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PARAMETERIZATION OF ENVIRONMENTAL INFLUENCES BY AUTOMATED CHARACTERISTIC DIAGRAMS FOR THE DECOUPLED FLUID AND STRUCTURAL-MECHANICAL SIMULATIONS

Thermo-elastic effects contribute the most to positioning errors in machine tools especially in operations where high precision machining is involved. When a machine tool is subjected to changes in environmental influences such as ambient air temperature, velocity or direction, then flow (CFD) simulations are necessary to effectively quantify the thermal behaviour between the machine tool surface and the surrounding air (fluid). Heat transfer coefficient (HTC) values effectively represent this solid-fluid heat transfer and it serves as the boundary data for thermo-elastic simulations. Thereby, deformation results can be obtained. This two-step simulation procedure involving fluid and thermo-structural simulations is highly complex and time-consuming. A suitable alternative for the above process can be obtained by introducing a clustering algorithm (CA) and characteristic diagrams (CDs) in the workflow. CDs are continuous maps of a set of input variables onto a single output variable, which are trained using data from a limited number of CFD simulations which is optimized using the clustering technique involving genetic algorithm (GA) and radial basis function (RBF) interpolation. The parameterized environmental influences are mapped directly onto corresponding HTC values in each CD. Thus, CDs serve as look-up tables which provide boundary data (HTC values along with nodal information) under several load cases (combinations of environmental influences) for thermo-elastic simulations. Ultimately, a decoupled fluid-structural simulation system is obtained where boundary (convection) data for thermo-mechanical simulations can be directly obtained from CDs and would no longer require fluid simulations to be carried out again. Thus, a novel approach for the correction of thermo-elastic deformations on a machine tool is obtained.

1. INTRODUCTION

Machine tools are susceptible to various environmental influences within a machine hall caused from waste heat from motors, frictional heat from guides, joints and tools or from the machine tool's environment during which large temperature or pressure swings can occur. Thermal gradients thereby created cause heat to flow through the machine structure

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and results in non-linear structural deformation whether the machine is in operation or in a static mode. Ultimately, the production accuracy and product quality are affected as suggested in the work by Bryan et al. [1].

A novel solution to the environmentally induced thermal error modelling is to create a Finite Element Analysis (FEA) model of the machine followed by the application of the proposed methodology in which thermal states and the corresponding deformations of the real machine and the simulated machine model are matched as discussed in the work by Naeem et al. [2]. Simulation occurs in two steps: Computational Fluid Dynamics (CFD) simulations are carried to predict the thermal parameters which define the interaction of the machine with its surroundings. The flow simulation data primarily constitutes the heat transfer coefficient (HTC) values. HTC is an important parameter, which effectively defines the amount of heat transfer per unit area on a solid body for a specific temperature difference between the solid face and the surrounding fluid area. This convection data serves as the boundary data for the thermo-mechanical simulations. This coupled method involving CFD and thermo-mechanical simulations is complicated and highly time-consuming especially when complex geometries are considered.

The basic idea of decoupling fluid simulations from thermo-mechanical simulations using Characteristic diagrams (CDs) was first introduced in the work by Glänzel et al. [3] and was validated on a simple u-shaped geometry. Glänzel et al. [4] adopted the approach on a stationary machine tool column with varying air temperatures, air speeds and flow directions. CDs decouple the two simulations, by providing boundary data directly as parameters (air temperature, air speed and directions of air flow) which quantify the ambient conditions to thermo-mechanical simulations. CDs are capable of interpolating the output variable (in-between values) for a particular load case based on the initial training data.

However, there was huge scope for improvement in this approach with regards to the vast amount of data (unclustered) used in interpolation and its impact on the computation time. This thought led to the training of CDs using data (from a limited number of CFD simulations) which is optimized using a clustering technique involving genetic algorithm (GA) and radial basis function (RBF) interpolation. Optimal subsets of FE-nodes are found on each face of the machine using the clustering algorithm such that, HTC values when interpolated using RBFs over a machine face using these optimal node points will have least possible error. A particular optimal subset is evolved gradually over each iteration/ generation in GA. Each CD corresponds to a single optimal node point where the parameterized environmental influences are mapped directly onto corresponding HTC values. After training, CDs serve as look-up tables which provide boundary data (HTC values along with nodal information) under several load cases (combinations of environmental influences) for thermo-elastic simulations. Ultimately, a decoupled fluid-structural simulation system is obtained where boundary (convection) data for thermo-mechanical simulations can be directly obtained from CDs and would no longer require fluid simulations to be carried out again.

The workflow adopted for the decoupling approach with clustering is described in the next Chapter. Optimal clustering of nodes using GA and RBF interpolation will be discussed in Chapter 3. Chapter 4 presents the procedure for parameterization of environmental influences into CDs. The implementation and validation of the approach on a machine tool will be discussed in Chapter 5. A brief summary and future scope of work of this approach are discussed in Chapter 6.

2. APPROACH FOR SIMULATION DECOUPLING

Understanding the interaction and quantifying the thermal parameters between the machine tool and its environment is necessary in order to predict the thermo-mechanical deformations caused by the environment induced thermal fluctuations. The decoupling approach eliminates the dependency of thermo-mechanical simulations on CFD simulations by introducing Clustering Algorithm and CDs in between the two simulation workflows as shown below:

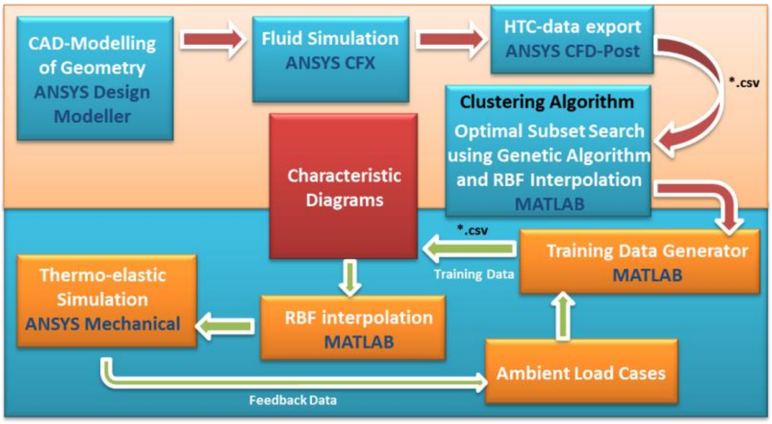

Fig. 1. Decoupling workflow

In preparation for the decoupling of the fluid and thermo-elastic simulations, the HTC values are exported as *.csv files for each machine face under varying ambient load cases (air temperature, air speed and directions of air flow) in ANSYS-CFX. The approach which involves the reduction of geometry nodes using RBFs as preparatory stage for interpolation using CDs was discussed in the work by Buhmann [5] and Glänzel et al. [4]. It enables adequate clustering of ambient parameters, so that more values are chosen in areas with big changes, e.g. along the edges, and fewer are placed in areas with small changes, e.g. nearly constant areas. Calculating CDs for the RBF nodes would eliminate the need to include the geometric grid of the machine tool surfaces in the CD grid. However, when complex geometries are involved it becomes computationally infeasible to incorporate this approach as the CDs have to be trained for a tremendous amount of data and it multiplies in magnitude if moving machine components are considered. To reduce the data needed to train the CDs, a clustering algorithm is developed. It incorporates optimal subset search of surface nodes using an optimization algorithm and subsequent interpolation of HTC values using RBF interpolation. Both operations are performed by using MATLAB scripts. As shown in Fig. 1, the HTC export data from ANSYS-CFX are served for clustering. GA involved finds the optimal subset of nodes which gives the least interpolation error between the current and RBF – interpolated HTCs for each face under a particular load case. The training data for CDs is generated based only on these selected optimal subsets. Thus, it drastically reduces the data needed for training.

CDs are formulated for each optimal node points which are capable of predicting HTC values for user-defined load cases based on the training data. The predicted HTC values for the optimal subsets serve are RBF points used to interpolate the HTC for the entire faces of the machine. This serves as the boundary (convection) data for thermo-mechanical simulations.

3. OPTIMAL CLUSTERING USING GENETIC ALGORITHM

Clustering is the task of grouping a set of objects in such a way that objects in the same group, called a cluster, are more similar (based on the objective) to each other than to those in other groups. Formally, given a data set of m dimensions and n points, $D \in R^{\{n,m\}} = \{d_1, \ldots, d_n\}$, clustering is the process of dividing the points up into k-groups (clusters) based on a similarity measure. Many algorithms have been developed to tackle clustering problems in a variety of application domains, including the hierarchical agglomerative clustering algorithm [6], k-means [7], and self-organizing maps [8]. The most popular algorithms are probably the fuzzy c-means [9] and the k-means algorithms. All of these clustering algorithms rely on Euclidean distances from cluster centroids as criterion function. Therefore they are limited to detecting spherical clusters and do not work well with non-Gaussian data. In simple words, the solution gets confined to local minima.

The search for a universal or more generic search algorithm led to the discussion on GAs. The GA attempts to find a very good (or best) solution to the problem by genetically breeding the population of individuals over a series of generations and effectively overcome local minima based on Darwinian principle of reproduction and survival of the fittest, analogous of naturally occurring genetic operations such as crossover and mutation (refer to the works by Koza [10] and Koenig [11).

As discussed in the previous section, the purpose of clustering in decoupling approach is to reduce the number of nodes and corresponding HTC values used for training CDs. Maintaining accuracy in interpolation even after reduction of nodes is very important. This is done by choosing optimal subsets of nodes with a fixed size m of node number values over each face of the machine, which will be used to build an interpolation function, based on RBFs. The GA addresses the "Optimal Subset Problem" (refer to the work by Glänzel et al. [12]) by minimizing the weighting function f as

$$\min_{\substack{S \subset V \\ |S|=m}} f(S) \tag{1}$$

where V is the set of node numbers on a particular face, $V = \{1, 2 \ldots N\}$ which corresponds with nodes $x_1, x_2, \ldots\ x_N$ of the finite element mesh and the simulated HTC values $w_1, w_2, \ldots\ w_N$ in these nodes. In the decoupling approach, the weighting function will calculate the interpolation error which occurs when the m nodes of S are used to interpolate the HTC values over an entire machine face, such that error measure in pointwise computed form (2), $f(S)$ becomes zero if $m = N$, and becomes greater than zero if $m < N$.

$$f(S) \coloneqq \max_{i=1 \ldots N} |f_s(x_i) - w_i| \tag{2}$$

The major advantage of GA is that it can be used in those situations where the numerical or mathematical models fail. GA, being an evolutionary algorithm, the progress can be viewed with each iteration. GA exploits historical information to direct the search into the region of better performance within the search space. In decoupling, GA is utilized to find a small optimum subset of points from the entire set of node points on a particular face, such that they give the best possible interpolation results using RBFs. This approach drastically reduces the computational time without compromising the solution precision.

The working principle of GA adopted for clustering is shown in Fig. 2. GA begins its search from a random initial population of solutions. For optimal subset search, the random node numbers (genes) on a particular machine/specimen face will constitute the population. A fitness value is assigned for each set (chromosomes) of node points based on the objective function discussed in equations (1) and (2). For this purpose, a fitness function is used which gives the norm error between actual HTC values (obtained from simulation) and RBF interpolated HTC values using a particular chromosome. The chromosomes are sorted based on the lowest fitness values i.e. least error. If the termination condition is satisfied the GA process will stop. The termination condition could be maximum number of generations or least permissible fitness. If the termination criterion is not satisfied, then changes have to be made to the population using genetic operators - selection, crossover and mutation. In general, the exploitation of the accumulated information resulting from GA search is done by the selection and crossover mechanism (as suggested by Umbarkar [13]), while the exploration to new regions of the search space is accounted for by mutation as discussed in [14].

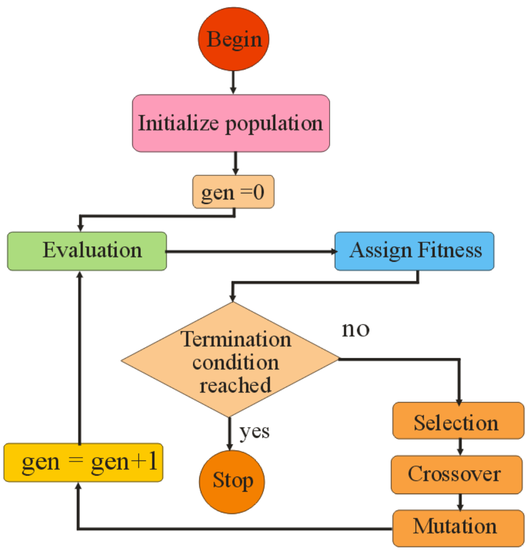

Fig. 2. GA working principle

The results obtained from the developed GA logic script were validated with GA toolbox (MATLAB) and they were observed to be in close acceptance as shown in Fig. 3. A simple cube specimen in a cubical air environment was considered for the evaluation. The best fitness value (least error between actual and interpolated HTCs) for five genes or five node points per face was observed to be 4.18056 on the face facing inlet air flow. The optimal set of points found from both the approaches was {13, 16, 45, 48, 61} for the same face. However, the developed logic converged faster towards the solution with lesser number of generations as observed in Fig. 3.

It could be further observed that the RBF interpolated HTC values converge closer to the actual HTC values with increased number of genes or generations which proved the feasibility of the developed GA logic in optimal subset search of nodes. As shown in Fig. 4, with increase in the number of genes the HTC values were better interpolated and the fitness values (error) decrease from 4.18 for five genes to 2.54 for ten genes.

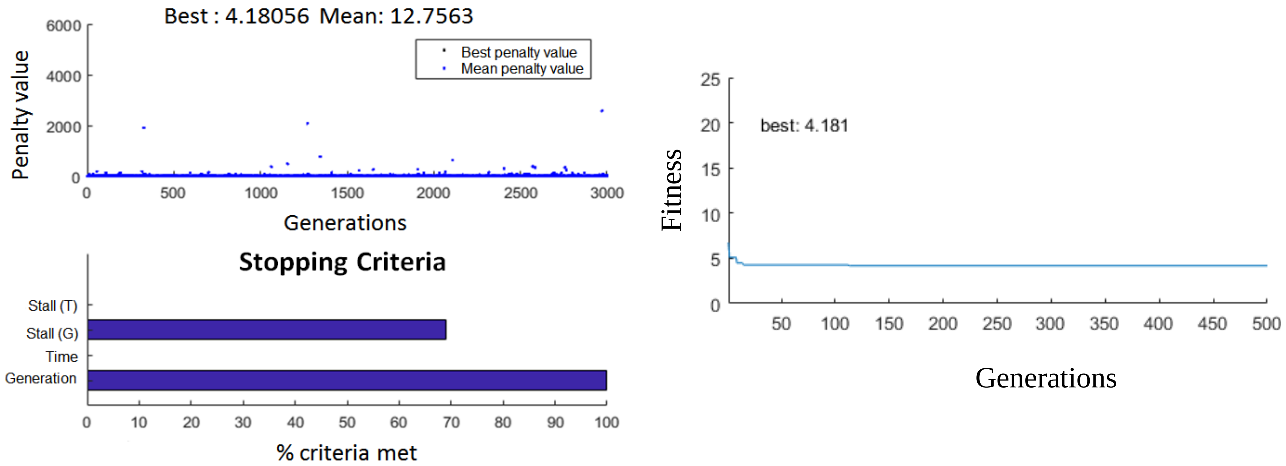

Fig. 3. GA toolbox (left) vs developed logic (right)

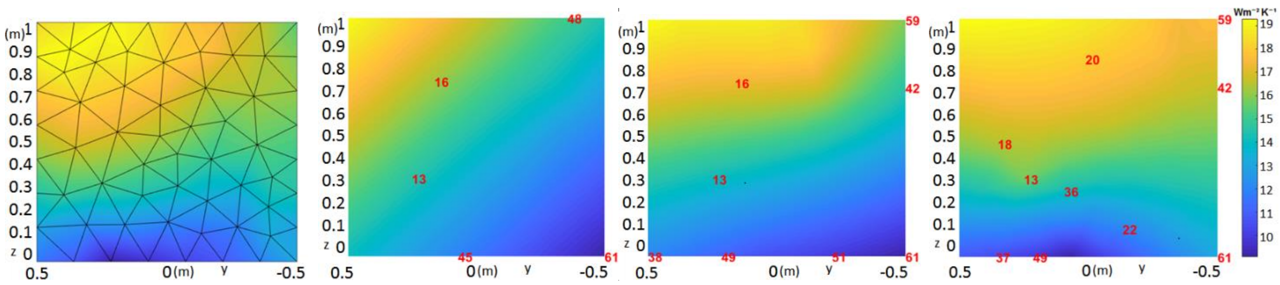

Fig. 4. Results with developed GA logic (Original HTC plot from ANSYS [first], HTC interpolated with 5 optimal nodes (second), HTC interpolated with 8 optimal nodes (third), HTC interpolated with 10 optimal nodes (fourth)

Interpolation of HTC values using RBFs is utilized in two stages of the decoupling approach - during optimal subset search in association with GA; and during convection data generation for thermo-elastic simulations. Interpolation using RBF has some major advantages as mentioned in the work by Glänzel et al. [15]. The clustering algorithm is implemented between the CFD simulations and training data generator (script written in MATLAB) for CDs as shown in Fig. 1. HTC values obtained over all the faces of the machine/ specimen for different load cases (ambient temperature, flow velocity, azimuth and elevation angles) serve as the input data for clustering algorithm. The parameters of GA such as population size, number of genes, crossover and mutation probability and number of generations are specified as user input. Optimal subsets are found for all the load cases and based on them the best optimal set is generated for each face.

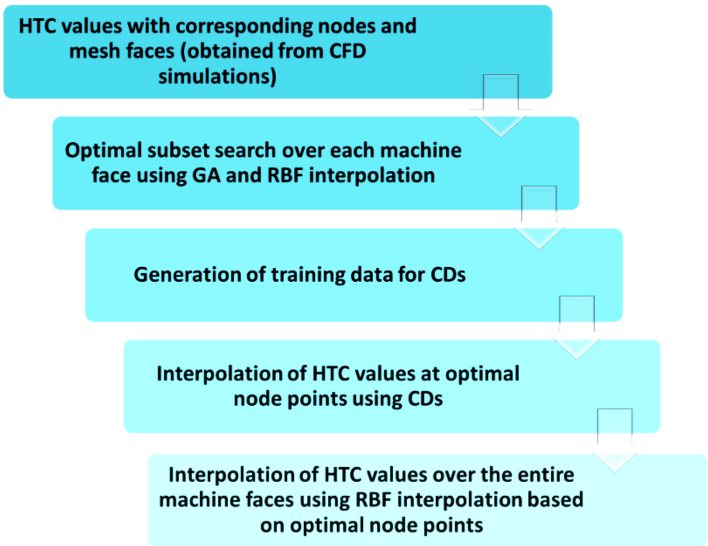

Fig. 5. Implementation of clustering algorithm

Training data for CDs are developed using optimal node points. Thus, each CD corresponds to a particular optimal node. HTC values are interpolated over the optimal nodes based on the user defined load cases. Finally, HTC values are interpolated again over the entire faces of the machine using HTC values on the optimal nodes. Thus, the algorithm involves three interpolation processes at different stages of the workflow. RBF interpolation is utilized initially to find the optimal subset and finally to interpolate HTC over all the faces. CDs are used to interpolate the HTCs over optimal node points.

4. PARAMETERIZATION OF ENVIRONMENTAL INFLUENCES

The environmental influences such as air flow temperature, velocity and directions of flow (azimuth and elevation angles) are parameterized and can be used as input parameters while training CDs. CDs are one of the most adopted tools by engineers to approximate real valued functions that depend on one or more input variables. The CDs used in this paper are based on smoothed grid regression technique suggested in the work by Priber [16]. It was later improved to high dimensional CDs which were able to approximate thermo-elastic deformations in machine tools.

CDs are continuous maps of a set of input variables onto a single output variable. They consist of a grid of support points along with kernel functions which describe the interpolation in between, refer to the work by Putz et al. [17]. The kernel functions can be anything from simple polynomials to complex wavelets, however, most kernel functions get smaller with increasing distance from their corresponding grid vertex and are only non-zero within its immediate vicinity. CDs are created by first discretizing each input variable in order to establish the grid, then choosing a type of kernel function adequate for describing the local dependency of the input variables on the output variable and finally calculating the parameters of the kernel functions for each support point based on training data from simulations or experiments. Considering a sufficiently fine grid, simple piecewise multilinear kernels are accurate enough and usually well suited for the approximation of thermal deformations as mentioned in Ihlenfeldt et al. [18]. After discretization, the next step involves gathering training data which is a combination of a set of input data and their corresponding output data (obtained from measurements or simulations). From the training data, data fitting equations are created in a least-squares error minimization approach. The resulting linear system then provides the coefficients of the kernel functions for each grid vertex and thereby defines the CD. A detailed account of the entire algorithm can be found in Priber [16] and Naumann et al. [19]. In Herzog et al. [20], a new finite element method (FEM) based algorithm is described and tested which permits a more efficient computation of CDs using multigrid solvers and thereby enables CDs with ten or more input variables.

In decoupling approach CDs have been utilized in the approximation of heat transfer coefficients for the accurate modelling of the heat dissipation through convection in thermal simulations of machine tools. The convection heat transfer coefficient (HTC) α depends mainly on the type of fluid (here: air), its temperature and in the case of forced convection the speed and direction from which the fluid streams against the surface, see [15]. For free convection, the shape and orientation of the surface is also very important but this is implicitly taken into account. Therefore the CD should approximate the mapping in correlation (3) for all points (*x*,*y*,*z*) on the machine tool surface, see [15].

$$(x, y, z, \vec{v}, T_{air}) \rightarrow \alpha \tag{3}$$

However, this sorting of mapping would involve an incredible amount of training data when complex geometries with huge number of nodes are considered. With introduction of clustering algorithm in decoupling approach, each optimal node point will be allotted its independent CD which would have the sets of input parameters mapped to their corresponding HTC values. Thus, it would eliminate the need to consider co-ordinates (*x*,*y*,*z*) as input variables in CDs. In the current implementation, air temperature, velocity, azimuth and elevations angles for each optimal node point would serve as the input parameters. Therefore, the main aim is to try and quantify the following correlation:

$$(T_{air}\,, \vec{v}, az, el\,) \rightarrow \alpha \tag{4}$$

Thereby, HTC data exported from a limited number of CFD simulations serve as the training data which is further reduced using clustering algorithm and confined to optimal node points obtained on each face of the machine tool. On smooth surfaces, the convection heat transfer coefficient is likewise smooth and continuous. On the edges between machine faces, however, the HTC will often jump abruptly. Therefore, CD interpolation may only be used if each machine face is considered separately. Therefore, it is recommended to transform all machine faces to 2D surfaces in Putz et al. [21]. This reduces the grid size while at same time improving the quality of HTC approximation.

5. CASE STUDY – MACHINE TOOL (AUERBACH ACW 630)

The idea behind parameterization of environmental influences on a machine tool using CDs and the resulting decoupling of CFD and thermal simulations is to predict the tool centre point (TCP) displacement of a machine tool with acceptable accuracy using a relatively small number of CFD simulations. The geometry chosen for this investigation is the machine tool- Auerbach ACW 630, a three-axis milling machine of the Chemnitz University of Technology. However, before implementing the decoupling approach on the actual machine tool, the workflow involving flow simulation, clustering, training of CDs and thermo-elastic simulations were initially tested on a simple cube model with an octagonal flow chamber, similar to Fig. 7 (it facilitates more flow directions for training CDs). This simple model has a total of just 267 nodes and 5 faces (sixth face is the base which has no solid-fluid interactions) for analysis. Performing the tasks on this model shows strong contrast with respect to the huge amount of time required on the actual model which has thousands of nodes and greater number of surfaces. Modelling and simulation of the simple model is performed in ANSYS CFX R18.1. The aim was to validate the coupled approach with the decoupled approach and to observe the difference in temperature and displacement contours for the simple cube. Table 1 shows the parametric values or load cases used for CFD simulations and for training of CDs. For each case, the air-flow was identified as turbulent, analytically and from simulations. Azimuth and elevation values of “0” suggest that the inlet flow is from the left-most face of the octagonal chamber (refer Fig. 6b). The mesh displacements were ultimately obtained for the test case with temperature 25°C, air velocity 4 m/s with air directions maintained the same as that during training.

Table 1. Load cases used for training CDs

Load Case	Air Temperature (°C)	Inlet Velocity (m/s)	Azimuth (degree)	Elevation (degree)
1	20	3	0	0
2	20	5	0	0
3	30	3	0	0
4	30	5	0	0

With increase in the number of genes (sets of nodes considered in GA) from eight to twelve, the average error in total mesh displacement between the coupled and decoupled approaches follows a decreasing trend as shown in Table 2. GA parameter set 3 yields better results even though lesser number of generations was used. Finding a balance between GA parameters such that they generate the best approximation in the shortest time is a matter of future research.

Table 2. Error observations for simple cube specimen

GA Parameter Set	Genes/Face	Generations	Population Size	Average error in total mesh displacement [%]
1	8	3000	60	8.72
2	12	3000	60	7.74
3	15	2000	42	6.62

With encouraging results from the simple cube specimen, the next task was to adopt the same workflow onto ACW 630. The CAD model was simplified by concentrating more on the machine column and regions of greater heat interactions, thereby ignoring and cropping certain faces and bodies such that a simpler mesh with lesser number of nodes can be generated. The blends, fillets, chamfers etc. have been removed and regions of curvatures and proximities which can involve a bulk of finite meshing have been relaxed/ straightened. The whole machine bed was redesigned, removing the air gaps inside and suppressing certain bodies in contact with it. The machine bed and its components are expected to have least influences on the TCP displacement as compared to machine column.

As discussed before, an octagonal flow environment (as shown in Fig. 6) with a prismatic roof is used which facilitates more number of air inlet and outlet combinations. This shape of the flow environment could aid to better simulation results when a moving spindle or a moving heat source is considered. The final mesh revealed 1483,864 elements and 554,053 nodes. Heat sources are defined at motor positions, friction guides and slides with experimentally recorded values. The inlet and outlet directions chosen as per Table 1 are shown in Fig. 7. The inlet is from the left and all the remaining faces act as outlet. The most prominent outer faces (see Fig. 8) on the machine column, which are expected to have the most thermal interaction with the surrounding air and most influence on TCP-displacement are chosen for HTC-export after CFD simulations.

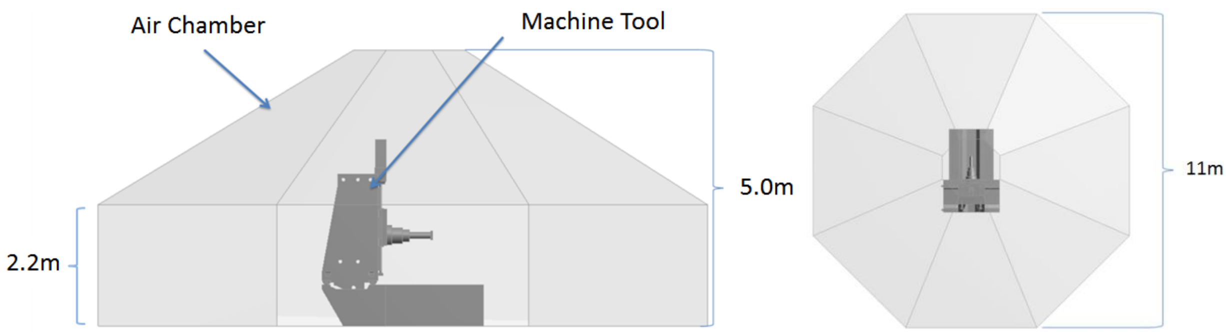

Fig. 6. Octagonal flow chamber with prismatic roof

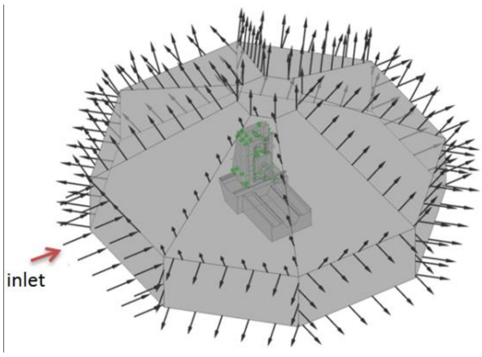

Fig. 7. Inlet and outlet faces

Load cases or environmental influences mentioned in Table 1 were used again for the simulations and HTC-export for all the FE node points on each of these eighteen faces for each load case was automated using a journal script which utilizes CCL and CEL commands. The data files exported from ANSYS-CFX (on all the selected faces at varying load cases) are imported into the developed clustering algorithm implementation in MATLAB as *.csv files.

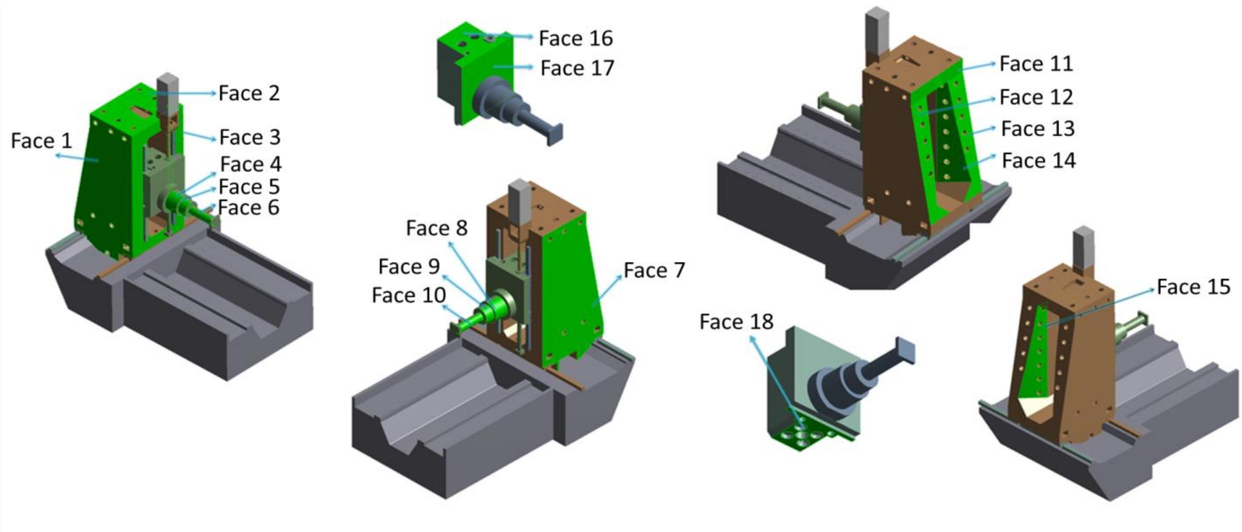

Fig. 8. Selected faces for HTC data export

As discussed earlier, optimal subset search operation (involving GA and RBF interpolation) is performed on the imported face nodes such that these subsets produce the best interpolation results relatable to HTC values obtained from fluid simulation. The accuracy of interpolated results (with optimal subsets) using GA depends on certain parameters such as population size, number of genes, crossover probability, mutation probability and number of generations. For each problem, suitable combinations of these parameters have to be tried out to yield the best results. The best results were observed for a crossover probability in the range of 0.7 to 0.9 and a low mutation probability between 0.07 to 0.09. Increasing the number of genes and population size naturally increases the accuracy of the results (see Gotshall et al [22]). If the number of generations is too large, the calculation time will increase drastically and could restrict the chances each individual has to explore its neighbourhood. If number of generations is too small, the coverage of the search space could be restricted. Similarly, if mutation rate is too high, it could risk individuals (nodes) “jumping” over a good solution and if it is too low, the search for optimal nodes could get stuck in a local minima. It should be noted that the user can alter the GA parameters such as population size, crossover probability, mutation probability and number of generations based on the desired accuracy and computation time (cost).

For the current validation of the proposed decoupling approach with coupled simulation technique, the GA parameters mentioned in Table 3 is chosen. Validation with experimental results is planned for future. CDs are formulated for each optimal node point and corresponding HTC values at these nodes are predicted (interpolated using trained CDs) for a user defined test case - with temperature 25°C, air velocity 4 m/s, a_z = 0, el = 0. With optimal node numbers known and corresponding HTC values obtained from CDs, RBF interpolation can be utilized again to interpolate the HTCs over all the selected faces of the machine. This interpolated data serves as the convection data for thermo-elastic simulations in ANSYS.

Table 3. GA parameters

Genes/Face	Population Size	Generations	Crossover Probability	Mutation Probability
8	400	1000	0.8	0.08

The primary region of this validation is the tool center point (TCP) of the machine tool. Figure 9 shows the temperature contour observations at the TCP region for coupled approach (top left), decoupled approach (top right) and the difference (error) contour of the two approaches. It can be observed that the temperature distribution for the approaches look almost the same. The results were obtained from ANSYS transient thermal analysis after 360 s with time steps of 12 s. The temperature is initialized at 22°C (295.15 K). To quantify this acceptance, a point is selected (marked in red) at the dummy tool vertex as the TCP. The readings at this point are tabulated in Table 4. The deviation in temperature at the TCP from the coupled approach was also found to be a very small value of 0.47%.

Table 4. Temperature Contour Observations

Region	Coupled [K]	Decoupled [K]	$\Delta T_{\text{coupled}}$ [K]	$\Delta T_{\text{decoupled}}$ [K]	Error [K]	Relative error [%]
red	295.636	295.633	0.486	0.483	0.0023	0.47

The temperature fields were imported into the ANSYS static structural simulation. Maximum deviation in displacement values from the coupled approach was observed in the X-direction at the TCP region as shown in Fig. 10. At the selected vertex (marked in red), which represents the TCP, errors of 21.3%, 7.4%, 1.2% were observed for the mesh displacements in *X*-, *Y*- and *Z*-directions respectively after 360 seconds. The difference in total mesh displacement (resultant) between coupled and decoupled approach was found to be a very small value of 4.1%. The observations have been tabulated in Table 5.

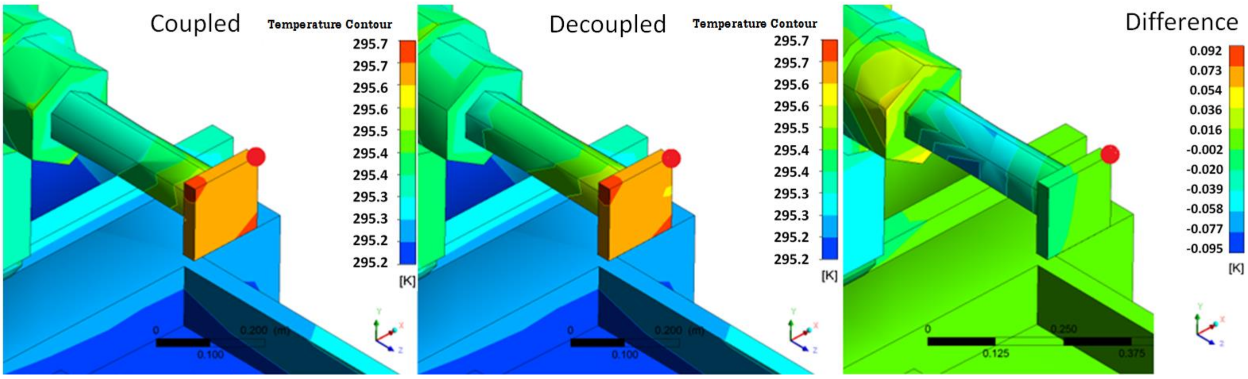

Fig. 9. Temperature contours-coupled (first), decoupled (second), error (third)

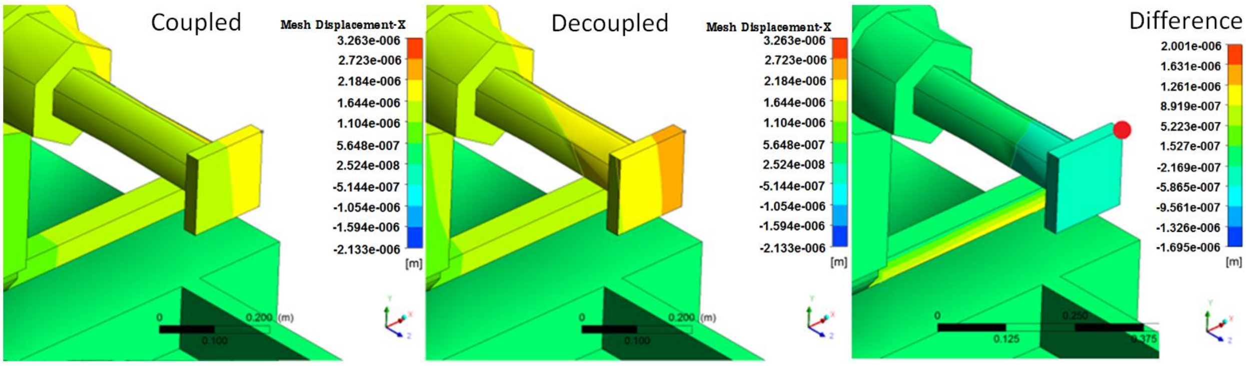

Fig. 9. Displacement contours- mesh displacement *X*-direction (coupled [first], decoupled [second], error [third])

Table 5. Displacement Contour Observations at TCP

Orientation	Coupled [µm]	Decoupled [µm]	Difference [µm]	Error [%]
X	2.101	2.549	.448	21.3
Y	2.355	2.181	.174	7.4
Z	3.076	3.116	.039	1.2
Total Mesh Displacement	4.407	4.579	.182	4.1

The validation on the simple cube specimen required at an average, 3000 generations and 50 genes (in total) to yield satisfactory results on a FE model with 562 nodes. Thus, for a FE model of the actual machine tool with 500,000 nodes would require approximately 10,000 generations and higher number of genes depending on the complexity (number of nodes on each face) of the model. Optimizing the GA parameters and independent GA approximation on each face could generate better clustering results.

6. SUMMARY, CONCLUSION AND OUTLOOK

This paper attempts the decoupling approach of fluid and thermo-elastic simulations for a machine tool through parameterization of environmental influences with help of clustering techniques and characteristic diagrams. Prediction of TCP displacement using this approach eliminates the need for extremely time-consuming fluid-structural coupled simulation routines. Using clustering technique which involves genetic algorithm (GA) along with RBF interpolation, optimal subset of node points are found on the faces of the machine such that they efficiently interpolate HTC values for varying environmental load cases. Thereby, the tremendous amount of data used for training CDs, which multiplies in magnitude when complex geometries or moving components are considered can be substantially reduced.

The prediction of HTC values on these optimal node points for a particular user defined test case was done using CDs trained from a limited number of flow simulation results for varying load cases. RBF interpolation is used again to interpolate the HTC values over the entire faces using optimal node points and their corresponding HTC values. These HTC values serve as convective boundary data for thermo-elastic simulations and TCP displacement is obtained.

Validation is performed for the proposed approach on the machine tool (Auerbach ACW 630). Temperature and displacement fields generated from interpolated HTCs obtained through decoupled approach are compared to those obtained from coupled fluid-structural simulations. Almost 80 %, 92 % and 98 % of the TCP displacements in X, Y and Z directions respectively were approximated successfully using the decoupled approach. With just thousand generations and eight super optimal nodes per face, the error in total mesh displacement at the TCP was found to be 4.1%. The deviation in temperature at the TCP from the coupled approach was also found to be a very small value of 0.47%. A diminishing trend in average error between the coupled and decoupled approaches were observed in temperature and displacement values for increasing GA parameters like genes and generations.

Further investigation into the decoupling approach would involve optimization of GA parameters such as number of genes, population size, crossover and mutation probabilities and generations. GA parameters extensively depend on the size of the search space i.e. depending on the number of nodes on a particular face, it would require more or less genes or population which needs to be optimized from a number of trials. This would enhance the speed with which optimal subsets are found on each machine tool face. The TCP displacement approximations discussed in the implementation is performed for a single, fixed kinematic configuration of the machine tool. Approximations including moving machine tool axes would increase the range of thermal configurations to be considered by the CDs. A proposed solution to this problem as discussed in [15] involves the use of axis positions as additional input variables for CDs. For the validation discussed in section 5, a very limited number of load cases are considered for training of CDs. An ideal scenario would involve hundreds of load cases which include different combinations of environmental parameters. Experimental studies are also being carried out in the climate chamber for the validation and verification of the decoupled simulation approach.

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