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A STUDY ON THE PREDICTIVE MAINTENANCE SYSTEM FOR CNC FACILITIES BASED ON INTELLIGENT CUTTING TOOL LOAD PREDICTION

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Abstract. *In order to build an advanced smart factory, a data-based predictive maintenance environment as well as real-time status monitoring of the automated production system must be configured. In particular, productivity/quality/work safety in automated production system, such as CNC, is very closely related to tool conditions, increasing the need for a predictive preservation system that can monitor problems caused by wear and tear of tools in real time. This study proposes an intelligent tool load prediction system consisting of IIoT middleware system for real-time spindle data collection, manufacturing big data DB system for high-speed data processing, and bi-directional LSTM model-based analysis system that shows good performance in time series data analysis for real-time analysis and prediction of spindle load values. As a result of predicting the CNC spindle load value for the actual manufacturing site, our proposed prediction model shows good performance of 0.002 to 0.003 MAE per second, and we can also confirm the possibility of a commercialization of a prototype of a predictive maintenance system.*

Keywords: CNC machine tool monitoring, Bi-LSTM (Bi-Direction Long Short-Term Memory), Predictive maintenance system, IIoT (Industrial IoT), Smart factory

1. **Introduction.** Smart factory can be said to be a digital factory that connects, collects, and analyzes a lot of data from PLCs (Programmable Logic Controllers) or controllers and sensors installed in various production facilities.

These smart factories can have four key KPIs as P (Production), Q (Quality), C (Cost), and D (Delivery). Especially, in production system based on precision automation facility such as CNC (Computerized Numerical Control) machine, it can be seen that the condition of the tool has great influence on the key KPIs and work safety. Figure 1 shows the main defect factors affecting CNC machine production & quality. These major defect factors in CNC machines greatly affect the performance or condition of the machining tool. Therefore, the core of CNC machining quality and productivity management is reliable machining tool management.

Currently, smart factory is being advanced from a level that enables simple data collection and simple real-time monitoring through connection with automated equipment or sensors to stage of data analysis-based facility predictive maintenance or digital twin environment establishment. In such a data analysis-based smart factory environment, an

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FIGURE 1. Main defect factors CNC machine production & quality

effective storage and processing environment for large amount of data generated at a high speed is also one of the important success factors.

Data generated and handled in such advanced smart factory or an IIoT (Industrial IoT) environment can be said to have time-series data characteristics, so a time-series DB environment can be more effective in data handling than Relational DataBase (RDB) or technologies such as NoSQL or Hadoop.

Recognizing the need for effective management of CNC machining tool, which is a key factor affecting the productivity and machining quality of CNC machines, this study proposes a prototype system for predictable algorithm and intelligent CNC tool monitoring through spindle load data-based AI analysis. In particular, for effective and reliable data analysis on spindle load values, a prediction algorithm based on a Bi-LSTM (Bi-Directional Long Short-Term Memory) showing good performance in time series data analysis was presented and verified.

2. **Related Works.** Monitoring and predictive maintenance of automated production facilities have been recognized as important, and many studies have been conducted in various ways. In [1], the authors proposed a system that can collect and monitor the machine's servo axis load, spindle load, and tool position information for CNC machining monitoring, but is not presented spindle load-based prediction technology.

Recently, research on predictive conservation using artificial intelligence techniques such as artificial neural networks is being actively conducted. [2] verified the possibility of detecting facility anomalies through an artificial neural network by learning PLC data including abnormal behavior using CNN, and in [3], a study was conducted on the development of a smart factory predictive maintenance solution based on Machine Learning (ML) and RNN (Recurrent Neural Network) to predict failure signs and failure times for petrochemical facilities.

RNN is a type of artificial neural network and has a characteristic that the connection between units has a cyclic structure. Since this structure allows the state to be stored inside the neural network to model time-varying dynamic features, it is possible to process the input in the form of a sequence using the internal memory, which is effective in analyzing sequential data such as speech or language, that is, time series data [4-6].

However, in the learning process of RNN, there is a limitation in considering the long-term dependency of the data because the vanishing gradient problem occurs when the main information passes through several time steps to process a long sequence [7]. LSTM is a type of recurrent neural network that can learn by considering long-term dependence designed to solve the gradient loss problem of RNN [4].

Many studies have been conducted for real-time prediction in various fields with time series data characteristics using such an LSTM model. [8] proposed a system architecture for real-time prediction service based on AWS cloud service is proposed under IoT environment, and mentioned IoT data prediction using LSTM. And [9] conducted a study to design and verify the LSTM model for power data prediction for energy saving production plants. However, these studies suggest a conceptual approach using LSTM for general IoT data analysis or a power prediction method at the production site but it did not present specific methods or system architectures for predicting CNC machining quality in a smart factory.

Therefore, in this study, we propose an algorithm using the Bi-LSTM model which supplements the limitations of the existing LSTM model, and a prototype predictive maintenance system based on it for reliable CNC machining quality prediction in smart factory.

3. **System Architecture & Deep Learning Model.** The tool load prediction system consists of 4 major process components: i) CNC machine raw data collection, ii) Manufacturing big data, iii) AI preprocessing & load prediction, and iv) Real-time monitoring. And the detailed architecture configuration for the load prediction prototype system developed in this study can be shown as Figure 2.

1) CNC machine raw data collection

The raw data collection module marked as No. ① in Figure 2 below is designed to collect the load value of machining tool (spindle) in ms (millisecond) units by interfacing with the PLC or controller of the CNC machine using IIoT (Industrial IoT) middleware.

2) Manufacturing big data

In order to observe and analyze meaningful data on CNC machining tools, a large amount of machining data (i.e., CNC machine's spindle load values) collected in a short period of ms (millisecond) is required, and high-speed data processing for the collected

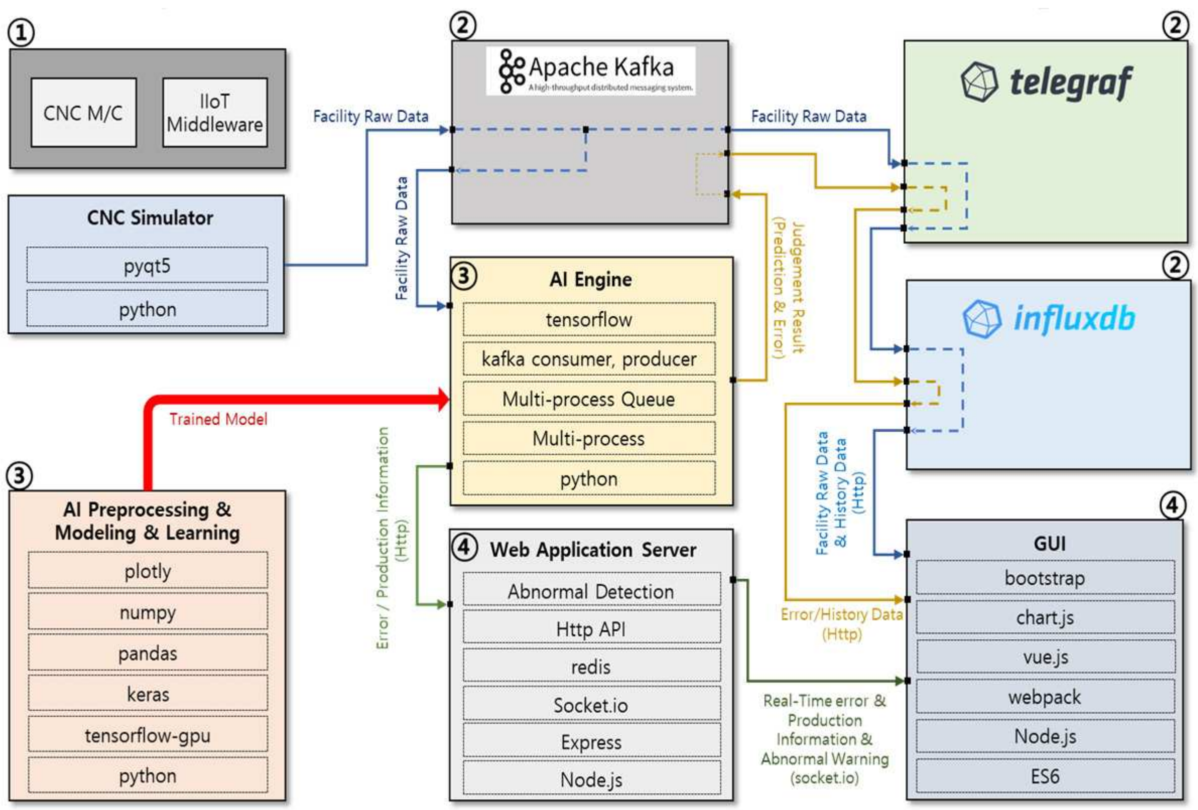


Figure 2. CNC machine tool load prediction prototype system architecture

data is essential. To meet these requirements, we judged that time series DB is the most suitable storage engine for manufacturing big data.

The manufacturing big data module marked as No. ② in Figure 2 consists of three objects as 1) Apache Kafka Platform, 2) Telegraf OSS (Open Source Server), and 3) InfluxDB. In this study, we first adopted "Apache Kafka Platform" to collect CNC machining data in real time. Kafka is solution that was specialized for large-capacity data log processing and is suitable for environments that require high performance and extendability for data processing, and secondly applied "time series DB engine based InfluxDB" which was verified as high-speed data processing for CNC machining big data in real-time collection. Finally, the system was designed to improve the performance stability and future scalability of the manufacturing big data system using "Telagraf OSS" as an agent that transforms the data collected in real time through Kafka and stably transfers into the InfluxDB.

3) AI preprocessing & load prediction

The AI analysis module of the intelligent CNC tool monitoring system proposed in this study consists of two modules: a module preprocessing data, modeling for AI algorithm, and learning preprocessed data, and an AI engine that predicts data using them, as shown No. ③ in Figure 2.

We preformed data preprocessing using "Mean Rolling Technique" to remove instantaneous noise and emphasize the trend of load values. Also, traditional statistical techniques (ARIMA) or AI techniques kernel method classification (SVM.RF, GBM, etc.) are not capable of data prediction accuracy and real-time prediction, so we applied LSTM techniques, a type of RNN, to use for load data prediction. Especially, in this study, the "Bi-LSTM" model was applied in order to reduce the loss of past information for long data.

Detection for anomaly detection used the Mean Absolute Error (MAE), and in this study, abnormalities were set to be detected when the mean absolute error within the set time (5 s) exceeded the baseline (0.005). The conditions and figures for such abnormality detection may be variably set according to the characteristics of the facility being applied.

We suggest AI engine that is designed and developed to operate as a module unit process to improve performance and scalability. Figure 3 shows process structure of such AI prediction engine. First, insert the data that has passed through the data preprocessing

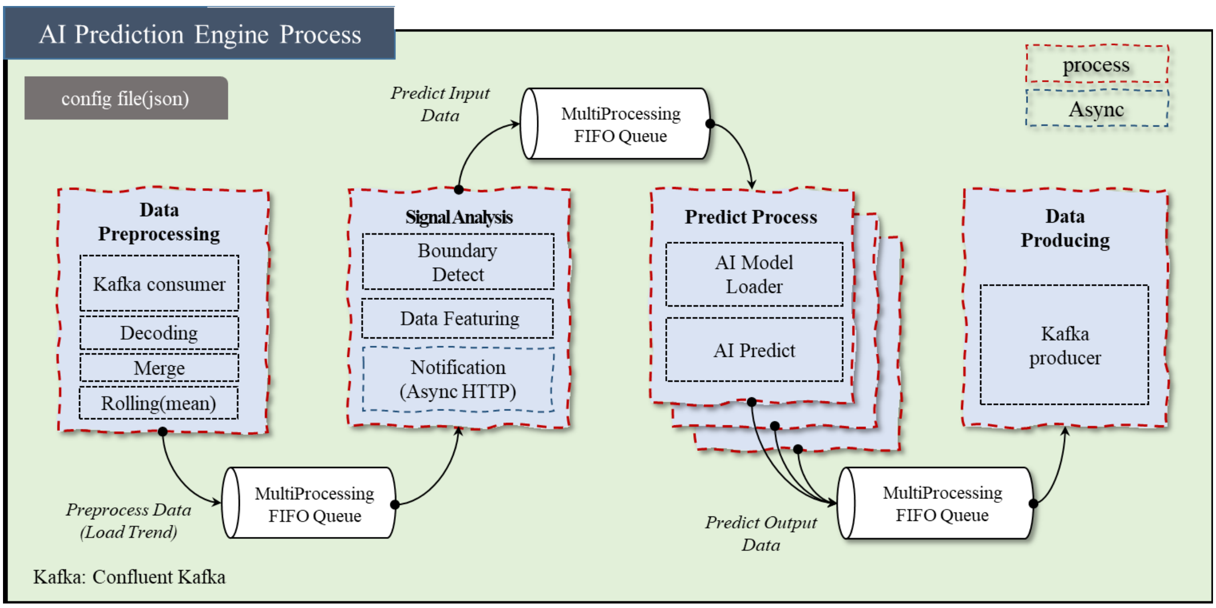


FIGURE 3. The process of AI prediction engine

module into the queue. Second, signal analysis module generates predict input data using preprocessed data in queue. Third, predict process module runs the AI model using predict input data and performs AI prediction. All of these series of processes are handled in an asynchronous and multi-processing method.

4) Real-time monitoring

The monitoring service for the CNC spindle load value and predicted value is the most core function provided, and the function was implemented to enable real-time monitoring during the machining time, not the prediction after product machining is completed. The main real-time monitoring items consist of actual spindle load values, pre-processed trend load values, AI predictions, and error rates. Real-time and visualization performances are obtained through temporal down sampling.

4. **Simulations and Results.** In this study, the data provided by an actual manufacturing company was studied and simulated. A detailed description of the simulation and results is as follows.

1) CNC machine raw data collection

We import spindle load data from the real CNC machine provided by the manufacturer to the CNC simulator to allow raw data to be generated, which is collected by IIoT middleware and passed to manufacturing big data (such as time series DB).

2) Data preprocessing & AI (deep learning) based load prediction

i) Data preprocessing

Load values with the same trend were observed for each production, and there was no fluidity in the time axis (processing time) for machining, but in the part where the load value had a range of 20% to 30% fluctuation and a point of rapid load rise was also identified at the time of operation of the spindle motor.

In this study, we processed the load data collected at 50 ms cycle with mean value down sampling at 100 ms cycle, and then applied mean rolling with a window size of 30 to canceling noise and emphasizing load trend characteristics. And we removed non-operating intervals (load value 200 or less) as data for AI learning and processed data normalization through Min Max scaling for optimal AI learning efficiency. Figures 4(a) and 4(b) illustrate examples of before and after data preprocessing.

And for LSTM layer, we proceed with data separation and arrangement by defining the first 50 (5 s) data (lookback = 50) as the model input value (when learning or predicting) as the correct answer for the 51st load value (see Figure 5).

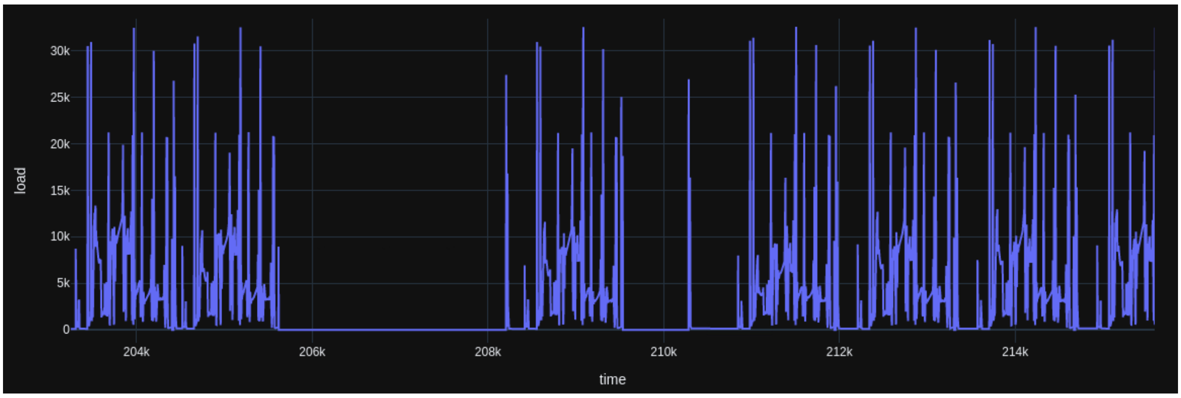
ii) Prediction modeling & training of CNC machine tool load value

The Bi-LSTM based model applied in this study has 4,466,689 training parameters (such as kernel, bias) and hyperparameter customization of the prediction model according to data complexity, learning rate, and target model accuracy is required (see Figure 6).

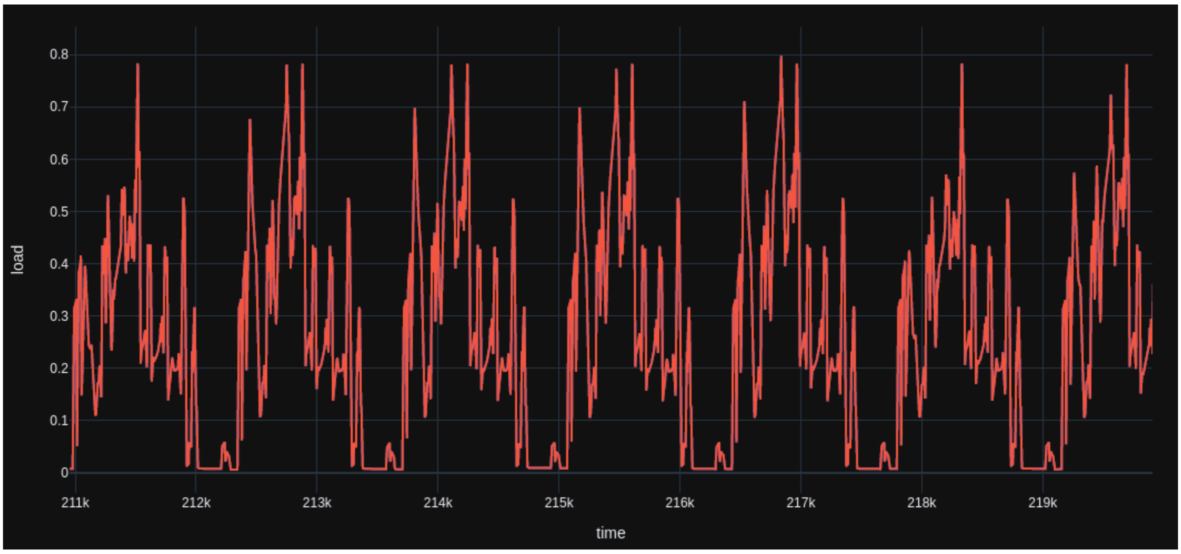
Bi-LSTM based model took an average of 4 minutes and 30 seconds per epoch for 860,000 data (1 day), and it took about 12 hours and 36 minutes a day to learn 500 times (based on RTX3090 Graphic Card).

It can be seen that 0 to 500 lessons were conducted at the ideal learning rate as shown in Figures 7(a) and 7(b), and that the learning rate (loss reduction rate) is significantly reduced at 500 to 1000 lessons.

Therefore, in order to obtain model performance of 0.003 or less based on MAE (Mean Average Error), the daily data was divided into 20 pieces and 200 epochs per fits were trained. "Early Stop" was applied (stop if there is no improvement in the learning rate for 80 epochs), and a model with performance of validation loss "0.002524" was obtained by conducting approximately 3,200 training sessions.



(a)



(b)

FIGURE 4. (a) Example of data before preprocessing; (b) Example of data after preprocessing

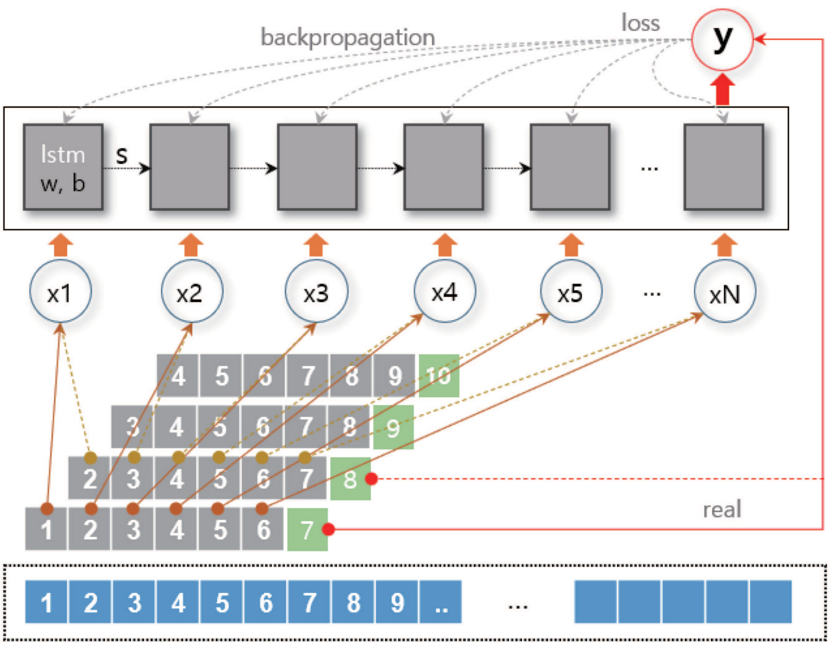
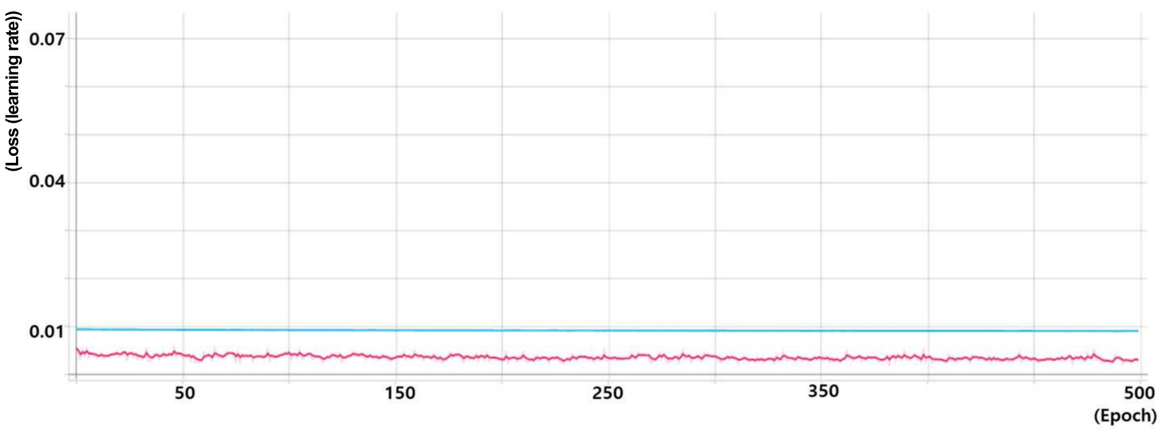


FIGURE 5. Example of one-dimensional input data

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional (Bidirectional (1, 50, 256)              133120
_________________________________________________________________
dropout (Dropout)            (1, 50, 256)              0
_________________________________________________________________
bidirectional_1 (Bidirection (1, 50, 256)              394240
_________________________________________________________________
dropout_1 (Dropout)          (1, 50, 256)              0
_________________________________________________________________
bidirectional_2 (Bidirection (1, 50, 256)              394240
_________________________________________________________________
dropout_2 (Dropout)          (1, 50, 256)              0
_________________________________________________________________
bidirectional_3 (Bidirection (1, 50, 256)              394240
_________________________________________________________________
dropout_3 (Dropout)          (1, 50, 256)              0
_________________________________________________________________
bidirectional_4 (Bidirection (1, 1024)                 3149824
_________________________________________________________________
dropout_4 (Dropout)          (1, 1024)                 0
_________________________________________________________________
dense (Dense)                (1, 1)                    1025
=================================================================
Total params: 4,466,689
Trainable params: 4,466,689
Non-trainable params: 0
```

FIGURE 6. Bi-LSTM based model

(a)



(b)

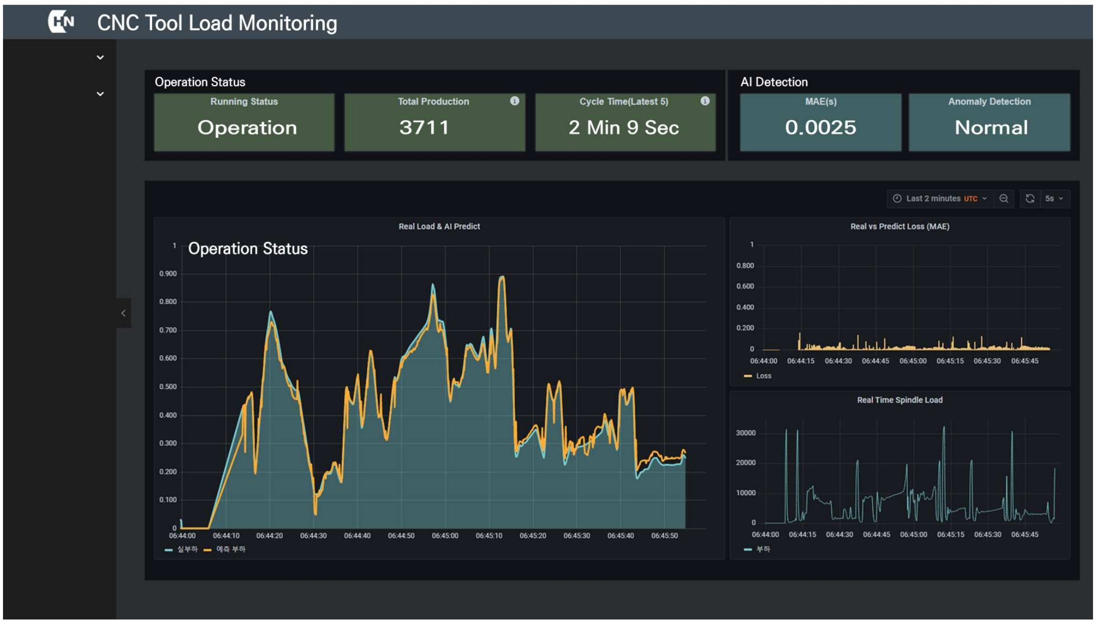
FIGURE 7. (a) Bi-LSTM model loss and validation loss for 0∼500 epochs; (b) Bi-LSTM model loss and validation loss for 500∼1000 epochs

3) Results

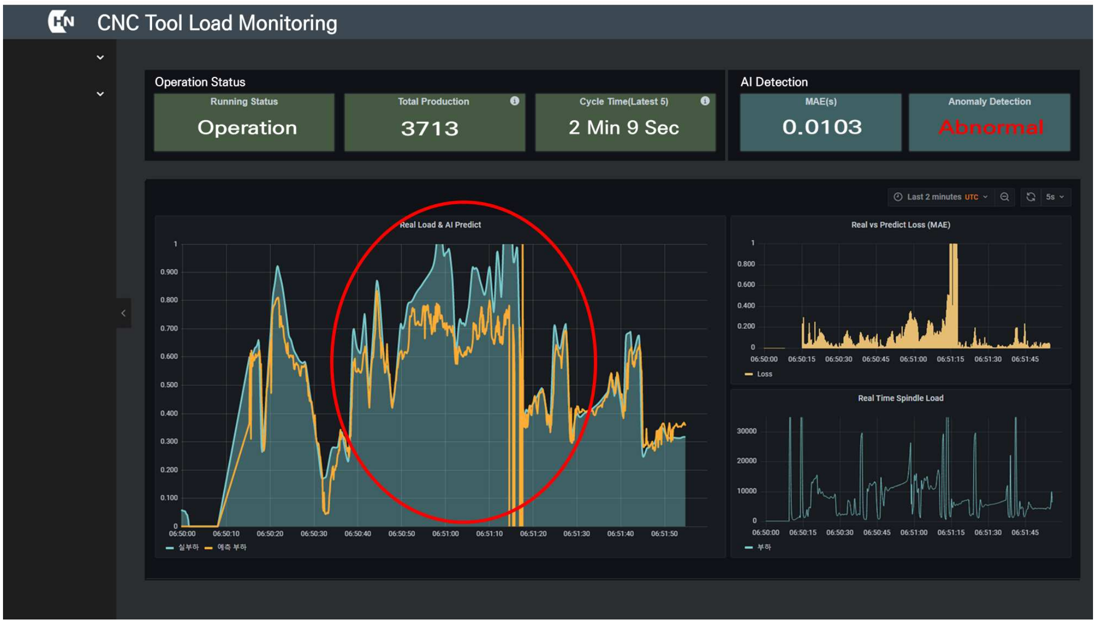
In order to verify the performance of the Bi-LSTM model suggested by this research, the prediction accuracy of the CNC machine's tool state such as normal or abnormal state was verified through experiments.

First, it was confirmed that the detection performance for the normal state exhibited a high performance error rate of 0.002 to 0.003 MAE per second as shown in Figure 8(a) below.

It can be said that the most important function of the predictive maintenance system is the ability to accurately recognize abnormal situations in advance, so it is essential to evaluate the prediction accuracy and performance of abnormal situations. In actual production sites, even though the CNC tool is in a normal state, the load value at a specific



(a)



(b)

FIGURE 8. (a) Normal prediction results with Bi-LSTM; (b) abnormal prediction results with Bi-LSTM

point in time is often increased by 20%∼30% from the average load value. Therefore, in this study, the data obtained by increasing the actual load value obtained by 40% was used to evaluate the detection performance for abnormal situations. As a result, as shown in Figure 8(b), it was confirmed that abnormal situations were also detected normally.

Therefore, it is expected the CNC machining tool predictive maintenance system to which the Bi-LSTM-based predictive in this study is applied, data-based intelligent tool predictive maintenance is possible rather than the CNC tool management that depends on user experience or intuition and it is expected that effects such as productivity and quality improvement and cost reduction can be expected.

5. **Conclusions.** In this study, AL engine for the development of predictive maintenance system based on prediction of CNC machine spindle load value, big data configuration and visualization service for results, etc. were described. In particular, it is expected to show reasonable reliability as it shows a high level of accuracy of AI models (Bi-LSTM models) applied for prediction.

In the future, it is thought that additional research on the expansion of the data set and the learning period will be necessary for the development of a faster and more accurate prediction model.

In addition, the model advancement and additional verification studies are required so that it can be applied to various data of the manufacturing site such as welding process data as well as CNC machine spindle load, and through this, it is expected to be able to provide differentiated services through advanced AI model application and convenient user interface.

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