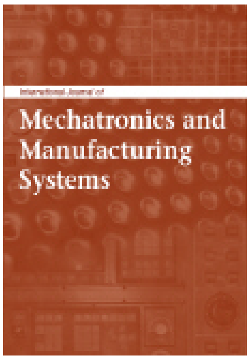

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Process concatenation to reduce thermal changes in machine tools

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Abstract: Thermal effects in machine tools are responsible for a significant amount of produced scrap. Therefore, various approaches have been investigated and applied on machine tools to reduce thermal changes during manufacturing. Most of them target the machine tool and its operational state and can therefore just react to the thermal changes caused by the process. This paper shows how thermal changes can be reduced already in the manufacturing planning stage. With the use of a virtual numerical control (VNC) and loss models, power losses can be estimated, enabling the concatenation of processes to achieve minimal jumps in power loss from one process to another.

Keywords: temperature; thermal error; heat treatment; machine tool; machining; energy efficiency; planning; simulation; optimisation; economics.

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1 Introduction

Over the last decades, energy efficiency of machine tools has become increasingly important due to environmental protection efforts and economic aspects. Out of this perspective, the conflict between productivity, accuracy and energy efficiency of machine tools grew in importance (Brecher, 2016; Großmann and Ott, 2015). In today's machine tools, thermal errors are one of the main reasons for the production of scrap (Mayr et al., 2012).

Thermal errors occur because of energy that is converted in an undesired manner, like the heat caused by the friction in a bearing. This heat spreads within assemblies and over joints to further assemblies, locally changing temperatures in the machine tool.

Since most materials have a significant thermal expansion coefficient, the heat causes a deformation, that can lead to a displacement and rotation of the tool centre point (TCP) directly affecting the machined surface.

To reduce thermal problems, various tempering approaches are investigated, which are described in Section 2. Most of them address the machine tool itself or its operational state. It is not considered that the manufacturing task (NC-program) contains essential information about occurring losses, which can be used to reduce thermal changes already at the manufacturing planning stage. This paper demonstrates how a loss forecast for complete manufacturing tasks can be achieved and used for a concatenation of multiple processes to reduce thermal changes without touching the processes itself.

The paper will first give an insight to the state-of-the-art in Section 2, followed by the description of the general approach in Section 3. Section 4 introduces a demonstrator for the practical application and an analysis of the approach. The loss forecast for complete manufacturing tasks will be discussed in section 5 and applied to three exemplary manufacturing tasks. Section 6 characterises how a concatenation of the processes from Section 5 can be applied to influence the thermal change in the machine tool during manufacturing. Sections 7 and 8 describe the experimental execution at the machine tool and corresponding temperature measurement, analysis and validation of the calculated concatenations. Finally, in Sections 9 and 10 the advantages and disadvantages of the approach are discussed and potential follow up research is stated.

2 State-of-the-art

Ramesh et al. (2000) distinguished three research directions in the field of error compensation in machine tools, which also allows a classification of current research work. These directions are:

- heat flow control into the machine tool
- constructive optimisation of machine tools to reduce the sensitivity to heat flow
- control-based compensation of thermo-elastic caused displacements.

A common and widely used strategy in the field of *heat flow control* is the integration of fluid-based cooling systems. Due to different machine tools with different heat sources, machine dimensions and drive powers, their design is highly machine-specific and mainly driven by the machine tool manufacturers. Kirchner et al. (2014) analysed that up to 30% of the energy consumption of cooling systems can be reduced by turning off the fluid pump if it operates in idle mode. Mori et al. (2019) applied a shutdown strategy to a spindle cooling system, resulting in energy savings between 15% and 75%, depending on the spindle operating state. Especially at low rotational speeds this leads to major energy savings, since the heat caused by friction within the spindle is neglectable compared to the heat generated by the fluid pump. The shutdown of the pump therefore reduces the energy consumption and additionally the heat transferred to the spindle, making the machine tool more efficient and accurate. Brecher et al. (2012) showed that the energy consumption of fluid-based cooling systems can be reduced by 30% to 60% if efficient energy consumers are used, like a digital scroll compressor or an electronically communicated fan.

Constructive optimisations are primarily achieved by the efficient application of thermally resistant materials in the machine tool. Möhring et al. (2015) gave a broad overview of developments in relevant materials for machine tools. The thermal relevant properties are conductivity, heat capacity and expansion coefficients. Metals have a relatively high expansion coefficient, leading to thermo-elastic deformations and drifts at the TCP. In machine beds, for example, stone and ceramic composites are widely used (Möhring et al., 2015) because they achieve high damping, low conductivity and low expansion, providing a solid basis for machine tools. Recent research in the field of constructive optimisation was done by Voigt et al. (2019) where the application of phase changing materials was analysed to reduce the thermal change in the nut of a ball screw drive. They showed that the temperature change within the nut can be damped by coupling phase changing materials to it. The heat capacity of the attached material increases significantly during phase change. Therefore, with reaching the phase change temperature, the heat capacity of the whole assembly increases. This solution can reduce thermal changes in assemblies, such as the machine table, and can be a valuable assistant tool for fluid-based cooling systems that struggle with the dissipation of dynamic heat.

Especially in the field of *control-based compensation*, intense research was done, reviewed in Mayr et al. (2012). Most of the strategies accept the thermo-elastic caused drift of the TCP and attempt to estimate the drift based on models with and without the integration of real time sensor signals. An accurate displacement estimation allows a transfer of the offset to the machine tool control for compensation. This solution is ecologically smart, since it can save the energy used for cooling and instead correct the error together with the machine tool control. With such motivation, Thiem et al. (2017) developed a correction strategy based on a structure model. The model represents the physical processes of heat generation, transition and corresponding deformation. The solution takes load-relevant data from the machine tool control and calculates loss powers, temperatures, deformations and transforms the displacements on the machine axes for correction with the machine tool control. Approaches like this require high effort in parameter tuning to make the underlying physical models of the simulation fit to reality (Schroeder et al., 2019). This requires multiple measures that are used for the adjustment of the model parameters. Mayr et al. (2012) described in detail the different measuring strategies for the characterisation of thermal errors in machine tools. The named strategies are mainly based on tactile measures or infrared cameras. A new approach is to use multiple video cameras to recalculate the global position of moving objects from the local position in the different pictures of the cameras (Riedel et al., 2016). This allows the deformation measurement of moving assemblies in a machine tool. The accuracy of this solution mainly depends on the resolution and the number of cameras, similar to the accuracy increase of global positioning systems (GPS) by receiving more satellite signals. Riedel et al. state an accuracy of 1/50 pixel, which is a few micrometres (1 μm/m) on the measured object with the specified setup.

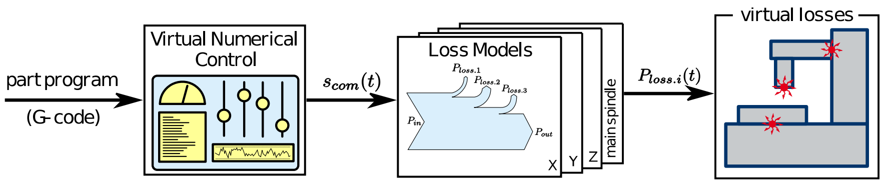
In summary, there are various strategies to determine and reduce thermal errors, each with their own advantages and disadvantages (Ihlenfeldt et al., 2018). Despite the heterogeneity of the solutions, they all address the machine tool and its manufacturing stage. The impact of the manufacturing task is often out of the solutions scope.

3 The approach

The manufacturing task (defined in the part program) has a major impact on the temperatures in the machine tool. It defines how the machine should move at a specific time. Different researchers pointed out that the machine internal losses at a specific loss source are predictable if the operation state is known (Jungnickel, 2010; Palmgren, 1957; Winkler and Werner, 2015). Typical loss sources are motors, bearings and guiding's (Ramesh et al., 2000).

With the use of a virtual numerical control (VNC), the task specific machine motions can be predicted, allowing a determination of the operational state at the loss source, e.g., the rotational speed of a bearing. With the VNC, loss models can be applied to estimate the time-dependant power losses in the machine tool, as illustrated in Figure 1.

Figure 1 Loss forecast procedure for complete part programs (see online version for colours)



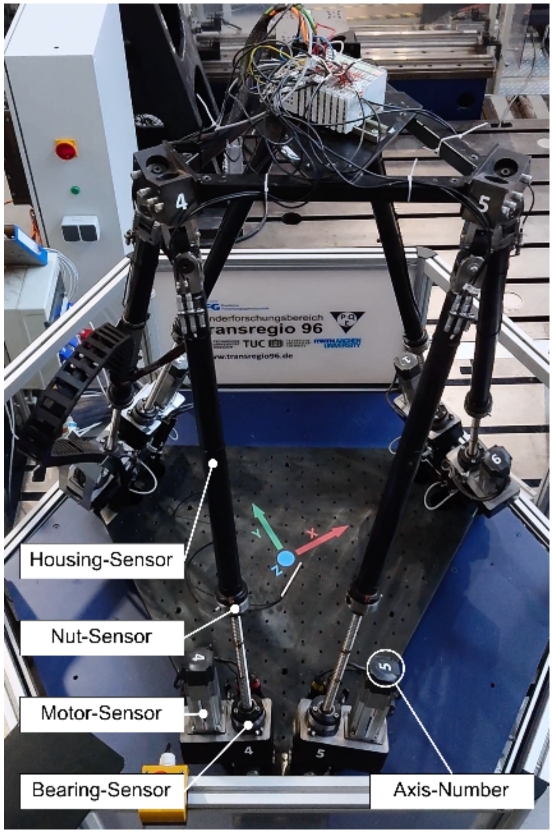
This procedure can be applied on multiple part programs (manufacturing tasks) to obtain the estimated losses that should occur during manufacturing. The estimated losses can be used for a process concatenation to achieve minimal jumps at the transition from one task to another without affecting the single processes. This should reduce thermal changes since changes in power dissipation are reduced, which are the root cause for thermal changes.

This approach is investigated and applied on a demonstrator machine to validate and quantify the resulting reduction of thermal changes in the machine tool.

4 Demonstrator machine

The approach was applied and investigated at a hexapod with six parallel linear axes, each mounted on the fixed base and the moved platform, as shown in Figure 2. This machine is used as a demonstrator for thermo-elastic problems and solutions within the collaborative research centre for thermo-elastic machine tools (CRC/TR96). It is equipped with four temperature sensors per axis, which are placed at the motor housing, the bearing seat, the nut seat of the ball screw drive and the screw housing. Each of the six axes has a movement range of 0.5 m and a maximum axis speed of 1 m/s. The machine is equipped with a Beckhoff control preceded by a HexaBOF. The HexaBOF performs the offline transformation from Cartesian movement to the six axes, work area monitoring, model-based corrections and generates a part program on axes level that is executed by the Beckhoff CNC to control the machine. This control setup is unique and was created to allow an easy integration and adaption of transformation and correction models (Kauschinger, 2006).

Figure 2 Demonstrator: Hexapod (see online version for colours)



The major advantages of the chosen machine tool are the included temperature sensors and the lightweight setup. Due to the lightweight setup, there are only small heat capacities and therefore fast thermal responses compared to standard machine tools. This behaviour supports the visualisation of the correlation between occurring power losses and temperatures without the need for a thermal simulation.

5 Loss forecast

5.1 Machine motion determination

The determination of the task dependent machine motion is a challenging task. First, the syntax of the part program must be considered to transform the program code into meaningful machine commands, like rapid linear movement. Second the commands have to be processed similar to the normal machine tool control to obtain the time dependant discrete positions the machine would move to. A reconstruction of these processes is very time consuming and often not accurate enough, because of complex and hidden processes that may vary between control developers (Suh et al., 2008). Therefore, it is advisable to use a VNC of the corresponding control type to obtain reliable positions with minimal effort.

A VNC mimics the behaviour of the real control and is in general provided by the control developer. Such VNC's are mostly used by machine manufacturers during machine development e.g., for a virtual commissioning of the machine. Thus, they are mostly provided as a library that can be integrated in other simulations, requiring a basic understanding of the general workflow and the functionalities of a CNC.

The VNC for the demonstrator performs three major tasks. At first, a self-written compiler is executed that takes the part program in standard G-code and transforms it into the syntax required by the HexaBOF. Then, the compiled file is passed to the HexaBOF that outputs the corresponding g-code on axis level. Finally, the developed Beckhoff-VNC (based on a VNC library provided by Beckhoff) is executed which processes the axis g-code and outputs a csv-file with the single time dependent positions of each axis for further processing. More details to the control design are given in (Wenkler et al., 2021).

The solution was applied in a virtual machine on multiple part programs from 80 k to 150 k blocks per file, representing processes from 10min up to 2h. Overall, the simulation time was approximately 50 times faster than the corresponding process time (at the real machine tool), showing that such VNC's could be efficiently used during planning stage.

5.2 Loss model application

Loss models describe the occurring loss at a given loss source and are specific for each assembly, like bearing, motor and guiding. The most common loss models are summarised in Jungnickel (2010). Further loss models exist that focus on other assemblies or vary in the degree of detail (Jurkschat et al., 2018; Palmgren, 1957; Winkler and Werner, 2015).

For the demonstrator machine three different loss models are used: bearing, ball screw drive and motor loss model. The models were analysed and applied within the CRC/TR96 for thermal simulations (Kauschinger and Schroeder, 2014, 2016; Schroeder et al., 2019; Thiem et al., 2017) and will now shortly be introduced.

5.2.1 Bearing loss model

The bearing loss model is going back to the research of Palmgren (1957). It distinguishes into three different reasons for losses: a hydrodynamic M_{hydro}, a load dependent M_{load} and a sealing loss M_{seal} which add up to the total bearing loss.

$$M_{bearing} = M_{hydro} + M_{load} + M_{seal} \tag{1}$$

The hydrodynamic losses M_{hydro} are speed dependent because of variations within the lubrication film, according to the speed. The parameters are: the bearing constant f_0, the average bearing diameter dm, the kinematic viscosity of the grease ν and the angular speed ω.

$$M_{hydro} = 4501 \cdot f_0 \cdot d_m^3 \cdot (\nu \cdot \omega)^{2/3} \tag{2}$$

The load dependant loss M_{load} is defined by the bearing load which is the sum of process and preload force. The bearing is designed out of two angular contact ball bearings oriented in opposite direction. Therefore, a process force would load one ring and unload the other ring for the same amount, allowing to neglect the process forces without increasing the model uncertainty (Kauschinger and Schroeder, 2016). The parameters are: the bearing constant f_1, the axial force F_a, the radial force F_r and the average bearing diameter d_m.

$$M_{load} = f_1 \cdot \left(1.4 \cdot F_a - 0.1 \cdot F_r\right) \cdot d_m \tag{3}$$

The sealing loss M_{seal} is caused by the build in sealing rings which keep the grease in the bearing and was mainly analysed by (SKF). Because the sealing ring is in contact with the inner and outer ring of the bearing, there is a relative movement causing frictional losses between inner ring and sealing or outer ring and sealing, depending on the bearing construction. The parameters are: the sealing ring coefficients K_{S1} and K_{S2}, the sealing ring diameter at which the relative movement occurs d_s and the sealing ring exponent β.

$$M_{seal} = K_{S1} \cdot \left(d_s^{\beta} + K_{S2}\right) \tag{4}$$

5.2.2 Ball screw drive loss model

The ball screw drive creates frictional losses similar to the bearing loss model and is the sum of a frictional loss of the rolling balls M_{roll} and a sealing loss M_{seal}.

$$M_{bsd} = M_{roll} + M_{seal} \tag{5}$$

The frictional loss caused by the rolling balls M_{roll} is used from Jungnickel and based on empirical research (Jungnickel, 2010). The parameters are: the spindle diameter $d_{spindle}$, the nut diameter d_{nut}, the number of groves i where the rolling elements are in contact, the preload force F_v and the dynamic load capacity C.

$$M_{roll} = 4.52 \cdot 10^5 \cdot d_{spindle}^{1.44} * d_{nut}^{1.33} \cdot i \cdot \frac{F_v}{C} \tag{6}$$

Equation (4) can be used for the sealing loss M_{seal}, since the effect is the same for the ball screw drive and the bearing loss model.

5.2.3 Motor loss model

The used motor loss model is based on the idea that the motors effective moment hast to be the sum of the frictional moments $M_{friction}$, acceleration moments $M_{acceleration}$ and moments caused by process forces. Because of the missing main spindle at the demonstrator machine, process forces do not occur, reducing the problem to:

$$M_{motor} = \frac{1-\eta}{\eta} \cdot \left(M_{friction} + M_{acceleration}\right) \tag{7}$$

The transfer from the effective to the loss moment is taken into account by the factor $(1 - \eta)/\eta$, where η is the motor efficiency. The frictional losses $M_{friction}$ are the sum of the loss moments caused by the bearing and the ball screw drive according to equations (1) and (5).

$$M_{friction} = M_{bearing} + M_{bsd} \tag{8}$$

The acceleration moment depends on the speed change of the axis and is independent from the movement direction. The parameters are: the moment of inertia J, the angular speed ω and the time change dt.

$$M_{acceleration} = J \cdot \frac{|\omega|}{dt} \tag{9}$$

5.3 *Application of the loss forecast on complete part programs*

Within Section 5.1 is explained how to forecast axis movements of a machine during the manufacturing of a specific part program by using a VNC. This information allows the recalculation of the operational state (e.g., rotational speed ω) at different loss sources, which is required for the loss model application. The corresponding power losses can be calculated by $P_{loss} = M_{loss} * \omega$. This procedure was applied on three different manufacturing tasks, shown in Figure 3 and briefly described in Table 1.

Figure 3 Demonstration manufacturing tasks (see online version for colours)

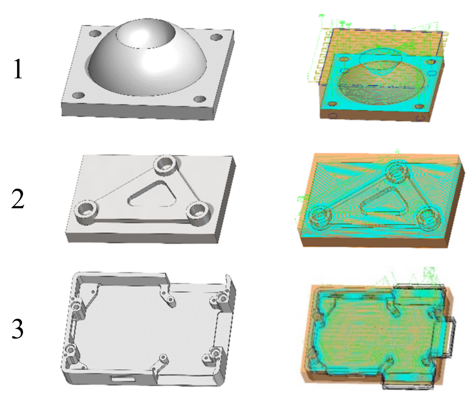
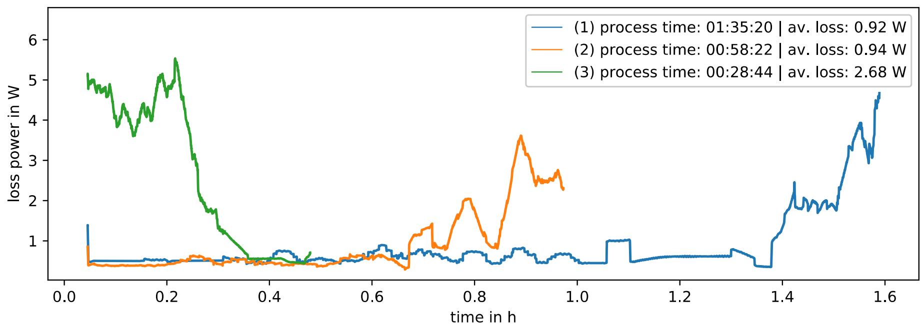


Table 1 Characterisation of the manufacturing tasks

Part	*Process time in h:m:s*	*G-code blocks*	*Part description*
1	01:35:20	38813	Seat for a ball joint
2	00:58:22	26011	Guide element as used in the hand baggage compartment of airplanes
3	00:28:44	16058	Steal case for a Raspberry Pi 3b and controller plates

A loss prediction for one of the three tasks leads to 18 power loss series representing the three losses at each of the six axes. To obtain understandable graphs the focus in this paper was put on the bearing loss of the first axis. Figure 4 shows the calculated power losses at the bearing of the first axis for the three different manufacturing tasks smoothed over 3 min with a moving average.

Figure 4 Forecasted power losses (see online version for colours)



6 Process concatenation

The predicted losses represent the origin for thermal changes in the machine tool. Assuming a constant power loss, the machine heats up until the emission to the environment is equal to the introduced heat by the power loss, and then remain its temperature. The major reason for thermal change is therefore the change in power loss. With a reduction of the changes in power loss, thermal changes are expected to reduce also.

The process internal changes in power loss cannot be affected, since they depend on the process steps that are necessary to manufacture the part. An editing would require knowledge about the manufacturing task and alternative production approaches, which is a complex multi criteria problem. A simpler approach is the concatenation of multiple independent processes to reduce the change in loss power in between.

Hence, the goal is to concatenate the processes in a sequence with minimal changes in power loss at the transition from one process to the succeeding one. Therefore, a heuristic approach was developed, which is summarised by Algorithm 1.

Algorithm 1 Heuristic for process concatenation

```
for each process in available processes:
  Initialize chain that only contains this process.
  while required chain length is not reached:
    for each process not in chain:
      calculate and save jump in loss power if process would trail the chain
      calculate and save jump in loss power if process would lead the chain
    if (min. leading jump) < (min. trailing jump):
      push process with min. leading jump at start of chain
    else:
      push process with min. trailing jump at end of chain
  store generated chain
return chain with minimal sum of jumps
```

The heuristic describes how a concatenation with minimum jumps can be achieved and with minor adjustments it can also be used to find a concatenation with maximum jumps. Since a heuristic does not necessarily provide an optimal solution, an exact optimisation approach based on a linear assignment model was developed to evaluate the quality of the heuristic.

Tests with synthetically generated data proved that the heuristic finds a concatenation comparable to the optimum. The test targets the concatenation of 8 processes to be formed from a pool of 8 to 64 randomly generated processes. The heuristic and optimal solutions (determined by solving a corresponding integer linear program) are compared based on the sum of the jumps in the concatenation. Focussing on this criterion, the heuristic proved to deliver in average 8.4% (max. 10%) higher values than the optimal solution. Having in mind the exponentially growing computing effort for the optimal solution, this result justifies the usage of the heuristic.

Therefore, the heuristic was applied on the forecasted power losses of the three tasks to find concatenations with min./max. jumps, which are used for comparison and further investigations. The determined concatenation with minimum jumps is shown in Figure 5 and statistics are summarised in Table 2, for the concatenation with maximum jumps it is Figure 6 and Table 3.

Figure 5 Concatenation with minimum jumps (see online version for colours)

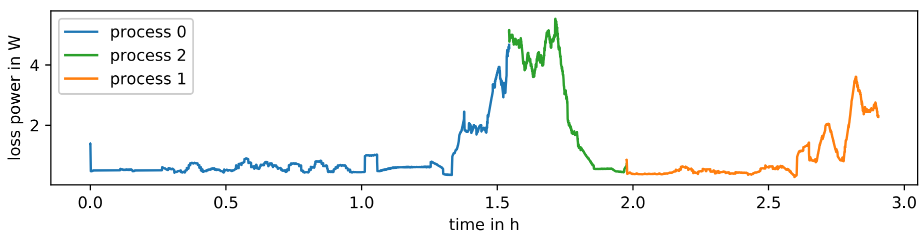


Figure 6 Concatenation with maximum jumps (see online version for colours)

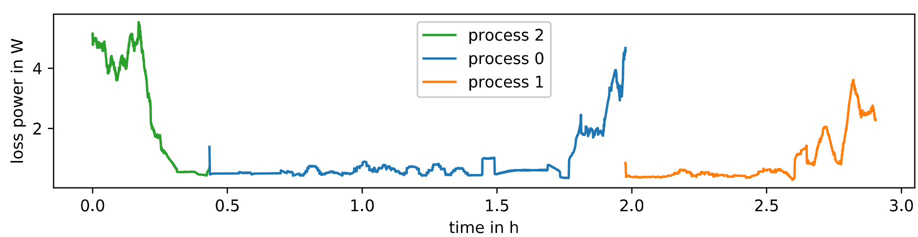


Table 2 Statistics for concatenation with minimum jumps

Position in chain	*Process index*	*Jump to next process in W*
0	0	0.443
1	2	0.148
2	1	0.919
	mean jump:	0.504

Table 3 Statistics for concatenation with maximum jumps

Position in chain	*Process index*	*Jump to next process in W*
0	2	0.679
1	0	3.817
2	1	2.810
	mean jump:	2.436

7 Experimental results

To analyse the impact of the process concatenation on the bearing temperature, both determined process sequences were executed and the corresponding temperatures in the machine tool were recorded. Due to the small changes in power loss (about 0 W to 5 W), side effects must be avoided. Preliminary measures showed two major problems:

One problem are *changes in environmental temperature*. To avoid these, the tests were performed at the weekend, when the hall heating is turned off to save energy.

The second major side effect is *excessive heating and cooling*, which mainly occurs at the start, break and end of the manufacturing. For example, a cold machine is heating up strongly, dominating the effect caused by the process dynamics. Therefore, the tasks were repeated continuously over the whole weekend. This allows to skip the first process executions, where the machine is heating up and additionally provides a broad data basis to compare both determined process sequences.

In summary, two series of measurement were performed, which led to 20 measures per concatenation ($\approx$ 60 h) in steady state with very slow changes in the environmental temperature ($\overline{\Delta\vartheta_{env}} \approx -0.03 K/h$). One characteristic measure for each concatenation is shown in Figures 7 and 8.

Figure 7 Measured temperature course while executing the minimum jump concatenation (see online version for colours)

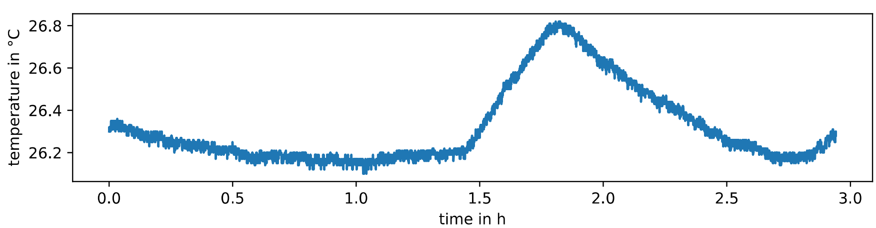
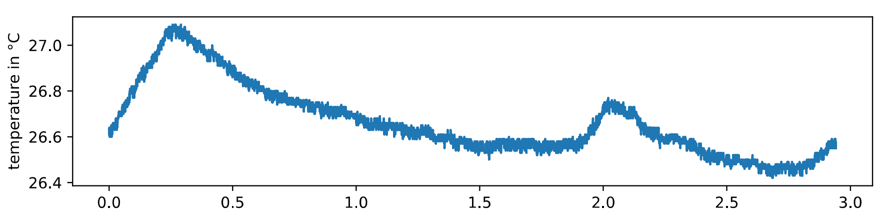


Figure 8 Measured temperature course while executing the maximum jump concatenation (see online version for colours)



8 Time series analysis

The measured temperature courses show a clear difference in the thermal behaviour. The temperature course from the minimum jump concatenation in Figure 7 is in general flat, except in the area from 1.5 h to 2.5 h, where a big temperature peak occurred. Compared to this, the temperature course from the maximum jump concatenation has a continuous drop with two smaller temperature peaks at approximately 0.3 h and 2 h. Now the question arises how the different concatenations influenced the dynamics of the whole course.

Preliminary investigations have focussed on gradient values, histograms of occurred temperatures and temperature variances. To suppress small temperature fluctuations at neighbouring measurement points, the temperature course was smoothed by a moving average over 3 min. However, information from the temperature gradients gave no evidence of thermal stability in specific areas within the course. Histograms turned out to be equally unsuitable since the time reference of the appearance is lost during assignment to the discrete containers. A consideration of variances cannot be rested on the whole series because a single peak can be evaluated similarly to a continuous drift. Therefore, a segment-wise analysis based on temperature variances is required. Immediately questions arise as to the location and the length of these segments has to be determined. One possible answer will be given by the concept of segmenting the series, which will be presented in the following.

The key idea is to construct segments in which the temperature fluctuations remain in a given domain. As long as the temperature points remain in the given domain, the point is assigned to the current segment. If a point leaves the domain, the actual segment is closed, and the next segment is initiated, centred at the corresponding temperature value that did not fit into the last segment. This will be repeated until all points in the course are assigned to segments. Since the processes are in continuous repetition, sections can flow over the course edges, so that a segment may run from the end to the start of the course. It is important to mention that the start point of the segmentation strongly influences the whole segmentation process. Therefore, each point was considered as potential starting point of a segment and the corresponding segment lengths were calculated. The start point for the segmentation was then chosen according to the global longest segment, repeating the segmentation procedure starting from the determined point. This procedure is summarised in Algorithm 2.

Algorithm 2 Segmentation procedure

```
define segment tolerance

# find biggest possible global segment
set biggest segment index to 0
set biggest segment length to 1
for each point in course:
  initiate segment
  set segment max. to point temperature + tolerance
  set segment min. to point temperature – tolerance
  set segment length to 1
  while next point is within segment borders:
    increase segment length by 1
  if segment length > biggest segment length:
    set biggest segment index to current point index

# segmentation starting with global biggest segment
for each point in course starting at biggest segment index:
  if point is within current segments domain:
    add point to segment
  else:
    close previews segment and open new one
    set segment centre to point temperature
    set segment max. to point temperature + tolerance
    set segment min. to point temperature – tolerance
    set biggest segment length to segment length
```

Figures 9 and 10 show the result of the segmentation process for both courses with a segmentation width of 0.22°C. A green segment indicates a flow over the course edges, as occurring in Figure 9. The segmentation for the minimum jump course holds the longest segment and fewer segments compared to the maximum jump course segmentation.

Figure 9 Segmentation of the minimum jump course with a segment width of 0.22°C (see online version for colours)

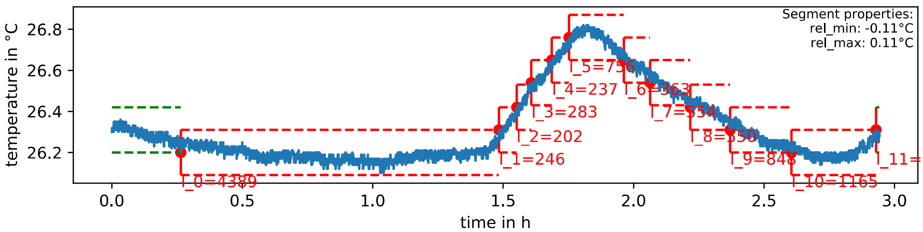
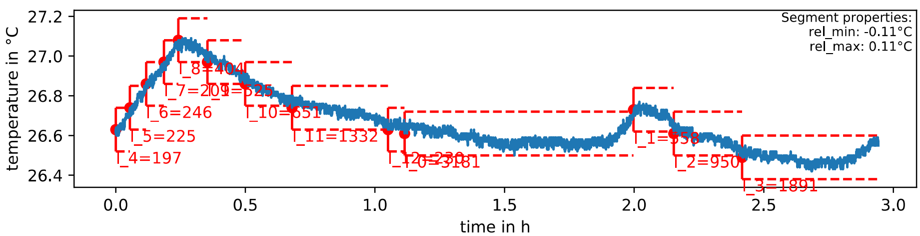
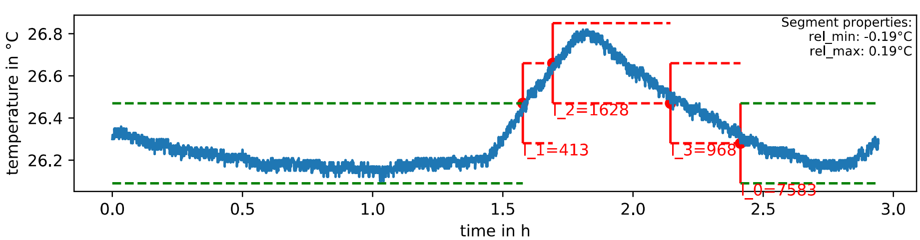


Figure 10 Segmentation of the maximum jump course with a segmentation width of 0.22°C (see online version for colours)



The rougher segmentation in Figures 11 and 12 with a segmentation width of 0.38°C behaves similar. Again, the minimum jump course holds the biggest segment, but now they have the same number of segments.

Figure 11 Segmentation of the minimum jump course with a segmentation width of 0.38°C (see online version for colours)



Since the segment width is influencing the segmentation result and a subjective chosen width could hide effects that would become visible with another width, multiple segmentation widths have been tested. The segmentations were performed for both courses, starting with a segmentation width of 0.1°C, increased in steps of 0.04 K until both courses fit into one segment. Figure 13 summarises the segmentations with respect to the lengths of the largest segment found.

Figure 12 Segmentation of the maximum jump course with a segmentation width of 0.38°C (see online version for colours)

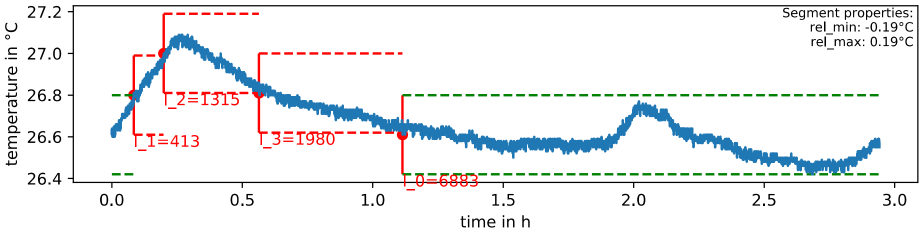
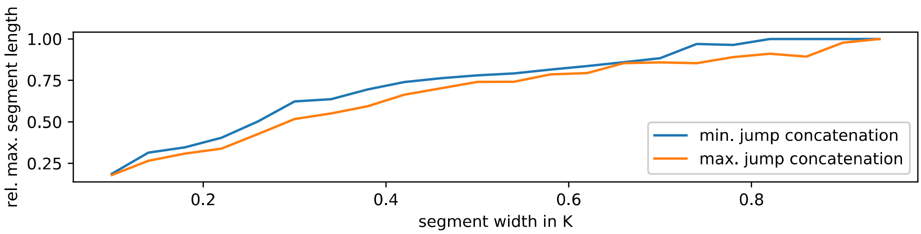


Figure 13 Relative length of the largest segment with varying segment width (see online version for colours)



For all considered segment widths, the concatenation with minimum jumps delivered the better results. The length of the largest segment is up to 20% higher compared to the concatenation with maximum jumps and 10% higher in average.

9 Summary

In this paper, the manufacturing task is assumed to have a great impact on the thermal behaviour of the machine tool. To extract the relevant thermal information out of the manufacturing task, a loss forecast strategy is presented.

This strategy divides the loss forecast in a motion determination with the use of a VNC and a loss model application based on the determined motion. Since the task-dependent power loss cannot be manipulated without affecting the manufacturing task itself, multiple tasks were used for considerations at the process planning level. The aim was to reduce thermal changes by rearranging the individual tasks in a sequence such that changes in power loss are minimised.

The loss forecast was therefore applied on these three tasks and the processes were concatenated by a constructed heuristic, which minimises the jumps of power losses at the transitions between different successive tasks. Additionally, a corresponding concatenation with maximum jumps was determined for comparison purposes.

To show that the specific concatenations cause characteristic temperature courses, each concatenation was performed 20 times at the machine tool whereby the corresponding temperatures were measured and recorded. Obvious correlations between forecasted loss and occurring temperatures have been shown.

To avoid subjective evaluations of temperature courses and achieve a quantification of the thermal changes, a segmentation algorithm was developed. The algorithm scans the course and divides it into segments where a specific temperature could be maintained. Overall, has been shown that the largest segment in the minimum jump concatenation is approximately 10% larger compared to the segment of the maximum jump, which reveals the influence of the concatenation on the thermal behaviour.

10 Outlook

The paper presents a strategy to reduce thermal changes in the machine tool by ordering processes depending on their caused power losses. Experimental results reveal a potential reduction of about 10% in thermal changes concerning the segmentation approach. The presented strategy is currently partwise automated but able to be fully automated for an industrial application.

Next research should focus on the application to a classical machine tool, to analyse the approach under real cutting conditions and big machine assemblies with major heat capacities.

An application of a similar approach during process planning could allow a consideration of thermal impacts beside technological criteria. This could reduce the thermal changes caused by a single manufacturing task and achieve much more significant results then only to consider the concatenation. Challenging is here that technological and thermal criteria must be considered holistically, which could be an interesting subject for further research. Resent research in the field of digital twins for machining applications shows that the digital twin could provide a suitable platform for such holistic approaches, since it collects, structures and standardises manufacturing relevant information (Hänel et al., 2021).

Additionally, the presented approach can support the energy efficient control of cooling systems. Since cooling systems account for a large part of the machine tool's energy consumption, efforts are made to achieve demand-oriented cooling (Weber et al., 2021). Because of rather inefficient activation procedures of cooling systems, the temporal concentration of cooling relevant areas can lead to a decrease in the activation number and therefore increase the overall efficiency of the cooling system while maintaining thermal stability.

References

Brecher, C. (2016) 'Motivation und Überblick', in Brecher, C. (Ed): *Thermo-Energetische Gestaltung Von Werkzeugmaschinen*, Verlag Wissenschaftliche Scripten, pp.5–14.

Brecher, C., Bäumler, S., Jasper, D. and Triebs, J. (2012) 'Energy efficient cooling systems for machine tools', in Dornfeld, D.A. and Linke, B.S. (Eds.): *Leveraging Technology for a Sustainable World*, Berlin, Heidelberg, Springer Berlin Heidelberg, pp.239–244.

Großmann, K. and Ott, G. (2015) 'Introduction', in Großmann, K. (Ed.): *Thermo-Energetic Design of Machine Tools*, Cham, Springer International Publishing, pp.1–11.

Hänel, A., Seidel, A., Frieß, U., Teicher, U., Wiemer, H., Wang, D., Wenkler, E., Penter, L., Hellmich, A. and Ihlenfeldt, S. (2021) 'Digital twins for high-tech machining applications–a model-based analytics-ready approach', *Journal of Manufacturing and Materials Processing*, Vol. 5, No. 3, p.80.

Ihlenfeldt, S., Brecher, C., Putz, M. and Billington, D. (Eds.) (2018) *Conference on Thermal Issues in Machine Tools: Proceedings: CIRP Sponsored Conference, Dresden 2018*, Auerbach/ Vogtland Verlag Wissenschaftliche Scripten.

Jungnickel, G. (2010) *Simulation Des Thermischen Verhaltens Von Werkzeugmaschinen: Modellierung Und Parametrierung*, Dresden, Inst. für Werkzeugmaschinen und Steuerungstechnik Lehrstuhl für Werkzeugmaschinen.

Jurkschat, T., Otto, M., Lohner, T. and Stahl, K. (2018) 'Bestimmung des verlustverhaltens und der wärmebilanz von wälzlagern', *Forschung Im Ingenieurwesen*, Vol. 82, No. 2, pp.149–155.

Kauschinger, B. (2006) *Verbesserung Der Bewegungsgenauigkeit an Einem Hexapod Einfacher Bauart*, Dresden, TU Dresden.

Kauschinger, B. and Schroeder, S. (2014) 'Methods to design the adjustment of parameters for thermal machine-tool models', *Advanced Materials Research*, Vol. 1018, pp.403–410.

Kauschinger, B. and Schroeder, S. (2016) 'Uncertainties in heat loss models of rolling bearings of machine tools', *Procedia CIRP*, Vol. 46, pp.107–110.

Kirchner, H., Rehm, M., Quellmalz, J. and Schlegel, H. (2014) 'Energy efficient measures for drive cooling systems of a machine tool by use of physical simulation models', *58th Ilmenau Scientific Colloquium*, pp.1–13.

Mayr, J., Jedrzejewski, J., Uhlmann, E., Alkan Donmez, M., Knapp, W., Härtig, F., Wendt, K., Moriwaki, T., Shore, P., Schmitt, R., Brecher, C., Würz, T. and Wegener, K. (2012) 'Thermal issues in machine tools', *CIRP Annals*, Vol. 61, No. 2, pp.771–791.

Möhring, H-C., Brecher, C., Abele, E., Fleischer, J. and Bleicher, F. (2015) 'Materials in machine tool structures', *CIRP Annals*, Vol. 64, No. 2, pp.725–748.

Mori, K., Bergmann, B., Kono, D., Denkena, B. and Matsubara, A. (2019) 'Energy efficiency improvement of machine tool spindle cooling system with on–off control', *CIRP Journal of Manufacturing Science and Technology*, Vol. 25, pp.14–21.

Palmgren, A. (1957) 'Neue unteruchungen über energieverluste in wälzlagern', *VDI-Berichte: Bd.* 20, Düsseldorf, VDI-Verlag, pp.117–121.

Ramesh, R., Mannan, M. and Poo, A. (2000) 'Error compensation in machine tools – a review: part II: thermal errors', *International Journal of Machine Tools and Manufacture*, Vol. 40, No. 9, pp.1257–1284.

Riedel, M., Müller, J., Klatte, M. and Wenzel, C. (2016) 'Messtechnisch basierte ansätze zur korrektur thermisch bedingter verlagerungen', *4.Kolloquium Zum SFB/TR*69, Aachen.

Schroeder, S., Kauschinger, B., Hellmich, A., Ihlenfeldt, S. and Phetsinorath, D. (2019) 'Identification of relevant parameters for the metrological adjustment of thermal machine models', *International Journal on Interactive Design and Manufacturing (IJIDeM)*, Vol. 13, No. 3, pp.873–883.

Suh, S-H., Kang, S.K., Chung, D-H. and Stroud, I. (2008) *Theory and Design of CNC Systems*, London, Springer London.

Thiem, X., Kauschinger, B. and Ihlenfeldt, S. (2017) 'Structure model based correction of thermally induced motion errors of machine tools', *Procedia Manufacturing*, Vol. 14, pp.128–135.

Voigt, I., Navarro de Sosa, I., Wermke, B., Bucht, A. and Drossel, W-G. (2019) 'Increased thermal inertia of ball screws by using phase change materials', *Applied Thermal Engineering*, Vol. 155, pp.297–304.

Weber, J., Steiert, C., Weber, J. and Shabi, L. (2021) 'Investigation of the thermal and energetic behavior and optimization towards smart fluid systems in machine tools', *Procedia CIRP*, Vol. 99, pp.80–85.

Wenkler, E., Hellmich, A., Schroeder, S. and Ihlenfeldt, S. (2021) 'part program dependent loss forecast for estimating the thermal impact on machine tools', *MM Science Journal,* Vol. 2021, No. 3, pp.4519–4525.

Winkler, S. and Werner, R. (2015) 'Thermo-energetic motor optimisation', in Großmann, K. (Ed.): *Thermo-Energetic Design of Machine Tools*, Cham, Springer International Publishing, pp.223–231.

Website

SKF The SKF model for calculating the frictional moment [Online]. Available at https://www.skf.com/binaries/pub12/Images/0901d1968065e9e7-The-SKF-model-for-calculating-the-frictional-moment_tcm_12-299767.pdf (Accessed 24 November, 2021).