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Thermal error modelling of a gantry-type 5-axis machine tool using a Grey Neural Network Model



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Keywords: Gantry-type 5-axis machine tool Modelling PSO Grey system theory Artificial neural network Grey neural network This paper presents a new modelling methodology for compensation of the thermal errors on a gantrytype 5-axis CNC machine tool. The method uses a "Grey Neural Network Model with Convolution Integral" (GNNMCI(1, N)), which makes full use of the similarities and complementarity between Grey system models and artificial neural networks (ANNs) to overcome the disadvantage of applying either model in isolation. A Particle Swarm Optimisation (PSO) algorithm is also employed to optimise the proposed Grey neural network. The size of the data pairs is crucial when the generation of data is a costly affair, since the machine downtime necessary to acquire the data is often considered prohibitive. Under such circumstances, optimisation of the number of data pairs used for training is of prime concern for calibrating a physical model or training a black-box model. A Grey Accumulated Generating Operation (AGO), which is a basis of the Grey system theory, is used to transform the original data to a monotonic series of data, which has less randomness than the original series of data. The choice of inputs to the thermal model is a non-trivial decision which is ultimately a compromise between the ability to obtain data that sufficiently correlates with the thermal distortion and the cost of implementation of the necessary feedback sensors. In this study, temperature measurement at key locations was supplemented by direct distortion measurement at accessible locations. This form of data fusion simplifies the modelling process, enhances the accuracy of the system and reduces the overall number of inputs to the model, since otherwise a much larger number of thermal sensors would be required to cover the entire structure. The Z-axis heating test, C-axis heating test, and the combined (helical) movement are considered in this work. The compensation values, calculated by the GNNMCI(1, N) model were sent to the controller for live error compensation. Test results show that a 85% reduction in thermal errors was achieved after compensation.

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1. Introduction

There is a focus of current research on high production rates on small machine tools. However, large machine tools are of great importance because of the significant demand for large highaccuracy parts, such as impellers, engine blocks, aeroplane sections, aerofoils, etc. The accuracy of a gantry-type 5-axis machine tool capable of manufacturing large parts is usually not as high as that of small, three-axis machine tools because there are a greater number of error sources, which are amplified by bigger volumes and longer axis strokes. High accuracy for smaller machines is often achievable by improved design or other "error avoidance" strategies. However, the same reductions in error are not always technically or commercially viable for larger machines.

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Thermal errors can have particularly significant effects on the accuracy of large machines. They come from thermal deformations of the machine elements caused by heat sources that exist within the structure (i.e. ball screws, bearings, axis drive motors, friction on the way surfaces, and the flows of coolant) and the ambient temperature changes. Those thermal errors have been reported to be approximately 70% of the total positioning error of the CNC machine tool [1], this differs from machine-to-machine. Although thermal errors might be reduced by making the machine from a material that has a low coefficient of thermal expansion, an error compensation system is often considered to be a more economical method of decreasing thermal errors. Compensation is a process where the thermal error present at a particular time is corrected by adjusting the position of a machine's axes by an amount equal to the error at that position. An extensive study has been carried out in the area of thermal error compensation. Researchers have employed various techniques such as a finite-element method [2] and finite-difference method [3] in modelling the thermal char-

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acteristics. However, building a numerical model can be a great challenge due to problems of establishing the boundary conditions and accurately obtaining the characteristic of heat transfer. Therefore, testing of the machine tool is still required to calibrate the model for successful application of the technique.

In contrast, other techniques use empirical modelling, where the model is based on the experimental measurements of the machine tool, rather than calibrating an existing model. Different model structures have been used to predict thermal errors in machine tools such as multiple regression analysis [4], types of artificial neural networks [5], fuzzy logic [6], an adaptive neuro-fuzzy inference system [7,8], Grey system theory [9] and a combination of several different modelling methods [10,11].

Early work by Chen et al. [4] used both a multiple regression analysis (MRA) model and an artificial neural network (ANN) model for thermal error compensation of a horizontal machining centre. To build their models, 810 data sets were collected from five different tests; each test was run for 6h for a heating cycle and then stopped for 10 h for a cooling down cycle. With their experimental results, the thermal error was reduced from 196 to 8 mm. Wang [10] used a Hierarchy-Genetic-Algorithm (HGA) trained neural network in order to map the temperature change against the thermal response of the machine tool. Wang [8] also proposed a thermal model by using an Adaptive Neuro Fuzzy Inference System (ANFIS) and optimised the number of sensors by Grey system model GM(1,m). A hybrid learning method, which is a combination of both steepest descent and the least-squares estimator methods, was used in the learning algorithms. Experimental results indicated that the thermal error compensation model could reduce the thermal error to less than 9 µm under real cutting conditions. Wang in Refs. [10,8] used 150 min and 480 min of data acquisition in order to build HGA and ANFIS models, respectively. However, both models require training cycles to calibrate the model how to respond to various changes in input conditions. Eskandari et al. [12] presented a method by which to compensate for positional, geometric, and thermally induced errors of three-axis CNC milling machine using an offline technique. Thermal errors are modelled by three empirical models: MRA, ANN, and ANFIS. To build their models, the experimental data were collected every 10 min while the machine was running for 120 min. The experimental data are divided into training and checking data sets. Their validated results on a free form, show significant average improvement of 41% of the errors. Abdulshahed et al. [13] proposed a thermal model by using an ANFIS with fuzzy c-means clustering. Different groups of key temperature points were identified from thermal images using a novel schema based on a GM (0, N) model and Fuzzy c-means clustering. Experimental results indicated that the thermal error compensation model could reduce the thermal error to less than 2 µm. Also, similar works have been carried out by the same authors in Refs. [11.14.15].

Wang et al. [9] proposed a systematic methodology for the thermal error compensation of a machine tool. The thermal response was modelled using a Grey model based on Grey system theory to predict the thermal errors with only 30 min of measured data. Unfortunately, their model lacks the ability of self-learning, self-adaption, self-organisation, and consideration of feedback correction. Therefore, their model obtained under one particular operating condition is not robust under other operation conditions. Gomez-Acedo et al. [16] proposed a parametric state space model for the compensation of thermal distortions in large machine tools. Only two-temperature sensors and spindle speed were used as model inputs. A small number of thermal sensors, however, might lead to poor prediction accuracy.

Whilst empirical models can be good at predicting thermal errors, they require a large amount of data with different working conditions to determine the governing laws of the system. However, a realistic governing law may not exist even when a large amount of data has been measured. Furthermore, the process of obtaining such data can take several hours for internal heating tests and several days or more for the environmental test.

The growing complexity of manufacturing systems drives research to develop techniques to imitate the underlying functionality of the system. In the past, the model had to be kept as simple as possible. For instance, although the ANN models are more accurate than the regression models, the calibration of the regression model coefficients is simpler (least squares approach). Nevertheless, there is still a strong argument for simplicity, where possible, to avoid over-constraining the system and introducing instability. Extensive research has also explored a number of metamodels, e.g. polynomial models, radial basis function (RBF), and ANN models. Metamodeling involves (i) choosing an experimental design, (ii) choosing a model, and then (iii) training/calibrating the model to the experimental data [17]. There are several options for each of these steps as illustrated in Ref. [17]. Hussain et al. [18] have used a metamodeling technique based on radial basis functions, which explored using factorial and Latin hypercube designs. The resulting metamodel was tested on seven different data sets, obtained from known input-output relationships. Simulation results indicate that the factorial designs generally provided better fit compared with Latin hypercube designs for metamodels using RBF, except in some instances near the centre of design space.

Properly designed experiments should be used to obtain an accurate model. The number of samples can vary greatly depending on the complexity of the system under consideration [19]. However, many other statistical models have been trained successfully with small amounts of training data [20,21,19]. Buragohain and Mahanta [19] have proposed an ANFIS based modelling method where the number of data samples employed for training was minimised by application of an engineering statistical technique called full factorial design. Furthermore in Refs. [20,21] they have applied another method called V-Fold technique. Although, their techniques were able to construct a model with a small number of training samples (as few as 7), they still used all the experimental samples in order to select the optimal ones. Data transformation can also change the smoothness and comparability of the data. For instance, Huang and Chu [22] have proposed a data transformation technique to simplify the fuzzy modelling procedures. The transformation method allows the whole raw data to be mapped to another domain such that there is no need to adjust the membership functions, and the fuzzification process is simply taking place on the fixed ones. Shmilovici and Aguilar-Martin [23] have also utilised Box-Cox transform to improve the quality of the fuzzy model, before parameter optimisation occurs. Therefore, optimisation in the number of training patterns and data domain used for training are of prime concern in the field of modelling.

To supplement the proposed model, we use the AGO to increase the linear characteristics and reduce the randomness from the measuring samples. This simple but effective technique allows us to build the thermal model under the condition of small training data. In short, the proposed model incorporates the AGO method into the modelling process to improve its prediction accuracy and robustness with minimal efforts.

The hysteresis effect is defined as a system that has memory, where the effects of the current input to the system are experienced with a certain delay in time [24]. Due to varying thermal time constant, thermal effects on CNC machine tools have the characteristic of memorising the previous thermal status. Therefore, the errors in a machine tool are not only dependent on the current thermal status measured at the surface, but also influenced by the previous conditions of the machine. The hysteresis behaviour will introduce error in each cycle, which in a worst case scenario can be seen in large machine tools with bigger volumes, longer strokes and

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