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Original Citation

Mian, Naeem S., Fletcher, Simon, Longstaff, Andrew P. and Myers, Alan (2012) An efficient offline method for determining the thermally sensitive points of a machine tool structure. In: 37th International Matador Conference, 25th-27th July 2012, Manchester, England. (In Press)

Paper No: 3208 – 37th MATADOR Conference

An efficient offline method for determining the thermally sensitive points of a machine tool structure

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Abstract. Whether from internal sources or arising from environmental sources, thermal error in most machine tools is inexorable. Out of several thermal error control methods, electronic compensation can be an easy-to-implement and cost effective solution. However, analytically locating the optimal thermally sensitive points within the machine structure for compensation has been a challenging task. This is especially true when complex structural deformations arising from the heat generated internally as well as long term environmental temperature fluctuations can only be controlled with a limited number of temperature inputs. This paper presents some case study results confirming the sensitivity to sensor location and a new efficient offline method for determining localized thermally sensitive points within the machine structure using finite element method (FEA) and Matlab software. Compared to the empirical and complex analytical methods, this software based method allows efficient and rapid optimization for detecting the most effective location(s) including practicality of installation. These sensitive points will contribute to the development and enhancement of new and existing thermal error compensation models respectively by updating them with the location information. The method is shown to provide significant benefits in the correlation of a simple thermal control model and comments are made on the efficiency with which this method could be practically applied.

Keywords: Finite element analysis, FEA, Matlab, Thermal error, Thermal error compensation, Thermally sensitive locations

1.1 Introduction

Thermal errors have been identified as a major contributor to the overall volumetric error of a machine tool, in many cases up to 70% [1]. Several techniques based on analytical, empirical and numerical methods have been established to control the effect of thermal errors. These techniques are widely used and applied with a basic ideology to establish a thermal model based on relationships between the measured temperature of the machine from various locations, used as temperature inputs and the displacement at the tool [2]. The temperature inputs however in some cases may be difficult to identify if propagation of the temperature gradients is complex due to the combined effect of internal and external heat sources and perhaps due to the complexity of the machine structure. These ambiguities therefore add complexities to identify sensitive locations within the structure and stands out to be a challenging task with a limited number of temperature inputs. It has been observed that the performance of the conventional empirical and statistical approaches such as Artificial Neural Network (ANN) and Linear Regression [3, 4] heavily rely on the data from sensitive location within the machine structure for effective and robust thermal compensation such as varying environmental conditions. Kang et al [5] used a hybrid model consisting of regression and NN techniques to estimate thermal deformation in a machine tool. The total of 28 temperature sensors were placed on (18) and around (10) the machine to acquire internal heating and environmental data. The training time for the model was 3 hours. Yang et al [6] tested a INDEX-G200 turning centre to model thermal errors. Temperature variables were selected using engineering judgement as temperature sensors were placed on or near the possible heat sources and Multiple Linear Regression technique was used to model thermal errors. Training time for the thermal model however was not mentioned. Krulewich [7] used the Gaussian integration method using polynomial fit to identify the optimum thermal points on the machine spindle. The spindle was put through heating and cooling cycles providing 3.5 hours of training data to locate three optimum measurement points where the results correlated to 96%. The author compared this method with a statistical technique and found that the Gaussian integration method requires significantly less training data.

It has been observed that a significant amount of data is generally required to identify sensor locations and train models which inevitably requires machine downtime therefore such methodologies can be impractical for general application. It is also the fact that machine structures are sensitive to environmental changes which means that the training data acquired in the first instance may not respond well to the new conditions and therefore a new set of training data may be required [7]. This paper presents an offline technique based on FEA. The technique provides the ability to identify optimised sensitive locations within the machine structure offline for any set of data either from internal heating or external environmental conditions. Being software based, using the Graphical User Interface (GUI) of the FEA software, this technique integrates the visual aspect to aid reviewing the location of the sensitive areas and the practicality for sensor installations. The application of this technique requires minimal machine downtime as any set of the measured thermal conditions can be assessed offline to obtain the thermal behaviour of the machine. This means that new sensitive areas inside the machine structure may be located according to the new thermal conditions. Satisfactory correlations between the measured and the FEA simulated results are a pre-requisite to the application of this technique. In this paper, this technique is applied on the results from simulation case study previously conducted.

1.2 Case Study

This study was conducted on a 3 axis Vertical Machining Centre (VMC) located on the shop floor with uncontrolled environmental temperature. The machine FEA model was created in Abaqus/Standard 6.7-1 FEA software [10] using manufacturer provided engineering drawings. Fig 1.1 shows the generated CAD model of the machine. The model of the machine was simplified by cutting into half because of the symmetry in the X axis direction and complex structures such as fillets and chamfers were simplified and represented using simple corners to avoid complexity of meshing and nodes.

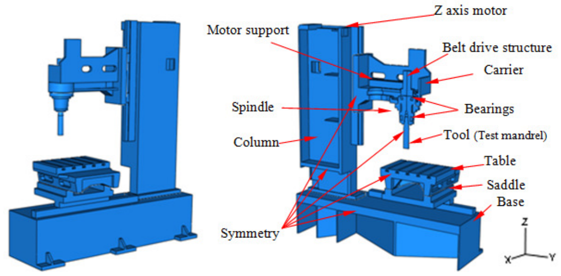


Fig 1.1 Generated CAD model of the machine assembly

Mian et al [8, 9] conducted tests to exploit the thermal behaviour of the VMC when subjected to the spindle heating and varying environmental conditions. Mian [8, 9] proposed a technique in which only one short term data set obtained during one hour internal heating is required to obtain thermal parameters and simulate the heat transfer within structures. This short term data set is used to create the FEA thermal model to simulate the machine for a variety of real world testing regimes. The results showed good correlation between the experimental results and the FEA simulated results typically between 70% and 80%. Mian [9] also conducted environmental tests where the machine was tested for three continuous days in two seasons (winter and summer). The aim was to achieve good correlation in results from one season test and validate the methodology with good correlation results in different environmental conditions i.e. in a different season. Both tests successfully validated the FEA environmental thermal model with good correlations typically above 60%. This technique in effect can remarkably reduce the machine downtime by creating the CAD model of the machine in the FEA software and simulate it to create an environmental thermal model that is able to simulate the effect of any set of varying environmental conditions.

This method therefore provides a platform to use FEA modelling as an offline tool to determine not only machine behaviour, but also help with the development of compensation models by determining the location of sensitive nodes/areas. The case study by Mian [8, 9] was therefore used for differentiating between areas sensitive to internal heating and environmental temperature fluctuations.

The remainder of the paper details a method and the developed software for the offline assessment of the FEA data and help determine the temperature-displacement sensitive nodes based on search parameters and their physical locations within the FEA model. The information can be used to retrofit sensors for compensation; however there can be practical limitations to their attachment.

1.3 Nodal data extraction

The Abaqus simulation software provides the facility to extract surface and sub-surface nodal data within the FEA model. Since the model has to be meshed for FEA analysis, the nodes from the mesh can be used to represent individual points on the structure. Therefore using this facility, the nodal data was extracted to find nodes of interest. The predicted error is obtained as the difference in displacement between a node on the table and a node on the tool. In this case the dependant parameters are slope and hysteresis.

The slope is simply the magnitude of displacement for any given change in temperature (°C/µm). Hysteresis is caused by the time lag involved with typical surface temperature measurement which is related to the distance between the temperature sensor and the true effective temperature which is causing the distortion. A node location with high slope sensitivity will require lower resolution in the measurement of temperature and induce less noise when applied in models as described later. The lowest hysteresis will represent that area that relates well to thermal displacement and responds in a linear fashion whether the machine is being heated or cooled. The nodal date is extracted from Abaqus and the files are converted and imported into Matlab software. Matlab functions were written to calculate the slope and hysteresis for each node and return the best ones with respect to an axis.

1.3.1 Matlab program routines

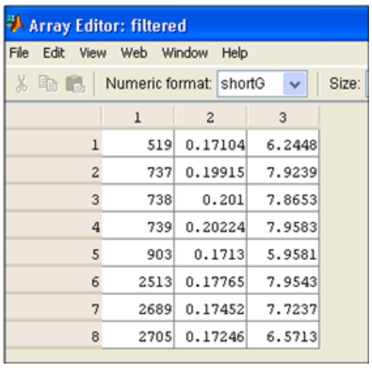
The function imports the nodal data from the FEA software and extracts the error between the tool and workpiece in each direction, and the temperature of all the nodes. Then it calculates the slope (°C/µm) using a linear least square fit and hysteresis (µm), using deviation from the straight line, for all nodes. These are compared against a predefined set of ranges to filter out the best nodes. The range may be set based on the resolution of the temperature sensors and required accuracy for compensation. There can be thousands of nodes depending on the mesh density of the machine model. If no nodes are found then the range must be widened. The nodes are filtered for slope and hysteresis separately to maintain flexibility so that different nodes can be used for different jobs, not always both. The final node numbers satisfying both filters are then used to locate their positions in the CAD model of the relevant structure. Fig 1.2 shows the function calls where comparison takes place using a specified range, in this case the range for the slope sensitivity is from 0.17 °C/µm (min) to 0.20 °C/µm (max) and 5.44 µm (min) to 8 µm (max) for the hysteresis. The first and second lines filter out node numbers for the slope sensitivity and hysteresis respectively using the range. The third line is then used to match node numbers in both arrays and obtain the matched nodes numbers. Fig 1.3 shows the Matlab array editor displaying 8 nodes filtered out from the total of 4113 from the carrier (Fig 1.6) structure mesh. The first column shows node number, the second column shows slope sensitivities and the third column shows the hysteresis values. These 8 nodes have shown to have the highest slope sensitivities (Fig 1.4) and the lowest hysteresis values and will effectively be used to place permanent temperature sensors for use in error compensation systems. It can also be observed that nodes 738 and 739 possess the highest slope sensitivity among the other filtered nodes and a slightly higher hysteresis values relative to other filtered nodes, however an agreement can be obtained to prioritize the selection of nodes that were located at the surface for practical installation of temperature sensors. This priority may not be the case if slope sensitivities and hysteresis values are significant at node positions inside the structure.

Minimum hysteresis sensitivity   Maximum slope sensitivity

```
chkSlope=filt_slope(:,2)<0.17 | filt_slope(:,2)>0.20;
chkHyst=filt_hyst(:,2)<5.44 | filt_hyst(:,2)>8;
chk= bitor(chkSlope, chkHyst);
```

Range

Fig 1.2 Part of Matlab program code for assigning range



	1	2	3
1	519	0.17104	6.2448
2	737	0.19915	7.9239
3	738	0.201	7.8653
4	739	0.20224	7.9583
5	903	0.1713	5.9581
6	2513	0.17765	7.9543
7	2689	0.17452	7.7237
8	2705	0.17246	6.5713

Fig 1.3 Filtered nodes

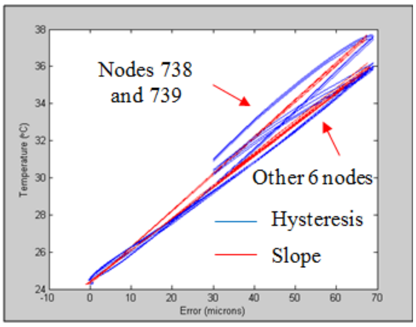


Fig 1.4 Slope and hysteresis plot

1.4 Internal heating test – Carrier sensitivity against the Y axis and Z axis displacement

Since the carrier holds the spindle in place, it is the most affected structure as the heat from the spindle flows directly into it. Therefore this structure was analysed to locate the temperature-displacement sensitive nodes for internal heating. Fig 1.5 shows the visual representation of the simulated deformation of the machine.

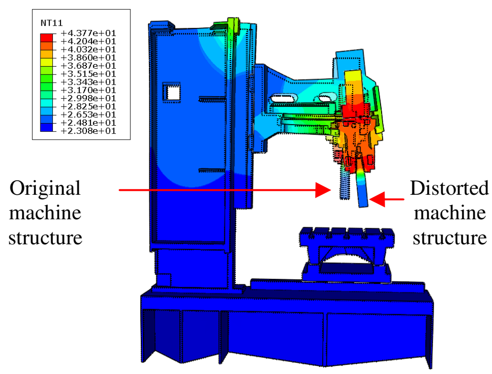


Fig 1.5 Simulated visual representation of deformation of the machine due to internal heating

Fig 1.6 shows the best surface nodes found using the Matlab search routine. Other visible nodes are inside the structure.

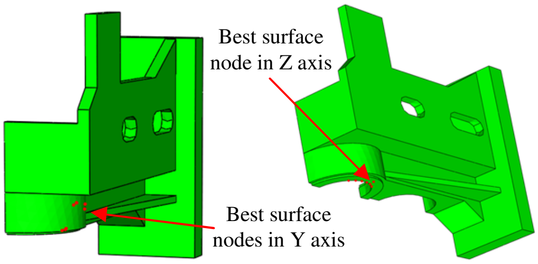


Fig 1.6 Nodes sensitive to spindle heating on the carrier

1.5 Validations

Using the similar approach shown in section 1.3.1, the best identified surface node (Fig 1.6) was checked which give the sensitivity of 0.20°C / µm and hysteresis of 7µm. This linear fit gives a simple model for the Y axis of $5\Delta t_{int}$ - 106.5. This was applied to measured temperature data from a sensor fitted to the machine surface close to the identified node position, with correlation to measured displacement of 84% as shown in Fig 1.7.

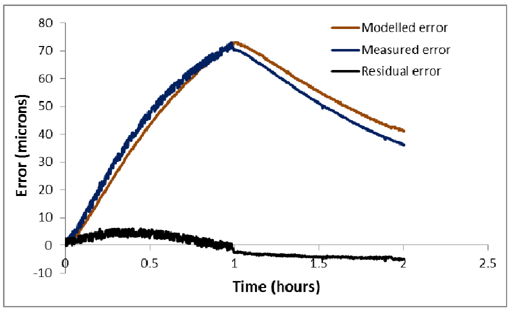


Fig 1.7 Validation of the FEA model against measured error due to internal heating

1.5.1 Environmental sensitive nodes inside the full machine structure

Using the similar procedure the nodes sensitive to the varying environmental conditions, including different seasons, were found in the machine structure. During this preliminary work, each structure was analysed individually for efficiency to locate sensitive nodes with the higher slope and lowest hysteresis approach. Future to consider the full machine structure as one component to locate the set of sensitive nodes. Fig 1.8 shows the full machine FEA model with highlighted environmental sensitive nodes individually located on components.

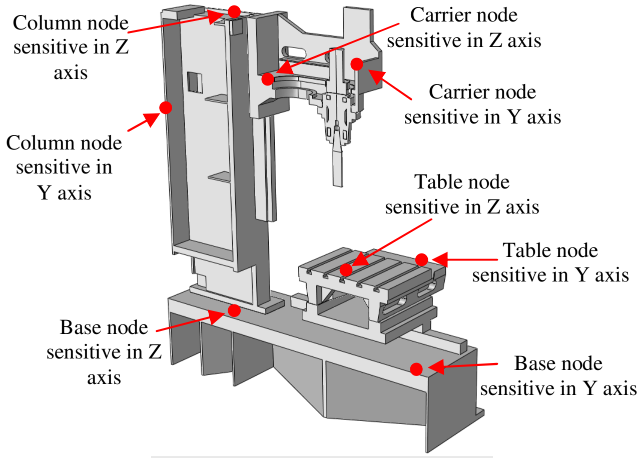


Fig 1.8 Environmental sensitive nodes within the full machine

1.6 Conclusions

It has been observed that the simulation of thermal behaviour of complex machine structures using FEA can provide a solid platform for offline assessment of the machine error and model identification. FEA results from previously conducted case studies were used to locate nodes in the structural elements of a 3 axis VMC that were sensitive to temperature change and movement of the machine structure in Y and Z axes. Matlab functions were used to manipulate the extracted data from the FEA software, calculate the hysteresis and slope for any given node and filter out the best node locations by using a range of highest slope sensitivity and lowest hysteresis value. The location of the filtered nodes were analysed using the Abaqus GUI. The priority is given to surface nodes rather than the internal nodes for practical temperature sensor installation on the machine. The validation result showed the predicted sensitive nodal location correlated to better than 84%. By determining the best linear relationships, simple models are available and compatible with the common thermal compensation methods available in most modern NC controllers.

Acknowledgements

The authors gratefully acknowledge the UK's Engineering and Physical Sciences Research Council (EPSRC) funding of the Centre for Advanced Metrology under its innovative manufacturing program**.**

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