Development of a tool spindle temperature rise thermal displacement and pull-in force dynamic measurement equipment

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Abstract

A smart tool holder was developed, utilizing strain gauges to capture spindle rotation data and variations in static and dynamic pulling forces. These forces were converted into displacements through modeling. Temperature sensors were also integrated to establish a thermal error model. Experiments at 5000rpm revealed the maximum temperature rise causing deformation occurred around 4000 seconds. Due to the machine's symmetric design, the Z-axis deformation was 28% and 71% larger than the Y and X axes, respectively. A BPNN predictive model was created and compared against actual values, yielding individual MAPE values of 3.2%, 3.4%, and 2.5% for the three axes, demonstrating high accuracy. It was also observed that during the heating process, the cutting force initially decreased by ~7% due to centrifugal forces but eventually increased along with the rising temperature.

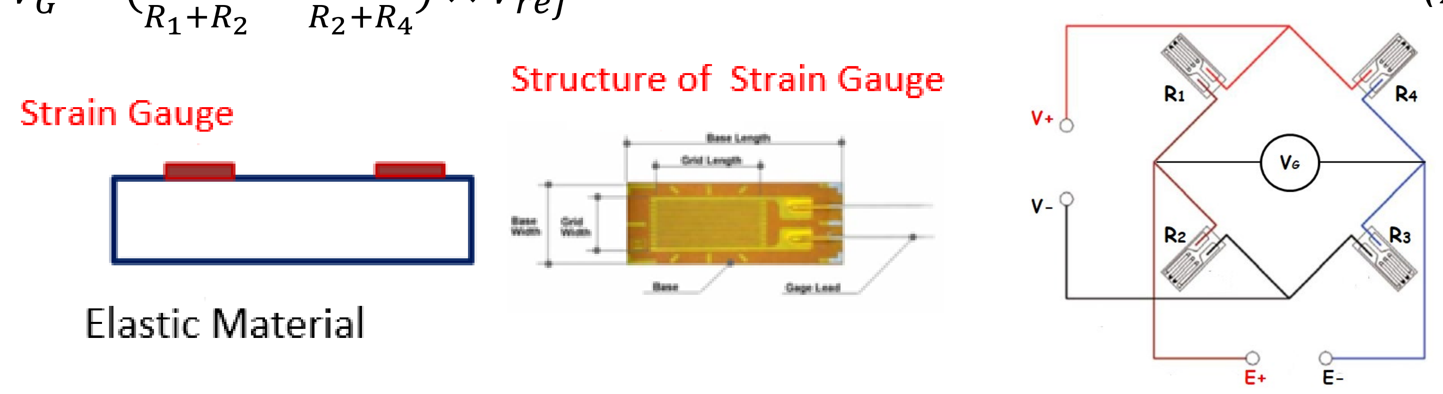
Method

Strain gauges and Wheatstone Bridge

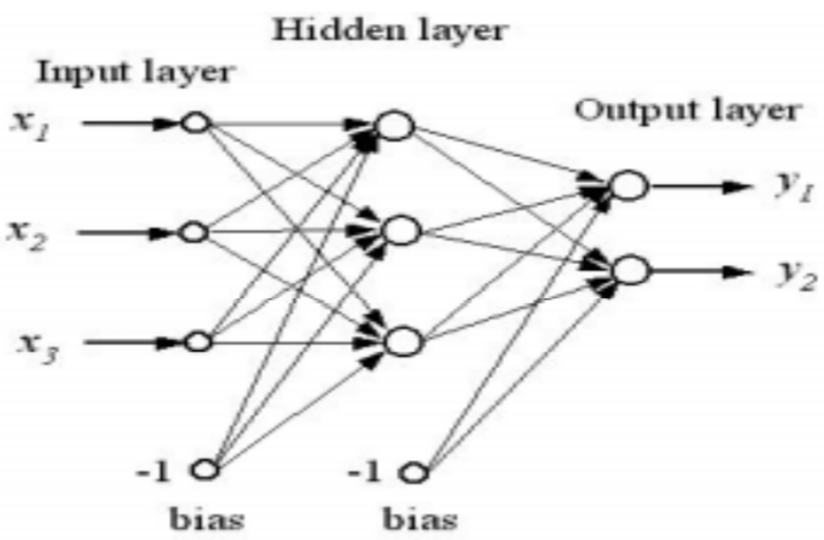
When $\frac{R1}{R2} \neq \frac{R4}{R3}$, $V_G \neq 0$. By using four well-matched resistors and a fixed voltage source, as depicted in Figure 2, the following can be obtained:

$$V_{R1} + V_{R4} = V_{R2} + V_{R3} = V_{ref} \tag{1}$$

$$V_G = \left(\frac{R_4}{R_1+R_2} - \frac{R_4}{R_2+R_4}\right) \times V_{ref} \tag{2}$$



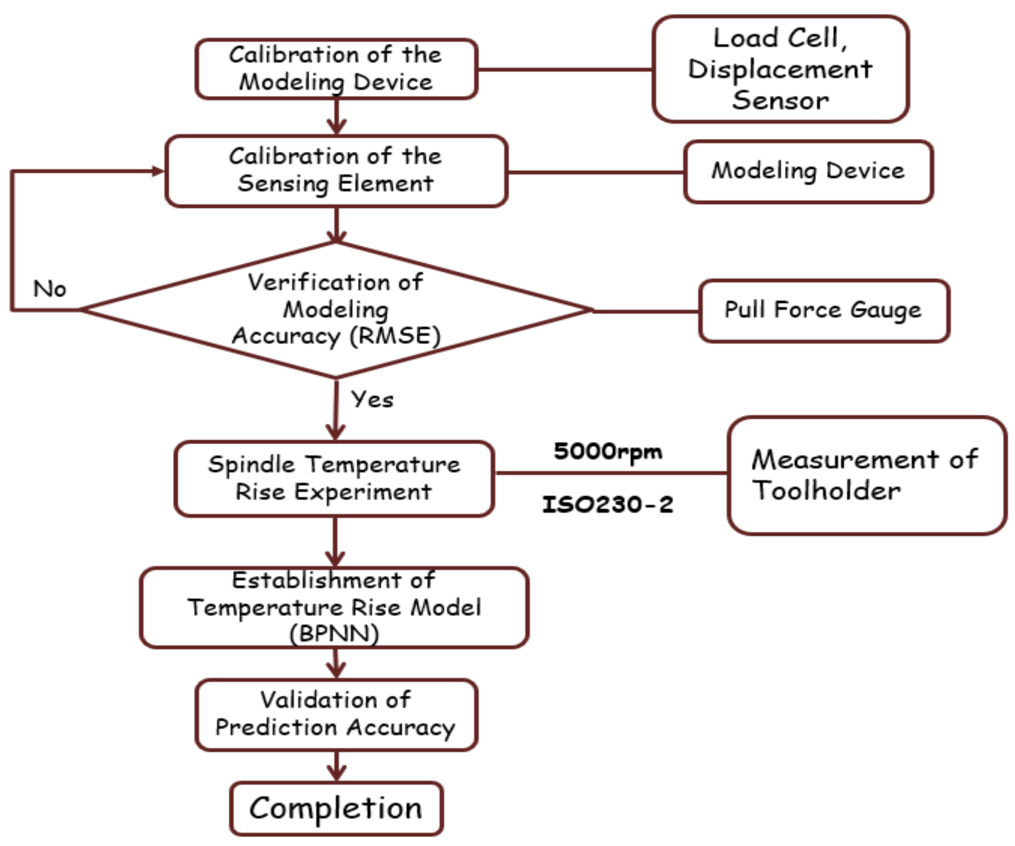
Back Propagation Neural Network (BPNN)



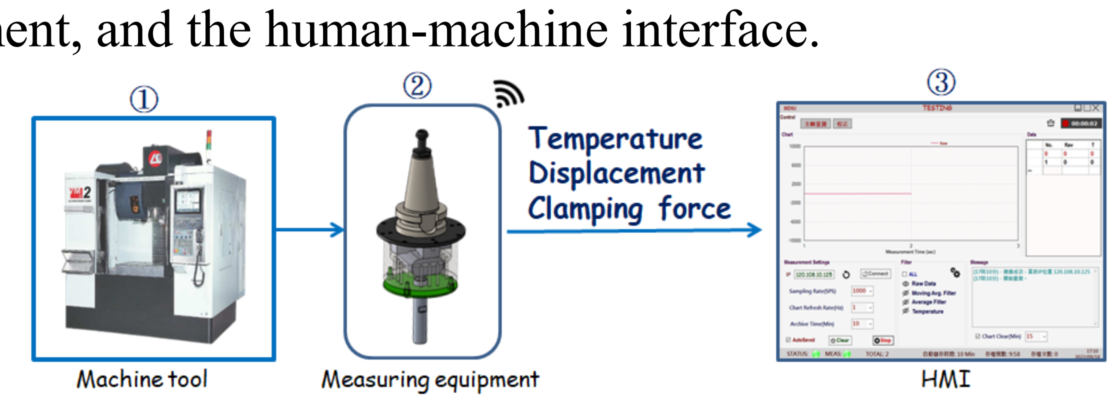
The backward pass involves propagating the error back through the same connections as in the forward pass. It adjusts the weights of each neuron in the hidden layer to minimize the error or bring it within the desired range. This process may be repeated iteratively until the desired output is achieved.

$$\mathrm{E} = \frac{1}{2}\sum_{K=1}^{K}(d_K - y_K)^2 \tag{3}$$

Experimental procedure and equipment



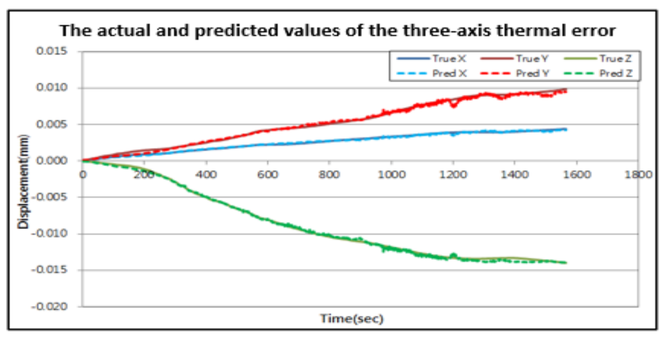
The system used in this study primarily consists of three main components: the machining center, self-developed measurement equipment, and the human-machine interface.



Experimental results

Thermal displacement measurement and predicted experiment

In this experiment, 70% of the data from the 5000 RPM experiment was used as the training set for the neural network model, with the remaining 30% used for validation. The prediction accuracy was evaluated using the Mean Absolute Percentage Error (MAPE) between the predicted and actual values, the Table shows that all MAPE values indicate a high level of prediction accuracy.



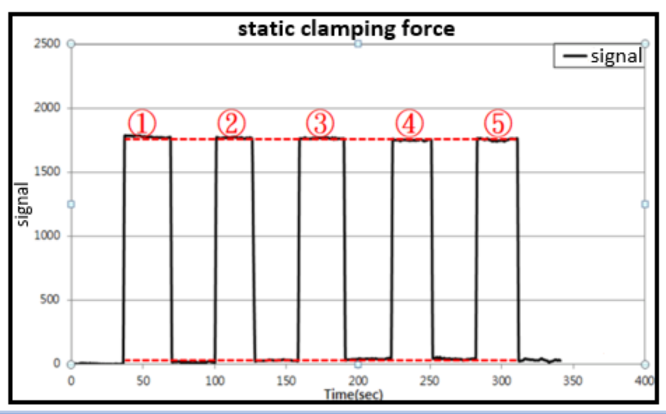
Predict error percentage

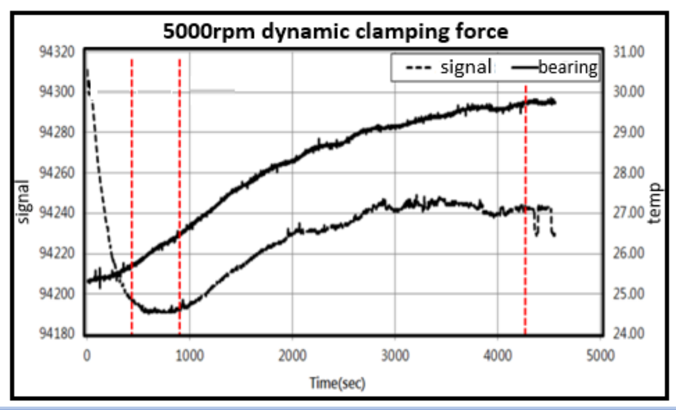
Axis	Average MAPE value
X	3.2%
Y	3.4%
Z	2.5%

Value	Level
MAPE<10%	High accuracy prediction capability
10%<MAPE<20%	Good accuracy prediction capability
20%<MAPE<50%	Reasonable accuracy prediction capability
50%<MAPE	Inaccurate prediction capability

Pull-in force experiment

Tests on static and dynamic pull-in forces were carried out on the spindle to ensure the sensor's reliability. The static test verified force measurement consistency, while the dynamic test heated the spindle from room temperature to confirm signal changes linked to pull-in force.





Conclusion

This study introduces a versatile tension-testing device with a thermal rise measurement module for static and dynamic applications. Key findings:

- Tension initially drops when the spindle rotates, stabilizes, then slightly rises due to thermal deformation. This trend will model spindle displacement for thermal compensation.
- Z-axis displacement peaks at 4000 seconds, with Y-axis increasing 28% and X-axis 78% due to machine design causing greater Y and Z deformation.
- Using temperature and displacement data, a neural network accurately predicts displacements along all three axes, with low MAPE values showing high prediction accuracy.

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