Angus Academic Press CCAM 2025
ISSN:3007-9640 DOI: https://doi.org/10.70114/acmsr.2025.2.1.P364

Data Mechanism-Driven Modelling of Environmental Thermal Errors in Large Gantry Five-Axis Machine Tools

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Abstract. Thermal deformation in large gantry five-axis machine tools significantly impacts machining precision. This study examines the influence of environmental temperature variations on thermal deformation in such machines. To improve the accuracy of predicting integrated environmental thermal errors, a Grey-Enhanced Long Short-Term Memory network with Physical Mechanism Modeling (GELPM) is introduced. The research focuses on a large gantry machine tool, combining finite element simulations with experimental analysis to study thermal drift errors at the tool tip caused by ambient temperature fluctuations. A comparative analysis of GELPM, CNN-LSTM, and GNNMCI(1, N) models is conducted. The results reveal that GELPM outperforms previous neural network models by addressing challenges of limited data and time-series prediction, offering enhanced prediction accuracy and robustness.

Keywords: Large gantry machine tools; Ambient temperature; Thermal error modelling; Data- and mechanism-driven; Short- and long-term time neural networks

1. Introduction

Thermal deformation is a critical factor in machining accuracy, especially during prolonged operations. The thermal errors resulting from internal heat sources and ambient temperature fluctuations can account for 40%-70% of the total machining error . Accurate prediction of thermal errors under varying environmental conditions is essential for improving the accuracy of large gantry CNC machine tools, requiring a precise and robust prediction model for effective thermal error compensation.Given the spatial distribution and time dependence of thermal errors, the integration of convolutional neural networks (CNN) [1] and long-short-term memory networks (LSTM) [2] forms the convolutional long-short-term memory neural network (CNN-LSTM). Ali M. Abdulshahed [3] proposed a novel method for thermal error compensation in gantry-type five-axis CNC machines, utilizing the "Grey Neural Network Model with Convolutional Integration" (GNNMCI(1, N)).

This paper proposes a Grey-Enhanced LSTM with Physical Mechanism Modeling (GELPM) to address challenges in thermal error prediction for large gantry machine tools. By combining LSTM's time-series modeling with physical mechanism insights, GELPM improves accuracy and reduces data requirements. The model uses grey correlation analysis for efficient feature selection, demonstrating superior performance over CNN-LSTM and GNNMCI(1, N). The study aims to enhance thermal error prediction by understanding the effects of ambient temperature on machine tools.

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2. Thermal Error Modelling Methods

The model proposed in this paper addresses the challenges of limited data and low computational efficiency in thermal error modeling for large gantry machines by using data preprocessing, physical mechanism modeling, grey correlation analysis, and LSTM to optimize predictions.The final thermal error prediction is obtained through mapping via a fully connected layer [4].

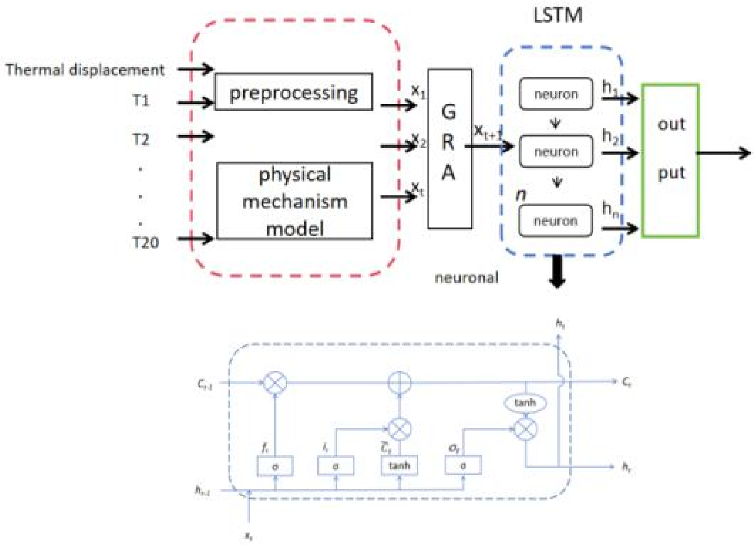

Fig.1 GELPM neural network model

The data preprocessing phase aims to clean, denoise, and normalize the multidimensional input data, while incorporating a physical mechanism model to account for thermal errors caused by temperature changes, material expansion, thermal conduction, and structural deformation.In order to efficiently filter out the most relevant features to the thermal error, the input features are analysed using grey correlation analysis (GRA)[5].It is assumed that the input feature set is $X=\{x_1,x_2,...,x_n\}$ and the output is Y (thermal error).The grey correlation is calculated as follows:

$$\xi_i(k) = \frac{\min_j|X_i(k) - Y(k)| + \rho\max_j|X_i(k) - Y(k)|}{|X_i(k) - Y(k)| + \rho\max_j|X_i(k) - Y(k)|} \quad (1)$$

Where $\xi_i(k)$ denotes the correlation between the ith feature and the thermal error Y at moment k, ρ is the discrimination coefficient, Xi(k) is the value of the ith feature at moment k, and Y(k) is the value of the thermal error at moment k.The grey correlation $\xi_i(k)$ obtained from the calculation is used to filter out the most influential features on thermal errors for subsequent model training.

The LSTM module is used to deal with long-term dependencies in time-series data, and is particularly suitable for the task of modelling thermal errors with temporal sequences.The state update process of the LSTM network includes the following key steps:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (2)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (3)$$

$$\widetilde{C}_t = tanh(W_C[h_{t-1}, x_t] + b_C) \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \quad (5)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + bo) \quad (6)$$

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$$h_t = o_t * tanh(C_t) \tag{7}$$

Where, f_t, i_t, o_t are the activation values of the forgetting gate, input gate and output gate respectively, Ct and ht are the memory cell and hidden state respectively, σ is the Sigmoid activation function, and tanh is the hyperbolic tangent function.The output h_t of the LSTM captures the long-term dependencies in the temporal data and is used in the prediction of thermal errors.

The features screened by grey correlation analysis are combined with the output of the LSTM model to enhance the model's ability to adapt to key factors.Assuming that the grey prediction result is x_{t+1} and the output of LSTM is h_t, the combination formula is:

$$h_{final} = \beta \cdot x_{t+1} + (1 - \beta) h_t \tag{8}$$

Where h_{final} is the composite feature and β is a balancing factor that controls the relative weights of grey prediction and LSTM output.This weighted fusion can effectively improve the model response to different influences.The final feature h_{final} is input to the fully connected layer, which maps the output to the target thermal error prediction.The mapping formula for the fully connected layer is:

$$\mathrm{y} = \mathrm{W_{out}} \cdot \mathrm{h_{final}} + \mathrm{b_{out}} \tag{9}$$

Where y is the final thermal error prediction, and W_{out} and bout are the weight and bias of the fully connected layer, respectively.With the fully connected layer, the model is able to transform the fused features into the target prediction values.

This method combines LSTM, physical mechanism modeling, and grey correlation analysis to optimize input features, capture time dependencies, and explain thermal error generation, significantly enhancing prediction accuracy and generalization in complex environments.

3. Thermal Characteristics Simulation

The 24-hour thermal simulation of the large gantry machine tool using ANSYS Fluent models fluid-solid heat transfer.Starting temperature of the machine is 25° .The surrounding space as well as the airflow temperature varies with time:

$$T = 25 + 2 \cdot sin(\pi \frac{t + 50400}{43200}) \tag{10}$$

Where T is the temperature and t is the simulation time.The local flow field map and temperature field distribution cloud is shown in Fig.2 .

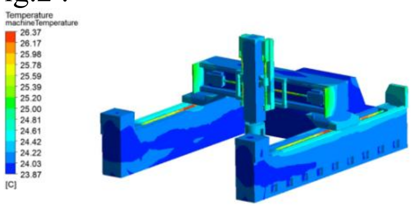

Fig.2 Temperature field cloud for machine transient simulation

In this simulation, displacement constraints in the X, Y and Z directions are applied to the bottom surface of the bed, thus limiting its degrees of freedom[6].The thermal deformation cloud diagram is shown in Fig.3.

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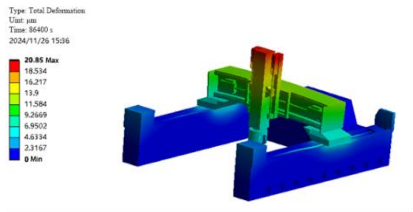

Fig.3 Transient simulation of machine tool deformation field cloud map

The thermal deformation analysis reveals that the machine bed, with higher thermal inertia, stabilizes its position, while components like the crossbeam and spindle experience more rapid thermal fluctuations, and the Z-axis, lacking axial constraints, shows the largest thermal displacement due to thermal expansion.

4. Thermal Error Experiment

4.1 Experimental Setup

This study examines a specific model of large gantry five-axis machine tools, using temperature sensors for 48-hour real-time monitoring and displacement sensors on the machining table, resulting in 97 data sets.Based on engineering experience and simulation analysis, 8 temperature sensors are arranged on the X, Y, and Z axes of the machine tool and its bed. 12 temperature sensors measure the ambient temperature without cooling the machine perimeter.Sensor layout location as shown in Table 1, the temperature sensor selection resolution of 0.1 ℃ PT100 RTD.A contact displacement sensor was used to monitor the thermal displacement of the tool tip relative to the workpiece as a thermal error, and the accuracy of the displacement sensor was 0.1 m.The experimental measurement is shown in Fig.5.

Fig.5 Experimental Measuring Devices

Table 1.Temperature sensor mounting position

Position	Sensor serial number
Environment	T1~T12
X-axis	T13~T14
Y-axis	T15~T116
z-axis	T17~T18
Machine tool bed and beam	T19 ~ T20

4.2 Analysis of Experimental Results

The ambient and temperature changes on each axis at 2.5m from the ground and the

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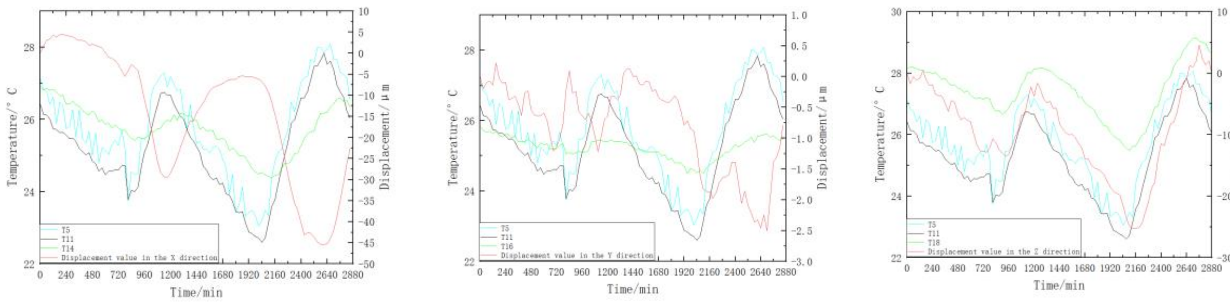
corresponding axial thermal errors are shown in Fig.7.



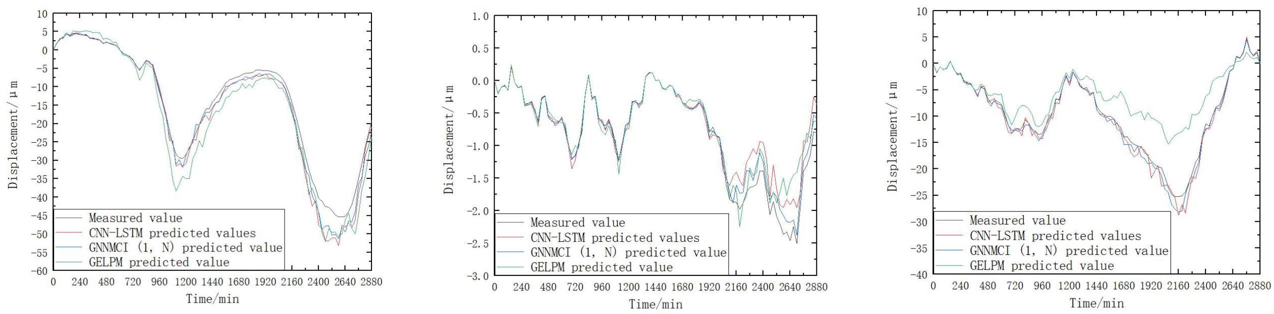
(a)X-axis direction (b)Y-axis direction (c)Z-axis direction

Fig.7 Temperature change and axial thermal displacement

The experimental data shows that the thermal displacement exhibits hysteresis, with the X-axis experiencing the largest thermal error due to its longest travel, while the Y-axis shows the smallest error due to symmetry.The Z-axis demonstrates minimal hysteresis because the motor generates significant heat during operation, accelerating heat transfer and reducing the delay in thermal response.

4.3 Model Predictions and Comparisons

The results of the GELPM model's thermal error prediction are shown in Fig. 8. The model effectively captures the continuous variation of thermal errors, demonstrating accurate prediction performance based on the training and validation data sets.



(a) X-direction (b) Y-direction (c) Z-direction

Fig.8 Comparison of predicted and measured thermal displacement values

The mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2) were used as evaluation indexes to calculate the average index of thermal error modelling of each model in order to objectively and intuitively evaluate the prediction performance of each model.

Table 2. Modelling indices for thermal errors in each axial direction

Modelling		Evaluation indicators	
	MAE/μm	RMSE/μm	R^2
CNN-LSTM	0.894	1.820	0.964
GNNMCI(1, N)	2.345	3.795	0.887
GELPM	0.728	1.390	0.975

As shown in Table 2, The GELPM model reflects its high accuracy and strong model fitting for

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thermal error prediction. The use of ambient temperature data as input further highlights the model's strong generalization capability and robustness in predicting thermal errors based on ambient temperature variations.

5. Summary

This research focuses on thermal error modeling of a large gantry five-axis machine tool under ambient temperature influences.The response of different components to temperature changes varies significantly.The combined use of simulation and experimental verification allowed for the qualitative analysis of thermal deformation distribution, confirming the simulation model's validity. The GELPM thermal error prediction model, which integrates LSTM with physical mechanism modeling, demonstrated a 14.41% and 47.79% improvement in prediction accuracy over CNN-LSTM and GNNMCI(1, N), respectively, and proved robust under small sample conditions, making it an important tool for thermal error compensation in machining.

Acknowledgements

The Fundamental Research Funded by Large Gantry 5-Axis Machining Centre Project 2022(grant number：TC220H05P)

References

[1] GUO J H, XIONG Q Y, CHEN J, et al.Study of static thermal deformation modeling based on a hybrid CNNLSTM model with spatiotemporal correlation[J].The International Journal of Advanced Manufacturing Technology, 2022, 119(3-4).

[2] HOCHREITER S, SCHMIDHUBER J. Long short-term memory [J]. Neural Computation, 1997, 9(8): 1735-1780.

[3] Abdulshahed M A ,Longstaff P A ,Fletcher S , et al.Thermal error modelling of a gantry-type 5-axis machine tool using a Grey Neural Network Model[J].Journal of Manufacturing Systems,2016,41130-142.

[4] Liu, S., Yang, Y., Forrest, J.YL. (2022). Grey Relational Analysis Models. In: Grey Systems Analysis. Series on Grey System. Springer, Singapore. https://doi.org/10.1007/978-981-19-6160-1_5

[5] Tzu-Li Tien,A research on the grey prediction model GM(1,n),Applied Mathematics and Computation,Volume 218, Issue 9,2012,Pages 4903-4916

[6] HUANG Zhi, LIU Yongchao, DENG Tao, ZHOU Tao, ZHU Yun.A Method for Thermal Error Modeling of FAMT[J].China Mechanical Engineering,2020,31(13):1529-1538.