# An Intelligent Thermal Compensation System Using Edge Computing for Machine Tools

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**Abstract.** This study explores the application of artificial intelligence in lathe cutting machine tools in smart manufacturing. Long-term processing will cause thermal deformation of the lathe cutting tool machine, which will cause displacement errors of the cutting head and damage to the final product. Using time-series thermal compensation, the research develops a predictive system that can be applied in industry using edge computing technology to predict the thermal displacement of machine tools. The study conducted two experiments to optimize the temperature prediction model and predict the five-axis displacement of the temperature point. Furthermore, a genetic algorithm is used to optimize the LSTM model to predict the thermal displacement of the machine tool. The results show that the GA-LSTM model achieved a thermal displacement prediction accuracy of 0.99, while the average accuracy of the LSTM, GRU, and XGBoost models was 0.97. Based on the analysis of training time and model accuracy, the study recommends using LSTM, GRU, and XGBoost models to design and apply to systems that use edge devices such as Raspberry Pi for thermal compensation.

**Keywords:** sensor · thermal compensation · time series model · edge computing

## 1 Introduction

With the rise of Industry 4.0, more and more manufacturing industries are moving towards the era of smart development. The emergence of edge computing (Edge Computing) that is closer to the source of data is mainly aimed at improving the problem of cloud computing, reducing latency, reducing dependence on the network, not excessively concentrating computing resources, and ensuring


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data privacy sex, and so on [1]. In the error of machine tool processing, thermal error is one of the most influential factors. The traditional way of thermal compensation is to use coolant to cool the inside of the machine, but this method has not completely improved the thermal error of the machine tool [2].

Therefore, the objective of this research was to leverage the power of deep learning models to forecast the axis displacement of a tool machine, and integrate it into a lightweight device for edge computing. This setup offered a direct connection to the tool machine and enabled enhanced machining precision. The study was divided into two parts. Ultimately, a user interface was developed at the Raspberry Pi edge to facilitate the thermal compensation of tool machine data by end-users. The contributions of this article are summarized as follows.

– Two experimental sets were designed to study the time-series data of the turning tool machine.
– A genetic algorithm (GA) was developed to enhance the accuracy of the LSTM model in predicting thermal displacement of the tool machine.
– Multiple time-series models were compared for their effectiveness in compensating for thermal data of the tool machine.
– A system was developed to apply thermal compensation on the tool machine using edge computing with Raspberry Pi.

## 2 Related Research

### 2.1 Machine Tool Thermal Compensation

FANUC developed a new AI function that can collect control data of machine tool feed axes and spindles through high-speed sampling [3]. It performs deep learning on the collected data and displays anomaly scores based on the current state of machine components. DMG MORI An adaptive thermal displacement compensation method based on deep learning was developed, and a reliability evaluation method for thermal displacement prediction based on Bayesian dropout was proposed [4]. This method can not only adapt to changes in ambient temperature, but also adapt to cutting heat and working heat generated by spindle rotation or axial movement.

### 2.2 Time Series Model

Yuan, J et al. [5] proposed a three-stage fault diagnosis method using the Gated Recurrent Unit (GRU) network to carry out intelligent fault diagnosis on large data in the industry, and the results showed very good results. Yangdong He et al. [6]Applying TCN to anomaly detection of time series, they trained TCN on normal sequence and used it to predict the trend of multiple time steps, and the effectiveness was confirmed on three real-world datasets. S.M. Taslim Uddin Raju et al. [7] An ensemble model combining Bagging (Random Forest Regression (RFR)), boosting (Gradient Boosting Regression (GBR) and Extreme Gradient Boosting Regression (XGBR)) and stacking (STACK) to forecast steel industry demand one month in advance.

### 2.3 Edge Computing for Smart Manufacturing

S. Ren et al. [8]This paper presents the design and implementation of a big data platform for a smart IIoT sensor monitoring system with prior predictions of upcoming errors. This paper proposes a design and implementation scheme of a manufacturing big data platform and an intelligent industrial IoT sensor monitoring system based on edge computing and artificial intelligence.

## 3 Research Architecture and Related Algorithms

### 3.1 Research Framework

In this research, the time series model training is first carried out in the Windows environment, and then the selected model is placed in the Raspberry Pi environment to build the human-machine interface system, as shown in Fig. 1 below.

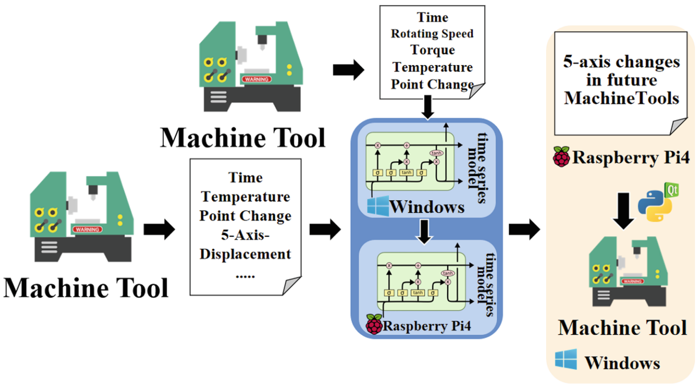


**Fig. 1.** Research flow chart of intelligent thermal compensation system for machine tools.

### 3.2 Related Algorithms

**GA Optimized LSTM.** This study combines GA with LSTM, and uses GA to optimize the parameters in the LSTM training process. The main parameters are the data time step (look_back, lb), the hidden layer of the LSTM model (lstm_nets, ls), the number of LSTM training (epochs, ep), and dropout (dp). These four parameters are optimized through GA. After obtaining the optimal parameter set, the five-axis displacement data set of the machine tool is used as the input data, and the predicted value of the five-axis displacement of the machine tool is used as the output matrix. Adapt to adjust the weight of the model, and finally combine it into a GA-LSTM model, and then train the data set through this model, and finally compare the predicted value with the real value, such as shown in Fig. 2 below.

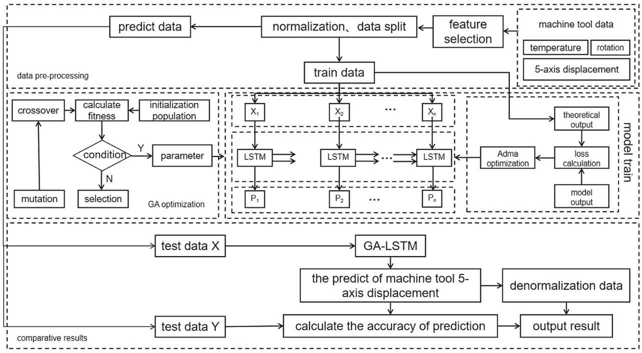


**Fig. 2.** GA-LSTM Architecture Diagram.

## 4 Experiment Introduction

### 4.1 Dataset Introduction

**Experiment1.** The acquisition of the data set for this research is mainly to collect field data on the machine tool in operation. This research captures the speed and torque of the machine tool in real time and saves it, and uses the infrared temperature sensor to monitor the temperature of the important points of the machine tool. Measure and record, the data set of this study mainly collects 4 temperature points, namely indoor temperature, condensing agent temperature, rotating shaft temperature and motor stator temperature. In this experiment, the changes of the four temperature points are recorded every minute, and the temperature points and the speed and torque of the machine tool are recorded through the production.

**Experiment2.** This data set is provided by the Industrial Technology Research Institute, mainly for the temperature change and 5-axis displacement of two machine tools under different conditions. Five-axis machining is a processing mode of digital machine tools, using X, Y, Z, For the linear interpolation motion of any 5 coordinates in A, B, and C, the machine tools used in five-axis machining are usually called five-axis machine tools or five-axis machining centers.

As shown in Table 1, the first machine tool mainly provides data sets in three situations, and it has 41 fields in total, which are time, rotational speed, 34 temperature points and displacement changes of 5 axes. The second machine tool provides data sets in four situations, and it has 60 fields in total, including time, rotation speed, 53 temperature points and displacement changes of 5 axes.

**Table 1.** Description of machine tool operating conditions

| Machine Tool | Operating Conditions |
|---|---|
| **Tool1** | Spray water to heat 10 degrees |
| | Spindle 2350 RPM-turn 8 stop 2 |
| | Water spray heating 10 degrees - spindle 2350 RPM - turn 8 stop 2 |
| **Tool2** | Room temperature plus 15 degrees |
| | Room temperature plus 15 degrees - spindle 2350 RPM - turn 8 stop 2 |
| | Room temperature plus 15 degrees - water spray heating 10 degrees |
| | Room temperature 20 degrees - spindle 2350RPM - turn 8 stop 2 - no cooling machine |

# 5 Analysis of Experimental Results

## 5.1 Experiment 1 Results and Discussion

For the data set of Experiment 1, there are a total of 300 records. In this study, the data set will be divided into training set and test set at a ratio of 8:2 to train the model. This time, RMSE is mainly used to check whether the requirements are met, such as Fig. 3 shows.Both the results of the GRU model and the LSTM model are evaluated at a lower level, which means that the results predicted by these two AI models are more accurate than the actual results.

Although most of the experimental results of the TCN model are also in the case of RMSE less than 1, compared with the LSTM and GRU models, the results are not good, and sometimes the loss value during training will not converge. If this model is used, it will Increased forecast instability. In addition, although the final prediction effect of the Stacking Ensemble Learning algorithm is generally good, this paper finds that if different rotation speeds are given for prediction, its results will vary greatly. Therefore, if the machine tool is working at a fixed speed, you can consider using this AI model, because its training speed and final accuracy are at a better level, but if the machine tool needs a large range of speed changes If so, it is not recommended to use this model.

## 5.2 Experiment 2 Results and Discussion

For the data set of Experiment 2, there are a total of 6433 data sets for machine tool 1 and 7423 data sets for machine tool 2. This research will divide each data set into a training set and a test set at a ratio of 8:2 to train the model. In this study, the data set of machine tools was screened according to the eight temperature points before the sensitivity analysis, and the same data set was put into the established deep learning model for training. The evaluation index

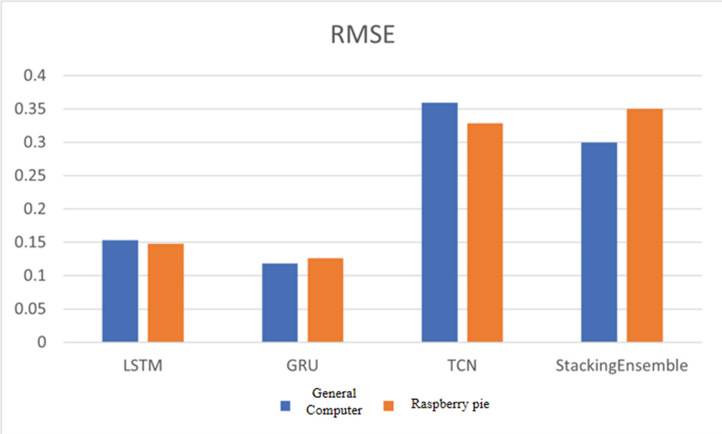


**Fig. 3.** Histogram of AI model result evaluation in Experiment 1.

of the model prediction results used the coefficient of determination (R2score), in the regression model, this coefficient mainly reflects the accuracy comparison between the predicted value of the model and the actual value. The larger the coefficient, the higher the prediction accuracy of the model, and the value ranges from 0 to 1, the calculation formula is asDownSurface Eq.(2–3).

$$S_n = \frac{X_1 + X_2 + \cdots + X_n}{n} \tag{1}$$

$$S_n = \frac{1}{n}\sum_{i}^{n} X_i \tag{2}$$

As shown in Fig. 4 below, it can be found that under the uniform usage of the same dataset and the same hardware environment, the research results of

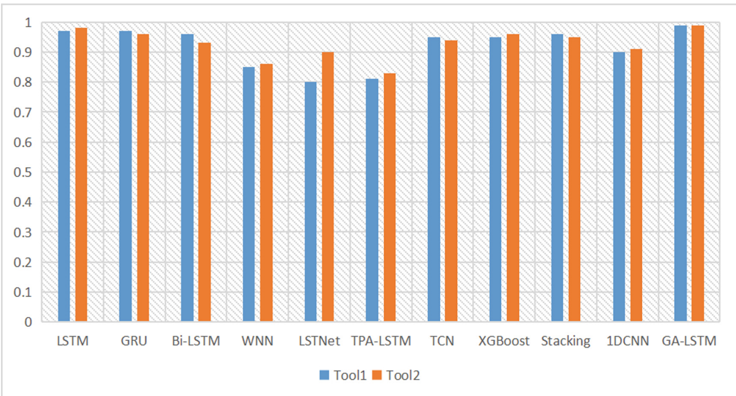


**Fig. 4.** Histogram of model R2score results of experiment 2.

this experiment can be found that the time series correlation models of this R2 score all reach above 0.8, and the GA optimized LSTM developed in this study also showed good results, with an accuracy of 0.99.

## 6 Conclusion

Based on the above two experimental studies, it is found that the final prediction results of putting the machine tool data set in different time series models are good, and the GA-optimized LSTM model developed in the second experiment also achieved the best results. In the future, this research will continue to optimize the problem of too long training time of GA-LSTM, and will also analyze the multiple temperature points of the machine tool thermal compensation data set with more algorithms, and hope that the temperature point can be selected in the future A number of recommended features are added to the smart thermal compensation system that has been developed on the Raspberry Pi so far. According to the research results, this study finally selected three AI models to be put into the edge computing terminal for development, and the effect also showed a good state. In addition, we modified the operating system of the system in this study so that it can also be downloaded and used on the machine cloud of the Industrial Technology Research Institute. Finally, the accuracy of the model in this study reached above 0.96, which is in line with the current situation that the manufacturing industry uses deep learning to improve processing thermal errors.

## References

1. Chen, B., et al.: Edge computing in IoT-based manufacturing. IEEE Commun. Mag. **56**(9), 103–109 (2018)
2. Ezugwua, E.O., et al.: Int. J. Mach. Tools Manufact. **45**, 1009–1014 (2005)
3. FANUC Corporation,"FANUC's new AI functions that utilize machine learning and deep learning", https://www.fanuc.co.jp/en.
4. Su, C.: Discussion on DMG Thermal Displacement Compensation Technology. http://www.maonline.com.tw/article_inside.php
5. Yuan, J., Tian, Y.: An intelligent fault diagnosis method using GRU neural network towards sequential data in dynamic processes. Processes **7**(3), 152 (2019)
6. He, Y., Zhao, J.: Temporal convolutional networks for anomaly detection in time series. J. Phys.: Conf. Series. **1213**(4), 042050 IOP Publishing (2019)
7. Raju, S.T.U., et al.: An approach for demand forecasting in steel industries using ensemble learning. Complexity **2022** 1–19 (2022)
8. Song, W., Shigeru, F.: Sensor data prediction in process industry by capturing mixed length of time dependencies. In: 2021 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM). IEEE (2021)