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Methodology for thermal optimization of motor spindles

Berend Denkena[1], Benjamin Bergmann[1], Heinrich Klemme[1]

[1]*Institute of Production Engineering and Machine Tools (IFW), Leibniz Universität Hannover, 30823 Garbsen, Germany*

klemme@ifw.uni-hannover.de

Abstract
Heat losses in motor spindles lead to thermal loads and thus to undesired effects on the spindle performance. To minimize these effects, the development of spindles must ensure a thermally advantageous design. Nowadays, a variety of software tools exist to support the design process. In particular, simulation models based on the Finite Element Method (FEM) have become widely established. Some commercially available simulation software offer specific tools for time-efficient optimization of multi-physical tasks. This article describes a methodology for an iterative optimization of the thermal behavior of a newly developed motor spindle applying these tools. An initial spindle is modelled, parameterized and thermally advantageous modification potential is identified by means of a parameter correlation analysis. The spindle is thermally optimized by appropriate adjustments to the design. The validity of the simulation model is evaluated by comparing the simulation results with experimental data of prototype analysis. The experimental findings are used to improve the simulation model by applying a parameter optimization. Lastly, improvements that could be achieved in the scope of an exemplary design iteration applying this methodology are shown.

Keywords: Motor spindle, FE-simulation, Thermal optimization

1. Introduction

The achievable accuracy in machining is significantly affected by the thermal properties of main spindle drives [1]. Today, motor spindles with roller bearings are mainly used in industrial practice [2]. Due to the conversion of electrical energy into mechanical energy, electrical losses occur in the motor resulting in heat. Bearing and fluid friction causes additional thermal load, which has an effect on the spindle system [3].

The effects of thermal loads can already be counteracted during the development phase of a spindle by skilfully selecting the design parameters. The variety of possibilities for improving the thermal behavior and the design parameters to be varied is large. Due to the high complexity of modern motor spindles and a wide range of available design parameters and materials, the identification and derivation of suitable measures for improvements is not trivial. Although simple, linear correlations can be quantified by analytical approaches. Such approaches fail with increasing complexity of the system. An analytical description of the thermal behavior of modern high-performance spindles is therefore not possible [4]. Simulations based on the Finite Element Method (FEM) have become widely established as a supporting tool for designers. Modern FEM programs offer possibilities for time-efficient modelling of multi-physical correlations. The determination of realistic parameter values, as well as sufficient mesh quality and a suitable modelling approach, is a challenge when developing simulations. If, however, a thermal model of a spindle exists, it can be used to improve its design with regard to the desired target values.

The aim of this project is to increase the maximum rotational speed or the initial bearing preload. Therefore, the temperature differences between inner and outer rings of the front and rear fixed bearing ($d\vartheta$ (FB_f), $d\vartheta$ (FB_r)) must be reduced [4]. In many simulation programs, analysis and optimization tools are already integrated to treat these problems. By using these tools, complex correlations between parameters and their interactions can be identified. Genetic algorithms can also be used to solve multicriterial thermal optimization tasks [5, 6]. In [7], a self-developed FE algorithm is used to optimize the dynamic behavior of a motor spindle. In [6], a genetic algorithm for the identification of realistic heat transfer coefficients is used to improve the thermal simulation model of a motor spindle.

In this article, a novel approach for multicriteria thermal optimization of a motor spindle is presented. Optimization measures are derived using a correlation analysis. The optimization is carried out manually within the scope of this work. As stated in[6], an additional optimization of the FE-model is carried out to improve the model validity. This is done by using a genetic algorithm. An illustration of the optimized spindle can be seen in Fig. 1. This concept with integrated lamellar heat exchangers and heat pipes is also shown in [8].

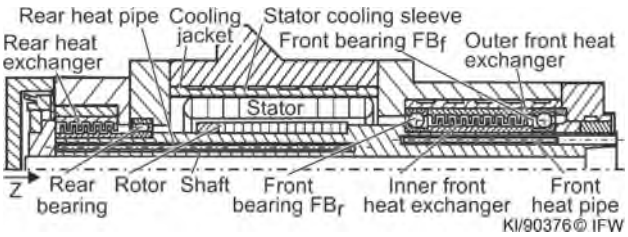

Figure 1. Considered spindle design according to Denkena et al. [8].

2. General approach

In the herein described design process, an initial spindle design is optimized in multiple design loops. The design loop is illustrated in Fig. 2. First, a primary CAD model of the spindle is geometrically simplified, so that a time-efficient meshing is possible for the next step. The model is then parameterized. During parameterization, thermal and mechanical boundary conditions are defined and modelled. In addition, material properties are associated to the bodies. Values of parameter inputs are determined analytically, experimentally and by considering tabular

data. The established simulation model is used to carry out a parameter correlation. This is done to quantify effects of model parameter value variations on the target parameter values ($d\vartheta$ (FB_f), $d\vartheta$ (FB_r)). The results of this parameter correlation are used for the direct manual optimization of the spindle design. This allows an initial improvement to be carried out at an early stage. For the purpose of this article, one spindle design was also prototypically realized. This prototype is described and metrologically evaluated in [8]. In addition, results of the experimental analyses are used to verify the simulation model and to improve the validity of the model parameters. Model parameters with improved validity were determined by applying an optimization algorithm. The aim of this optimization was to achieve a better agreement between simulation results and experimentally determined values (model fitting). Based on the verified and fitted simulation model, subsequent design iteration could be simulated with increased validity. The process of spindle design optimization ends when certain target values of the target parameters ($d\vartheta$ (FB_f), $d\vartheta$ (FB_r)) are reached or no significant optimization progress can be stated. In the following chapters, the individual steps of an exemplary design loop with prototype verification are explained in more detail.

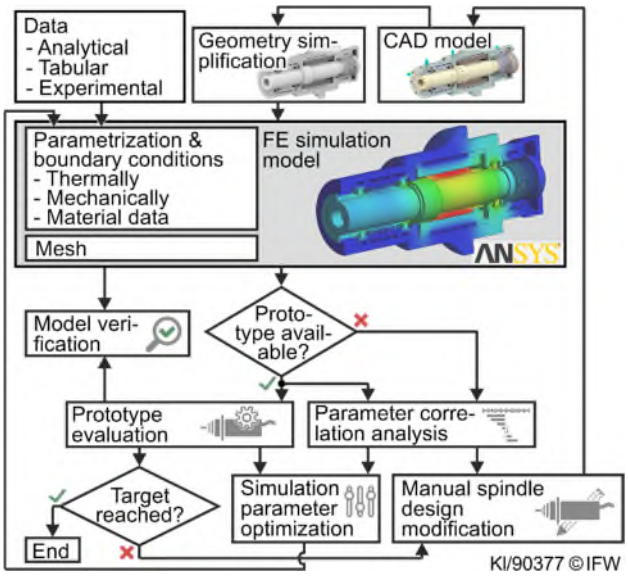

Figure 2. Process of spindle design optimization.

3. Simulation model

Simulations were carried out time-independently since only steady-state values were relevant. First, an initial CAD drawing of the spindle was geometrically simplified. This facilitated subsequent meshing and reduced the model size. During simplification, chamfers, undercuts, screw as well as through and blind holes were removed. Bearing rolling elements were modelled according to [9] as circumferential bodies. The sufficient meshing of bodies was ensured by a mesh study following the modelling and parameterization. The spindle was modelled according to [10]. Parameter values were determined according to Tab. 1. Analogy parameters were defined to simplify the parameterization. For example, material thermal conductivities were varied, instead of varying a body's wall thickness. A decrease of material conductivity led to a proportional decrease of thermal resistance. By reducing the length of heat transport by the same percentage, the same quantitative effect was achieved due to the linear correlation between thermal resistance and length of heat transport. Consequently, the influences of the spindle components' wall thicknesses could be evaluated by varying their materials' thermal conductivities instead of varying the geometry itself.

Table 1. Sources for the determination of parameter values.

Model parameter	Source
Convection at rotating cylinders, cooling channels, ambient	[11]
Convection in air gap of two cylinders	[12]
Convection at rotating discs	[13]
Convection on rolling bearing elements	[14, 15]
Heat transfer between bearing elements	[16]
Heat transfer coefficient, heat exchanger & conductivity heat pipes	experimental
Heat losses of bearings & motor	manufacturer
Heat transfer between solid bodies	[17, 18]

In consultation with the spindle manufacturer, variable design parameters and their value ranges were agreed according to this procedure. Tab. 2 summarizes some of these parameters and their values determined for one load case (20 000 rpm, idle run) according to Tab. 1. The heat transfer parameters were parameterized using an APDL script so that they could be used and varied for the following parameter correlation analysis and parameter optimization.

Table 2. Considered control parameters and initial values (20 000 rpm)

Nb.	Control parameter	Initial value
P1	Heat transfer coefficient inner lamellas – outer lamellas of heat exchanger front	185 W/m²/K
P2	Heat transfer coefficient outer front heat exchanger – outer bearing ring FB_r	5 200 W/m²/K
P3	Thermal conductivity heat pipes front	10 000 W/m/K
...	...	...
P41	Thermal conductivity material outer heat exchanger lamellas at front	120 W/m/K
P42	Thermal conductivity stator cooling sleeve material	43 W/m/K

4. Parameter correlation

The parameter correlation is based on the determination of the thermal transfer functions between individual control and target parameters. For this purpose, the value of each control parameter is varied around an initial value. The values of other parameters remain constant. The effect of this parameter value change on the target value change is then determined. The target parameters are given by $d\vartheta$ (FB_f) and $d\vartheta$ (FB_r). The control parameters and their initial values are defined according to Tab. 2. Within the scope of this work, the parameter correlation according to Pearson [19] is used. The Pearson correlation determines the magnitude of a linear correlation between two parameters. The determined significance S adopts values between -1 and +1. It is approximately 0 if there is no correlation at all. A negative value indicates a shift of the target parameter value to lower values due to an increasing control parameter value. An increase of the target parameter value due to an increasing value of the control parameter results in positive values of S.

Before the correlations are calculated, a lower and upper value limit (P_- and P_+) of the variation range must be defined for

each parameter. The range size $|P_+ - P_-|$ has significant influence on the results of the parameter correlation. It is particularly important to determine the initial parameter values as realistically as possible. If these are determined insufficiently, non-linear correlations between control and target parameters may result in considerably lower or higher significance of a control parameter than actually present. If the parameter values do not have to be defined stepwise due to technical reasons (e.g. number of heat pipes (see [8]), it is advisable to define relatively equal limits for each parameter [20]. For the purpose of this investigation, the initial values of each parameter were varied by ± 15% as this is the average expected inaccuracy of the parameter value determination. The prioritized target parameter in this work is $d\vartheta$ (FB_r) since the temperature rise of the inner ring of the fixed bearing close to the motor is particularly critical due to its proximity to the motor's secondary part. The number of applied samples for the correlation analysis is 100.

The results of the parameter correlation are shown as bar charts in Fig. 3. A significant decrease of both target values is achieved by increasing the value of design parameter P1 from P_- to P_+. This is indicated by the relative significances S which are -0.66 for FB_r and -0.36 for FB_f. Thus, an optimization of the heat transfer behavior of the fin-shaped heat exchangers leads to a significant decrease of the temperature differences as more heat is transferred from both inner bearing rings. Increasing P2 results in a comparatively high increase of 0.15 for $d\vartheta$ (FB_r). The effect of P2 on $d\vartheta$ (FB_f) is less significant. However, increasing P2 leads to lower values of $d\vartheta$ (FB_f). This is due to increased heat transport between the outer bearing ring of FB_r, which reduces the outer ring temperature of FB_r. However, this leads to an increased heating of the outer front heat exchanger. Hence, temperature difference between the outer front heat exchanger and the outer bearing ring of bearing FB_f is reduced. This in turn leads to a decrease of $d\vartheta$ (FB_f). Increasing the value of P3 leads to a significance of -0.13 for $d\vartheta$ (FB_r). The effect on $d\vartheta$ (FB_f) is negligible with a value of 0.02. Better heat conduction of the heat pipes results in increased heat transfer from FB_r in direction of FB_f. As a result, $d\vartheta$ (FB_r) is reduced and the front area of the spindle heats up. This leads to an increase of $d\vartheta$ (FB_f). Increasing the values of P41 and P42 leads to an increase of S and thus an increase of target parameter values. These effects, however, are minor.

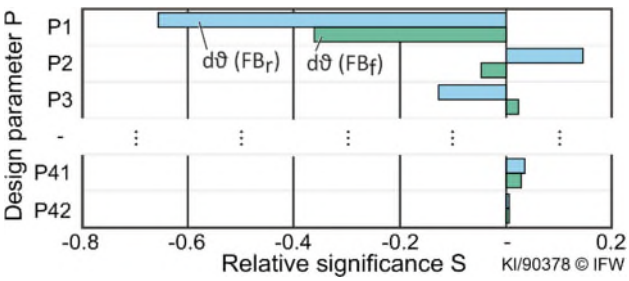

Figure 3. Parameter correlations with determined significances.

The results of this correlation analysis are used to derive measures for optimizing the spindle design. The adequate order of the optimization steps is based on the level of the determined significances. The optimization of a parameter with high significance is prioritized. However, the spindle designer must consider the degree to which a parameter value can be changed. Otherwise, inadequate changes of geometrical or material parameters may worsen the mechanical behavior. In addition, the manufacturability and assembling ability as well as other cost-related effects of design changes must be evaluated and taken into account by the designer.

5. Model fitting

The aim of the model fitting is to adjust the simulation parameters in such a manner that the simulated temperature values correspond as closely as possible to the measured temperatures. For this purpose, ANSYS provides a toolbox for handling multi-criteria optimization tasks. A particular challenge of parameterization is the dependency of parameters on mechanical and thermal load variations as well as variations of other boundary conditions [2]. The model fitting was therefore only carried out for the thermally most critical load case at 20 000 rpm.

Prior to optimization, the simulation parameters were parameterized so that they could be varied in the optimization algorithm. The procedure is similar to that of the correlation analysis in chapter 4. Instead of design parameters, however, thermal loads of the bearings and the motor as well as the convection coefficients values and heat transfer coefficients were varied. The thermal conductivities of the materials were also parameterized. For the optimization of the parameters, the genetic MOGA algorithm (multi-objective genetic algorithm) was applied. This algorithm was implemented in ANSYS. MOGA is a variant of the NSGA-II algorithm (non-dominated sorted genetic algorithm-II), based on the controlled elitism concepts [21]. By searching for global optima, several optimization goals can be defined.

In the simulation, temperature values were obtained as target values. These points correspond to the sensor locations in the experimental investigation of the spindle prototype. In the experimental analysis of the prototype, the temperatures of the bearing inner and outer rings were determined. The experimentally determined temperatures served as constraints for the optimization. The algorithm attempted to achieve the specified constraints by varying the parameter values within these limits. The principle of this optimization is shown in Fig.4.

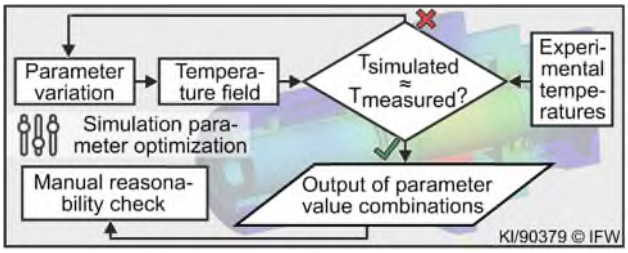

Figure 4. Simulation model optimization principle.

A range for each parameter, in which its values are to be varied, must be defined prior to optimization. The upper and lower limits of a parameter value result from uncertainties to be expected when determining the initial value. The limits of the parameter value ranges were defined by values of ± 30% of the initial value in this paper. By considering this comparatively wide range, possible global optima located further away from the previously determined parameter values were also taken into account. Otherwise, it is possible that the optimal approximation of actual parameter values could not be determined by the optimization algorithm. This may occur especially in cases where a precise determination of parameter values is difficult. Especially the convection boundary conditions of high-speed bearings and contact heat transfer parameter are difficult to determine [2]. As a result of the optimization, several parameter value combinations were obtained, achieving similar simulation results. If parameter values of different parameter value combinations are nearly similar, it can be assumed that these values are more likely to be physically valid. If individual or several values differ significantly, the relevance of the affected parameters must be

weighted and evaluated using a correlation analysis. Such a correlation analysis of the simulation parameters was carried out automatically in ANSYS during the optimization, analogous to chapter 4. If the parameter significance is high, the value determined by the optimization algorithm must be adjusted with higher priority to the respective optimized value. Consequently, deviations from values of a parameter with high significance lead to particularly high deviations between simulation and experiment. Parameters with low significances < ± 0.1 are not considered to optimize the model. Values of parameters with low significances vary when comparing different parameter sets and can often already be identified in this way. These parameters were kept to their previously determined values. Due to the widely selected value range of some parameters, individual parameters may dominate disproportionately. This makes it difficult to interpret the optimization results. Nevertheless, this procedure is particularly suitable for identifying parameters with very low significances.

6. Evaluation of the methodology

An initial spindle design was optimized in several steps according to the procedure described above. Fig. 5 illustrates the result of an exemplary optimization of a design i to a design i+1. A design i was initially used for the simulative evaluation of optimization measures. By simulating the load case at 20 000 rpm, the temperature differences (ϑ_i - ϑ_o, see Fig. 5 top) were determined with $d\vartheta$ (FB_f) = 14.8 K and $d\vartheta$ (FB_r) = 16.0 K. Based on the knowledge obtained from the simulations, the spindle design was then optimized by the spindle manufacturer. The optimized design i+1 was again simulatively evaluated and also prototypically realized. The metrological evaluation of the design i+1 can be found in [8]. The temperature differences of the design i+1 $d\vartheta$ (FB_f) and $d\vartheta$ (FB_r) were determined to be 7.5 K and 8.2 K, respectively. The results of the metrological analyses were used to validate the i+1 simulation model. The deviations between simulated and experimentally determined values were 1.7 K ($d\vartheta$ (FB_f)) and 2.7 K ($d\vartheta$ (FB_r)). So far, no model fitting has taken place. For this reason, the agreement between simulation and experiment is very good. The experimental results were used in the further course of the project to carry out a fitting according to chapter 5. The fitted model was then used for more precise simulation of further optimization potential. The methodology of further optimization steps is similar to those described in this article.

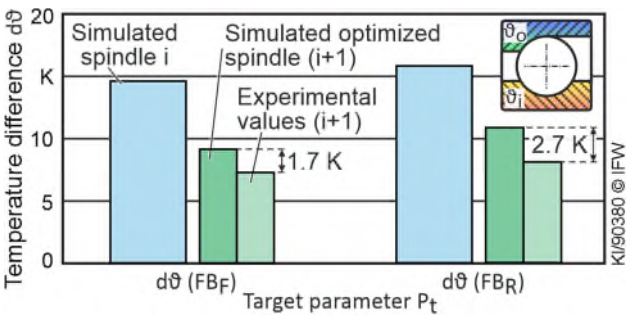

Figure 5. Evaluation of the simulation and optimization measures.

7. Conclusion and outlook

In this article, a methodical approach for the iterative thermal and thermo-elastic optimization of a motor spindle design was presented. With the help of an FE model and a parameter correlation analysis, parameters, which had significant effects on the defined target values, were first identified. These findings were used to optimize the design. In addition, the results of the parameter correlation were used to optimize the FE model. The optimization was carried out with the help of a multi-criteria optimization algorithm. Experimentally determined values of a prototype were used to define target functions for the algorithm. This fitting improved the validity of the model parameters and thus the interpretability of the simulated significances. This methodology was used to optimize the spindle shown in [8] so that the highest possible efficiency of the therein applied heat transfer elements was achieved. By applying this method, simulatively determined temperature differences between the bearing inner and outer rings of the front fixed bearing were reduced by 38% and those of the rear fixed bearing were reduced by 31%.

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