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OPTIMIZATION OF CHARACTERISTIC DIAGRAM BASED THERMAL ERROR COMPENSATION VIA LOAD CASE DEPENDENT MODEL UPDATES

The compensation of thermal errors in machine tools is one of the major challenges in ensuring positioning accuracy during cutting operations. There are numerous methods for both the model-based estimation of the thermal tool center point (TCP) deflection and for controlling the thermal or thermo-elastic behavior of the machine tool. One branch of thermal error estimation uses regression models to map temperature sensors directly onto the TCP-displacement. This can, e.g., be accomplished using linear models, artificial neural networks or characteristic diagrams. One of the main limitations of these models is the poor extrapolation behavior with regard to untrained load cases. This paper presents a new method for updating characteristic diagram based compensation models by combining existing models with new measurements. This allows the optimization of the compensation for serial production load cases without the effort of computing a new model. The new method was validated on a 5-axis machining center.

1. INTRODUCTION AND STATE OF THE ART

THERMAL EFFECTS are one of the main causes of positioning errors in machine tools [1]. According to a 2018 international survey by Regel and others among a large number of machine tool manufacturers, the **thermal error** constitutes on average roughly a third of the total positioning error [2]. It is caused by shifting temperature distributions in the machine tool, which lead to thermo-elastic deformations. These temperature fields are shaped by heat sources and sinks, such as waste heat from the cutting process, friction from guides and bearings, power loss from motors, coolants and the environment [3].

The **compensation** of thermo-elastic deformations involves the prediction or measurement of temperature or deformation fields and using them to offset and thus correct the tool center point (TCP) position [4]. Compensation strategies can be categorized by the level

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of realism of their models. Some of the most detailed ones use finite element method (FEM) simulations to model the entire physical process of thermo-elastic deformation with all relevant aspects and parameters, although with simplifications and limited resolution [5]. Black-box methods completely or at least mostly ignore the underlying physical effects and instead use (large) databases to map the input-output behaviour of the system. Prominent are Regression Analysis [6] and Artificial Neural Network (ANN) based methods [7, 8]. In between these extremes lie, e.g., simplified representations of the physical processes modelling only the input-output behaviour. This can be done by using transfer functions to compute deformations from the power loss of motors and other components. PT_1 and PT_2 elements (first and second order time delay functions) can, for instance, be used to approximate the time-dependent thermo-elastic behaviour of simple structures [9].

Regression Analysis, or more accurately Multiple Regression Analysis (MRA), usually maps several temperature inputs directly onto the tool center point (TCP) displacement, based on sample data derived from measurements or simulations [10]. The often-used least-squares approach minimizes the sum of the squared error across all training data samples.

There are a large number of different regression models and most of them can theoretically be used for thermal error compensation. Examples are characteristic diagrams [11], B-Splines [12], Radial Basis Functions (RBFs) [13], wavelets [14] or even single analytic functions (e.g. multivariate polynomial functions) [15].

Some **advantages** of thermal error compensation based on MRA (or ANN, etc.) are that they are comparatively simple, require only minimal information on the underlying thermo-elastic processes, can be trained with simulation and/or measurement data and are online-capable. They are usually applicable for all machine tools of the same type without adjustment because they only map how thermal states affect the TCP, which is dependent on material properties but mostly independent of manufacturing deviations, machine tool wear, preloads, lubrication, etc. They can also always be improved with more training data and/or more temperature sensors.

The **disadvantages** are that they typically require a large amount of training data to cover a broad range of operating conditions, typically require at least five to eight temperature sensors to function properly and can only perform well if the temperature sensor locations are suitably chosen. They are also generally not able to extrapolate to thermal states that were not included in the training data, rarely achieve very high accuracy in practice for untrained load cases and are highly susceptible to overfitting.

The above mentioned properties make MRA based thermal error compensation more suitable for large-volume production, provided the load cases for these cutting operations have been included in the training data. For large-volume production, this is economically feasible. Small-batch production, on the other hand, has constantly changing load scenarios and therefore makes it very likely, that some segments of the cutting operations include thermal states that are not known to the compensation model and must then be extrapolated, usually with mixed results. Retraining or updating the compensation model for only one or perhaps a few work pieces dramatically increases the unit cost and is therefore rarely done.

The actual **method for updating** regression based compensation models depends on the type of model used. What is needed for such an update is generally a set of additional training data comprising temperature sensor readings, measured (relative) TCP displacements and the absolute TCP coordinates. Depending on the selected input variables, additional sensor or other input information may also be needed. Naumann and others have listed and evaluated a large number of potential input variables for characteristic diagram based compensation in [16].

Updating ANN based models with additional data is easy. Since most ANN models in this application use supervised learning, the new input and output data are simply fed into the model and the model weights (of neurons and/or edges) are optimized using backpropagation.

For standard MRA models, updating typically requires a complete recalculation of the entire model. The new data is added to the original training data and the MRA is repeated with the expanded dataset. This requires no new algorithm for the model update and the updated model represents a global optimum across the entire dataset. However, it also has a relatively large computational effort (even if only a single new data point is added). Depending on the characteristic diagram grid size and especially its dimension, very large linear systems must be solved, which can take several hours on current PCs. In addition, model updates cannot happen online (during continuous model usage) and there is no guarantee for continuity between the new and the previous model. The lack of continuity means that extrapolations that worked well before the model update and that are not specifically part of the update data might no longer work at all after the update.

This paper presents a new method for updating compensation models to account for new, unknown thermal load cases. Special emphasis will be placed on the problems of updating large composite compensation models using measurement data. Chapter 2 briefly describes the demonstration machine tool DMU 80 eVo and the implemented characteristic diagram based compensation method. Chapter 3 describes the new update method and the problems of using measurement vs simulation data for the updates. Chapter 4 demonstrates the new update method on the DMU 80 eVo by comparing the uncompensated to the compensated error and the error after the model update. Finally, Chapter 5 gives a summary of the work and describes how this new update method can best be used in practice. An outlook on future research concludes the paper.

2. THERMAL COMPENSATION FOR THE DMU 80 EVO

The DMG Mori DMU 80 evolution is a five axis machining center with a workspace of about 800×650×550 mm (X, Y and Z axis), see Fig. 1. Its table can rotate around an oblique axis between the horizontal and vertical orientation (B axis) and can also spin around its own center in a turning motion (C axis). It is fully housed, includes a large tool changer and has a comprehensive cooling system for the drives, the guides and the table. There are also additional systems for cooling, cleaning and evacuation of the workspace.

To account for these complex conditions and the limitations of MRA based compensation, the thermal error was split into several components. Firstly, the thermal error was subdivided geometrically in a column component (X-, Y- and Z-axis) and a table component (B- and C-axis). This separation allows for smaller (less input variables) and more targeted MRA models and thereby also reduces the amount of training data required for creating these models.

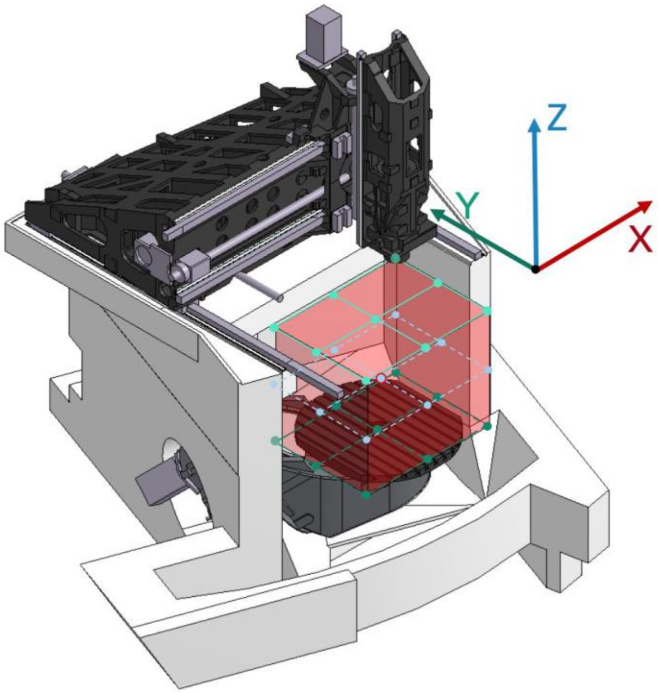

Fig. 1. Workspace of the DMU 80 eVo without housing [17]

As a simple example, the table deformation is neither dependent on the X-, Y-, Z-position nor the motor spindle temperature. Note: The table error is of course dependent on the X-, Y- and Z-position. This distinction of deformation and error is used in the next model separation. The thermo-elastic deformation is separated from the machine pose. By discretizing the workspace into a small set of discrete support points (here 27, see Fig. 1), the thermal error can be calculated for each support point separately. This way, the individual MRA models do not need to consider the current TCP position, which significantly reduces their input variables. Good MRA models use as few as possible input variables so that they are easier to train, faster to compute, easier to store and less prone to overfitting. The geometric interpolation between the support points is done in a second, independent step. This interpolation is completely independent of any thermal effects and only needs the current axis positions as inputs. This separation of thermal and geometric errors has the additional advantage that the thermal models can be run in larger intervals, e.g. every few seconds, while the simpler geometric interpolation can be run in the NC tact.

Lastly, the thermal model is further subdivided into an internal and an external model. The internal model considers only the heat sources and sinks which are associated with the machine tool operation (drives, guides, spindle, coolant, etc.). The external model considers only ambient effects, which include mainly changes in the ambient temperature or the founda-tion temperature. This last separation is somewhat complex and has severe limitations but has shown good results for the DMU 80 eVo under even large ambient temperature changes. A detailed description of this method of dealing with ambient effects in correlative thermal error compensation was published by Naumann and others in 2021 [18].

In general, the first two model separations are useful for most complex machine tools with more than three axes. The last one is a compromise between training data acquisition and accuracy and, if necessary, has to be carefully developed and validated for each machine tool. In combination, all three separations significantly reduce the amount of training data required for MRA model creation. While less training data is required, the data has to be far more specific. Therefore, this type of composite compensation model has to be trained by thermo-elastic simulations. Measuring all of these thermal effects separately and for all workspace support points is not economically feasible. Nevertheless, some measurements are still needed to parametrize the simulation models and validate the simulations. The compensation model for the DMU 80 eVo was trained with dozens of FE simulations and a much smaller number of measurements, see [18]. The error reduction of the training data was above 50%, for the independent test data it was generally below 50% and varied with the load cases.

In the end, for the thermal error compensation method used in the DMU 80 eVo, each of the 27 workspace support points has three error parameters (for *dx*, *dy* and *dz*) and there are 10 additional parameters describing the table deformation. In total, this makes 91 parameters. Since this is only for the internal thermal effects, there are two more such parameter sets for the ambient model (see [18]). Each parameter is modelled using an MRA model, a characteristic diagram or a transfer function and each has its own set of input variables from the nine available temperature sensors installed in the demonstration machine. This means, that there are a lot of small, simple compensation models instead of a few large complex ones. The final step of the geometric error interpolation is done by computing the table error component using simple vector arithmetic and the column error component by quadratic interpolation of the 27 workspace support points.

For the generalization of the following results, it is recommended to maintain the separation of the geometric from the thermal error. It is not relevant, which exact thermal model is used. Using an efficient model order reduced simulation to calculate the thermal displacement of the support points will work just as well with suggested updated method as any MRA based method.

3. CHARACTERISTIC DIAGRAM BASED UPDATE METHOD

3.1. ALTERNATIVE UPDATE STRATEGIES

There is more than one way to update MRA based compensation models. The first method, which was already suggested in the introduction, is to add the new data to the old data and recalculate the entire models. This is, however, very time-consuming and may also affect parts of the model that were unrelated to the new data.

The second method requires only local changes of the compensation models. This is possible for some MRA models, e.g. characteristic diagrams but not for others, e.g. simple polynomial models. In characteristic diagrams, the grid vertices near the new data points can be adjusted to fit the new data. This may, however, cause a loss of the smoothness of the characteristic diagram in these parts of the grid and it may also negatively affect predictions of the original training data. There is also no guarantee that the new data still correlates to the originally selected input variables.

The third method was also hinted at in the introduction. ANN based compensation is easy to update with new data. In general, for any MRA model, one can create an ANN model that can produce the same input-output behaviour. It is therefore possible to convert the MRA models into ANN models, update these with the new data and then transform them back into MRA models [19]. To do this, step one is to find suitable ANN model types for each MRA model type used in the compensation. Step two is to create large datasets of input-output pairs from the MRA models for training the ANN models. Step three is to create some more datasets to validate the ANN model predictions. Step four is the extended training with the new update data. Step five is to once again create input-output pairs, this time from the ANN models. Step six is to use these datasets to calculate MRA models again. As before, a validation with independent data may be added. This method is a bit convoluted and it raises the question of why ANN models are not used to begin with. Just as the second method, it also has the disadvantage of having fixed input variables for the new data. However, once the MRA-ANN model type pairings are known, method three should be faster than method one and create better results than method two. Also, using ANN models as a kind of bridge, as has been suggested here, one can combine the flexibility of ANN with the reliability and interpretability of the MRA. Figure 2 illustrates this update method.

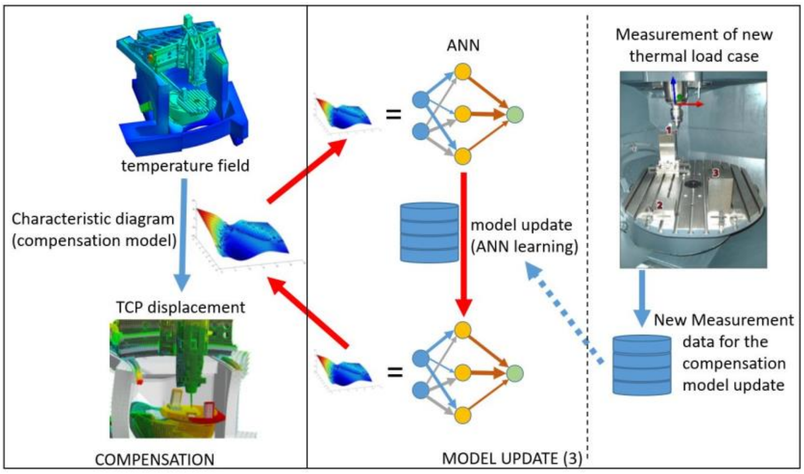

Fig. 2. MRA model updates via ANN training

3.2. THE NEW UPDATE METHOD

The new update method is a kind of mix of methods one and two. The update method uses characteristic diagram based compensation to create a new global optimum [20] but it does so with limited disturbance of the original model.

This method becomes very simple if it can be trained with new simulation data. In this case, new displacement data can be calculated for each workspace support point for the new unknown thermal load cases. Similarly new table deformations can be computed for different tilt values (B-angles). In this case, step one is to compute the displacement predictions for these load cases. Step two is to subtract these predicted displacements from the simulated displacements. Step three is to calculate three new characteristic diagrams for each workspace support point (dx, dy, dz). Each can be optimized individually in terms of grid size and input variables. Some algorithms for selecting input variables are described in [16]. The optimization of the grid size and structure is described in [21]. The authors recommend starting with coarse equidistant grids and increasing the grid fineness by halving the grid elements until no significant improvement occurs. These characteristic diagrams now present the update model.

Ideally, the original training data is also still available. In this case, both the new and the original data can be combined with data weights (see [20]) set in accordance with the user preference. The authors recommend using an algorithm to optimize the data weights. Such an algorithm could be as follows:

Step 1: Compute characteristic diagrams with only the new data to obtain a reference solution. All subsequent solutions will be worse w.r.t. the new data.

Step 2: Choose a norm to rate the solutions, e.g. the root mean square error (RMSE)

Step 3: Choose thresholds to stop the algorithm, e.g. $RMSE_i > 2 \cdot RMSE_{new}$

Step 3: Set initial data weights, e.g. $w_{orig} = 1$; $w_{new} = 10$;

Step 4: REPEAT:

Compute the characteristic diagrams of iteration i with the weighted training data and check the resulting error norms:

IF ($RMSE_i > 2 \cdot RMSE_{new}$) THEN stop and use last acceptable solution

ELSE adjust weights, e.g. $w_{new} = w_{new} \cdot 0.7$.

The update method becomes more complicated if measurement data is used. This is also the more realistic case, since the new update method is meant to be used in the production environment where running new training simulations is generally not feasible. Using the new update method with measurement data also allows the compensation to react to the residual error between simulation and reality. There are two significant problems with this approach. The first is that the new displacement data can generally no longer be obtained for all of the workspace support points. This is because some of the points on the edge of the workspace are difficult to reach for the measurement procedure (here: touch probe mounted as tool). Even if all could be reached or a nearby location was used instead, the measurement of so many locations would take quite long and filling the workspace with calibrated measurement objects would prevent many machine motions during the load case. Using external laser-based measurement systems might however solve this issue. The other major problem is that these displacement measurements would deliver only relative errors. Adjusting all of the myriad parameters of the composite model described in the previous chapter would be impossible because the error components could not be separated within the measured data.

A possible solution for these problems starts with choosing the input variables. In the composite thermal model, the authors have used in the DMU 80 eVo (see Chapter 2 and [18]), the temperature inputs are chosen from the internal model only. This requires that the external, ambient model is already sufficiently accurate. Since the update is meant for new load cases representing the cutting operation of a specific workpiece, this makes sense. In practice, the user would make one measurement of this load case to obtain the necessary training data and the update would be calculated from this data. The update model must then be valid for all manufacturing operations of this workpiece independent of ambient day-night-cycles or seasonal changes. If a compensation model without this separation of internal and external effects is used, then the best option would be to measure the load case twice, once under warm and once under cold ambient conditions. The update can then be computed from the combination of both datasets.

Having the temperature inputs, the simplest strategy would be to add the axis positions to the characteristic diagram input variables. This would significantly increase the degrees of freedom of the characteristic diagram but would also immediately solve the problem of not having measured at the workspace support points. The biggest downside to this option is that this would negate the separation of the thermal model from the displacement model (see Chapter 2).

A better and more complicated method is to add an intermediate step of calculating temporary geometric characteristic diagrams. For this, it is advisable to structure the measurement data so that each sample contains a set of temperature readings from all of the sensors and the (relative) displacement at each measurement position. Now, the following is repeated for each sample. First, the relative thermal error is calculated for every workspace support point for the given set of temperatures. Now all of the measured displacements are added to these calculated ones. Both sets should be weighted, giving preference to the measured data. Now three 3D characteristic diagrams are calculated with the axis positions as input variables and the x-, y- and z-displacements as output variables. The degree of smoothness of these characteristic diagrams may also be adjusted (see [20]). Next, these characteristic diagrams are evaluated at the workspace support points.

Figure 3 illustrates this step using colour-coded values for a single thermal state. Both figures show the table represented by a grey circle and the three measurement cuboids with their 12 measurement positions.

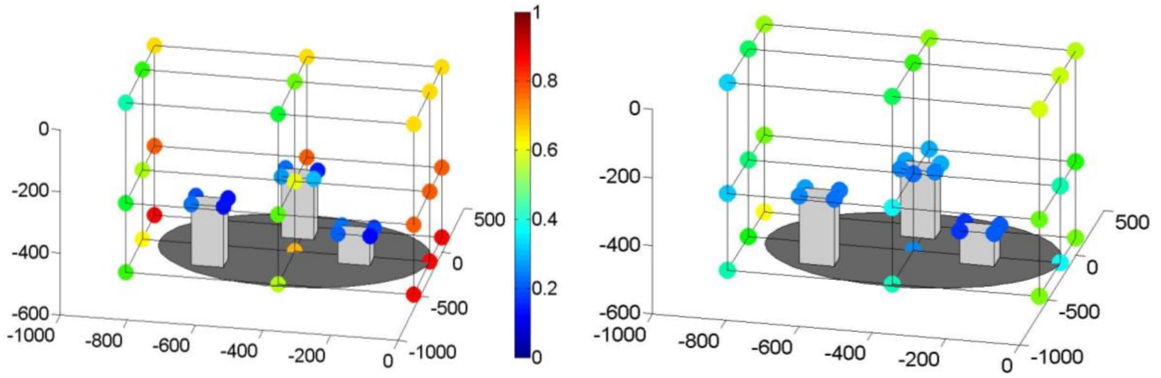

Fig. 3. Workspace support points and measured points (with colour-coded values), left: original values, right: values after all points have been fitted with characteristic diagram

Additionally there are the 27 workspace support points connected by grid lines. On the left, the estimated displacements differ noticeably from the measured values at the cuboid locations. The right figure shows the adjusted values at the support points and the measurement locations after they have been fitted by a 3D characteristic diagram. The colour changes indicate that the displacement at the measurement locations have changed very little, while the support points, especially for lower z-locations have been reduced significantly to match the measured displacements. This example has used data weights that were ten times as high for the measurement points as for the support points.

Once this has been repeated for all measurement samples, the actual update models can be calculated for each workspace support point using characteristic diagrams with only temperatures as inputs. Here again, as suggested above, it makes sense to optimize the input variables and grid structures of these characteristic diagrams. This method maintains the separation of thermal and displacement models and thereby creates many more, but smaller and more manageable update models. It also creates a good and easily adjustable compromise between the original model and the measurement data. What was ignored during this last description was the B-angle. Measurements may well include positions with different B-angles. In this case, the best option is to use 4D geometric characteristic diagrams instead of the 3D ones suggested above and add the B-angle there. The 3D version from above is very easy to use, since the error component from the update model can simply be added to the tool error. These leaves the table error models unaffected and therefore the overall implementation can stay the same. The 4D version, however, mixes the table and tool error components and is thus harder to integrate. One downside to this method, which should be mentioned here, is that calculating so many characteristic diagrams for creating the update model is quite time consuming, resulting in computation times of up to two hours. This already includes the parallel computation of the characteristic diagrams. Improving the algorithms and using faster linear solvers should reduce this time in the future to maybe 10-15 minutes for current PCs.

One last optional aspect used by the authors is to add small errors to the measured temperature data in order to create more robust characteristic diagrams and reduce the level of overfitting. Obviously, the proposed method relies heavily on purposely using overfitting to improve the thermal error predictions of the selected load case at the cost of worsening the predictions of other thermal load cases. It is, however, important to keep in mind, that even performing the exact same cutting operation twice will show slight changes in the measured temperatures even though the corresponding displacements will change little or not at all. It is therefore very important to make sure, that the resulting characteristic diagrams are robust enough to handle these slight deviations while still producing good error improvements.

In terms of potential improvements yielded by the update method, they share the same limitations as the MRA based compensation in general. Namely, the method maps temperature states of the machine tool onto TCP displacements and identifies these temperature states using a limited number of temperature sensors. Therefore, large displacements that do not correlate well with any noticeable temperature changes or identical temperature sensor readings with vastly different displacements are impossible to compensate. As a result, a bad temperature sensor placement or the use of too few sensors can severely limit the usefulness of the update method. The proposed method does not rely on the use characteristic diagrams. Different MRA or ANN models should work as well.

4. VALIDATION OF THE UPDATE METHOD

In order to validate the proposed method for updating thermal error compensation models with new measurement data, it is first necessary to obtain a baseline measurement for reference. This chapter will first show the uncompensated thermal error for the DMU 80 eVo using a standard thermal test regime used by Deckel Maho Seebach.

This regime lasts roughly 16 hours and is air cutting only but contains spindle heat, cyclic motions of all five axes, sections with and without the use of coolant and cool-down periods with only standby heat losses. The machine is in standby for the first 5 hours. The next hour (5–6) all axes are moved sequentially periodically with about 2000 mm/min simulating milling operations with coolant. The next hour (6–7) uses the same motion without coolant. Following this is an hour of standby. Following this, are another three hours (8–11) with similar motion using fast G0 movement and again with coolant, then without and finally standby. The next few hours (11–15) only the spindle is running and again first with coolant, then without, followed by standby. The final six hours (15–21) each axis is moved periodically (x, y, z, b, c) without coolant. The regime was not used for training the original characteristic diagram based compensation model and can therefore be considered an unknown/untrained load case. The next step is to show the thermal error using active thermal compensation which is running online in the machine NC. Lastly, this second measurement is used to compute the update models and a final measurement using active compensation including the update model is used to validate the method.

The test uses three measurement cuboids mounted on the table of the DMU 80 eVo. The top four corners of these cuboids were used for the displacement measurements, yielding a total of 12 measurement points, see Fig. 2 (right) and Fig. 3. While the height of these cuboids is limited, their position is spread out on the table so that at least in the x- and y-dimension, the samples within the workspace differ a lot. Only the horizontal table position was measured, i.e. B-angle 0°.

Figure 4 shows the temperatures of the test regime. For the two subsequent measurements, the temperatures are within +/- 1K of these and are not displayed.

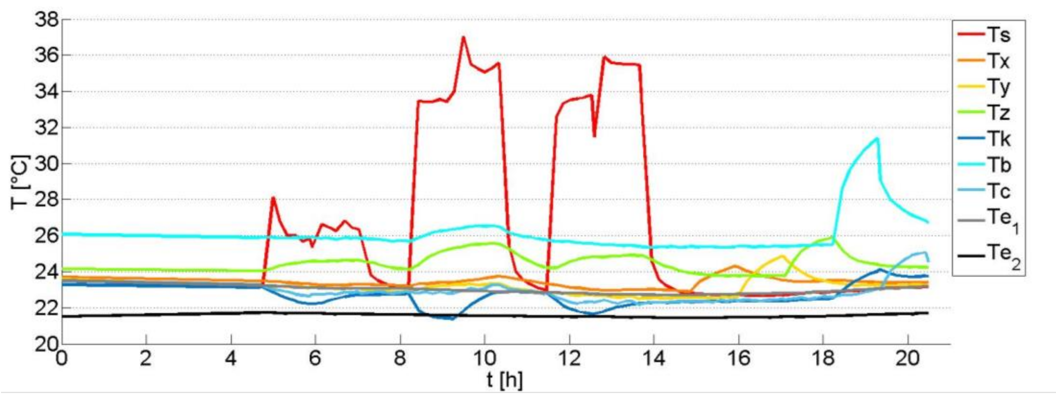

Fig. 4. Temperatures of the test regime (Ts: spindle, Tx: x-axis, Ty: y-axis, Tz: z-axis, Tk: table console, Tb: table b-axis, Tc: table c-axis, Te_1/Te_2: ambient sensors near the back of the DMU)

Figure 5 shows the uncompensated displacements. For brevity, only the dominant *z*-displacement is shown. For reasons of confidentiality, the exact displacement amplitudes have been redacted but the scale is linear with uniform spacing. Figure 5 shows a significant influence of the workspace location only for a short time, roughly between 18 and 20 hours. This is coincidence rather than design. This spatial influence is more notable for the *x*- and *y*-error, where it occurs throughout the measurement.

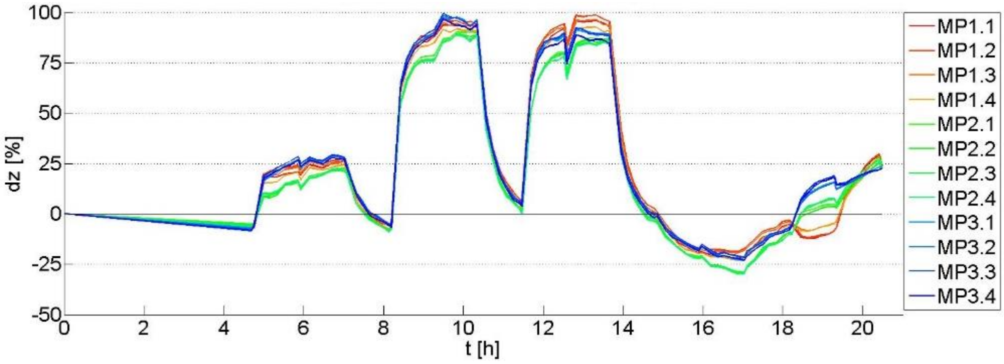

Fig. 5. *z*-displacement test regime uncompensated

Figures 6 shows a notable error reduction. The 3D RMSE improvement is ca. 59%. As is often the case for MRA based compensation, the error becomes more "spiky" after the compensation, especially whenever the loads change dramatically, e.g. when switching from full load to idle or after turning the coolant on or off. There is also a noticeable increase in the spatial variation of the thermal error after the update. The section where the spatial variation was relatively large before the compensation is now reduced. There are various reasons for this increasing variation such as modelling errors in the FEM training data and the simplified error modelling of the MRA compensation models. Figure 6 shows the compensated displacements before the model update.

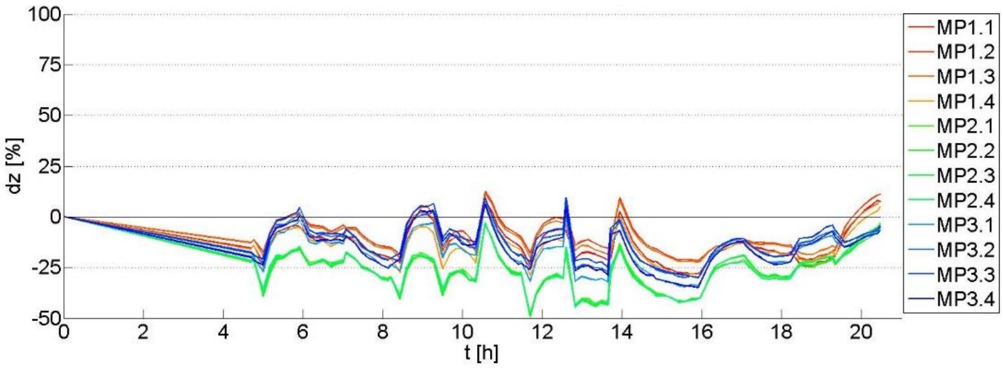

Fig. 6. *z*-displacement test regime compensated

Figure 7 shows the compensated displacements after the model update. It shows a further error reduction with a 3D RMSE improvement of ca. 21%, making it a total of 67% compared to the uncompensated error.

A validation based on a single experiment is of course not truly reliable but based on the authors experiences, the method will generally improve the average error by about 10 to 30% depending on the type and complexity of the load case. Load cases involving frequent changes between heating and cool-down, e.g., will generally be more problematic due to the time-invariant nature of the MRA. Also, load cases with B-angles other than 0 or 90 will likely be less accurate because the base model has only been trained with these two configurations and uses interpolation in between.

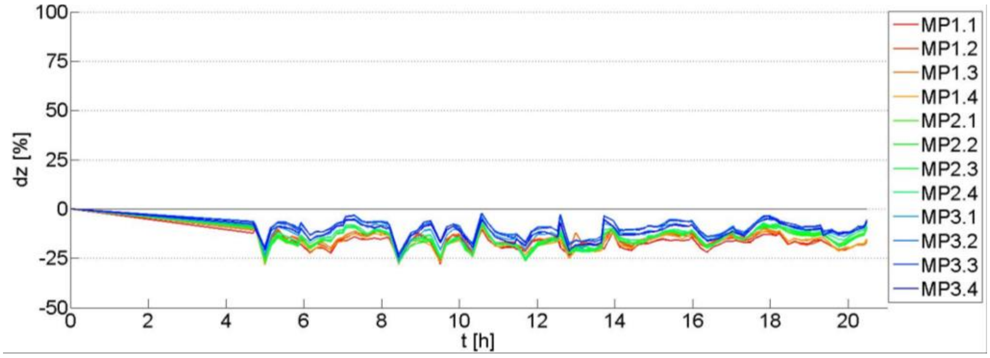

Fig. 7. *z*-displacement test regime compensated including update

For normal 3D milling operations without large pauses, the accuracy should significantly improve with these update models. A further improvement of the update method may also be achieved by using more measurement cuboids, since with only three cuboids, most of the workspace still has an unknown thermal error. A repeated use of the update method for the same load case, whether with the same or new data, will not yield further improvements, at least not beyond what can be achieved with a single update and optimal selections for data weights and smoothing parameters.

From the viewpoint of the user, there is another advantage to this method. The computation of the update model automatically delivers a fairly accurate estimation of how much the update model will improve the accuracy. The user can then decide to use or discard the update model based on these estimates.

5. SUMMARY AND OUTLOOK

One way of reducing thermal errors in machine tools, is by using data-driven black-box approximation algorithms which map inputs, e.g. from temperature sensors, directly onto the TCP displacement. This can be accomplished using MRA, ANN or similar models. Other compensation methods include the use of transfer functions or FEM simulations.

While FEM simulations theoretically allow for the exact calculation of the thermal error for any thermal load case, the accuracy of MRA, ANN, etc. is generally limited by the available sensors and training data. Therefore, the latter can usually only achieve very high precision for the thermal load cases that the models were specifically trained for.

The paper suggests a new update method based on deliberate, controlled overfitting to improve the accuracy of a given thermal load case. In general, such model updates can be accomplished most easily by either recomputing the entire compensation model with an expanded set of training data or through the use of ANN models.

In order to improve the usefulness of the new method, it was designed for a specific composite compensation model, which separates not only the thermal from the geometric (elastic) effects but also separates the operational, internal thermal effects from ambient effects. The new update method also uses measurement data for model training so that new data can be gathered by the operator without much effort. The operator basically just runs his

NC file, only instead of the actual milling he, periodically measures measurement objects to obtain the training data for the update. Alternatively, he can do the actual milling and place the measurement objects around the workpiece to avoid collisions or just use suitable surfaces on the workpiece for the error measurement. In the future, a program will support any necessary adjustments of the NC program for running the measurement routine and will automatically check the program for possible collisions.

The geometric model of the compensation uses a discretization of the workspace with 27 support points. For each data sample containing at least the temperature sensor values and the measured relative deformations, the thermal error at all support points is calculated using characteristic diagrams. Then, the update models, in this case also characteristic diagrams, are computed for each support point using this new displacement data and the temperatures.

The method was validated with a 16h thermal test regime, which was not part of the original training data for the compensation model. The compensation model achieved an improvement of 59% (measured by the RMSE) and the update method improved that result by another 20%.

The new method allows the user to measure the relative error at relevant locations within the workspace for a given milling operation and to use that information to make subsequent runs of the same NC program significantly more accurate. The method becomes much more useful, however, when it is used regularly. The composite model structure and the use of MRA based compensation allows the user to use any measurements from any machine of the same type. If every time an update measurement is performed, the measured data is sent to a global storage, e.g. a cloud, then all machines of that type with access to that storage could use that data. Then, the users would, in theory, no longer even need to make new measurements. They could just run the milling operation once, log the temperatures and use these to select the parts from all the available measurements matching these temperatures to compute the update model. Once a large enough pool of data is available, it is also possible to use it to recompute or refine the base compensation model in order to further improve the accuracy. Investigations into this distributed updating scheme will be a part of future research.

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