Comparison of regression-based thermal compensation techniques for motorized spindle

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Abstract

Thermal errors account for a large percentage of total errors in a machining center. Thermal compensation provides a convenient and an efficient way of reducing thermal errors. Classically, a majority of the modeling techniques have been empirical in nature: employs a few critical temperature sensors and/or real-time machine information in the form of speed and load and predicts the Tool Center Point (TCP) distortion. One of the challenges has been to select those critical temperature sensors which describe a multi-linear relation with the TCP distortion. Notwithstanding, in the recent years, several new compensation algorithms have been proposed including Ridge Regression (RR), Principal Component Regression (PCR), and Elastic Net Regression (ENR) for improving the predictive capability of the model. The focus of this paper is to compare these methodologies with the conventionally employed Multi-Linear Regression (MLR). To this end, models are calibrated using the above-mentioned techniques through extensive experimentation on a motorized spindle affixed with nineteen temperature sensors at various sensitive regions. The calibrated models are checked for their predictive capabilities and it is observed that the PCR estimated better than others. Further, as a part of the model building process, multivariate statistical techniques including fuzzy clustering, *k*-means clustering, grey-correlation, and sensitivity analysis are used to reduce the redundancy of training datasets and help to choose a so-called optimal set of temperature sensors. In addition to these techniques, a new grouping methodology called dot product analysis is also proposed in this work.

1. Introduction

A large percentage of machining errors are due to thermal issues [1], which are primarily caused by the change in the thermal state of the machine tool because of various heat sources. In order to account for these errors, specifically due to the motorized spindle, cooling is typically employed and also made adaptive to the heat generation rate [2]. This has resulted in the reduction of errors to an extent but is not completely eliminated and therefore real-time thermal

compensation can be employed to negate the residual errors by appropriately re-adjusting the reference of the machine tool axes using predictive models. These models are generally built using techniques like regression, transfer function, neural network, etc. with field variables including temperatures, spindle speed, and load. Among them, the temperature is widely chosen as the field variable [1] for most of the frameworks and therefore employed in this work. The objective here is to build compensation models using regression methodologies and compare their relative performance. The primary requirement for compensation model calibration is the selection of optimal temperature sensor points.

2. Selection of optimum temperature sensitive points

The experimental setup to acquire temperature and displacement data are similar to the one used in our previous work [2] with nineteen temperature sensors affixed at various points as per engineering judgment on the spindle along with four non-contact high precision capacitive displacement sensors. It is not a good idea to employ numerous temperature sensors for model calibration as highly correlated data or redundant information might lead to non-robust models in addition to the higher capital cost. Hence, optimum location(s) of sensors on the motorized spindle are required to be decided. As per literature, the selection process of these temperature points depends majorly on the combination of two principles: first is by grouping the highly correlated temperature sensors together and choosing one from each set as one of the independent variables (correlation analysis, fuzzy clustering, *k*-means clustering); second is on the basis of the sensitivity of TCP displacement with respect to individual temperatures (grey-correlation analysis, sensitivity analysis). A summarised description of different techniques applied to select the optimum temperature points is as follows [3]: I- Correlation analysis uses statistical concepts of mean and standard deviation to calculate correlation among different temperature sensors. Temperatures with a higher correlation than the threshold are grouped together. II- Fuzzy clustering is an extension of correlation analysis to group temperature sensors using normalized or fuzzy correlation coefficients. III- *k*-means clustering is a conventional clustering algorithm to group data as per the Euclidean distance between different data points from one mean data value per cluster. IV- Grey-correlation analysis is used to correlate the displacement with temperature data. The degree of closeness between the two series of data is determined by the grey-correlation coefficient. V- Sensitivity analysis is also another method to provide a measure of the impact of the change in the displacement data with the change in temperature. VI- Dot-product analysis is a method being proposed in this work which quantitatively measures the degree of closeness between the temperature and the displacement data. In this methodology, the measured temperature and TCP distortion are converted to vector form and the usual dot product is performed between the displacement vector and temperature vector (one at a time) to calculate the angle between them**.** A lesser angle implies more closeness and hence high correlation between the two and vice-versa.

The methodology followed to select the optimum temperature point(s) is a combined result of deductions from both principles. In a sequential manner,

the correlated temperature points are grouped together first and then one temperature from each group(s) is selected for which the thermal distortion is much more responsive to temperature changes. Table 1 depicts the results obtained on the basis of the aforementioned principles using the corresponding techniques. All the correlation and clustering analysis techniques groups the sixteen temperature points in four groups (eight at the two Front Bearing (FB) sets; five at the two Rear Bearing (RB) sets; one each at housing, ambient, and motor), which implies that one temperature point from each group can be considered to build a predictive model. Further, before finalizing the temperature points for model calibration, the sensitivity of thermal distortion with respect to each temperature point is calculated using grey-correlation, sensitivity, and dot product analyses. Even here, the results (in the decreasing order of sensitivity: motor/RB, RB/motor, ambient, FB) are similar except for the fact that the sensitivities for motor and RB are interchanged. It is interesting to note that although the FB temperature set had higher correlation within their group, it is least sensitive to TCP distortion because of the employed spindle cooling strategy [2]. It seems that correlation analysis is a simpler technique among the three from a computational effort perspective. In a similar way, the dot-product analysis is a relatively straightforward technique among the three techniques used to compute sensitivities of TCP distortion with respect to temperatures. As a result of these analyses, three temperature sensors: one from the RB set along with motor and ambient, are selected for building models.

Table 1: Optimum temperature points obtained from different methods.

Methods:	**Results**
Correlation analysis, fuzzy clustering, *k*-means clustering	**Groups (4):** FB set + housing (9); RB set (5); motor (1); ambient (1)
Grey-correlation analysis, sensitivity analysis	**Groups in decreasing order:** motor; RB; ambient; FB
Dot-product analysis	**Groups in decreasing order:** RB; motor; ambient; FB

3. Comparison of various model building techniques:

The next step after selecting the so-called optimal temperature points is to select the appropriate model framework and then to calibrate the model parameters by conducting suitable experiments. As the objective of this study is the comparison of different aforementioned linear regression models, they are briefly summarized here: I- MLR is a simple multi-linear regression method with multiple independent variables and one dependent variable. The model parameters are fit from the over-determined temperature and displacement data. II- PCR is a similar approach to MLR, with the exception that instead of applying regression analysis on the original data, it is applied on the prominent principal components (i.e., with higher variances) of temperature data. III- RR is an extension of MLR with the objective of avoiding both over-fitting and under-fitting. A regularization parameter is added along with the ordinary least square to further minimize the cost function. IV- ENR is also a regularization

methodology with the penalty parameters of both RR and Least Absolute Shrinkage and Selection Operator (LASSO).

4. Results and conclusion:

The training data set for the experiments consisted of 2-hour experiments ranging from 2000 rpm to 15000 rpm. In total, the training data set included 20 experiments with most of them being constant speed throughout the timeline. While to add more variations in the data, some of them were with speeds varying in a random manner as well. On the other hand, validation of the developed models is done through an experiment comprising of around 29 hours. Figure 1 illustrates the prediction results of the four compensation methodologies (Δz is the axial spindle distortion) along with the spindle speed profile (N) and the relative temperature change profile (ΔT) for selected temperature points. All models predicted a pattern similar to the experimentally observed one (R^2 value for MLR, PCR, RR, and ENR are 0.43, 0.68, 0.44 and 0.44 respectively) with the best fit model being PCR. The prediction capability of MLR, RR, and ENR are very similar as they are fit on original data. On the other hand, PCR also follows the least squares, but instead on a dimensionally reduced data-space and hence fares the best. In passing, it is noted that more diverse experimental datasets can be used during model calibration to further improve the predictive capability of models.

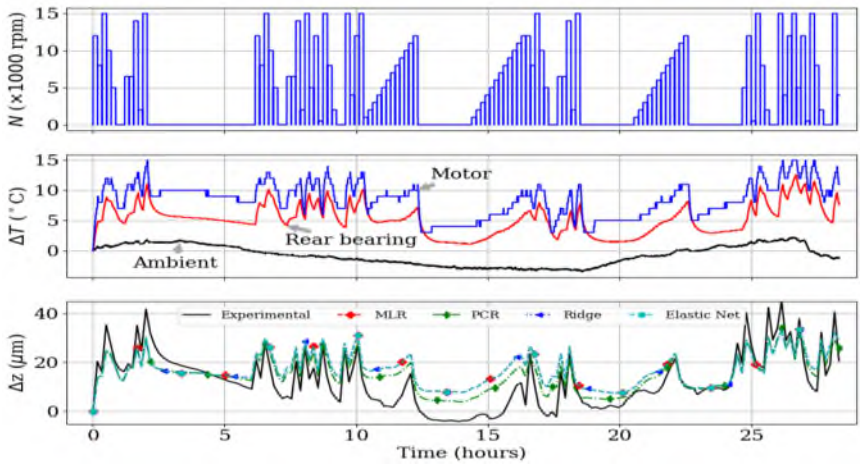

Figure 1: Comparison of different compensation methods for a validation test.

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