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# Energy Consumption Estimation of Machine Tool Using Machine Learning

**Wontaek Song[1], In-Wook Oh[1], Joon-Soo Lee[1], Chaeeun Kim[1,2], Eunseok Nam[2] and Byung-Kwon Min[1,#]**

1 School of Mechanical Engineering, Yonsei University, Republic of Korea
2 Digital Transformation R&D Department, Korea Institute of Industrial Technology (KITECH), Republic of Korea
# Corresponding Author / Email: bkmin@yonsei.ac.kr, TEL: +82-2-2123-6611

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*In the manufacturing industry, interest in energy consumption reduction of machine tools is increasing for cost reduction and sustainable production. To improve the energy efficiency of machine tools, energy estimation models have been studied. In particular, physics-based models that reflect machine tool dynamics are widely used to enhance energy estimation accuracy. However, such conventional models require an understanding of complex physical behaviors and many computational loads for the various components of machine tools. In this paper, we studied machine learning algorithms to estimate the energy consumption of machine tools. Also, we proposed energy estimation models based on such algorithms without the physical model. The proposed models were built using different algorithms such as LSTM (long short-term memory), GRU (gated recurrent unit), and 1D CNN (convolution neural network), respectively. These algorithms, which are mainly applied to time-series data, were used to estimate time-varying energy consumption. Training and test datasets were collected by performing machining experiments on the commercial machine tool. These datasets include power consumption and CNC (computerized numerical control) data measured by power meter and CNC controller, respectively. The proposed models, which were learned using the training datasets, estimate the energy consumption of each machine tool component from the input NC code. To calculate the estimation accuracy of the proposed models, estimated energy was compared with the measured energy. Through these comparison results, we showed the most suitable machine learning algorithm for energy estimation of machine tools.*

**NOMENCLATURE**

RNN = Recurrent Neural Network
LSTM = Long Short-Term Memory
GRU = Gated Recurrent Unit
1D CNN = 1Dimensional Convolutional Neural Network
RMSE = Root Mean Squared Error

## 1. Introduction

Worldwide, interest in carbon neutrality and green growth is increasing to solve energy problems such as the climate crisis. In the manufacturing industry, strategies for improving energy efficiency have been developed according to this trend [1]. Among them, energy estimation model of machine tool was studied for energy consumption reduction such as process monitoring and optimization.

In general, physics-based models were used to estimate energy consumption with high accuracy [2]. Such models have limitations to computation load by high-fidelity based on physical principles. Therefore, recently data-driven models based on machine learning algorithms have been studied as an alternative to conventional models [3].

This paper proposes energy estimation models using time-series machine learning algorithms. The estimation performance of the proposed models is compared. To train models, three machine learning algorithms were selected by considering the time-series characteristics of energy consumption. Process information such as feed rate and spindle speed were used as input data, and the measured power consumption of each component was used as output data. Machine tool requires many components for the machining process, and they are mainly divided into main units and auxiliary units. Therefore, the proposed model estimates the energy consumption for each unit. The estimation performance of the proposed models is discussed numerically through comparison with the measured data.

## 2. Time-series machine learning models

In the machining process, energy consumption has fluctuated value according to time series. Accordingly, time-series machine

Table 1 Hyper-parameters used in models

| | | |
|---|---|---|
| Hyper-parameters | Learning rate | 0.001 |
| | Time-step | 10 |
| | Optimization | Adam |
| | Batch size | 64 |
| | Dropout | 0.1 |
| | Epoch (max) | 1000 |

Table 2 Experimental conditions used in experiments

| | | |
|---|---|---|
| Machining conditions | Material | Al 7075 |
| | Tool | 16 Ø end-mill |
| | Spindle speed | 3000 ~ 5000 rpm |
| | Feed rate | 600 ~ 1000 mm/min |
| | Number of experiments | 6 (toolpath: zigzag, parallel spiral) |

learning algorithms were used for energy estimation: LSTM (long short-term memory), GRU (gated recurrent units), and 1D CNN (convolution neural network). LSTM and GRU, which are types of RNN (recurrent neural network), are commonly used to estimate time-series data such as weather and stock prices. LSTM was initially proposed to solve the gradient vanishing at conventional RNN. GRU using a simplified structure of LSTM was proposed to improve training speed. In addition, CNN is known as superior in the process of multi-dimensional data and image recognition. In particular, 1D CNN can be used to estimate 1D time-series data by applying convolutional filters. Therefore, energy estimation models were built based on the characteristics of these algorithms. All algorithms are implemented in MATLAB environment. Hyper-parameters of the proposed models were selected empirically through an iterative process. Table 1 shows the hyper-parameters used in model training.

## 3. Experimental setup and data processing

The 3-axis commercial machine tool (Doosan NX 5500 II) was used to build and validate the energy estimation model. This testbed contains main units (3-axis feed drive systems and spindle system) and 5 auxiliary units (cooler, coolant, mist catcher, chip conveyor, and ATC). The commercial CNC controller (FANUC model 31i) was used to control the overall machine tool according to command. NI DAQ (NI compact DAQ) was installed to measure the power consumption of the machine tool.

Table 2 shows the machining conditions used for the experiment. The process information and power consumption are obtained from the CNC controller and NI DAQ during the machining process, respectively. Measured process information such as position and velocity were used as input data. In addition, operating status data of auxiliary units acquired from NC code was also used as input data. Measured power consumption of machine tool components was used as output data.

A total of 6 experiments were conducted under various conditions to obtain a dataset. The entire dataset is divided into training part (70%), validation part (17%), and testing part (13%). In the training process, the normalization that generates the values with a balanced scale was used to improve training performance.

## 4. Results

The proposed models were built by applying three machine learning algorithms respectively. Fig. 1 shows estimation results of power and energy consumption in time series. It compares the training results of the models for each machine tool component. Most of the prediction results fit the ground truth well. In particular, the performance difference of models is noticeable in main units with a lot of fluctuations.

Table 3 numerically represents the estimation performance of the three models. To determine the error according to time series, RMSE was calculated as power consumption. Estimation accuracy was calculated as total energy consumption integrated with power consumption. These evaluation indicators were used as the average value for each unit. As shown in Table 3, 1D CNN represents the best performance considering RMSE and accuracy. This result is due to the architectural characteristics of the algorithm. Compared to other algorithms, 1D CNN effectively trains time-dependent data by performing convolution operations [4]. As a result, 1D CNN is the most appropriate algorithm for the energy prediction of machine tools.

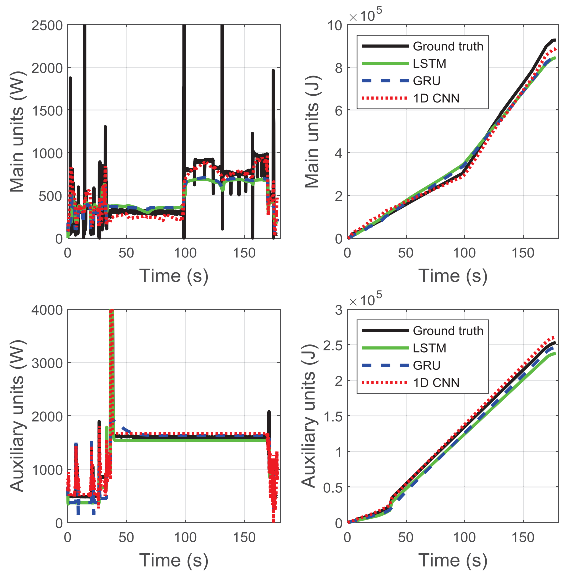


Fig. 1 Estimation results of the proposed models for machine tool components

Table 3 Comparison of model performance

| Algorithm | RMSE | | Accuracy (%) | |
|---|---|---|---|---|
| | Main units | Auxiliary units | Main units | Auxiliary units |
| LSTM | 205.2 | 197.6 | 91.1 | 91.5 |
| GRU | 194.5 | 453.5 | 91.3 | 97.3 |
| 1D CNN | 163.7 | 214.1 | 95.7 | 94.7 |

## 5. Conclusions

In this paper, machine learning-based energy estimation models were proposed. The proposed models used time-series machine learning algorithms such as models LSTM, GRU, and 1D CNN. During the machining process, process information and power consumption data were obtained from the commercial machine tool. These datasets were used to train the model. The estimation accuracy of the models was discussed by comparing the test results for machine tool components. Based on the comparison results, 1D CNN was validated as the most appropriate algorithm for energy consumption estimation. Therefore, the energy estimation model based on the 1D CNN can be usefully used for energy monitoring and energy reduction strategies in the future.

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