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Decoupling of fluid and thermo-elastic simulations on machine tools using characteristic diagrams

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Abstract

Thermo-elastic effects are one of the major reasons for positioning errors in machine tools. Next to friction and waste heat from drives, the heat exchange with the machine's surroundings influences the temperature field inside the machine tool significantly. The thermal parameters necessary to describe this heat transfer can be obtained through computational fluid dynamics (CFD) simulations. This paper presents a new method aimed at decoupling these CFD simulations from the thermo-elastic simulations in order to provide the heat transfer parameters quickly and efficiently for transient environmental conditions. This is done by defining a suitable set of load scenarios for the CFD simulations, clustering the resulting parameters with radial basis functions and interpolating them using characteristic diagrams.

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Keywords: Machine tool; Simulation; Thermal effects; Characteristic diagrams; Radial basis functions

1. Introduction

Machine tool deformation occurs during operation due to waste heat from motors and frictional heat from guides, joints and the tool, while coolants act to reduce this influx of heat. Additional thermal influences come from the machine tool's environment and foundation. This leads to inhomogeneous, transient temperature fields inside the machine tool which displace the tool center point (TCP) and thus reduce production accuracy and finally the product quality [1].

Next to approximation strategies such as characteristic diagram based [2] and structure model based correction [3], the most reliable way to predict the TCP displacement is via thermo-elastic finite element (FE) simulation. A CAD model of a given machine tool serves as the basis for this approach. On it an FE mesh is created. After establishing the partial differential equations (PDEs) describing the heat transfer within the machine tool and with its surroundings, FE simulations are run in order to obtain the temperature fields of the machine tool for specified load regimes. Using linear thermo-elastic expansion, the deformation can then be calculated from each temperature field and the displacement of the TCP read from this deformation field, see [4].

The accuracy of this latter approach depends on the correct modelling of the heat flux within the machine tool and the exchange with its surroundings. In order to calculate the correct amount of heat being exchanged with the environment, one may use known parameters from well-established tables. However, if the surrounding air is in motion or otherwise changing, computational fluid dynamics (CFD) simulations are required to accurately determine these transient parameters. This two-step approach makes realistic thermo-elastic simulations particularly complicated and time-consuming. Methods aiming at real-time thermo-elastic simulations based on model order reduction must therefore rely on the inaccurate predetermined parameter sets [5]. This could be helped if all the necessary CFD simulations could be run in advance and supplied to the thermo-elastic models when they are needed. This paper presents such an approach which employs high-dimensional characteristic diagrams.

Characteristic diagrams are well suited for mapping combinations of air flow parameters (e.g. air temperature,

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flow direction and velocity, air pressure, etc.) onto the heat transfer coefficients (HTCs) which describe convection on the surface of the machine tool.

To reduce the data needed to train these characteristic diagrams and to make the large FE meshes more manageable, clustering algorithms can be used to group nodes with similar thermal behavior. Here radial basis functions (RBF) will be used for the clustering. Similar to characteristic diagrams, RBFs can be used for interpolation in order to approximate high-dimensional real-valued functions [6].

The paper starts by introducing radial basis functions and two types of clustering. Then characteristic diagrams will be introduced and with it, the decoupling of fluid and thermo-elastic simulations explained. A sample U-shaped geometry will be used to validate the approach numerically.

Nomenclature

N	number of sampling points
x_i	sample point
$\Theta_i(x)$	radial basis function
ξ	ansatz function
r	distance of x and x_i
p	polynomial function
π_m	polynomial degree
M	number of polynomial function
β^{RBF}, β^{POLY}	unknown coefficients
y	right hand side
α	heat transfer coefficient
λ	thermal conductivity of the fluid
L	characteristic length
Nu	Nusselt number, dependent on:
Re	Reynolds number
Pr	Prandl number

2. Interpolation-approach for thermal parameters

2.1. Basics of radial basis functions

The main difficulty in the use of radial basis functions [7] is in solving an interpolation problem of N arbitrary sample points x_1, $x_2 \ldots x_N$ in R^d with given values y_1, $y_2 \ldots y_N$ in R to find a function f: $R^d \rightarrow R$, fulfilling the interpolation condition

$$f(x_i) = y_i \quad \text{for i=1…N.} \tag{1}$$

The first step is to find an ansatz for (1). For this, some basic functions will be introduced.

A function Θ_i: $R^d \rightarrow R$ is a radial basis function if a function ξ: $R \rightarrow R$ exists, which satisfies $\Theta_i(x)=\xi(\|x-x_i\|)$ for a fixed point x_i in R^d. Commonly used types of RBF ansatz functions $\xi(r)$ with $r=\|x-x_i\|$ are

Gaussian: $\xi(r) = \exp(-\beta r^2)$ for $\beta > 0$ (2)

Multiquadric: $\xi(r) = \sqrt{r^2+1}$ (3)

Polyharmonic spline:

$$\xi(r) = \begin{cases} r^k & \text{if k is odd} \\ r^k \log(r) & \text{if k is even} \end{cases} \tag{4}$$

Thin plate spline: $\xi(r) = r^2 \log(r)$ (5)

Further variations, especially for large data sets are RBFs with compact support, e.g. “Wendland functions” [6]. Such basis functions lead to a sparse interpolation system.

Now let such a radial basis function Θ_i be defined in every sample point x_i, i=1…N. The usual ansatz for an interpolation function is:

$$f(x) = \sum_{i=1}^{N} \beta_i \phi_i(x) \tag{6}$$

With (1), this ansatz leads to the linear equations

$$f(x_i) = \sum_{j=1}^{N} \beta_j \phi_j(x_i) = y_i \qquad \text{i=1…N} \tag{7}$$

which can be written as a linear system:

$$\Phi \beta^{RBF} = y \tag{8}$$

The components of (8) are defined by the system matrix $\Phi:=[\phi_j(x_i)]$ for i,j=1…N, the vector $\beta^{RBF}=[\beta_1,\beta_2 \ldots \beta_N]^T$ of the unknown coefficients and the right hand side $y=[y_1,y_2 \ldots y_N]^T$. The system matrix Φ is obviously symmetric. In [8], it is shown that Φ also positive definite for a vast variety of RBFs.

The sole disadvantage of the RBF ansatz is that a large number of sample points are needed to get a sufficiently exact approximation of a constant or linear function. One possible way to cope with this is to add a polynomial part p(x)

$$f(x) = \sum_{i=1}^{N} \beta_i^{RBF} \phi_i + p(x) \tag{9}$$

The d-variate polynomial $p,\pi_m(R^d)$ of degree at most m is defined as

$$p(x) = \sum_{j=1}^{M} \beta_j^{POLY} p_j(x), \tag{10}$$

with $M=\dim(\pi_m(R^d))$ and basis polynomials p_j for j=1…M. Consequently, this ansatz has (N+M) unknown coefficients, while the interpolation system (1) consists of only N equations, therefore an added condition is imposed

$$\sum_{j=1}^{N} \beta_j^{RBF} p(x_j) = 0 \qquad \text{for all } p,\pi_m(R^d) \tag{11}$$

This leads to a linear matrix system of dimension (N+M)

$$\begin{bmatrix} \Phi & P \\ P^T & 0 \end{bmatrix} \begin{bmatrix} \beta^{RBF} \\ \beta^{POLY} \end{bmatrix} = \begin{bmatrix} y \\ 0 \end{bmatrix} \tag{12}$$

A simple and good choice for $\pi_m(R^d)$ are linear polynomials, e.g.