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Thermal Deformation Prediction and Cooling System Optimization for the Accuracy Improvement of Machine Tool Spindles Using Machine Learning

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Abstract - Machine tools (MTs) are prone to thermal deformation, primarily caused by heat generated from internal and external rotating components, electrical subsystems, and environmental temperature fluctuations. These thermal effects can significantly impact machining precision, dimensional accuracy, and the performance of the machine. To mitigate such effects, cooling systems are integrated into machine tools. However, varying machining loads and operating conditions require that the cooling system be dynamically adjusted to meet specific demands. Accurately predicting thermal deformation is therefore crucial to maintaining the stability and precision of machine tools, especially in high-precision machining environments. Therefore, this study presents the development of an artificial neural network (ANN) model to predict the thermal deformation of a computer numerical control (CNC) machine tool spindle. One of the significant challenges in building an effective predictive model is selecting the appropriate input parameters, which significantly influence prediction accuracy. To address this, a firefly algorithm (FA)-based optimization model is proposed to identify the most suitable combinations of input parameters for the cooling system at various spindle speeds, specifically 6000, 8000, and 10,000 rpm. The ANN model demonstrates strong predictive performance, with R^2 values ranging from 0.89 to 0.93 across the tested spindle speeds. To validate the model in a real-world scenario, the optimized parameters are implemented in a CNC machine, resulting in prediction accuracies between 95.46% and 97.03%. Experimental verification confirms that the spindle's thermal deformation is effectively controlled within 0.88 µm.

***Keywords*:** Thermal Deformation; Machine Tool; Sustainable Manufacturing; Cooling System Optimization; Artificial Neural Network; Firefly Algorithm

1. Introduction

In the current industrial era, the precision of manufactured components is a key determinant of product quality, competitiveness, and customer satisfaction. The accuracy of machine tools (MTs) directly governs the dimensional precision, surface quality, and reliability of the parts produced. With the growing demand for higher productivity, cost efficiency, and miniaturization, motorized spindles have been increasingly adopted in modern machining systems. These spindles enable rapid material removal and improved throughput; however, their compact structure and elevated rotational speeds increase thermal challenges. Heat generated by the spindle motor, stator windings, and rolling bearings raises the internal temperature of the spindle assembly, leading to thermally induced errors. It has been widely reported that thermal errors account for nearly 60-70% of the total inaccuracy of machine tools [1], while approximately 75% of geometric deviations in finished components can be attributed to thermal effects [2]. This thermal load induces axial expansion, radial deformation, and misalignment within the spindle system, which significantly compromise machining accuracy and part quality. Addressing these thermally induced errors is therefore essential to ensure machining precision, process reliability, and long-term energy efficiency in computer numerical control (CNC) manufacturing.

To mitigate these effects, several active cooling and thermal compensation strategies have been developed. Among them, coolant-based control systems have been particularly effective, especially those capable of regulating supply temperature and flow rate. By circulating coolant through the spindle housing, such systems stabilize temperature gradients and suppress thermal expansion [3]. Experimental studies have shown that varying the coolant supply temperature within the range of 12 °C to 26 °C can substantially reduce spindle deformation [4]. More advanced approaches, such as variable oil volume (VOV) control and adaptive temperature regulation, have further enhanced thermal stability, reducing spindle deformation by up to 41.7% while also lowering energy consumption [5,6]. In addition, soft computing approaches, such as adaptive neuro-fuzzy inference system (ANFIS)-based control, have been used to dynamically predict and regulate cooling demand, achieving deformation prediction accuracy within 4.745 μm [7]. These developments highlight that while conventional cooling and compensation approaches can mitigate thermal effects, their performance often depends on accurate predictive models that capture the nonlinear dynamics of spindle behavior under diverse operating conditions.

Recent advances in artificial intelligence (AI) and metaheuristic optimization have offered powerful tools to address such nonlinear and multi-objective challenges. AI-based models, particularly artificial neural networks (ANNs), have demonstrated strong capability in learning complex input-output relationships without requiring explicit physical models. When integrated with optimization algorithms, ANNs can be tuned to improve prediction accuracy and enhance process control. Hybrid approaches combining ANNs with genetic algorithms (GA) have been successfully applied in various engineering fields, such as machine tool thermal error prediction [8] and welding process optimization [9]. At the same time, swarm intelligence algorithms such as the firefly algorithm (FA) have gained attention for their global search capabilities, flexibility, and robustness in solving nonlinear optimization problems. FA has been effectively employed in various applications, including bulk material handling [10], thin-wall machining [11], optimization of bucket elevator performance [12], and pedestrian detection [13]. These applications demonstrate the versatility and effectiveness of FA in parameter tuning, predictive modeling, and optimization under uncertain and dynamic conditions.

Despite such progress, the domain of spindle thermal error modeling remains constrained by several limitations. Many existing studies rely on empirical formulations, which often face slow convergence, local optima, and reduced accuracy under varying operating conditions. Moreover, while ANN-GA models have been successfully applied, limited research has investigated the potential of swarm intelligence-based optimization, particularly FA, for optimizing process parameters and controlling spindle thermal deformation. This represents a significant research gap, as the nonlinear, time-dependent, and multi-variable nature of spindle thermal behavior makes it a good fit for AI–metaheuristic hybrid modeling. To address these gaps, this study proposes an integrated ANN-FA model for predicting and optimizing spindle thermal deformation in CNC MTs. The ANN is leveraged for its superior learning ability in approximating nonlinear thermal behavior, while the FA provides efficient global search and parameter optimization. The model systematically evaluates coolant supply temperature, flow rate, and inlet-outlet temperature difference as input parameters, aiming to minimize thermal deformation. Using ISO 230-3 compliant experimental data, the developed model achieves better deformation control, leading to improved machining precision and more sustainable operation of CNC machines.

2. Methodology

2.1 Experimental Setup

This study focuses on predicting the thermal deformation of an MT spindle system and optimizing its input parameters, which are then applied to a CNC machine to validate the developed model. The CNC machine is equipped with a spindle capable of a maximum rotational speed of 12,000 rpm and powered by a 7.5 kW motor. A 300 mm test bar was mounted on the spindle, and eddy current displacement sensors (AEC S-06) were used to measure thermal deformation with GL840 M. PT-100 thermistors were installed at both the inlet and outlet of the industrial refrigeration system to monitor coolant temperatures, with data collected using a PR20 signal recorder. The coolant supply flow rate was measured by a flow meter positioned at the spindle inlet. The cooling system was further equipped with a circulation pump to ensure continuous coolant flow, supporting effective heat removal during spindle operation.

The cooling system was designed with two circulation loops: a coolant loop and a refrigerant loop. The coolant loop consisted of the spindle under cooling, a storage tank, and a circulation pump, which together ensured continuous coolant flow through the spindle. The refrigerant loop consisted of a compressor, condenser, expansion valve, and plate heat exchanger, which worked in combination to extract heat from the coolant and maintain stable operating conditions. In this study, the system employed R410a refrigerant. The supply coolant temperature could be adjusted between 10 °C and 35 °C (±0.5 °C).

The dataset used for model development was obtained from experimental measurements conducted in accordance with the ISO 230-3 standard, with the spindle operating continuously for one hour. A total of 120 datasets were selected after data processing under steady-state conditions at different spindle speeds of 6,000, 8,000, and 10,000 rpm. During the experimental analysis, the ambient temperature of the workshop was maintained at 26 ± 0.5 °C. Fig. 1 illustrates the integrated workflow of the proposed method, which combines ANN modelling and FA optimization to control thermal deformation in machine tools.

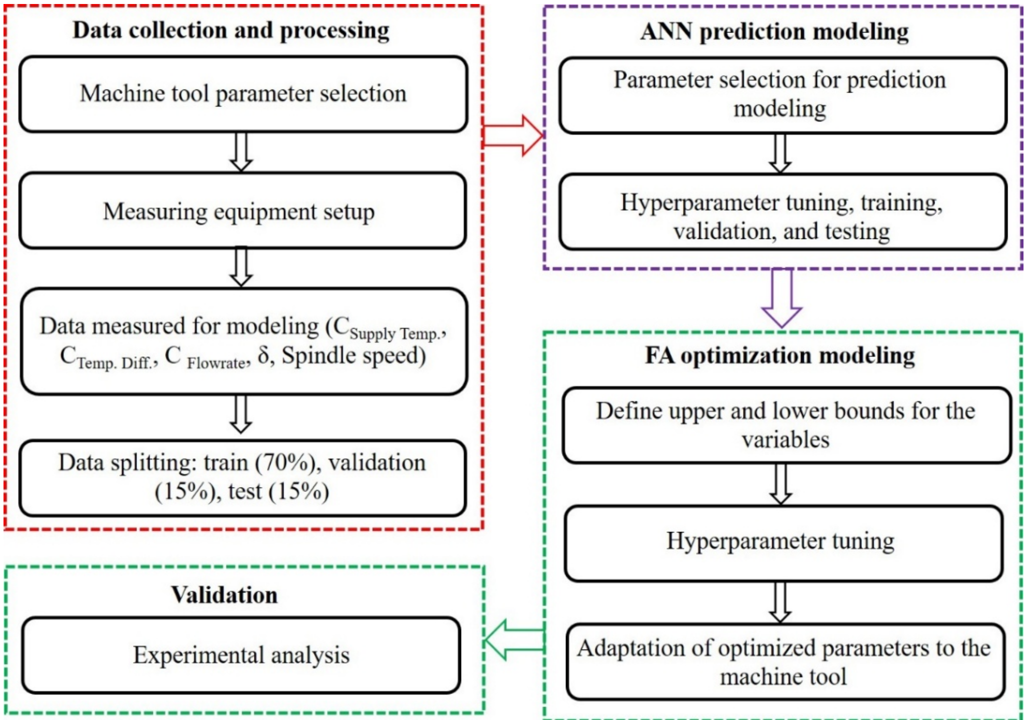

Fig. 1: Integrated workflow of the proposed ANN-FA modelling.

2.2 ANN Modelling

The ANN used in this study consists of three layers: an input layer (coolant supply temperature, coolant temperature difference between the inlet and outlet, and coolant flow rate), a hidden layer, and an output layer (thermal deformation). Since the number of hidden neurons depends on the specific problem, several configurations were tested and evaluated using the coefficient of determination (R^2). The best performance was achieved with 10 hidden neurons, leading to the adoption of a 3:10:1 topology. For model validation, the dataset was randomly split into 70% for training, 15% for testing, and 15% for validation. In this study, the mathematical modelling of the ANN was directly adopted from the literature [8,9] and applied to the specific operating conditions.

2.3 FA-Based Optimization Modelling

The FA, inspired by the flashing behavior of fireflies, is a population-based metaheuristic optimization method. The principles of attractiveness, light intensity, and random movement govern its search mechanism [11].

The light intensity I at a distance r from a firefly can be calculated as:

$$I(r) = I_0 e^{-\gamma r^2}, \tag{1}$$

Where I_0 is the original light intensity, Υ is the light absorption coefficient, and r is the distance between two fireflies.

The attractiveness function is given by:

$$\beta(r) = \beta_0 e^{-\gamma r^2}, \tag{2}$$

Where β_0 is the attractiveness at $r = 0$.

The Euclidean distance between fireflies i at position X_i and firefly j at position X_j can be defined as:

$$r_{ij} = \sqrt{\sum_{k=1}^{d} (X_{i,k} - X_{j,k})^2}, \tag{3}$$

Where d is the number of decision variables.
The movement of firefly i toward a brighter firefly j can be calculated as:

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2} \left(X_j - X_i \right) + \alpha \, (rand - 0.5), \tag{4}$$

Where α is the step size of random movement, and $rand$ is the random number between 0 and 1.
The fitness function of the FA can be calculated as [8]:

$$Fitness\ Function = Error_{Minimum}, \tag{5}$$

$$Error = \left(\frac{Output_{Exp.} - Output_{Pred.}}{Output_{Exp.}} \right), \tag{6}$$

Where $Exp.$ is the experimentally measured thermal deformation, and $Pred.$ is the predicted thermal deformation by the ANN model. The FA iteratively adjusts the solution space to minimize this error. The overall ANN-FA modelling framework is illustrated in Fig. 2.

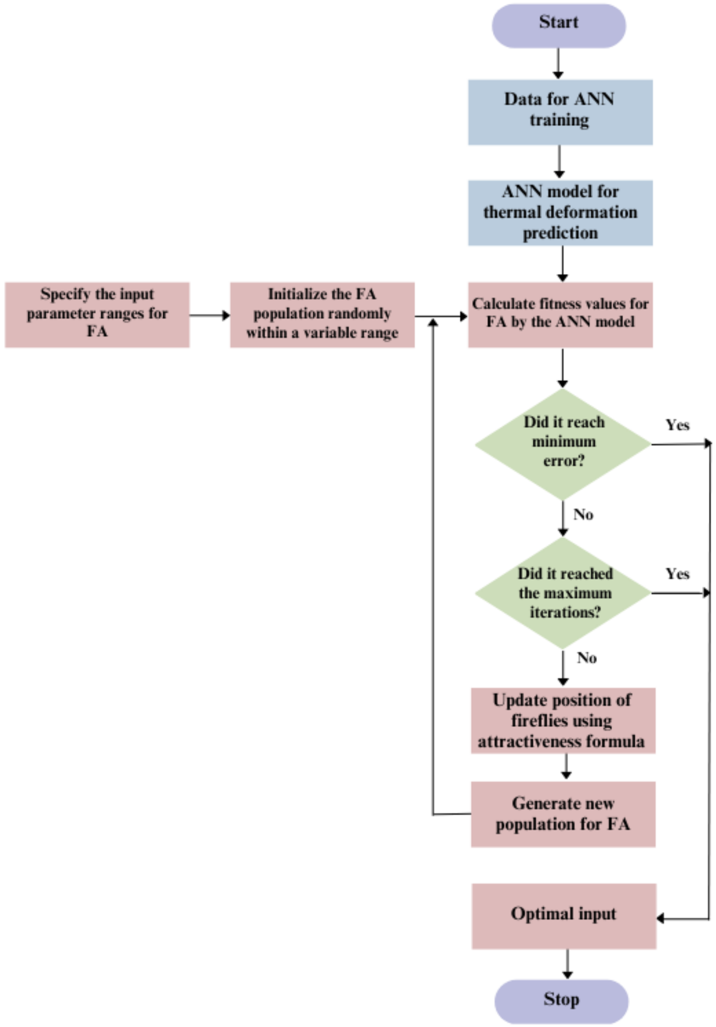

Fig. 2: Process flowchart of the proposed ANN-FA modelling.

The thermal deformation prediction accuracy (A) of the proposed model is calculated as:

$$A = 100\,\% - \frac{|\,(\delta_{Exp.} - \delta_{Pred.})\,|}{\delta_{Exp.}} \times 100, \tag{7}$$

Where $\delta_{Exp.}$ is the experimentally measured thermal deformation, and $\delta_{Pred.}$ is the predicted thermal deformation by the ANN model.

3. Results and discussion

The ANN used in this study was configured with 3 input neurons, 1 output neuron, and 10 hidden neurons. The neural network was trained for up to 1000 epochs with a learning rate of 0.1, while the accuracy threshold was set at 0.001 to ensure stable convergence. For the optimization modelling, the FA was integrated with the ANN. The FA was implemented with 17 fireflies and a maximum of 250 iterations. The other parameters of the FA were set to α = 0.29, β = 1, and γ = 0.6. The process parameters and their respective ranges are presented in Table 1.

Table 1: Process parameters and their respective ranges for the developed model.

Parameter	**Range**

$C_{Flowrate}$ (lpm)	0.5-3.5
$C_{Supply\ Temp.}$ (°C)	15-30
$C_{Temp.\ Diff.}$ (°C)	0.5-3.5
Spindle Speed (rpm)	6000-10,000

Table 2 illustrates the optimized cooling system parameters and the predicted thermal deformation at various spindle speeds. At 6000 rpm, the model predicted a deformation of 13.68 µm with an R^2 of 0.89. As the spindle speed increased to 8000 and 10,000 rpm, the deformation increased to 18.42 µm and 21.44 µm, with corresponding R^2 values of 0.93 and 0.91, respectively. These results highlight that thermal deformation increases with spindle speed, while the ANN-FA model maintained high predictive accuracy across different operating conditions.

Table 2: Optimized parameters for the cooling system and predicted thermal deformation at various spindle speeds.

Speed (rpm)	**$C_{Flowrate}$ (lpm)**	**$C_{Supply\ Temp.}$ (°C)**	**$C_{Outlet\ Temp.}$ (°C)**	**$C_{Temp.\ Diff.}$ (°C)**	**$\delta_{Pred.}$ (µm)**	**R^2**
6000	0.85	26.00	27.85	1.85	13.68	0.89
8000	0.92	2570	28.03	2.33	18.42	0.93
10,000	1.14	25.34	27.99	2.65	21.44	0.91

Table 3 and Fig. 3 compare the proposed ANN-FA model with experimental analysis of thermal deformation at different spindle speeds. The model shows excellent agreement with the experimental data, with absolute errors below 0.88 µm across all spindle speeds. Prediction accuracy ranged from 95.46% to 97.03%, confirming the robustness of the developed ANN-FA model. These results indicate that the integrated optimization approach can effectively model the nonlinear thermal behavior of the spindle and provide reliable compensation strategies for precision machining applications.

Table 3: Thermal deformations of the proposed model and experimental analysis with evaluation metrics.

Speed (rpm)	**$\delta_{Pred.}$ (µm)**	**$\delta_{Exp.}$ (µm)**	**Absolute Error (µm)**	**Accuracy (%)**
6000	13.68	14.21	0.53	96.27
8000	18.42	19.30	0.88	95.46
10,000	21.44	22.10	0.66	97.03

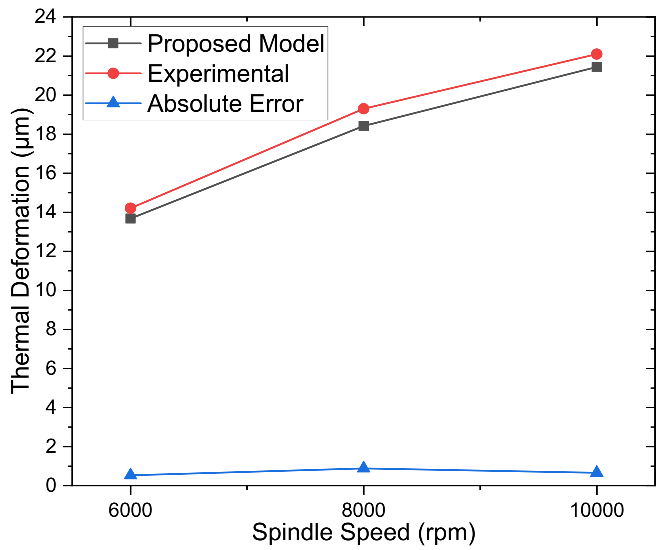

Fig. 3: Thermal deformations of the proposed model, experimental analysis, and absolute error at various spindle speeds.

4. Conclusion

This study developed an ANN-FA model to predict and optimize spindle thermal deformation in CNC MTs. Using ISO 230-3 compliant experimental data, the model achieved high predictive accuracy, with R^2 values ranging from 0.89 to 0.93, and thermal deformation can be controlled within 0.88 μm. Prediction accuracy ranging from 95.46% to 97.03% confirmed the robustness of the approach. Results showed that thermal deformation increases with spindle speed but can be effectively controlled through optimized coolant flow rate and supply temperature. The integrated ANN-FA model provides a reliable and sustainable approach for modelling nonlinear thermal behavior, enhancing machine precision, and supporting advanced thermal error compensation strategies.

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