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ON THE SELECTION AND ASSESSMENT OF INPUT VARIABLES FOR THE CHARACTERISTIC DIAGRAM BASED CORRECTION OF THERMO-ELASTIC DEFORMATIONS IN MACHINE TOOLS

It is a well-known problem of milling machines, that waste heat from motors, friction effects on guides and most importantly the milling process itself greatly affect positioning accuracy and thus production quality. An economic and energy-efficient method of correcting this thermo-elastic positioning error is to gather sensor data from the machine tool and the process and to use that information to predict and correct the resulting tool center point displacement using high dimensional characteristic diagrams. On the one hand, the selection of which and how many input variables to use in the characteristic diagrams is critical to their performance. On the other hand, however, there are often a great number of possible variable combinations available and testing them all is practically impossible. This paper will discuss the suitability of many different input variable types and present a new method of input variable selection which will be compared to existing methods and demonstrated on measurements performed on a machine tool.

1. INTRODUCTION AND STATE OF THE ART

THERMAL EFFECTS present one of the leading causes of positioning errors in machine tools [1]. They are caused by shifting temperature distributions inside the machine tool which lead to thermo-elastic deformations. These temperature fields are shaped by a large number of heat sources and heat sinks. Important heat sources are waste heat from the cutting process, friction from guides and bearings or power losses from motors. Major heat sinks are coolants and the environment. Other relevant factors which influence the time-dependent temperature distribution inside a machine tool are the heat transfer coefficients and the thermal capacity which influence the rate at which heat is transferred and stored. It is this multitude of influences which makes thermal issues so difficult to handle [2].

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Generally, there are two main strategies of dealing with thermal errors in machine tools: correction and compensation strategies. Correction 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. Compensation on the other hand seeks to prevent or divert the influx of heat or to prevent or direct the deformation to reduce the TCP displacement [3]. These definitions follow the conventions within the German Research Foundation project CRC/TR96 on the thermo-energetic design of machine tools and may deviate from some literature sources.

Sample correction strategies are the structure model based correction [4, 5], the indirect correction based on transfer functions [6], the characteristic diagram based correction [7, 8] or the correction based on integrated deformation sensor (IDS) measurements [9, 10].

Sample compensation strategies are active cooling [11], switchable heat storage through phase change materials (PCM) [12, 13], design optimization such as the thermo-symmetric design of machine tools [14] or the use of materials with negative thermal expansion [15].

This article focuses on the characteristic diagram based correction of thermo-elastic deformations. It uses sensor and control data as input variables to predict the TCP displacement. The underlying model for this prediction, i.e. the characteristic diagram is trained using measurement or simulation data. These contain datasets for the input variables along with their corresponding measured or simulated TCP displacements. Using this apriori trained model, fast control-internal correction algorithms can be used to calculate TCP offsets from the current sensor readings in real-time in order to improve a machine tool’s positioning accuracy [16]. Characteristic diagrams are just one representative of machine learning based data-driven prediction models. Other such models include artificial neural networks [17] or prediction models based on fuzzy logic [18]. Therefore the results obtained in the investigations on input variable selection also apply to many of the other prediction models.

The achievable accuracy of these data-driven models depends largely on the selection of the input variables and on the quantity and quality of the training data. Gathering training data from thermo-elastic simulations usually provides large amounts of data which is free from stochastic and measurements errors. However this requires an accurate CAD model, from which a sufficiently fine FE model needs to be created, boundary conditions and material parameters must be set, heat sources and sinks must be defined and finally the finished simulation model has to be verified through measurements [19]. This process is not only very complicated and time-consuming, it also requires many simplifications and thus induces discretization and simulation errors. Gathering training data from measurements can be easier and faster, especially if no FE model exists. However this requires the measurement design, the set-up of measurement equipment and installations, the availability of sufficiently accurate measuring instruments and a lot of time and expertise for the measurement execution and subsequent data preparation. It also produces relatively little data and induces systematic and stochastic measurement errors [19]. In the end the choice of how the training data is acquired usually depends on the availability of equipment and resources and the skills of the responsible personnel.

The selection of input variables also depends on several factors. The list of available input variables contains all quantities that can be measured with high frequency during production and all quantities that one can compute from them with little computational effort. A selection of some of these variables along with a short assessment of their usefulness will be given in Chapter 3. Before this, Chapter 2 will give a brief introduction into characteristic diagram based correction of thermo-elastic deformations. Chapter 4 will then continue by describing some of the most important methods of input variable selection along with a new method designed especially for characteristic diagrams and related prediction models. Chapter 5 will describe the measurements performed to test and compare the methods of input variable selection and assess the results of this comparison. Finally, a summary and conclusion of the paper and an outlook on further research will be given in Chapter 6.

2. CHARACTERISTIC DIAGRAM BASED TCP CORRECTION

Characteristic diagrams are a fundamental tool of engineers used to approximate real-valued functions that depend on one or more input variables. The characteristic diagrams used in this paper are based on the smoothed grid regression introduced by Priber in 2003 [20] and later improved to enable efficient, high-dimensional characteristic diagrams able to approximate thermo-elastic deformations in machine tools [8]. These characteristic diagrams comprise a rectangular grid of support points and a set of kernel functions used to interpolate between them. Popular kernels are polynomials or splines, where higher-dimensional kernels are usually created by multiplying one-dimensional kernels (see [20]).

The creation of a characteristic diagram starts with the selection of input variables needed to approximate the output variable. It is usually of vital importance to include all relevant input variables. A good characteristic diagram algorithm will however not mind the inclusion of unnecessary additional variables so long as the total grid size remains manageable. The next step is to define and discretize the domain of each variable where the fineness of the discretization depends on the variability of the directional derivative and the type of kernel used. The type of kernel is thus usually chosen along with the grid fineness in order to obtain optimal grids and avoid overfitting. Given a sufficiently fine grid, simple piecewise multilinear kernels are sufficiently accurate and generally well suited for the approximation of thermal deformations [8]. While complex grid structures may sometimes be useful in minimizing the necessary degrees of freedom of a characteristic diagram, simple equidistant grids often perform equally well and are best at avoiding overfitting in thermal error estimation [21]. The next step is the gathering of training data which comprises a set of input data and their corresponding output data. These may be obtained from measurements or simulations and should cover as much of the input domain as possible. From this training data, data fitting equations are created in a least-squares error minimization approach. Since the data is most often sparse in comparison to the rather large grids, the assumption of smoothness is used to turn the underdetermined system into an overdetermined system by adding smoothing equations. The resulting linear system then provides the coefficients of the kernel functions for each grid vertex and thereby defines the characteristic diagram. A detailed account of the entire algorithm can be found in [7] and [20]. In [16], a new finite element method (FEM) based algorithm is described and tested which permits a more efficient computation of characteristic diagrams using multigrid solvers and thereby enables characteristic diagrams with as many as ten or more input variables [8].

One possible application of characteristic diagram based interpolation is the estimation of thermal deformations from a small set of temperature sensors (strategically distributed across the machine tool surface) and the axis positions, which has been thoroughly investigated and tested in [7, 8, 16]. Another application is the approximation of heat transfer coefficients for the accurate modelling of the heat dissipation through convection in thermal simulations of machine tools [22].

3. INPUT VARIABLES FOR DATA-DRIVEN PREDICTION MODELS

Characteristic diagram based prediction of thermo-elastic deformations in machine tools maps a vector of input variables onto a single output variable, such as the TCP displacement in x-direction. As previously mentioned, this input vector can theoretically contain any quantity that can be measured with high frequency during production and any quantity that one can compute from other such quantities with little computational effort. These restrictions come from the desire to use the prediction model in an online correction algorithm which provides offsets to the commanded TCP position in real-time. For standard characteristic diagrams, all input variables should also be continuous to allow their interpolation. If any discrete variables are required, then the smoothing equations for these variables need to be removed [7, 20] or better yet, separate characteristic diagrams should be computed for each discrete value. Some possible input variables are:

- (measured) **temperatures** on or inside the machine tool,
- the **commanded TCP position** (3D/6D from the machine tool control),
- the **commanded axis positions** (one per axis from the machine tool control),
- the (measured) **ambient temperature** (s),
- the **commanded speed** (in axis/Cartesian coordinates from machine tool control),
- **acceleration** from the machine tool or external sensor data,
- the **tool length,**
- the **motor current** (from the machine tool control),
- integrated **deformation** sensor data,
- control data from the **cooling system**,
- temperature/deformation data from **real-time simulations** (from the control),
- (measured) **temperature gradients** on or inside the machine tool,
- positions from (axis) **measurement systems**,
- information about **ambient conditions** and many more.

As Chapter 2 explained, even highly efficient characteristic diagrams can handle not much more than ten input variables. While it is possible to combine several of these variables, e.g. using principle component analysis [21], there are still far too many to use them all. Nor should they all be used, since not all of them are well-suited for characteristic diagrams. In addition, many of them are hard to come by or require expensive measuring equipment.

Temperatures on or inside the machine tool are perhaps the best input variables for characteristic diagram based thermo-elastic correction. Temperature sensors are cheap, easy to install and use and they can measure at high frequency (though this not required here). Since the deformation field of a machine tool is mostly determined by its temperature field, a few well distributed temperature sensors can give a good view of the TCP displacement.

Temperature gradients (dT/dt) can likewise be very useful in distinguishing different temperature distributions. These gradients describe whether a certain location is currently warming up or cooling down. They can freely be obtained for any already installed temperature sensor. The time difference dt is determined by the measurement frequency during the training data measurement or simulation and is thus fixed. Gradients are usually less valuable for prediction than the temperatures themselves and should thus only be added as additional inputs once all the more important variables have been included and the grid is not yet too large.

The **temperature of the environment** is usually not a useful input variable for characteristic diagram based correction since it has no direct correlation with the TCP displacement. If the ambient temperature were to increase by 10 °C, then it would take many minutes until even a small change would be visible in the machine tool. At that point, however, the temperature sensors on the machine tool would have already picked up the change. Since characteristic diagrams are mostly not time-dependent, the effect of a change in any input variable should (ideally) be immediately reflected in a change in the output variable. Any time lag will cause approximation errors. The same is true for most other potential **ambient input variables**. Measuring air flows, solar or ambient radiation and similar quantities is difficult to realize in a production setting and provides no real benefit for characteristic diagram based correction. The same is also true for any data coming from the **cooling system**, independent of what type of cooling is being used.

Commanded axis positions are very import input variables if the machine tool possesses moving assemblies, i.e. any NC controlled kinematic axis. That is because thermo-mechanical deformations usually affect the TCP displacement differently for each machine pose. Since characteristic diagrams are real-valued and can thus only predict one of the Cartesian displacements at a time, they usually don't need all of the axis positions but typically at least one or two. The same thing can be said of c**ommanded TCP positions.** Naturally, one usually only uses either the Cartesian TCP coordinates or the axis coordinates as input variables but in some cases a combination of both may also work well. Which one is better suited can depend on the kinematic structure of the machine tool but most often either pose representation can be used.

Speed, **acceleration** and **motor current** can be freely obtained from the machine tool control but are very poor input variables for characteristic diagrams because they can change greatly in fractions of a second while their effect on the machine tool's temperature field is small and slow. In theory, all three, if properly filtered, provide information on the current level of heat flowing into the machine tool through friction and electric losses, but this heat takes time to flow through the machine structure which again causes a great time lag between the inputs and the deformation. **Acceleration sensors** provide additional information on the oscillations of the machine tool and are therefore often used in the study and optimization of the dynamic properties of machine tools. Integrating their measurements is sometimes also used to measure distances but this cannot yet reach the required accuracies needed for thermo-elastic correction.

Direct axis measurement systems are great for maintaining accuracy. They are sometimes installed in or on individual machine axes and keep track of the actual current axis position so that the control unit can make the necessary adjustments. If they are temperature-invariant, then that specific axis can be considered exact. What this means for the correction algorithm depends entirely on the machine tool structure. If all axes have direct measurement systems, then the pose is correct and the correction algorithm can focus on other areas such as the spindle, the tool or the foundation. If only some axes have them, then the correction algorithm may be simplified, e.g. with less or different inputs, or it may even have no significant impact on the correction at all. Direct axis measurement systems can also be used as input variables. They can either be used directly instead of the commanded axis positions or the difference between commanded and measured axis position can be used as a measure of its deformation/elongation. How well the latter might work as an input variable has not yet been tested and is difficult to predict. The greatest difficulty would likely be turning the corresponding control data into a useful input data stream, since computing the axis offset might not be easy and even then the distribution of the deformation along the axis length would be hard to predict.

The **tool length** is definitely an important variable. Estimations of the tool expansion can, e.g., be made from nearby temperature sensors [19] but require the length of the (cold) tool. Theoretically, the tool expansion can be included in the characteristic diagram based correction but it is best done separately. Either way, the measurements or simulations for gathering training data must place the TCP at the tool tip or near the tool holder depending on whether or not tool expansion is included in the model.

Thermal or thermo-elastic simulations, provided they are online capable and that they can be integrated into a machine tool control, can also be used as input variables. The can, e.g., be used as virtual temperature sensors or compute the deformation of certain assemblies. If their values are sufficiently accurate, then these additional inputs can be valuable additions to actual sensors. Since these simulations can also be used as a separate thermo-elastic correction strategy [4, 5], mixing both strategies requires a great set-up effort and then still needs to prove that it performs better than either method does individually.

Integrated deformation sensors (IDS) are a great way of measuring local deformations in machine tools [9, 10]. If they are permanently integrated into a machine tool structure, they can also be used for characteristic diagram based correction. Since they measure the deformation directly and accurately, they often give even better predictions of the TCP displacement than temperature sensors [23]. Because they require a certain installation space and are not as cheap as temperature sensors, a combination of both sensor types can give a more extensive view of the overall deformation of the machine tool.

In summary, the best input variables for characteristic diagram based correction and similar prediction models are temperature sensors, integrated deformation sensors, axis or TCP coordinates and possibly temperature gradients.

4. METHODS OF INPUT VARIABLE SELECTION

Chapter 3 listed a large number of possible input variable types. Temperature sensors, e.g., can however be placed rather freely across most of the machine tool surface. Along with the many variable types, this creates a nearly infinite number of different input variable combinations. This is why a truly optimal design of characteristic diagrams cannot be achieved. In practice, however, there are several useful strategies for finding good combinations of input variables.

If a thermo-elastic simulation model is available, then a **sensitivity analysis** is a good way of optimizing the positions of the temperature sensors. In [16] and [24] adjoint based sensitivity analysis is used to sequentially place each temperature sensor so that it provides the maximum amount of new information about the machine tool deformation. This method picks the locations of the temperature sensors from the nodes of the FE mesh so that there are a finite number of possibilities to choose from. In [16] this approach is combined with characteristic diagram based correction and tested on a machine tool column. This approach has, however, two disadvantages. Firstly, the need for a fully parametrized thermo-elastic simulation model negates many of the advantages of characteristic diagram based correction. The other problem is that the state-of-the-art sensitivity analysis can only optimize the sensor positions for a single machine tool pose. Despite this, sensitivity analysis still provides good sensor configurations. Researchers within the CRC/TR96 are currently working on the global optimization of sensor positions and may soon deliver even better algorithms for input variable selection. Even then, however, sensitivity analysis (in its current form) can only optimize temperature sensor locations. It cannot select variables from different input variable types.

If there is no simulation model available or the effort of a sensitivity analysis is judged too great, there are also a number of other methods of variable selection which take a more abstract approach and are therefore able to select variables from among different variable types. They generally also try to select variables that both have a large effect on the TCP displacement and are at the same time as independent of the previously chosen variables as possible. These methods require a manageable set of possible input variables to start from.

Often, training data is acquired from measurements. Without a sensitivity analysis to guide sensor placement, the responsible technician will usually place as many sensors as he/she has on the machine tool surface in places that are easy to reach. The sensor locations will typically be more or less evenly distributed according to the intuition of the technician. The result of this is that there are measurements of perhaps 10–20 temperature sensors along with the corresponding commanded axis configurations available for characteristic diagram based correction. From each temperature sensor, one can calculate the temperature gradient, adding another 10–20 potential input variables. In some cases, perhaps 5–10 integrated deformation sensors are also available. In total, this scenario would deliver some 50 or so input variables from which about 10 must be selected to form the characteristic diagram grid. This selection may of cause be different for each of the three characteristic diagrams needed to predict x-, y- and z-displacement.

A very popular method of input variable selection is **principal component analysis (PCA)**. PCA tries to minimize the linear dependencies within the input variables by creating a new orthogonal basis through orthogonal transformation [25]. This is done in such a way that each transformed vector has the maximal variance while being orthogonal to every previously transformed vector. The use of PCA in combination with characteristic diagram based correction was tested in [21]. In [21] the aim was the optimization of grid structures with a fixed number of input variables, where PCA brought no significant benefit. For variable selection, however, PCA can be a very useful tool. The orthogonal transformations of the PCA deliver a set of new grid axis vectors and the transformed set of input vectors. Both are already sorted by their "degree of additional information", so that the first few coordinates are the most important and the last few are the least important ones. In theory, one can just take the measurements from these 50 potential input variables, perform the PCA and then choose the first ten or so transformed input variables. While this will probably deliver good results, it also requires the use of each of the installed sensors, even if they contribute very little to the prediction of the deformation. The other problem with this approach is that the PCA only minimizes the dependencies in the input variables and says nothing about each variable's dependence on the TCP displacement. That it still provides good results for thermal error correction was demonstrated in [26] and [27].

The next method is a **sequential heuristic based on trial and error**. While it is impossible to try every combination (of which there may be more than 50^{10}), it is possible to construct the characteristic diagram grid bottom-up by sequentially selecting the next best variable to add to the grid. Per dimension of the final characteristic diagram, say one to ten, every free variable is added to the existing set of grid variables (one-by-one) to get a new grid which is one dimension higher. So for each step L, the dimension of the previous grid was (L–1) and you have (50–(L–1)) new grids of dimension L. All of these grids are tested using the training data and the best one is selected for the next step (L+1). This way, you have less than (number of variables, e.g. 50) × (max. number of grid vectors, e.g. 10) characteristic diagrams to compute and test, which can be done with acceptable effort. If during this procedure, the quality of the approximation seems sufficient, one can even stop before the maximum number of inputs is reached. To start the algorithm, one can either test all 1D characteristic diagrams or instead simply choose the variable that has the largest covariance with the output variable.

A variation of this heuristic adds some additional steps to the algorithm. After the grid is complete, one removes each variable one-by-one. In this example, this would produce ten new grids of dimension nine, which would again have to be tested. If any of these produces no greater approximation error than the full grid, then the removed variable can be replaced by a new one, as was done in the original algorithm. This procedure of removal and replacement can be repeated until all selected input variables contribute to the approximation quality of the characteristic diagram. Naturally, this variant increases the computational effort, but only perhaps by a factor of two or three.

One problem of this sequential heuristic (in either version) is that it rather blindly computes a large number of characteristic diagrams. Normally characteristic diagrams need to be optimized in terms of grid structure and smoothing coefficients (see [7, 20, 21]) in order to achieve the best results. Here, however, all grids are treated the same way, which may not lead to the optimal choice. To compensate this, one might run the algorithm several times with different characteristic diagram "settings".

The last method to be presented here is specifically tailored to characteristic diagram based correction and might, e.g., be called stability analysis. A characteristic diagram assigns one TCP displacement value to each point on the grid while making sure that small changes in the input values (i.e. small steps across the grid) do not lead to large changes in the output variable. This is due to the smoothing equations (see Chapter 2) and also the reason why some of the potential input variables are not suited for characteristic diagram based correction (see Chapter 3). The characteristic diagram is good if its predictions match the data used to train and test them. The idea behind the stability analysis is therefore to check each pair of input data vectors to see how well they comply with this stability requirement. Say you have 100 measurements each consisting of 50 values, that is one for each of the 50 potential input variables. In addition you have the 100 measured TCP displacements as output values.

$$M = \begin{bmatrix} x_1 & y_1 & z_1 & T_1^1 & T_1^2 & \dots \\ x_2 & y_2 & z_2 & T_2^1 & T_2^2 & \dots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \\ x_{100} & y_{100} & z_{100} & T_{100}^1 & T_{100}^2 & \dots \end{bmatrix} \in M_{100,50}, \quad \overrightarrow{dx} = \begin{pmatrix} dx_1 \\ dx_2 \\ \vdots \\ dx_{100} \end{pmatrix} \tag{1}$$

First you take each input variable and norm it to the interval (0,1), where 0 is the smallest value and 1 is the largest. Now you take each pair of measurements and subtract them from one another. Using the Gaussian sum formula, this will give you (99×50) new 50-dimensional vectors which now form the basis for the algorithm. Likewise, you save the corresponding absolute difference in the TCP displacement in another vector.

$$dM = \begin{bmatrix} |x_1 - x_2| & |y_1 - y_2| & |z_1 - z_2| & |T_1^1 - T_2^1| & \dots \\ |x_1 - x_3| & |y_1 - y_3| & |z_1 - z_3| & |T_1^1 - T_3^1| & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \\ |x_{99} - x_{100}| & |y_{99} - y_{100}| & |z_{99} - z_{100}| & |T_{99}^1 - T_{100}^1| & \dots \end{bmatrix} \in M_{4950,50}, \overrightarrow{ddx} = \begin{pmatrix} |dx_1 - dx_2| \\ |dx_1 - dx_3| \\ \vdots \\ |dx_{99} - dx_{100}| \end{pmatrix} \tag{2}$$

Now, for every grid you want test, you take the corresponding vector entries (e.g. columns 1,2,5,7,...) of all 4950 vectors and multiply them for each vector. For each of the 4950 combinations, this will give you a scalar value (between 0 and 1) describing how close the corresponding input values are. Next you take the scalar product of one minus this vector with the output difference vector to get a scalar measure of the instability of the chosen grid. For the 3-dimensional grid with the grid vectors (x,y,z), you get the instability i^{xyz} by:

$$\overrightarrow{dM}^{\mathrm{xyz}} = \begin{pmatrix} 1-|x_1 - x_2| \cdot |y_1 - y_2| \cdot |z_1 - z_2| \\ 1-|x_1 - x_3| \cdot |y_1 - y_3| \cdot |z_1 - z_3| \\ \vdots \\ 1-|x_{99} - x_{100}| \cdot |y_{99} - y_{100}| \cdot |z_{99} - z_{100}| \end{pmatrix}, \overrightarrow{ddx} = \begin{pmatrix} |dx_1 - dx_2| \\ |dx_1 - dx_3| \\ \vdots \\ |dx_{99} - dx_{100}| \end{pmatrix} \rightarrow \overrightarrow{i^{\mathrm{xyz}}} = \overrightarrow{dM}^{\mathrm{xyz}} \cdot \overrightarrow{ddx} \tag{3}$$

Depending on the number of input variables, the maximum grid size, the number of training data measurements and the available computational capabilities, one can now either test all possible combinations of grid variables or use a sequential strategy like in the previous method. The main advantages of this method in comparison with the previous method are that it specifically tests the theoretical suitability of each combination of input variables for characteristic diagram based correction (independent of kernel or grid structure) and that the testing of each grid requires only a few vector products rather than the computation and evaluation of a characteristic diagram. If there are relatively large measurement errors and the same measurements are repeated several times, then the algorithm will likely blame the instability of the measuring equipment on the characteristic diagram, which might exclude some good combinations of input variables. The algorithm will also not work well, if there are too few training data measurements to work with.

5. EXPERIMENTAL VALIDATION AND COMPARISON

After the theoretical foundations of input variable selection have been laid in Chapters 3 and 4, a number of measurements will now be used to verify and compare some the algorithms presented in the previous Chapter. The experimental investigations were carried out on a 3-axis machining center, see Fig. 1. The machine tool is equipped with a system of 24 IDS (see Fig. 1a) and 27 temperature sensors.

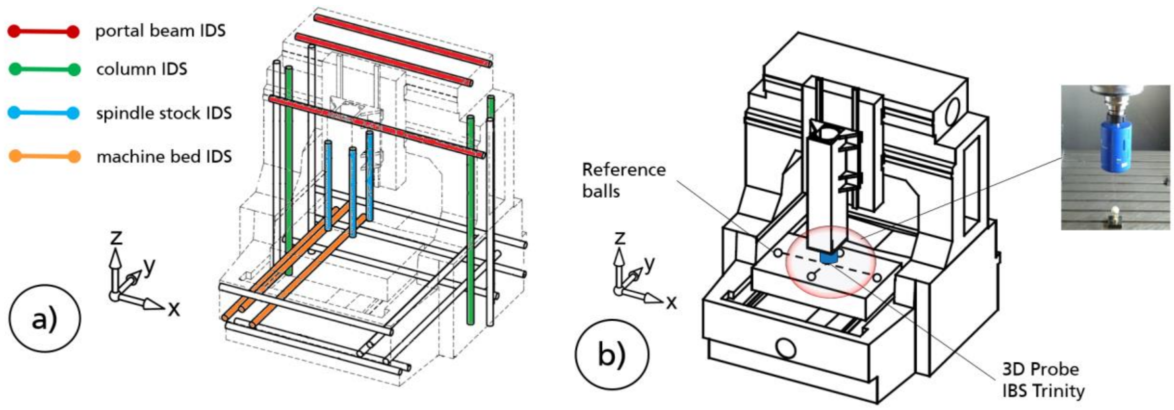

Fig. 1. Structure of demonstrator machine illustrated with a) Integral Deformation Sensors (IDS) and b) temperature sensors

The setup for the external measurement of the TCP displacement is shown in Fig. 1b. Four reference balls are mounted on the work piece carriage in the depicted cross configuration to measure the relative displacement between TCP and workpiece for different configurations. A wireless probe is used to gauge the distance to each probe.

In order to introduce thermal loads, all three linear axes (*X*-, *Y*- and *Z*-) as well as the spindle were set to execute a repeated motion with 100% feed rate (80 m/min) or 100% spindle speed (18,000 rpm) for approximately two hours. This motion prescribes a Helix across the three-dimensional workspace with all axes moving almost to their full travel range. The machine enters then standby to cool down while the control is still active. All measurements continue for an additional six hours during the cool-down phase. The TCP displacement was measured approximately every fifteen minutes with two measurements taken at each reference ball. The IDS and temperature sensors were recorded continuously with a sample rate of 2 Hz.

Using the data from these experiments, the principal component analysis, the sequential heuristic and the stability analysis were tested and compared for different maximum grid size. The result of this comparison can be seen in Fig. 2 which shows the average approximation error over the number of input variables for each of the three selection algorithms. The chosen output variable is the x-displacement. For this investigation, 80% of the measurement data were randomly selected to train the models and the remaining 20% were used to test the models. This process of random data selection and model test was repeated 100 times for better statistical security. The version of stability analysis used here, tested all combinations up to dimension 3. After that, for each subsequent dimension the previous optimum was used as a basis. If dimension 3 found the best stability for the variable combination ($\mathrm{var}_1,\mathrm{var}_2,\mathrm{var}_3$), then for dimension 4 all combinations of the following types were tested: ($var_1,var_2,\ldots,\ldots$), ($var_1,var_3,\ldots,\ldots$), ($var_2,var_3,\ldots,\ldots$). For all higher dimensions there was likewise always one removed and two were added. This maintained fast computability while yielding good results. For the sequential heuristic the first variant was used.

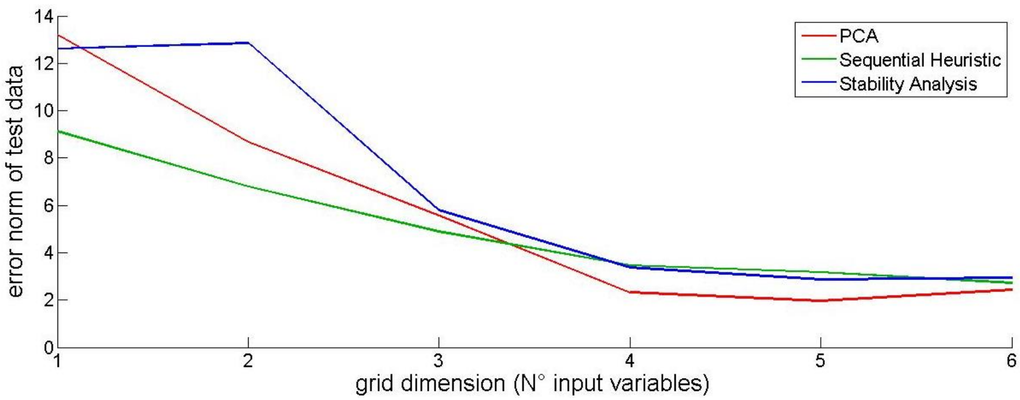

Fig. 2. Comparison of variable selection algorithms using measurement data

Figure 2 shows the comparison of the three variable selection algorithms using the measurement data from the experiments detailed above. It shows that all three algorithms work similarly well. The sequential heuristic has the smallest error for one-dimensional grids but this is to be expected because it actually computes and tests all one-dimensional characteristic diagrams. Starting from dimension three, all optimized grids are equally good. Starting from dimension four, the average approximation error no longer improves. This is because of the relatively limited measurement data. Higher dimensional grids are too sparsely populated with data points so that any potential improvement from more complex grids is cancelled out by overfitting.

The conclusion of these investigations is that all three algorithms can be used to select grid variables for characteristic diagram based correction from a large pool of possible input quantities. The selection of which to choose should thus be made according to the properties of each algorithm as described in Chapter 4. Principal component analysis is the easiest to use but requires the use of all input quantities. The sequential heuristic works particularly well for small dimensions but it depends somewhat on the characteristic diagram settings. The stability analysis is based on the theoretically best suited combination of input variables for the given training data and, like the PCA, it is simple and does not require computing characteristic diagrams.

6. SUMMARY, CONCLUSION AND OUTLOOK

Thermal effects in machine tools continue to be one of the major sources of positioning errors in machine tools. Different compensation and correction strategies can be used to mitigate these thermal errors. Characteristic diagram based correction presents a data-driven machine learning approach which maps a set of input variables directly onto the tool center point displacement. The achievable quality of this error estimation depends mostly on the selection of the input variables and on the quantity and quality of the training data, which may come from simulations and/or measurements. The best input variable types for characteristic diagram based correction and similar prediction models are temperature sensors, integrated deformation sensors, axis or TCP coordinates and possibly temperature gradients. Poorly suited input variable types are, e.g., speed, acceleration, motor current or ambient variables.

Which specific input variables lead to the best approximation results is typically hard to say. Nevertheless, there are a number of methods for input variable selection which lead to good combinations of input variables for characteristic diagrams and similar methods. If a finite element model for thermo-elastic simulations is available, then a sensitivity analysis presents a good way to find optimal locations for temperature sensors which can be used as inputs. If there are a large number of input variables of mixed types available to choose from, then principal component analysis may be used. Another possibility is a sequential heuristic which keeps expanding the grid by the next best free input variable which it determines by testing the characteristic diagrams of every possible combination of grid variables. The last selection method presented here is a stability analysis which tests the suitability of all combinations of grid variables for mapping the training data. It is based on the assumption, that two measurement points with similar inputs must have similar outputs. All three methods of input variable selection were tested on measurement data from a 3-axis machining center and have proven to be similarly proficient. Therefore the choice of which method to use should be made according to each method's strengths and weaknesses.

Further research on characteristic diagram based correction will be focused on optimal experimental design. Since it has been repeatedly established that characteristic diagrams are only a good as the data used to train them, the challenge is to develop a method which describes the load cycles that a machine tool measurement needs to comprise in order to generate good training data in as little time as possible.

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