Project Assistant Professor with the Industry 4.0 Implementation Center and the Center for Cyber-Physical System Innovation, National Taiwan University of Science and Technology. His research interests include tool condition monitoring, machining dynamics, signal analysis of manufacturing processes, the IoT, machine learning, and intelligent systems for industry 4.0.

MAHMOUD ELSISI was born in Cairo, Egypt, in 1989. He received the B.Sc., M.Sc., and Ph.D. degrees from the Electrical Engineering Department, Faculty of Engineering at Shoubra, Benha University, Cairo, Egypt, in 2011, 2014, and 2017, respectively. Since 2017, he has been working as an Assistant Professor with the Electrical Engineering Department, Faculty of Engineering at Shoubra, Benha University. He is currently a Postdoctoral Researcher with the Industry 4.0 Implementation Center and the Center for Cyber-Physical System Innovation, National Taiwan University of Science and Technology, Taiwan. His research interests include studying the power system dynamics, such as stability and control, artificial intelligence techniques, robotics, industry 4.0, the IoT, and applied machine learning.

MENG-KUN LIU received the Ph.D. degree in mechanical engineering from Texas A&M University, in 2012. Since 2014, he has been joined the Department of Mechanical Engineering, National Taiwan University of Science and Technology, as an Associate Professor. His research interests include time-frequency analysis of the manufacturing process, sensorless fault diagnosis of induction motors, robot force control, and chaos control.

VIET Q. VU received the bachelor's degree in mechanical engineering from the Thai Nguyen University of Technology, Vietnam, in 2007, the master's degree in materials engineering from Wollongong University, Australia, in 2012, and the Ph.D. degree in materials engineering from the University of Lorraine, France, in 2021. He is currently an Assistant Professor with the Faculty of International Training, Thai Nguyen University of Technology.
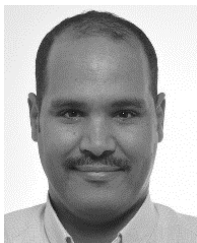
KARAR MAHMOUD (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from Aswan University, Aswan, Egypt, in 2008 and 2012, respectively, and the Ph.D. degree from the Electric Power and Energy System Laboratory (EPESL), Graduate School of Engineering, Hiroshima University, Hiroshima, Japan, in 2016. Since 2010, he has been with Aswan University, where he is currently an Associate Professor with the Department of Electrical Engineering, Faculty of Engineering. He has authored or coauthored several publications in top-ranked journals, including IEEE journals, international conferences, and book chapters. His research interests include power systems, renewable energy sources, smart grids, distributed generation, optimization, applied machine learning, the IoT, industry 4.0, and high voltage. Since 2021, he has been a Topic Editor in *Sensors* and *Energies* (MDPI) journals and also a Guest Editor for two special issues in *Catalysts* and *Forecasting* (MDPI) journals.

MOHAMED M. F. DARWISH was born in Cairo, Egypt, in 1989. He received the B.Sc., M.Sc., and Ph.D. degrees in electrical engineering from the Faculty of Engineering at Shoubra, Benha University, Cairo, Egypt, in May 2011, June 2014, and January 2018, respectively. From 2016 to 2017, he joined Aalto University, Finland, as a Ph.D. student with the Department of Electrical Engineering and Automation (EEA) and the Prof. M. Lehtonen's Group. He is currently working as an Assistant Professor with the Department of Electrical Engineering, Faculty of Engineering at Shoubra, Benha University. He is also a Postdoctoral Researcher with the Department of EEA, School of Electrical Engineering, Aalto University. He has authored in several international IEEE journals and conferences. His research interests include HV polymer nanocomposites, nano-fluids, dissolved gas analysis, fault diagnosis, renewables, optimization, applied machine learning, the IoT, industry 4.0, and control systems. He received the Best Ph.D. Thesis Prize that serves industrial life and society all over the Benha University Staff for the academic year (2018–2019). Since 2021, he has been a Topic Editor in *Catalysts* (MDPI) journal, also a Guest Editor of the special issue in *Catalysts* (MDPI) journal.

ALMOATAZ Y. ABDELAZIZ (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from Ain Shams University, Cairo, Egypt, in 1985 and 1990, respectively, and the joint Ph.D. degree in electrical engineering according to the channel system from Ain Shams University, Egypt, and Brunel University, U.K., in 1996. He is currently a Full Professor with the Faculty of Engineering and Technology, Future University in Egypt, Cairo. He has been a Full Professor in electrical power engineering with Ain Shams University, since 2007. He has authored or coauthored more than 400 refereed journal articles and conference papers, 25 book chapters, and three edited books with Elsevier and Springer. His research interests include applications of artificial intelligence, evolutionary and heuristic optimization techniques to power system planning, operation, and control. He is a member of IET and the Egyptian Sub-Committees of IEC and CIGRE. He has been awarded many prizes for distinct researches and international publishing from Ain Shams University and Future University in Egypt. He is the Chairperson of the IEEE Education Society Chapter, Egypt. He is a Senior Editor of *Ain Shams Engineering Journal* and an Editor of *Electric Power Components and Systems Journal*. He is an editorial board member, an editor, an associate editor, and an editorial advisory board member for many international journals.
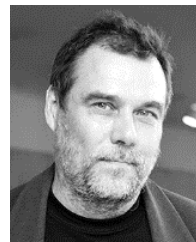
MATTI LEHTONEN received the master's and Licentiate degrees in electrical engineering from the Helsinki University of Technology, Finland, in 1984 and 1989, respectively, and the Doctor of Technology degree from the Tampere University of Technology, Finland, in 1992.

He was with VTT Energy, Espoo, Finland, from 1987 to 2003, and since 1999, he has been a Full Professor and the Head of the Power Systems Group and High Voltage Engineering Group, Aalto University, Espoo, Finland. His research interests include power system planning and assets management, power system protection, including earth fault problems, harmonic related issues, high voltage systems, power cable insulation, and polymer nanocomposites. He is an Associate Editor of *Electric Power Systems Research* and *IET Generation, Transmission & Distribution*.

● ● ●