**QUEEN'S
UNIVERSITY
BELFAST**

Structural design optimization of moving component in CNC machine tool for energy saving

Li, C., Ji, Q., Zhu, D., Jin, Y., Lv, Y., & He, J. (2019). Structural design optimization of moving component in CNC machine tool for energy saving. *Journal of Cleaner Production*. <https://doi.org/10.1016/j.jclepro.2019.118976>

Published in:
Journal of Cleaner Production

Document Version:
Peer reviewed version

Queen's University Belfast - Research Portal:
[Link to publication record in Queen's University Belfast Research Portal](#)

Publisher rights

Copyright 2019 Elsevier.

This manuscript is distributed under a Creative Commons Attribution-NonCommercial-NoDerivs License

(<https://creativecommons.org/licenses/by-nc-nd/4.0/>), which permits distribution and reproduction for non-commercial purposes, provided the author and source are cited.

General rights

Copyright for the publications made accessible via the Queen's University Belfast Research Portal is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy

The Research Portal is Queen's institutional repository that provides access to Queen's research output. Every effort has been made to ensure that content in the Research Portal does not infringe any person's rights, or applicable UK laws. If you discover content in the Research Portal that you believe breaches copyright or violates any law, please contact openaccess@qub.ac.uk.

Journal Pre-proof

Structural design optimization of moving component in CNC machine tool for energy saving

Congbo Li, Qianqian Ji, Daoguang Zhu, Yan Jin, Yan Lv, Jixiang He

PII: S0959-6526(19)33846-6

DOI: <https://doi.org/10.1016/j.jclepro.2019.118976>

Reference: JCLP 118976

To appear in: *Journal of Cleaner Production*

Received Date: 26 March 2019

Revised Date: 17 August 2019

Accepted Date: 19 October 2019

Please cite this article as: Li C, Ji Q, Zhu D, Jin Y, Lv Y, He J, Structural design optimization of moving component in CNC machine tool for energy saving, *Journal of Cleaner Production* (2019), doi: <https://doi.org/10.1016/j.jclepro.2019.118976>.

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2019 Published by Elsevier Ltd.

Structural design optimization of moving component in CNC machine tool for energy saving

Congbo Li^{a,*}, Qianqian Ji^a, Daoguang Zhu^a, Yan Jin^b, Yan Lv^a, Jixiang He^a

^a State Key Laboratory of Mechanical Transmission, Chongqing University, Chongqing 400044, China

^b School of Mechanical and Aerospace Engineering, Queen's University Belfast, Belfast BT9 5AH, UK

Abstract: With the increase of energy price and environment problem, the energy consumption of machine tool is attracting more attention. The moving components of machine tools consume a large amount of energy in the operating stage. Structure optimization of moving components is a key strategy for energy saving in machine tools design. Traditionally, structural optimization of machine tools is carried out for reducing energy consumption or improving static and dynamic performance. Given that these factors are important to the structure optimization in machine tools design, this paper presents a structural design optimization method for comprehensively considering energy consumption, static and dynamic performance of machine tool. Firstly, the energy consumption model of the moving components is proposed, and the structural performance indicators of the moving components are analyzed. Then, based on the experiment data obtained by uniform design method, five structure parameters that have great influence on performance indicators are selected as decision variables through sensitivity analysis. To improve the computation efficiency, approximation functional relationship between the five decision variables and the four performance indicators are built through response surface method (RSM). After that, an optimization objective is formulated by combining the four performance indicators through principal component analysis (PCA). Finally, a new hybrid algorithm which integrates Simulated Annealing (SA) and Particle Swarm Optimization (PSO) algorithm is developed to solve the structure optimization problem. Through calculation and analysis, it is found that there is a linear relationship between the moving part mass and energy consumption. The results show that the energy consumption of optimized structure is reduced while ensuring the static and dynamic performance.

Key words: Energy-saving design, Moving components, Structural optimization, Static and dynamic performance

1 Introduction

With the development of manufacturing industry, wide attention has been paid to energy and global environment. According to relevant statistics, the manufacturing sector is responsible for about 33% of the primary energy use and for 38% of the CO₂ emissions globally (Li et al, 2019). Machine tools, as a major part of the manufacturing sector, have the low energy efficiency. Previous studies have estimated that only 10-15% of this amount is consumed by machine tools for machining operations (Apostolos et al., 2013). An example given by GUTOWSKI indicated that the energy efficiency of machine tools is only 14.8% (Gutowski et al., 2009). In recent years, many researchers and organizations have put forward corresponding policies and regulations in order to improve the energy efficiency of machine tools. For the operating stage, Li et al. (2017) and Xiao et al. (2019) reduced energy consumption of machine tools with process parameters optimization for energy efficient milling and turning. For the design stage, Next Generation Production Systems is to produce green machine tools with high energy efficiency (Bueno, 2013). International Organization for Standardization (ISO) has issued a set of standards ISO 14955 machine tool environmental protection evaluation to guide machine tool designers to design high-efficient

and energy-saving machine tools (ISO 14955-1, 2017). Research investigates that the energy consumption of machine tools considered in the design stage can effectively improve the energy efficiency of machine tools in the operating stage and reduce the impact on the environment. The design optimization of machine tools has attracted interests due to the increasing processing requirement and the rising energy crisis. The existing research on machine tools design can be divided into two categories.

A first group of research focused on structure optimization of machine tools for improving the static and dynamic performance of machine tools. Wang et al. (2017) presented a novel integrated framework for design and optimization of a machine tool structure. By using response surface method (RSM) to optimize the structural parameters in a four-axis horizontal machining center, the results showed that total weight of the entire machine was minimized by 8.14% while sufficient static and dynamic stiffness was maintained even increased by 5.59%. The study conducted by Liu (2015) had some resemblance to Wang et al.'s, the orthogonal experimental design method and RSM were adapted to achieve lightweight design of structural parts. The mass of machine tool was reduced by 8.19% while the reduction of maximum deformation and maximum stress was near 8% as well as the increase of first natural frequency was 12.15%. Park et al. (2011) used an integrated design strategy based on individual modeling and simulations of key parameters (i.e. volumetric error and machine working space, as well as thermal, static and dynamic stiffness) for ensuring good microscale machine performance and providing proper dimensions for miniaturized milling machine. Law et al. (2013) developed an efficient dynamic model of a machine tool to evaluate and improve dynamic performance at the design stage. Targeted productivity 25% was achieved with 15% mass reduction. Li et al. (2014) introduced a novel approach for designing the stiffener layout inside large machine tools by applying the self-optimal growth principle of plant ramifications in nature, which offered unique possibilities of improving first natural frequency 18.55% and reducing maximum deformation 23.6% for stiffened machine tools structure.

A second group of research investigated the structural optimization of machine tools for reducing processing energy. For instance, He et al. (2015) found that the decisions made at the design stage of machine tools has a profound impact on energy consumption and carbon footprint in the operating phase of its life cycle. Kroll et al. (2011) discussed the general influence of lightweight design approaches on energy efficiency in machine tools, and it showed that a load reduction of 30% is resulted from the lower electrical power losses of a servo drive. A similar study was conducted by Zulaika et al. (2011) where an integrated approach was provided for designing large milling machines, and dealt with the design of the machine in order to achieve the targeted productivity while consuming 13% less energy due to 20% mass reduction of structural components. Bustillo et al. (2015) outlined a comprehensive design methodology to reduce energy consumption of machine tool. Tests showed that energy consumption was reduced by 35% during no-load motions of the tool, while maintaining or even increasing productivity. He et al. (2016) also stated that the lightweight design was a valid approach to achieve low-carbon footprint. The lightweight of machine body was realized on the basis of structure and mode analysis with minimizing the mass of machine body as the optimization objective. Results showed that the smaller the mass of machine body, the less carbon footprint. In these studies, very little about the energy consumption model has been proposed to optimize moving components of machine tools for energy saving. It is shown that the energy consumption factor is not taken into account in the optimization model, thus the energy consumption of machine tools can not be minimized.

At present, finite element method is widely used in structure optimization of machine tools for reducing the weight of machine tools (Ding et al., 2010). When the structural parameters are changed, it is necessary to rebuild the 3D model, exert boundary conditions and solve results. This repeated calculation

normally takes a long time, resulting in the decrease of efficiency. In the herein paper, finite element method is only used to assess dynamic and static performance at the beginning. Then, the approximation relationship between the structure parameters and the performance indicators are constructed through fitting method, thereby directly computing performance indicators including energy consumption, first natural frequency, maximum deformation and maximum stress based on functional relation. RSM can model the response in terms of significant parameters, their interactions and square terms (Rajeswari and Amirthagadeswaran, 2017). For instance, Liu (2015) built the response surface approximation model of machine tool slide-seat's optimization design. Iqbal et al. (2016) concluded that RSM can predict the effect of parameters on response and was a better tool for optimization. To reduce the complexity and increase the computation efficiency, the method for dimension reduction is employed to establish an optimization objective combining the four indicators. Principal component analysis (PCA) is a dimensionality-reducing multivariate statistical method, which can more easily capture the main contradiction of things and simplify the problem (Huang et al, 2019), and is conducted in this paper with consideration of a clear correlation between the four performance indicators.

A perusal of current literature concludes that the existing researches about structure optimization of machine tools are more concentrated on structural performance such as static performance and dynamic performance. While some efforts have been made to reduce weight of machine tools, resulting in the reduction of energy consumption. The interactions between mass and energy consumption of machine tools is complicated. However, there is very little work which explores such relationship in depth. In addition to energy consumption, different structure parameters would also show major impacts on the structural performance, which has great influence on processing performance of machine tool. Motivated by these remarks, this paper attempts to fill the research gap and makes contribution in the following three aspects. Firstly, the energy characteristics of moving components in machine tools is explicitly modeled, and a structural optimization design model of moving components is developed by taking energy consumption, static and dynamic performance as objective. Secondly, four methods, including uniform design method, sensitivity analysis, RSM and PCA, are integrated to comprehensively establish the structure optimization model of moving component, which can better reveal the interaction mechanism of structure parameters on energy consumption and structural performance. Thirdly, a hybrid algorithm that combines PSO with SA is proposed to solve the optimization model, which can greatly improve the convergence speed and guarantee the global search ability.

The rest of the paper is organized as follows. Section 2 presents a process of optimizing the structure of moving components for energy saving, and the optimization indicators of moving components is expounded. Section 3 establishes a comprehensive performance optimization model of machine tool moving components. Section 4 develops a hybrid algorithm to solve the optimization model, and analyzes the optimization results, followed by the conclusion in section 5.

2 Energy consumption function of moving component

The feed driving system of a CNC machine tool mainly consists of servo motor and mechanical transmission, and the latter is composed of an axial joint, screw, nut, guide rail, slider and moving components, a typical case is shown in Fig. 1.

Fig.1 Feed driving system of CNC machine tool

The movement of feed drive system of machine tools includes two directions, one is horizontal motion, and the other is vertical motion (Hendrawan et al., 2018). In the two motion types, the vertical motion has the same motion direction as gravity, and the mass of moving components is more sensitive to energy consumption (Yoon et al., 2018). Thus, this paper mainly formulates energy consumption model for vertical driving system by analyzing the kinematics and dynamics characteristics. The kinematic diagram of feed driving system is shown in Fig. 2.

Fig. 2 The kinematic diagram of feed driving system

The power of the drive system is supplied by the servo motor. The dynamic equation of the motor shaft is shown as Eq. (1) (Chen et al., 2004).

$$\vec{T}_m = J_m \frac{d\vec{\omega}_m}{dt} + B_m \vec{\omega}_m + \vec{T}_l \quad (1)$$

where J_m is the rotary inertia of the motor shaft. ω_m is the angular velocity of the servo motor. B_m is the damping coefficient of the servo motor. T_l is the output torque of the servo motor.

The axial joint transfers the torque of the servo motor to the ball screw and increases the torque with transmission ratio. The dynamic equation of axial joint is shown as Eq. (2).

$$\vec{T}_l = J_l \frac{d\vec{\omega}_m}{dt} + \frac{1}{i\eta_l} \vec{T}_{ls} \quad (2)$$

where J_l is the moment of inertia of the coupling. i is the transmission ratio of the coupling. η_l is the axial joint efficiency. T_{ls} is the output torque of the coupling, which is used to drive the ball screw to rotate.

The leadscrew transforms the rotation of the coupling into the linear motion of the moving components, and converts the output torque of the coupling into the power of the moving components. The dynamic equation of the leadscrew is shown in Eq. (3).

$$\vec{T}_{ls} = J_{ls} \frac{d\vec{\omega}_{ls}}{dt} + \frac{1}{\eta_t} \vec{T}_t \quad (3)$$

where J_{ls} is the moment of inertia of the ball screw. ω_{ls} is the angular velocity of the ball screw. η_t is ball screw efficiency. T_t the output torque of ball screw, as denoted in Eq. (4).

$$\vec{T}_t = \frac{L}{2\pi} \vec{F}_t \quad (4)$$

where L is the ball screw pitch. F_t is load of moving component.

The load of moving components consists of inertia force, gravity, guideway friction force and cutting

force, as expressed in Eq. (5). When the moving component moves along the guideways, friction force is generated between guideways and sliders, as modeled in Eq. (6).

$$\vec{F}_t = (M_t + M_a) \frac{d\vec{v}}{dt} + (M_t + M_a) \vec{g} + \vec{F}_{friction} + \vec{F}_{cutting} \quad (5)$$

$$\vec{F}_{friction} = \mu_v \cdot \vec{v} + \mu_c \vec{F}_N \quad (6)$$

where M_t and M_a is the mass of moving components and additional components, respectively. v is velocity of moving component. g is the gravity acceleration. $F_{friction}$ is the friction force on guideways. $F_{cutting}$ is the cutting force. μ_v is the viscous friction coefficient. μ_c is the coulomb friction coefficient. F_N is the equivalent force exerted on guideway by moving component.

$$\vec{F}_N = 4 \cdot \frac{(M_t + M_a) \left(\vec{g} + \frac{d\vec{v}}{dt} \right) (l_3 + l_4) + \vec{F}_{cutting} (l_3 + l_5)}{2 \cdot l_1} \quad (7)$$

where l_1 is the distance between the two sliders. l_2 is the distance between the two guideways. l_3 is the distance from the center of gravity of accessory to the axis of ball screw. l_4 is the distance from the center of gravity of accessory to the centre line of moving component. l_5 is the distance from the action point of cutting force to the centre line of moving component.

Cutting force will be generated in gear hobbing, which is closely related to cutting parameters and can be expressed in Eq. (8).

$$\left| \vec{F}_{cutting} \right| = 18.2m^{1.75} z^{0.27} a_p^{0.81} f_z^{0.65} |v_c|^{-0.26} K_1 K_2 K_3 / d \quad (8)$$

where m the normal modulus of hob. z is the number of teeth of the gear. a_p is the cutting depth. f_z is the axial feed rate of hob. v_c is the cutting speed of hob. d is the outer diameter of hob. K_1 , K_2 and K_3 are the correction coefficients of workpiece.

The velocity of moving component is associated with the speed of ball screw, as expressed in Eq. (9).

$$\vec{v} = L \frac{\vec{\omega}_{ls}}{2\pi} \quad (9)$$

The angular velocity of ball screw ω_{ls} is related to the angular velocity of servo motor, which can be modelled as Eq. (10)

$$\vec{\omega}_m = i \vec{\omega}_{ls} \quad (10)$$

where i is gear ratio of the coupling.

The dynamic equation of the motor shaft can be formulated by summing up Eqs. (1) - (10), as elaborated in Eq. (11).

$$\begin{aligned} \vec{T}_m = & (J_m + J_l + \frac{J_{ls}}{i^2 \eta_l} + \frac{P^2 \mu_c (l_3 + l_4) M_a}{2\pi^2 i^2 \eta_l \eta_t l_1}) \frac{d\vec{\omega}_m}{dt} + \frac{P^2 (M_a + M_t)}{4\pi^2 i^2 \eta_l \eta_t} \frac{d\vec{\omega}_m}{dt} + (B_m + \frac{P^2 \mu_v}{4\pi^2 i^2 \eta_l \eta_t}) \vec{\omega}_m \\ & + \frac{P}{2\pi i \eta_l \eta_t} (M_a + M_t) \vec{g} + \frac{P \mu_c (l_3 + l_4)}{\pi i l_1 \eta_l \eta_t} M_a \vec{g} + \frac{P[2(l_3 + l_5) + l_1]}{2\pi i l_1 \eta_l \eta_t} \vec{F}_{cutting} \end{aligned} \quad (11)$$

According to the relationship among output power, output torque and angular velocity of servo motor, $P_{out} = T_m \cdot \omega_m$, the output power of the servo motor can be obtained, as denoted in Eq. (12).

$$P_{out} = (J_m + J_l + \frac{J_{ls}}{i^2 \eta_l}) |\vec{\omega}_m| \cdot \frac{d \vec{\omega}_m}{dt} + \frac{P^2 (M_a + M_t)}{4 \pi^2 i^2 \eta_l \eta_t} |\vec{\omega}_m| \cdot \frac{d \vec{\omega}_m}{dt} + (B_m + \frac{P^2 \mu_v}{4 \pi^2 i^2 \eta_l \eta_t}) |\vec{\omega}_m|^2 + \frac{P \mu_c}{2 \pi i \eta_l \eta_t} (M_a + M_t) |\vec{g}| \cdot |\vec{\omega}_m| + \frac{P(2l_4 + l_1)}{2 \pi i l_t \eta_l \eta_t} |\vec{F}_{cutting}| \cdot |\vec{\omega}_m| \quad (12)$$

As a result, the energy consumption function of feed drive system is obtained, as shown in Eq. (13).

$$E(t) = \int_0^t P_{out} dt \quad (13)$$

where t is the working time of feed drive system.

3 Multi-indicator optimization model

Energy consumption optimization of moving components is a non-deterministic polynomial problem with nonlinear, multivariable, multi-indicator, constrained and coupled properties. In view of this, this paper integrates four methods- uniform design method, sensitivity analysis, RSM and PCA to efficiently analyze experimental data and propose a comprehensive optimization model. Firstly, the structure parameters are preliminarily selected by analyzing the geometric model of moving components, and the optimization indicators are preliminarily determined. Secondly, based on the uniform design method and sensitivity analysis, the parameters which have great influence on the indicators are selected as decision variables. Then, RSM models are built to approximate indicator functions, and a comprehensive performance objective is established with combining the performance indicators through PCA. Finally, a multi-indicator optimization model is easy to acquire. Fig. 3 illustrates the framework of the optimization model.

Fig. 3 Framework of the optimization model

In order to better understand the modeling process, this paper takes the high-speed dry-cutting hobbing machine as an example to illustrate the modeling process in detail. Fig. 4 shows the structure of moving component in the hobbing machine, and Table 1 lists the specifications of the hobbing machine. The moving components of high-speed dry-cutting hobbing machine tool have high speed, especially in the direction of axial feed, and the mass of moving components is also very large. The optimization of moving components with axial feed motion has great energy saving potential (Campatelli et al., 2015), which is of important significance to the structure optimization of machine tools.

Fig. 4 high speed dry-cutting hobbing machine tool

Table 1 Specifications of the hobbing machine

Item	Value
Maximum machining diameter	210(mm)
Maximum machining modulus	4(mm)
Stroke of tool slide	300(mm)
Maximum radial velocity	8000(mm/min)
Maximum axial velocity	4000(mm/min)
Maximum tangential velocity	2000(mm/min)
Total weight of machine tools	12000(kg)

3.1 Preliminary determination of parameters and indicators

3.1.1 Structure parameter

The 3D model of the moving component is a multi-body structure with complex features. In order to facilitate analysis, some small features that have little influence on the use condition are simplified, such as chamfers, rounded corners, etc. In order to ensure the installation conditions of the moving component unchanged, the external dimensions of the moving component are considered to be constant, and the internal dimensions are designed for structure optimization of moving component. It is preliminarily determined that the structure parameters are base plate thickness x_1 , x_2 , front slope width x_4 , box thickness x_3 , x_5 , inner ring thickness x_7 , x_8 , x_9 , rib thickness x_6 , x_{10} , as shown in Fig. 5.

Fig. 5 Primary structure parameters of moving component

3.1.2 Performance indicator

Moving components play an important part in machine tools. Their energy consumption, static and dynamic characteristics directly affect the energy efficiency, processing ability and processing quality of the whole machine tools. Therefore, the energy consumption is considered as an optimization indicator as modeled in Eq. (13), as well as the key dynamic and static performance indicators should be taken into account to optimize the moving components.

(1) Dynamic performance

Dynamic performance of machine tool is the properties and characteristics of the machine tool structure under dynamic load, and dynamic performance indicators mainly include vibration modal and damping. The natural frequencies in vibration modal of machine tool structure is expressed as Eq. (14)

$$[-f_i^2[M] + [K]] = 0 \quad (14)$$

where $[M]$ is mass matrix, $[K]$ is stiffness matrix, and f_i is the i th natural frequency.

The damping matrix $[C]$ is assumed to be proportional to the mass and stiffness matrices, which can be obtained by Eq. (15).

$$[C] = \alpha_R[M] + \beta_R[K] \quad (15)$$

where α_R and β_R are coefficients for the mass and stiffness, respectively.

Even though the static performance of a machine tool meets the requirements of the design standard, its dynamic performance will also affect the machine tool machining accuracy and workpiece surface quality (Altintas et al., 2005). Moving components are the key parts of machine tools, their dynamic performance determine the machining accuracy of machine tools. In the machining process, the change of cutting force induces resonance of machine tools, which aggravates tool wear, reduces the surface quality and affects machining accuracy of machined workpieces.

Modal analysis determines the mode shapes and natural frequencies, which can identify weak links of machine tools. Natural frequency is an evaluation index of structural dynamic performance, in which the first natural frequency is lower and is easy to resonate with the external excitation frequency, which influences the machining accuracy and surface quality (Yu et al., 2010). In the context of dynamic motions and rigidity, one of the most important parameters is the first natural frequency, which indicates the dominant motion (Son et al., 2010). Since damping has little effect on natural frequency and mode shape, the value of damping is set as zero. In this paper, the first natural frequency 316.66Hz is close to the excitation frequency 150Hz, which is easy to cause resonance. Therefore, the first natural frequency of the moving component is taken as a key indicator to improve the dynamic performance. Moreover, the improvement of the first natural frequency can improve the processing performance of the machine tools.

$$H(x) = \max[f_1] \quad (16)$$

where f_1 is the first natural frequency of the moving component.

(2) Static performance

The static performance refers to the characteristics of the machine tool structure under constant load, and static performance indicators include deformation and stress. The node deformation of machine tool structure is modeled in Eq. (17).

$$[K]\{\Delta\} = \{F\} \quad (17)$$

where $[K]$ is stiffness matrix, $\{\Delta\}$ is deformation vector, $\{F\}$ is external load vector.

The stress of machine tool structure is related to the deformation, as expressed in Eq. (18).

$$\{\sigma\} = [D][B]\{\Delta\} \quad (18)$$

where $\{\sigma\}$ is stress vector, $[D]$ is elasticity matrix, $[B]$ is strain matrix.

When moving components are subjected to static and invariable loads, the deformation and stress of moving component have an impact on machining accuracy and working stability of machine tools (Liu, 2015). Under the same working load, the smaller deformation and stress of moving component are, the better the static performance of machine tool is. Therefore, as the crucial static performance indicators, the maximum deformation and maximum stress of the moving component should be minimized.

$$F(x) = \begin{cases} \min[\Delta_{\max}] \\ \min[\sigma_{\max}] \end{cases} \quad (19)$$

where $\Delta_{\max}$ is the maximum deformation of moving component. $\sigma_{\max}$ is the maximum stress of moving component.

3.2 Decision variable

It can be seen from Section 3.1 that there are many structure parameters in the primary selection. But it is very difficult to optimize many structure parameters at the same time. Moreover, some parameters have little influence on the indicators, which not only makes the optimization model more complex and redundant, but also makes the convergence speed of the algorithm slower and the ideal results cannot be obtained quickly.

To determine the primary parameters, the experiment data of performance indicators is obtained by uniform design method, based on which sensitivity analysis is conducted to calculate the sensitivity of all structure parameters. The parameters that have greater impact on the indicators are selected decision variables.

3.2.1 Uniform design method

Considering the complexity and non-linearity of structural optimization of moving components, the 10 structure parameters are selected as experimental variables. Based on the practical experience and installation conditions, 10 structure parameters are preliminarily selected and the range of each structure parameter is determined. The optimal level is 12 by trial-and-error, in which the data and results are much better. The arithmetic progression is applied to determine the 12 levels of each parameter, as shown in Table 2. Since there are 10 structure parameters and each structure parameter has 12 levels, plenty of experiments are carried out to acquire the results with the four indicators. In order to reduce the number of experiments and obtain most of the information, uniform design method is chosen to conduct experiments. The uniform design table $U_{12}^*(12^{10})$ is selected in this paper (Fang et al., 2000), as shown in Table 3, where subscript 12 is the number of trials, superscript 10 is the maximum factor number and normal 12 is the level number, respectively.

On the basis of the uniform test points in Table 3, the energy consumption is calculated by MATLAB, the first natural frequency, maximum deformation and maximum stress are computed by ANSYS with modal analysis and static analysis module. The first step is to establish 3D model of the moving component. Then, the structure is discretized and divided into infinitesimal elements with the tetrahedral grid. Finally, the fixed constraint is applied to the six bottoms of the bolts in the optimization pretreatment process, and the loads consisting of gravity and load forces are exerted on the moving part surface. The results are shown in Table 4.

Table 2. Experimental variables and levels

Level	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
1	50	24	114	316	26	88	88	246	138	20
2	52	25	116	318	28	90	90	250	140	22
3	54	26	118	320	30	92	92	254	142	24
4	56	27	120	322	32	94	94	258	144	26
5	58	28	122	324	34	96	96	262	146	28
6	60	29	124	326	36	98	98	266	148	30
7	62	30	126	328	38	100	100	270	150	32

8	64	31	128	330	40	102	102	274	152	34
9	66	32	130	332	42	104	104	278	154	36
10	68	33	132	334	44	106	106	282	156	38
11	70	34	134	336	46	108	108	286	158	40
12	72	35	136	338	48	110	110	290	160	42

Table 3. Uniform design table $U_{12}^*(12^{10})$

Trial	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
1	50	25	118	322	34	98	102	278	156	42
2	52	27	124	330	44	110	92	262	150	40
3	54	29	130	338	28	96	108	246	144	38
4	56	31	136	320	38	108	98	282	138	36
5	58	33	116	328	48	94	88	266	158	34
6	60	35	122	336	32	106	104	250	152	32
7	62	24	128	318	42	92	94	286	146	30
8	64	26	134	326	26	104	110	270	140	28
9	66	28	114	334	36	90	100	254	160	26
10	68	30	120	316	46	102	90	290	154	24
11	70	32	126	324	30	88	106	274	148	22
12	72	34	132	332	40	100	96	258	142	20

Table 4. Uniform test results

Trial	E/J	f_1/Hz	Δ/mm	σ_{max}/MPa
1	2063.7	295.54	7.486E-03	13.717
2	2088.81	295.1	7.171E-03	14.416
3	2088.71	298.17	6.926E-03	13.16
4	2095.07	301.67	6.73 E-03	9.4592
5	2132.40	302.56	6.581E-03	10.459
6	2135.42	305.37	6.384E-03	10.429
7	2113.68	298.46	7.012E-03	9.4267
8	2117.76	300.73	6.801E-03	9.8794
9	2154.71	303.11	6.57 E-03	11.815
10	2159.16	306.57	6.412E-03	8.9456
11	2150.63	309.19	6.255E-03	9.1699
12	2185.21	308.26	6.103E-03	8.1168

3.2.2 Sensitivity analysis

There are ten structure parameters of the moving component considered in the structural optimization, while the degree of influence of each parameter on the performance indicators is different. Based on the six sigma judging principle, these structure parameters which have great influence on the performance indicators are determined by using the global variable method so as to complete the sensitivity analysis (He et al., 2016).

Through sensitivity analysis, the influence of each structure parameter on the energy consumption, first natural frequency, maximum deformation and maximum stress can be obtained. Regardless of the interaction effects among the parameters, the sensitivity of a parameter shows its effect on value of the indicators. This method could significantly reduce the complexity of simulation and calculation.

Let $f(x)$ be the indicator function of the moving component. The parameter sensitivity S is defined to be the relative variation of $f(x)$ with respect to $(x_1, x_2, \dots, x_9, x_{10})$ the variation of a structure parameter, which is typically written in a normalized form, as expressed in Eq. (20) (Wang et al., 2017).

$$S = \frac{df(x)}{dx} \text{ or } S = \frac{\partial f(x_i)}{\partial x_i} \quad i = 1, 2, 3, \dots, n \quad (20)$$

Based on the experimental points obtained by uniform design method, the indicator data of design points are obtained by Simulink and Workbench, as shown in Table 4. Then, the sensitivity of each influence factor to the indicator is calculated by MATLAB. As shown in Fig. 6, structure parameters x_1, x_2, x_3, x_5 have the greatest impact on the energy consumption, structure parameters x_1, x_2, x_5 have the greatest impact on the first order resonance frequency, structure parameters x_1, x_2 have the greatest impact on the maximum deformation, and structure parameters x_1, x_2, x_3, x_9 have the greatest impact on the maximum stress. Based on the above analysis, the structure parameters x_1, x_2, x_3, x_5, x_9 have significant effect on the four indicators, so they are chosen as decision variables for structural optimization of moving component.

a. Energy consumption b. First order resonance frequency c. Maximum deformation d. Maximum stress

Fig. 6. Sensitivity of variables to indicators

3.3 Comprehensive performance objective

Given the complex performance characteristics of moving components and multi-indicator of the optimization procedure, this paper seeks a suitable approximation method to build the relationship between the indicators and the decision variables. In order to converge quickly in the optimization process and obtain ideal results, a reasonable method is found to reduce the dimension of the performance indicators.

3.3.1 Response surface method

Response surface method (RSM) proposed by Box and Wilson (1951) in the early 1950s, has received considerable attention due to its good empirical performance in modeling. The RSM is a well-known approach for constructing approximation models based on physical experiments and experimented observations (Li et al., 2016). It is a set of mathematical and statistical techniques that provide well-fitting models between input parameters and responses without taking complex interactions of variables into consideration (El-Taweel and Gouda, 2011).

Since the energy consumption of machine tools is a non-linear process, a second-order polynomial response surface mathematical equation is utilized as shown in Eq. (21), coefficients of the function can be obtained by least squares method.

$$y = \beta_0 + \sum_i \beta_i x_i + \sum_{i < j} \sum_i \beta_{ij} x_i x_j + \sum \beta_{ii} x_i^2 + \varepsilon \quad (21)$$

where y denotes performance indicators, x represents the structure parameters (x_1, x_2, x_3, x_5 and x_9). β_0, β_{ij} and β_{ii} are the coefficients of each term, ε is a residual error.

Table 5. Fitting coefficient of indicators

Term	$y_1(E)$	$y_2(f_1)$	$y_3(\Delta_{\max})$	$y_4(\sigma_{\max})$
------	----------	------------	----------------------	----------------------

β	1333	1449	1.97E-02	577
x_1	8.47	-29.42	5.10E-05	-3.13
x_2	-0.49	-24.09	1.99E-04	-0.75
x_3	7.86	-5.67	-1.38E-04	-3.5
x_5	-1.787	13.43	- 7.20E-5	8.1
x_9	-0.638	3.666	- 8.0E-05	-4.89
x_1^2	-0.0144	-0.06786	0.2E-05	0.0308
x_2^2	8.60E-03	-0.2789	0.4E-05	0.0625
x_3^2	-0.0307	-0.0718	0.2E-05	0.019
x_5^2	-0.01327	0.03586	0	-0.003
x_9^2	-2.97E-03	-0.01412	0	0.0121
x_1x_2	0.0198	-0.1393	0.2E-05	0.0073
x_1x_3	-0.02569	0.313	- 0.3E-05	-0.0025
x_1x_5	6.05E-03	-0.0812	0.1E-5	-0.0026
x_1x_9	6.83E-03	0.01725	0	-0.004
x_2x_3	-1.80E-03	0.3737	- 0.5E-05	-0.051
x_2x_5	3.43E-03	0.00706	0	7.33E-03
x_2x_9	6.54E-03	-0.00354	0	0.02272
x_3x_5	0.01832	-0.1097	0.1E-05	-0.0471
x_3x_9	4.56E-03	-0.01008	0	0.01041
x_5x_9	5.53E-03	0.02435	0	-0.0117

The fitting coefficient of each indicator model is shown in Table 5, and the variance analysis of each indicators model is shown in Table 6. R -Sq is defined as the ratio of the explained variation to the total variation, indicates the accuracy of the model. In the Table 5, it is clear to see that all values are greater than 95%, which indicate that the RSM models could be successfully applied as prediction models.

Table 6. Variance analysis of indicators

Project	E	f_1	$\Delta_{\max}$	$\sigma_{\max}$
R -Sq	100%	99.96%	100%	95.73%
R -Sq(adj)	100%	99.76%	99.99%	96.48%

3.3.2 Principal component analysis

Principal Component Analysis (PCA) is a commonly used dimensionality reduction method in multivariate statistics. Its basic idea is to use several principal components to replace the original multiple related indicators, and the new objective is expressed as a linear combination of the original related indicators. Considering that correlation among performance indicators, the PCA is conducted to transform four indicators into a comprehensive indicator.

The selected new indicator is called principal component, and the principle of selection is to retain the information contained in the original indicators as much as possible (Hervé et al., 2010). Let the indicator data $Y = (y_{ij})_{12 \times 4}$ consist of 12 scheme and 4 indicators, y_{ij} is the value of the j^{th} indicator in i^{th} scheme. Then the indicators data are standardized by Eq. (22).

$$z_{ij} = \frac{y_{ij} - \bar{y}_j}{s_j} \quad (22)$$

$$Z = (z_{ij})_{12 \times 4} \quad (23)$$

where $\bar{y}_j$ and $\bar{s}_j$ is the averages and the mean square error of the j^{th} indicator value, respectively.

Then the correlation coefficient matrix $R=(r_{ij})_{4 \times 4}$ of standardized data is established by Eq. (24). If the matrix $R=(r_{ij})_{4 \times 4}$ has q eigenvalues ($\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_q \geq 0$) and corresponding normal orthogonal eigenvector is $A=(a_1, a_2, \dots, a_q)$, the q principal components can be obtained, as shown in Eq. (25).

$$R = \frac{1}{n-1} Z^T Z \quad (24)$$

$$\begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_q \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ \vdots & \vdots & \vdots & \vdots \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} z_{i1} \\ z_{i2} \\ z_{i3} \\ z_{i4} \end{bmatrix} \quad (25)$$

The contribution rate of principal component g_i to original indicators is shown as Eq. (26).

$$w_i = \frac{\lambda_i}{\sum_{j=1}^n \lambda_j} \quad (26)$$

The contribution rate w_i reflects that the percentage of the i^{th} principal component involves the original indicators information. Therefore, the contribution rate of the first principal component is the largest, and other principal components decrease progressively. In order to reduce the dimension of the optimization indicators, if the cumulative contribution rate of the first m principal components reach 70%~90%, it is used to substitute the original four indicators. A comprehensive evaluation function consisting of m principal components is shown in the Eq. (27).

$$F = w_1 g_1 + w_2 g_2 + \dots + w_m g_m \quad (27)$$

As a result, summing up Eqs. (22) - (27) obtains the matrix $R=(r_{ij})_{4 \times 4}$, as expressed in Eq. (28). The eigenvalue and contribution rate is shown in Table 7.

$$\begin{bmatrix} g_1 \\ g_2 \\ g_3 \\ g_4 \end{bmatrix} = \begin{bmatrix} 0.230 & -0.953 & 0.033 & 0.192 \\ 0.585 & -0.020 & -0.312 & -0.748 \\ 0.539 & 0.173 & 0.821 & 0.075 \\ -0.560 & -0.246 & 0.477 & -0.631 \end{bmatrix} \begin{bmatrix} Z_1 \\ Z_2 \\ Z_3 \\ Z_4 \end{bmatrix} \quad (28)$$

Table 7. Principal component eigenvalue and contribution rate

Project	m_1	m_2	m_3	m_4
Eigenvalue	2.8292	0.9682	0.1923	0.0102
Proportion	0.707	0.242	0.048	0.003
Cumulative	0.707	0.949	0.997	1

Based on the analysis above, the comprehensive performance objective is modeled in Eq. (29).

$$F = 0.707 g_1 + 0.242 g_2 \quad (29)$$

3.4 Optimization model

On the basis of the above analysis, an optimization model is then formulated, which finds the optimal structure parameters to minimize the energy consumption and improve the static and dynamic performance of machine tool.

$$\begin{aligned}
\min F(X) &= \min(0.707g_1 + 0.242g_2) \\
X &= (x_1, x_2, x_3, x_5, x_9) \\
s.t. \begin{cases} x_{i\min} \leq x_i \leq x_{i\max} & (a) \\ \Delta_{\max} - [\Delta] \leq 0 & (b) \\ \sigma_{\max} - [\sigma] \leq 0 & (c) \end{cases} & \quad (30)
\end{aligned}$$

In practical optimization process, a wide variety of constraints are set to satisfy specific design requirements. Constraint (a) controls the structure parameters to be within its acceptable ranges, where $x_{i\min}/x_{i\max}$ are the minimum/maximum structure parameter value. Constraint (b) and constraint (c) ensure that the maximum deformation and stress do not exceed the allowable deformation and stress of moving component, respectively.

4 Optimization solution via a hybrid algorithm

A hybrid algorithm integrating Simulated Annealing (SA) with Particle Swarm Optimization (PSO) has attracted widespread traction since it is presented. A hybridization of algorithms can be considered as a way to develop a more effective and efficient searching strategy to overcome the weaknesses of a pure single algorithm (Jamili et al., 2011). For instance, Shieh et al. (2011), Geng et al. (2015) and Yu et al. (2014) proposed the hybrid algorithm for parameters selection. The hybrid algorithm takes both of the advantages of good solution quality in SA and fast searching ability in PSO, which meets the requirements of multiple parameters selection in structural design optimization.

4.1 A hybrid algorithm Particle Swarm Simulated Annealing

In this paper, a hybrid algorithm combined SA with PSO is developed to solve the optimization model. The inertia weight of adjacent solutions is controlled by annealing temperature, and the inferior solutions of local and global optima are accepted with a certain probability. The acceptance probability mode of SA and Metropolis criterion are not changed. The key steps of the algorithm are described as follows:

(1) Initialization parameter. The maximum temperature is $T_{\max}$, the end-off temperature is T_0 , the cooling rate is α , the learning factor c_1, c_2 . The population S of 30 particles is generated randomly. The position vector of each particle is the structure parameter of moving components $[x_1, x_2, x_3, x_5, x_9]$, and the range of each parameter is defined.

(2) The fitness value of each particle is calculated and regarded as the current historical optimal p_{best} . The optimal particle among all particles is selected as the current global optimal g_{best} .

(3) Each particle is updated by Eq. (31) (Perez et al., 2012).

$$\begin{cases} V_i^{k+1} = \omega \times V_i^k + c_1 r_1 (X_{i\text{best}}^k - X_i^k) + c_2 r_2 (X_{g\text{best}}^k - X_i^k) \\ X_i^{k+1} = X_i^k + V_i^{k+1} \end{cases} \quad (31)$$

where r_1 and r_2 are the random number between $[0, 1]$ and V_i^k particle renewal speed.

In order to make particles jump out of local minimum quickly at high temperature and converge quickly at low temperature, the inertia weight of temperature control is used, as shown in Eq. (32).

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \frac{\ln(T_{\text{current}}/T_{\max})}{\ln(T_0/T_{\max})} \quad (32)$$

where T_{current} is the current annealing temperature.

(4) The fitness value of each particle is recalculated, and then Metropolis criterion is introduced to compare the fitness value of the new particle with the historical optimal p_{best} of the corresponding particle. If $f(x_i) < p_{\text{best}}$, the updated particle will be accepted; if $f(x_i) > p_{\text{best}}$, the updated particle will be accepted with

a certain probability. Similarly, the global optimal particle g_{best} is updated according to the Metropolis criterion.

(5) Reduce temperature.

(6) Judging the stopping condition, if the condition is not satisfied, return to (3), otherwise, finish the iteration and output g_{best} . The specific algorithm flow is shown in Fig. 7.

Fig. 7 Flow chart of particle swarm simulated annealing algorithm

4.2 Optimization results

In this paper, the high speed dry-cutting hobbing machine is taken as example, and the 3D model is shown in Fig. 5. The hobbing machine adopts high-speed dry cutting technology and the hob moves with high speed, thus the moving speed of the tool holder is high. Fig. 8 shows the detailed material removal process from hob cut in and out of the workpiece.

Fig. 8 Cutting process of moving component

In the process of hobbing, the hob moves slowly from A position along X axis to B position, B position along Z axis at fixed feed speed through path U_e (approaching safety allowance), U_a (exit safety allowance) and B_{OT} (over-cut protection stroke). Then, the hob is quickly retreated to the original A position of the machine through position C and D. With the geometric analysis above, the movement of tool slide is analyzed in detail to establish the relationship between the mass of moving component and energy consumption. As stated in Section 3, it is of great significance to optimize the structure of the

hobbing machine for energy saving.

4.2.1 Energy saving analysis

Based on the actual cutting process of the high-speed dry-cutting hobbing machine tool in Fig. 8, the moving component energy model proposed in the paper is used to verify the relationship between the mass and energy consumption of the tool slide. The original mass of the tool slide is measured to be 458.62kg, the material is QT700-2 and the density is 7200kg/m^3 . The additional mass on the tool slide is 500kg.

The structure parameters have influence on the mass of moving component, resulting in the change of energy consumption. Through simulation calculation, the relationship between the mass and the energy consumption of the tool slide is shown in Fig. 9. It can be seen that energy consumption of tool slide increases linearly with the increment of mass, which means that the smaller the mass of the tool slide, the smaller the energy consumption of machine tool. Thus, the structure parameters of moving part are optimized to reduce its mass for energy saving.

Fig. 9 Relationship between mass and energy consumption of tool slide

The structural optimization of the moving component aiming at energy saving should ensure the machining accuracy of the machine tool. Therefore, the energy saving effect of the moving component is greatly affected by the machining accuracy. The deformation error of the end face of the tool slide is shown in the Eq. (32), and the error is evenly distributed to the guideways, tool slide and support part. Thus the maximum deformation allowed by the tool slide is obtained.

$$[\Delta] = 8 + 0.5\sqrt{L_a} \quad (32)$$

where $[\Delta]$ is the permissible maximum deformation, L_a is the movement stroke of the tool slide, $L_a=500\text{mm}$.

4.2.2 Optimization Results

The model is solved by programming with MATLAB software. Fig. 10 shows the convergence effect of the hybrid algorithm used in this paper compared with SA and PSO. It can be seen from Fig.10 that the convergence rate of the hybrid algorithm is faster than other two algorithms, which validate the better performance of the proposed hybrid algorithm.

Fig. 10 Comparison diagram of algorithm convergence

In order to verify the maximum energy-saving effect of the tool slide of the high-speed dry-cut hobbing, the tool slide mass is taken as single objective, and the static and dynamic performance are taken as the constraints, which minimizes the mass of tool slide on the basis of guaranteeing machining accuracy of machine tool. Table 8 depicts the outcomes obtained through optimization algorithm. It can be seen from Table 8 that the maximum lightweight result shows that the energy consumption is reduced by 3.22% with mass reduction of 8.14% in moving part, the first natural frequency is increased from 298.23Hz to 306.9Hz, which is increased by 2.91%, and both maximum deformation and maximum stress are increased. The first natural frequency, maximum deformation and maximum stress nephogram based on the maximum lightweight result is shown in Fig. 11.

From the optimization results in Table 8, it can be seen that the energy consumption is reduced 3.06% with the mass reduction of 7.34% in moving component. The first natural frequency of the moving component increases from 298.23Hz to 306.3Hz, which is increased by 2.87%, and the maximum deformation and maximum stress have a little increase. However, the maximum deformation 0.007038mm still satisfies the design requirements of the tool slide, and maximum stress 12.589MPa is within the allowable range of materials. Thus, the optimized moving component structure still meets the design requirements of machine tool structure, and the increase of static performance will not affect the machining accuracy of machine tool. The first natural frequency, maximum deformation and maximum stress nephogram after and before optimization are shown in the Fig.12 and Fig.13, respectively. It can be seen that the optimized structure increases the maximum deformation and maximum stress compared to the original structure. Since the thickness of base plate, the box body and the rib plate are decreased, the stiffness in several locations of moving component is reduced. When the moving part is subjected to the same load, the deformation will be increased. On the other hand, since the structure of moving component becomes thinner, it is easy to generate stress concentration, resulting in the increase of stress.

Table 8. Optimization Results

Project	x_1	x_2	x_3	x_5	x_9	$E/10^3\text{J}$	f_1/Hz	$\Delta_{\max}/\text{mm}$	$\sigma_{\max}/\text{MPa}$
Before optimization	65	30	128	40	160	1.862	298.23	0.006614	8.824
After optimization	56.5	34	140	20	132	1.805	306.82	0.007038	12.589
Maximum lightweight	53.5	34.5	135	29	140.5	1.802	306.9	0.007184	12.96

Fig.11 First natural frequency, maximum deformation and maximum stress nephogram of maximum lightweight structure

Fig. 12 First natural frequency, maximum deformation and maximum stress nephogram after optimization

Fig. 13 First natural frequency, maximum deformation and maximum stress nephogram before optimization

Fig.14 represents the comparison curve of the energy consumption of the tool slide among the original structure, maximum lightweight structure and optimized structure. As can be seen from the figure, the optimized results can effectively reduce the energy consumption of moving components. Compared with the original structure, the energy consumption of optimized structure is reduced by 3.06%, and the energy consumption of maximum lightweight structure is reduced by 3.22%.

Fig. 14 Energy consumption of original structure, maximum lightweight structure and optimized structure

From the data in Fig.12, Fig.13 and Fig. 14, it can be seen that the optimized structure can achieve the same energy-saving effect as the maximum lightweight structure. The proposed method does not change the first natural frequency, reduces the maximum deformation by 1.76%, decreases the maximum stress by 2.86% compared to the maximum lightweight design. By establishing a direct energy consumption model, the energy consumption of moving component can be reduced more intuitively. We can conclude that the proposed structural optimization method can minimize the energy consumption of moving component on the basis of guaranteeing static and dynamic performance.

4.2.3 Influence of structure parameters on performance indicators

The change of the energy consumption, first natural frequency, maximum deformation and maximum stress with respect to different structure parameters are plotted, as shown in Fig. 15 to Fig. 19.

Fig. 15 shows the influence of the structure parameter x_1 on the four indicators. With the raise of x_1 , the mass and stiffness of the tool slide will be increased, resulting in the increase of the energy consumption and decrease of the first natural frequency. With the raise of the mass, the load force is increased. At first, with the increment of x_1 , the increase of stiffness is larger than that of load force, resulting in the decrease of the deformation. Then, the increase of stiffness is smaller than that of load force, leading to the increase of the deformation. The stress is related to elasticity matrix, strain matrix and deformation, in which strain matrix is constant and elasticity matrix is associated with deformation, which causes that the stress does not always increase or decrease, but has an inflection point on the tendency curve, before which the stress decreases and after which it increases. Fig. 16 states the impact of structure parameter x_2 on the four indicators. As shown in Fig. 16, the change trend of each indicator is same as that in Fig. 15.

Fig. 17 illustrates the effect of the structure parameter x_3 on the four indicators. With the raise of x_3 , the mass and stiffness of the tool slide are increased, which leads to the increase of the energy consumption.

The first natural frequency is related to the stiffness and mass. Firstly, with the increase of x_3 , the increment of stiffness is larger than that of mass, causing the increase of the first natural frequency. Then, the increment of stiffness is smaller than that of mass, which leads to the reduction of the first natural frequency. The change trends of deformation and stress are similar with that in Fig. 15.

Fig. 18 represents the influence of the structure parameter x_5 on the four indicators. It can be seen that four indicators always increases with increment of x_5 . With the raise of x_5 , the mass and stiffness of the tool slide are increased, resulting in the increase of the energy consumption. The increment of stiffness is larger than that of mass, which leads to the increase of the first natural frequency. The deformation is associated with the stiffness and load force. The increment of load force is larger than that of stiffness, and the deformation always increases, resulting in the increase of stress.

Fig. 19 gives the effect of the structure parameter x_9 on the four indicators. As shown in Fig. 19, with the raise of x_9 , the mass and stiffness of the tool slide is decreased, resulting in the reduction of load force and energy consumption. The decrease of stiffness is smaller than that of mass, which causes the decrease of the first natural frequency. With the increase of x_9 , the reduction of load force is larger than that of stiffness, resulting in the decrease of the deformation. The stress is associated with deformation, but the relationship is complex. The trend of stress in the Fig. 19 is similar with that in the Fig. 15.

As the increment of five structure parameters, the four indicators show different change. Generally, with the decrement of structure parameters, the mass and stiffness of the tool slide are reduced, which results in the reduction of the energy consumption and first natural frequency. The deformation and stress are related to the mass and stiffness of the tool slide, which are changing all the time. There are different inflection points on the tendency curves of the maximum deformation and stress, before which the deformation and stress decrease and after which they increase.

Fig. 15 Influence of structure parameter x_1 on performance indicators

Fig. 16 Influence of structure parameter x_2 on performance indicators

Fig. 17 Influence of structure parameter x_3 on performance indicators Fig. 18 Influence of structure parameter x_5 on performance indicators Fig. 19 Influence of structure parameter x_9 on performance indicators

5 Conclusions

Given that a large number of machine tools consume a lot of energy, but the energy efficiency is quite low. It is urgent to optimize the machine tools to reduce energy consumption. The design of machine tools has a great impact on the energy consumption in the machining process. The energy consumption factors of machine tools are considered in the design stage, which can effectively reduce the energy consumption of machine tools. In the paper, a structural design optimization method of moving component in CNC machine tool for energy saving is presented, the conclusions from optimization results and simulation analysis are drawn as follows:

The energy consumption function of the feed drive system with regard to mass of moving component is formulated based on the dynamic analysis. Then, a structural optimization model of moving part is

presented by taking energy consumption, static and dynamic performance into account, which integrates uniform design method, sensitivity analysis, RSM and PCA. Finally, a hybrid algorithm combining PSO with SA algorithm is proposed to solve the model.

Based on the energy consumption model of moving components proposed in this paper, the relationship between the mass and energy consumption of the tool slide of high-speed dry-cutting hobbing machine tool under actual working conditions is obtained. On this basis, in order to verify the energy-saving potential of the tool slide, this paper takes the static and dynamic performance of the tool slide as the constraints for lightening the tool slide weight. The energy consumption is reduced by 3.22% with maximum lightweight structure. Moreover, the structure optimization model is solved by the proposed hybrid algorithm, the results show that the proposed hybrid algorithm can effectively improve the convergence speed. By analyzing and simulating the optimization results, we can conclude that the proposed moving component optimization method can achieve the same energy saving effect as the maximum lightweight structure and improve the static and dynamic performance of the moving component.

Based on this study, the research can be extended in several directions. For instance, the moving components and supporting components of machine tools have great influence on the processing performance of machine tools. In order to improve the rationality of the overall structure and ensure the processing capacity of the machine tool, it is necessary and challenging to further establish the optimization model of the moving components and supporting components of the machine tool. Then the moving components are combined with supporting components to optimize the structure of machine tool. More factory data is also needed to validate the proposed methodology in the future.

Acknowledgements

This work was supported in part by the National Natural Science Foundation of China (No. 51975075), Chongqing Technology Innovation and Application Program (No. cstc2018jszx-cyzdX0183) and the Fundamental Research Funds for the Central Universities of China (No. cqy2018CDHB1B07).

Reference

- Altintas, Y., Brecher, C., Weck, M. and Witt, S., 2005, "Virtual Machine Tool," *CIRP Annals*, 54(2), pp.115-138.
- Apostolos, F., Alexios, P., Georgios, P., Panagiotisa, S. and Georgea, C., 2013, "Energy Efficiency of Manufacturing Processes: A Critical Review," *Procedia CIRP*, 7, pp. 628-633.
- Box, G. E. P. and Wilson, K. B., 1951, "On the experimental attainment of optimum conditions," *J. R. Stat. Soc. Ser. B-Stat. Methodol.*, 13, pp.1-45.
- Bueno R., 2013, "Final Report-NEXT generation production systems," July, 10, 2013, <http://www.cordis.europa.eu/documents/document/120142271EN19.doc>
- Bustillo, A., Oleaga, I., Zulaika, J. J. and Loix, N., 2015, "New methodology for the design of ultra-light structural components for machine tools," *Int. J. Comput. Integr. Manuf.*, 28(4), pp.339-352.
- Campatelli, G., Scippa, A., Lorenzini, L. and Sato, R., 2015, "Optimal workpiece orientation to reduce the energy consumption of a milling process," *Int. J. Precis Eng Manuf-Green Technol.*, 2(1), pp.5-13.
- Chen, J. S., Huang, Y. K. and Cheng, C. C., 2004, "Mechanical model and contouring analysis of high-speed ball-screw drive systems with compliance effect," *Int. J. Adv. Manuf. Technol.*, 24(3-4), pp.241-250.
- Ding, X., Chen, Y. and Liu, W., 2010, "Optimal design approach for eco-efficient machine tool bed," *Int. J. Mech. Mater. Des.*, 6(4), pp.351-358.

- El-Taweel, T. A. and Gouda, S. A., 2011, "Performance analysis of wire electrochemical turning process—RSM approach," *Int. J. Manuf. Technol.*, 53(1-4), pp.181-190.
- Fang, K. T., Lin, D. K. J., Winker, P. and Zhang, Y., 2000, "Uniform Design: Theory and Application," *Technometrics*, 42(3), pp.237-248.
- Geng, J., Li, M. W., Dong, Z. H., Liao, Y. S., 2015, "Port throughput forecasting by MARS-RSVR with chaotic simulated annealing particle swarm optimization algorithm," *Neurocomputing*, 147(1), pp.239-250.
- Gutowski, T. G., Branham, M. S., Dahmus, J. B. and Jones, A. J., 2009, "Thiriez Alexandre. Thermodynamic analysis of resources used in manufacturing processes," *Environ. Sci. Technol.*, 43(5), pp.1584-1590.
- He, B., Wang, J., Huang, S. and Yan, W., 2015, "Low-carbon product design for product life cycle," *J. Eng. Design*, 26(10-12), pp.321-339.
- He. B., Tang, W., Huang, S. and Hou, S., 2016, "Towards low-carbon product architecture using structural optimization for lightweight," *Int. J. Adv. Manuf. Technol.*, 83(5-8), pp.1419-1429.
- Hervé, A. and Williams, L. J., 2010, "Principal component analysis," *WIREs Comp. Stat.*, 2(4), pp.433-459.
- Hendrawan, Y. M., Simba, K. R. and Uchiyama, N., 2018, "Iterative learning based trajectory generation for machine tool feed drive systems," *Robot. Cim-Int. Manuf.*, 51, pp.230-237.
- Huang, Y. S., Shen, L. and Liu, H., 2019, "Grey relational analysis, principal component analysis and forecasting of carbon emissions based on long short-term memory in China," *J. Clean. Prod.*, 209, pp.415-423.
- Iqbal, U. M., Kumar, V. S., and Gopalakannan, S., 2016, "Application of Response Surface Methodology in optimizing the process parameters of Twist Extrusion process for AA6061-T6 aluminum alloy," *Measurement*, 94, pp.126-138.
- ISO 14955-1:2017. Machine tools -- Environmental evaluation of machine tools - Part 1: Design methodology for energy-efficient machine tools.
- Jamili, A., Shafia, M. A. and Tavakkoli, M. R., 2011, "A hybrid algorithm based on particle swarm optimization and simulated annealing for a periodic job shop scheduling problem," *Int. J. Adv. Manuf. Technol.*, 54(1-4), pp.309-322.
- Kroll, L., Blau, P., Wabner, M., Frieß, U., Eulitz, J., Klärner, M., 2011, "Lightweight components for energy-efficient machine tools," *Cirp J. Manuf. Sci. Tech.*, 4(2), pp.148-160.
- Law, M., Altintas, Y. and Srikantha, P. A., 2013, "Rapid evaluation and optimization of machine tools with position-dependent stability," *Int. J. Mach. Tool Manu.*, 68, pp.81-90.
- Li, B., Hong, J. and Liu, Z., 2014, "Stiffness design of machine tool structures by a biologically inspired topology optimization method," *Int. J. Mach. Tool Manu.*, 84, pp.33-44.
- Li, C. B., Xiao, Q. G., Tang, Y. and Li, L., 2016, "A method integrating Taguchi, RSM and MOPSO to CNC machining parameters optimization for energy saving," *J. Clean. Prod.*, 135, pp.263-275.
- Liu, S. H., 2015, "Multi-objective optimization design method for the machine tool's structural parts based on computer-aided engineering," *Int. J. Adv. Manuf. Technol.*, 78(5-8), pp.1053-1065.
- Li, C. B., Chen, X. Z., Tang, Y. and Li, L., 2017, "Selection of optimum parameters in multi-pass face milling for maximum energy efficiency and minimum production cost". *J. Clean. Prod.*, 140, pp.1805-1818.
- Li, C. B., Li, L. L., Tang, Y., Zhu, Y. T. and Li, L., 2019, "A Comprehensive Approach to Parameters Optimization of Energy-aware CNC Milling," *J. Intell. Manuf.*, 30(1), pp.123-138.

- Orlando, D., Luis, P. and Batocchio, A., 2012, "Optimization of modular structures using Particle Swarm Optimization," *Expert Syst. Appl.*, 39(3), pp.3507-3515.
- Park, H.W., Park, Y. B. and Liang, S. Y., 2011, "Multi-procedure design optimization and analysis of mesoscale machine tools," *Int. J. Adv. Manuf. Technol.*, 56(1-4), pp.1-12.
- Perez, R. E. and Behdinan, K., 2012. "Particle swarm approach for structural design optimization," *Comput. Struct.*, 85(19), pp.1579-1588.
- Ren, W. X. and Chen, H. B., 2010, "Finite element model updating in structural dynamics by using the response surface method," *Eng. Struct.*, 32(8), pp.2455-2465.
- Rajeswari, B., Amirthagadeswaran, K. S., 2017. "Experimental investigation of machinability characteristics and multi-response optimization of end milling in aluminium composites using RSM based grey relational analysis," *Measurement*, 105, pp.78-86.
- Son, H., Choi, H. J. and Park, H. W., 2010, "Design and dynamic analysis of an arch-type desktop reconfigurable machine". *Int. J. Mach. Tool. Manu.*, 50(6), pp.575-584.
- Shieh, H. L., Kuo, C., C. and Chiang, C. M., 2011, "Modified particle swarm optimization algorithm with simulated annealing behavior and its numerical verification," *Appl. Math. Comput.*, 218(8), pp.4365-4383.
- Wang, J. Q., Niu, W. T., Ma, Y., Xue, L. J., Cun, H., Nie, Y. and Zhang, D., 2017, "A CAD/CAE-integrated structural design framework for machine tools," *Int. J. Adv. Manuf. Technol.*, 91(1-4), pp.545-568.
- Wang, Y., Niu, S. and Fu, W., 2017, "Sensitivity analysis and optimal design of a dual mechanical port bidirectional flux-modulated machine," *IEEE Trans. Ind. Electron.*, 65(1), pp.211-220.
- Xiao, Q. G., Li, C. B., Tang, Y., Li, L. L. and L, L., 2019, "A knowledge-driven method of adaptively optimizing process parameters for energy efficient turning," *Energy*, 166, pp.142-156.
- Yoon, H. S., Singh, E. and Min, S., 2018, "Empirical power consumption model for rotational axes in machine tools," *J. Clean Prod.*, 196, pp.370-381.
- Yu, Z., Nakamoto, K., Ishida, T. and Takeuchi, Y., 2010, "Interactive design-assistance system of machine tool structure in conceptual and fundamental design stage. *Int. J. Autom. Technol.*, 4(3), pp.303–311
- Yu, H., Yang, Z., Yang, Y. and Zhang, L., 2014, "An Improved Particle Swarm Optimization Algorithm Based on Simulated Annealing," *10th International Conference on Natural Computation*, pp.529-533.
- Zulaika, J. J., Campa, F. J. and Lacalle, L. N. L. D., 2011, "An integrated process-machine approach for designing productive and lightweight milling machines," *Int. J. Mach. Tool Manu.*, 51(7), pp.591-604.