# Chapter10 Digital Twin Driven Lean Design for CNC Machine Tools

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## Abstract

Computer Numerical Control Machine Tools (CNCMTs) play an important role in smart manufacturing. In the current complex and changeable market environment, improving the performance of CNCMTs at the design stage becomes an urgent task for equipment manufacturers. Lean Design (LD) has its overwhelming advantages in many aspects (e.g. high efficiency of realization mode, greater flexibility in the changing market, and full involvement of stakeholders) compared to traditional design methods. But in the LD process of CNCMTs, inaccurate CNCMT models and manual-setting workload data (e.g. spindle speed, spindle temperature, feed speed) will lead to inaccurate design analysis results and thereupon increase design time. To solve these problems, Digital Twin (DT) is introduced into LD, which provides high-fidelity models and real-time mapping of accurate workload data. Based on the DT prototype of CNCMTs, as established in Chapter 9, a DT-driven LD method for CNCMTs is presented in this chapter, which combines the advantages of both LD and DT. The method consists of design of the workload-DT model, generation of workload data, and optimization and evaluation methods for CNCMTs. In addition, a case study focusing on the design of CNCMT feed system is carried out to verify the feasibility and effectiveness of the proposed method.

**Keywords:** Digital Twin; Lean Design; CNC Machine Tools; Workload-DT model

## 10.1 Introduction

As an essential part of manufacturing equipment [1], Computer Numerical Control Machine Tools (CNCMTs) greatly affect the whole manufacturing system along its life cycle, and thus it plays an important role in smart manufacturing. Good performance of CNCMTs improves not only manufacturing efficiency but also product quality. The performance of CNCMTs depends on many stages throughout its lifecycle such as design, commissioning, operation and maintenance. Among these stages, design is the most basic one, which determines the initial performance of CNCMTs. In fact, 70% of the product cost depends on the design of CNCMTs [2]. Therefore, it becomes a challenge for today’s equipment manufacturers to improve performance of CNCMTs at a relatively small cost at the design stage.

Over the years, many researchers have been committed to the exploration of different design methods in the early design stage of CNCMTs. For example, Dehong et al. proposed an integrated dynamic design and modelling approach, which supports analysis and optimization of a machine’s overall dynamic performance [3]. Cho et al. used carbon/epoxy composites and resin concrete to design and fabricate a small desktop structure of CNCMTs, which reduces the weight, and enhances the structural stiffness and damping capacity [4]. In addition, related research includes innovative solutions for the structure of Ultra High Precision (UHP) CNCMTs [5, 6], design methods for dimension optimization of CNCMTs [7, 8], methods for improving stability of CNCMTs dynamically [9-12], etc.

Although traditional design methods can optimize CNCMTs performance to some extent, design of parameters mainly rely on the experience of engineers, which could lead to imperfect decision-making because of the lack of participation of suppliers or customers. In addition, the above-mentioned research only focuses on the design stage without consideration of later stages, which means the usage and maintenance of CNCMTs provides little guidance to design. These challenges promote the urgent need for more advanced design methods to guide the design of CNCMTs.

At the same time, Lean Design (LD) method, which provides a more powerful tool for lean implementation, has been gradually accepted and applied in product design. The term “lean” is derived from “lean production” and recognized as an extension of lean thinking [13]. Reducing cost without quality sacrifice through eliminating unnecessary functions or components is the purpose of LD [14]. The differences between LD and traditional design can be summarized from three aspects as shown in Tab.10.1.

**Tab.10.1** Differences between LD and traditional design

|  |  |  |
| --- | --- | --- |
|  | Traditional design | LD |
| Realization mode | Design mainly relies on experience of designers with a little help of computer-aided technology [15]. | Design is based on team work in line with lean thinking, mainly relying on computer-aided technology [16]. |
| Flexibility | Design scheme is rigid and thus can hardly adjust to external changes easily [17]. | Design scheme is dynamic and visualized and thus can adjust to external changes with lower cost in a shorter time [18]. |
| Participants | Decision making only depends on design engineers | Decision making depends on any person who understands LD concept (e.g. enterprise managers, design engineers, customers, suppliers) |

Through the comparisons above, it is obvious that LD method is superior to the traditional design method. However, there are still some unsolved problems in LD, such as inaccurate models for simulation and unrealistic manual-setting simulation conditions (defined as workload in this chapter, which refers to external working conditions imposed on CNCMTs), which will be elaborated on in Section 10.2.

In this context, this chapter aims at applying the DT-driven LD method to CNCMTs design based on high fidelity of DT model and authenticity of workload. The rest of this chapter is organized as follows. The previous works on LD methods and DT-driven design methods are reviewed in Section 10.2. The implementation of DT-driven LD is described in detail in Section 10.3, followed by the proposed design of workload-DT model in Section 10.4 and demand-oriented application method of workload data in Section 10.5. Section 10.6 elaborates on the evaluation and optimization method for CNCMTs. A case study of LD for CNCMTs feed system is introduced in Section 10.7 to demonstrate the feasibility of the proposed method. Finally, future work is recommended in Section 10.8.

## 10.2 Related works

LD and DT-driven design are the basis of the proposed design method for CNCMTs. Therefore, previous research related to these two design methods are reviewed in this section separately.

### 10.2.1 Related works on LD methods

The volatile market and rapid development of the manufacturing industry has put forward higher requirements for enterprises to provide better products with lower cost. More work needs to be done in the design stage for a good start over the product life cycle, in which customers’ ideas are conceptualized into physical models, and customers’ requirements are deﬁned into procedures, drawings and technical specifications.

Over the years, many scholars and institutions have been committed to the LD related research. Hines et al. introduced lean concept into new product development and discussed the importance of realizing lean concept in design process through cost cutting and time slashing methodology [19]. Dombrowski et al. analyzed a vast range of qualitative design principles for the various approaches [20]. There are also studies on LD theory that reflect the value of lean thinking [21], including a survey on lean practices in the Indian CNCMTs industries [22], Product Service System LD Methodology (PSSTLDM) [23], lean principles for product lifecycle management (PLM) solutions[24, 25], etc. Under the guidance of the LD theory, Yang et al. designed a fishing net manufacturing system through simulation optimization [26]. Domingo et al. improved an assembly line using lean metrics, which attempts to reduce the dock-to-dock time and increase the lean rate [27]. Gupta et al. studied factors that assess the leanness (wastage removal) in CNCMTs and then proposed a method for both static and dynamic analyses using FEM package for the prevention of over-design [2].

While the LD theory is widely used across the above-mentioned research, there are also many applied studies in related fields, which can provide relevant theoretical support and guidance for LD of CNCMTs. However, the research on LD of CNCMTs design is still at an early stage, and thus it is inevitable that the current LD work still has some shortcomings such as inaccurate models and unrealistic workload data (e.g. spindle speed, spindle temperature, feed speed, etc.):

**(1) From model aspect.** The model in LD is generally used to describe CNCMTs according to the ideal definition given by CNCMTs designers. The inconsistency between the model and the physical CNCMTs might be due not only to the processing and assembly errors of components, but also to the performance degradation of subsystems. In this case, the model will not be able to reflect the physical CNCMTs accurately, which will limit the effectiveness of the design for CNCMTs significantly.

**(2) From workload aspect.** When conducting simulation analysis, workload data is usually manually set based on design requirements or empirical data, which cannot truly reflect the actual work conditions of CNCMTs. Furthermore, the traditional workload calculation method does not consider feedback from the product usage and maintenance stages. As a result, the simulation analysis in the design stage cannot reflect the updated requirements timely.

### 10.2.2 Related works on DT-driven design methods

The definition of DT (see Chapter 1 for reference) emphasizes two important characteristics. Firstly, it emphasizes the connection between the physical entity and the corresponding DT model. In other words, the DT model is a replica of the physical entity [28, 29]. Secondly, this connection is established through the collection of real-time data using sensors. The two characteristics show that DT can provide an accurate model and precise workload data through real-time mapping between the physical space and virtual space.

At present, the potential application of DT in intelligent manufacturing has attracted increasing attention. Tao et al. presented six principles for DT applications and fourteen typical applications of DT in view of corresponding key scientific problems or technologies based on the DT concept [30]. In addition to theoretical research, there are also DT-based applications in health maintenance [31], additive manufacturing [32], modeling as-manufactured geometry [33] etc.

Many studies on DT-driven design have also been conducted. In order to provide more realistic virtual models for rapid customized workshop design, Benjamin et al. proposed a comprehensive reference model based on the concept of skin model shapes [34]. To meet the requirement of customized production line design, Zhang et al. proposed a fast design scheme based on DT, which provides accurate virtual models reflecting the real production lines [35]. There is also research on DT-driven methodology for rapid customized design of automated flow-shop manufacturing system [28]. Dassault corporation indicated the huge potential of DT in product design [36]. For example, Tao et al. proposed a new method for product design based on the DT technology and analyzed the framework of DT-driven product design [37, 38].

In theory, DT-driven design can contribute to the consistency between simulation results and actual processing results by providing accurate models and realistic workload data from real-time mapping.

Combining the advantages of DT technology and LD concept, a new ideal for the optimization design of CNCMTs is obtained, which is called DT-driven LD method. This method will not only save time and cost, but also provide more design guidance based on the more accurate simulation results. The DT-driven LD method will be introduced in detail in the following sections.

## 10.3 Framework of DT-driven LD

Chapter 9 has introduced the multi-domain model of CNCMTs, mapping strategy between digital space and physical space and the performance attenuation updating mechanism, which provide the theoretical and model basis for this chapter. The implementation of DT-driven LD for CNCMTs will be introduced in terms of digital space and physical space separately in this section.

### 10.3.1 DT-driven LD in digital space

As shown in Figure 10.1, the implementation of DT-driven LD in digital space takes a more important role, and it mainly consists of three parts.

**(1) Design of workload-DT model.** Workload-DT model involves pre-categorization of hierarchical representation of CNCMTs working conditions. It facilitates the organization, reconstruction and invocation of working condition information.

**(2) Application of workload data.** Workload data is used to instantiate the designed workload-DT model, which reflects actual working conditions. The steps of workload data application are shown as follows.

**Step 1：Workload data generation.** Raw data are preprocessed and analyzed to obtain complete workload data (e.g. spindle speed, spindle temperature, feed speed), which are then stored in a database by categories.

**Step 2：Workload data selection.** Target performance indicators (e.g. precision, stiffness, thermal deformation) of CNCMTs determine the type of LD simulation (e.g. fluid mechanics simulation, structural mechanics simulation, thermodynamics simulation), and accordingly, workload data can be selected.

**Step 3：Workload-DT model instantiation.** The selected workload data are filled in the corresponding part of the workload-DT model to realize the certain type of simulation, which should meet the requirements imposed by the target performance indicators of CNCMTs.



**Figure 10.1** Implementation of DT-driven LD system

**(3) Optimization and evaluation for CNCMTs.** Optimization and evaluation are the core of implementing LD for CNCMTs. The specific steps of optimization and evaluation for CNCMTs are enumerated below.

**Step 1：LD simulation.** Target performance indicators of CNCMTs determine the LD algorithm (e.g. genetic algorithm, ant colony algorithm, eigenvalue solving algorithm), which drives LD simulation with the aid of the DT model for CNCMTs and the instantiated workload-DT model. Then optimal simulation parameters (e.g. bed structure parameters, feed system topology parameters, spindle thermal deformation parameters) can be obtained during this process and can be used to update the DT model for CNCMTs as well as to guide the design of next-generation prototypes of CNCMTs.

**Step 2：LD evaluation.** Optimal parameters offered by LD simulation need to be checked to ensure they meet the target performance indicators. If all the indicators are satisfied, these optimal design parameters are output. Otherwise, products need to be re-designed, which means the DT model of CNCMTs is adjusted and all these steps for implementing DT-driven LD design should be executed again.

### 10.3.2 DT-driven LD in physical space

Data acquisition and prototype manufacturing are the two main tasks that need to be implemented in physical space for DT-driven LD.

**(1) Data acquisition.** Data collected by sensors include not only status of CNCMTs, but also those related to production such as workpiece and environmental information. These data are the basis for DT-driven LD because they support the update of DT model for CNCMTs and workload loading in simulation.

**(2) Prototype manufacturing.** The manufacturing of next generation prototypes is guided by the optimal simulation parameters. Then, tests on performance of the new generation prototypes should be carried out to map the actual processing data into the digital space for LD evaluation.

Since the data acquisition method has already been introduced in Chapter 9, and prototype manufacturing does not involve methodology, this Chapter only focuses on the implementation for DT-driven LD in the digital space, which will be described in detail in Section 10.4 to Section 10.6.

## 10.4 Design of workload-DT model

A workload-DT model is for pre-categorization of hierarchical representation of CNCMTs working conditions, which facilitates the organization, reconstruction and invocation of working condition information. A workload-DT model is designed in this section, with the analysis of workload for a start.

### 10.4.1 Analysis of workload

Analysis of the workload of CNCMTs starts from the physical entities (e.g. CNCMTs, workpiece and environment) that participate in the machining process. As a multi-layer system, the physical CNCMTs need to be analyzed meticulously at the subsystem and component level to reveal the complex workload data. As shown in Figure 10.2, the CNCMTs can be divided into different functional subsystems (e.g. spindle system, tool system, feed servo drive system, etc.) and these subsystems can be further divided into smaller unit at component level.

After classification, data to be collected from the physical entities are determined based on the analysis of factors that influence the performance of CNCMTs during processing. This analysis provides a guidance for sensor selection and installation. Taking the thermal stability of the spindle of CNCMTs as an example, the influencing factors include spindle speed and temperature distribution axially along the spindle. However, it is impossible to collect temperature values at continuous points along the spindle. In this case, only the temperature at both ends of the spindle and the spindle speed need to be collected, and then the intermediate temperature can be calculated using formulas. This example suggests that some collected data cannot directly reflect the working conditions of CNCMTs and thus implicit workload data for subsequent use need to be calculated through processing the raw data (see Section 10.5.1.2 for reference).

For LD of CNCMTs, different types of simulation (e.g. fluid mechanics analysis, structural mechanics simulation, thermodynamic simulation, etc.) will be carried out using different workload data to make the design of CNCMTs meet target performance indicators. To collect and utilize the workload data efficiently, these data are divided into several categories (e.g. structural mechanics workload, thermodynamics workload, fluid mechanics workload, etc.). Taking the thermodynamic workload data of spindle for example, the thermodynamic workload contains not only temperature data such as spindle temperature, environment temperature and tool temperature, etc., but also data related to thermodynamic simulation such as spindle speed. It might be noted that the same data can belong to different workload categories as long as it plays a role in certain types of simulation.



**Figure 10.2** Detailed analysis of CNCMTs workload

**10.4.2 Construction of workload-DT model**

In order to integrate the workloads with the CNCMTs DT for simulation in LD, a workload-DT model should be established based on the analysis of workload above, as shown in Figure 10.3. The workload-DT model is a hierarchical representation of the working conditions of CNCMTs with clear classification. For example, to meet the target performance indicators of spindle vibration, structural mechanics simulation for the spindle should be carried out. This type of simulation can obtain corresponding workload data efficiently according to the structural mechanics workload-DT model.



**Figure 10.3** Workload-DT model of CNCMTs

After the workload-DT model is constructed, it can be stored in an XML file, which is machine readable, well organized, reusable and capable of transmission.

There are two advantages of introducing the workload-DT model into LD as follows:

(1) The workload-DT model can be reused to avoid repeated domain knowledge modelling. The ambiguity caused by different definitions and expressions for design concepts and terms can be eliminated by building a unified model with well-organized structure. Therefore, data interaction will become more convenient and efficient based on this workload-DT model.

(2) As a result of the clear hierarchical presentation of the workload-DT model, data collection and utilization during LD process becomes more efficient. Furthermore, simulation based on the instance of the workload-DT model will generate more precise and realistic results to guide design of CNCMTs.

## 10.5 Application of workload data

Workload data come from the collected raw data, some of which can be directly used, while some need further calculation. According to the simulation requirements and workload-DT model, suitable workload data are selected from the database and used to instantiate the corresponding part of the workload-DT model for a workload instance generation.

### 10.5.1 Workload data generation

Generation of workload data mainly includes three steps, namely, data preprocessing, data analysis and data storage. The process and role of each step are described in detail below.

**10.5.1.1 Data preprocessing**

In order to maintain consistency between workload instance and actual working conditions, it is necessary to install a large number of different types of sensing devices on CNCMTs and other physical entities for data collection during operation of CNCMTs. These sensing devices usually have low tolerance for noise and electromagnetic interference. Besides, a high data acquisition rate is usually required to capture instantaneous changes in working conditions. As a result of the facts above, the collected data usually have problems such as missing, abnormal, heterogeneous, redundant, etc. If these defective data (e.g. abnormal data, missing data, noisy data, etc.) are used directly as boundary conditions for simulation in LD of CNCMTs, the accuracy of simulation results will be affected and thus cannot provide effective guidance for the design of CNCMTs. Therefore, data preprocessing needs to deal with the above problems existing in the collected raw data. Through preprocessing, the data become more accurate, complete, and regular. Data preprocessing includes data cleaning, data integration, data reduction, and data transformation, as shown in Figure 10.4. Selection of data preprocessing technology depends on the characteristics and application purposes of the raw data.



**Figure 10.4** Data preprocessing

**10.5.1.2 Data analysis**

The pre-processed data are time-discrete data which cannot fully express the entire workload of CNCMTs. Therefore, it is necessary to further exploit the implicit information through data analysis. In other words, the implicit workload data can be calculated based on the pre-processed data through relevant rules or formulas (e.g. thrust calculation, Archard adhesion theory, empirical formula for cutting force, etc.).

**10.5.1.3 Data storage**

After data preprocessing and data analysis, the entire workload data are generated and need to be stored for subsequent utilization. Though the amount of workload data is smaller than that of the collected data, column-oriented database (e.g. HBase) with distributed storage capacity is still recommended. Because of the current volatile market, arrangement of equipment in the shop floor usually changes frequently to rebuild production lines for new products, which also leads to the change of workload data. While the column-oriented database has characteristics of adding column dynamically, which helps it to adapt to workload changes quickly without stopping running.

Time-discrete data and time-continuous data represented by functions are stored separately into two tables of the column-oriented database. To access data effectively, subsystems can be named as column family, while the combination of simulation type and workload data can be named as column. Row key can be defined as the combination of timestamp and a random number after utilizing MD5 (Message-Digest Algorithm) to guarantee its uniqueness and fixed length.

### 10.5.2 Workload data selection

Workload data provides the simulation foundation for LD. This subsection will introduce the two steps of workload data selection before simulation. First is the analysis of target performance indicators of CNCMTs. Then, based on the target performance indicators, the required workload data of CNCMTs LD can be analyzed and selected.

**10.5.2.1 Analysis of target performance indicators of CNCMTs**

Womack pointed out that proper identification of performance requirements provided by customers is the first step for any LD process [39]. Target performance indicators of CNCMTs generally include precision, stiffness, thermal deformation, etc., as shown in Figure 10.5. These target performance indicators come from two sources. Namely, some are requested by customers (e.g. thermal deformation, vibration resistance, precision, etc.), and others come from statistical analysis on historical data of the CNCMT DT model by engineers (e.g. moving range of feed axis, common spindle speed, ultimate spindle speed, etc.). For example, the target performance indicators of the machining space of CNCMTs can be obtained through statistical analysis on the data of the moving range of each feed axis.



**Figure 10.5** Target performance indicator of CNCMTs

In the LD process of CNCMTs, different LD methods and different parts of workload data are selected for simulation according to different target performance indicators. Assuming that the spindle cannot dissipate heat in time, it will undergo axial expansion deformation and will finally affect the machining accuracy. Thus, there should be a target performance indicator for the spindle design to give a threshold for spindle thermal deformation.

**10.5.2.2 Analysis of required workload data of CNCMTs LD**

After target performance indicators of CNCMTs are determined, the next step is to select appropriate workload data for simulation to check whether the designed CNCMTs can meet these indicators. For example, finite element analysis (FEA) is a common simulation method and the type of analysis and simulation boundary conditions have to be determined before starting the simulation. The setting of boundary conditions needs corresponding working condition data to provide data support. Then, the type of analysis is determined according to the target performance indicator. For example, thermal stability of lead screw requires FEA to perform thermodynamic analysis.

### 10.5.3 Workload-DT model instantiation

After determining the workload data type, the last step is to retrieve the related data from the database designed in 10.5.1.3 and instantiate the corresponding part of the workload-DT model.



**Figure 10.6** Example of workload-DT model instantiation

Time-discrete workload data are retrieved according to the start timestamp, since there is no end timestamp of the time-discrete workload data. Nevertheless, time-continuous workload data represented either by a constant value or by a function are retrieved according to start timestamp, end timestamp and other data related to the function.

Multiple XML files will be generated based on different simulation types and each file organizes workload data according to the workload-DT model. An example of the workload-DT model instance in XML format is shown in Figure 10.6. Taking thermal deformation of spindle for example, after deciding the target performance indicators, thermodynamic FEA is carried out on the thermal deformation of the spindle by loading relevant workload instance (i.e. an XML file that contains data such as spindle speed, etc.), and then the thermal deformation of the spindle at different rotational speed can be obtained to check whether it exceeds the threshold. If the thermal deformation results do not meet the target performance indicators of CNCMTs, the design parameters of the spindle system should be adjusted for multiple iterations until the thermal deformation results are all within the allowable range.

In the DT-driven LD of CNCMTs, workload data come from actual working conditions of CNCMTs during machining and thus provide more accurate and authentic boundary conditions for the simulation to support the design of CNCMTs with more practical guidance. Thereby, subjective errors of workload occurring in manual setting in traditional LD design of CNCMTs can be reduced. Besides, feedback time of design defects becomes shortened due to the real-time data mapping of DT, so that LD of CNCMTs becomes more adaptive to the current volatile market.

## 10.6 Optimization and evaluation for CNCMTs

Theworkflow of DT-driven LD mainly contains two functions, which are optimization and evaluation, as shown in Figure 10.7. The DT model for CNCMTs, LD algorithm library, LD simulation module, and LD evaluation module are the key parts to guarantee the realization of DT-driven LD.

### 10.6.1 Optimization for CNCMTs



**Figure 10.7** Framework of DT-driven CNCMTs optimization and evaluation method

When a LD requirement is proposed, a suitable LD algorithm will be selected from the LD algorithm library and the corresponding DT model of CNCMTs will be loaded according to the analysis of LD requirement. The selected LD algorithm and DT model provide algorithm foundation and model foundation for LD simulation separately. At the same time, the required workload data are also loaded into the DT model for subsequent LD simulation.



**Figure 10.8** The workflow of DT-driven LD simulation

The implementation method for LD simulation guided by the analysis of LD requirement is shown in Figure 10.8. Genetic algorithm (GA) is taken as an example to explain the DT-driven LD simulation in detail. The simulation module and the GA optimization module using genetic algorithm are the key parts in this simulation process. The main functions of each module are introduced as follows:

**(1) Simulation module.** Simulation analysis is carried out based on the loaded CNCMT DT model and workload data. Before starting simulation, this CNCMT DT model needs to be updated according to the output of the GA module (only if there is output from the GA module) based on the attenuation updating mechanism introduced in Chapter 9. Then, if the target performance indictors cannot be met according to the simulation analysis results, design parameters of the model are relayed back into the GA optimization module.

**(2) GA optimization module.** After iterations of optimization based on the GA algorithm, the design parameters that meet the performance indicators can be output to the simulation module to check their validity based on the DT model.

Finally, the optimized design parameters acquired using the DT-driven LD scheme are obtained to guide the next generation prototype of CNCMTs.

### 10.6.2 Evaluation for CNCMTs

Although the optimization process using LD simulation can guarantee all parts of CNCMTs to have reached the target performance indicators, it is still necessary to test the actual performance of the next generation CNCMTs prototype with the optimized design parameters. The performance data obtained during the operation of the CNCMTs can be used to determine whether the target performance indicators are met through LD evaluation analysis. If the performance of the CNCMTs prototype is satisfactory, the final design parameters are output to guide the production of CNCMTs. At the same time, the DT model will be updated according to these new design parameters, so that it can be consistent with the new generation of CNCMTs. To the contrary, if the performance of the CNCMTs prototype is not satisfactory, CNCMTs needs to be redesigned in accordance with the workflow illustrated in Figure 10.7.

## 10.7 Case study

In order to verify the feasibility of the DT-driven LD method for CNCMTs, a feed system is taken as an example in this section. The influence of system parameters on the first-order natural frequencies of the feed system is analyzed through the DT-driven LD method.

### 10.7.1 Problem description

At present, the combination of servo motor and ball screw is still one of the most commonly used forms to design CNCMTs feed system. The feed system in the example comes from a certain type of CNCMTs. Configuration of the system parameters is shown in Tab.10.2.

An end milling cutting tool is selected to machine a plane surface. When the spindle speed reaches 3820 *r/min*, the cutting frequency becomes close to the axial first-order natural frequency of the feed system, which is 254.65 *HZ*. This phenomenon indicates the appearance of resonance, which results in the cutting instability.

If a higher cutting speed is needed, it is necessary to improve the first-order natural frequency of the feed system by modifying its design parameters. The higher the first-order frequency is, the larger will be the threshold of cutting speed that causes resonance. Then, occurrence of resonance at the required cutting speed could be avoided.

**Tab.10.2** Parameter values for feed drive system

|  |  |
| --- | --- |
| System parameters | Parameter values |
| Left rolling bearing set stiffness / () | 1.3×109 |
| Ball screw stiffness / () | 1.76×108 |
| Stiffness of the screw nut and its nut seat / () | 5.1×108 |
| Right rolling bearing set stiffness / () | 8.5×108 |
| Ball screw weight / (*kg*) | 9.78 |
| Worktable weight / (*kg*) | 100 |
| Ball screw length / (*mm*) | 1200 |

### 10.7.2 DT-driven LD for the feed system of CNCMTs

In order to verify the effectiveness of the proposed method, the effect of position and weight of machine table on the axial first-order natural frequency of the feed system is analyzed respectively.

**(1) Influence of worktable position on the axial first-order natural frequency**

It is inevitable to move the worktable when analyzing the effect of its position on the axial first-order natural frequency. Therefore, when performing simulation analysis, structural mechanics workload data of the feed system during worktable moving from one position to another are selected and set as the boundary conditions. After selecting the suitable algorithm (e.g. eigenvalue solving algorithm) and carrying out simulation based on the DT model, the position-frequency curve can be obtained, as shown in Figure 10.9. It can be seen that the axial first-order natural frequency turns lower when the worktable moves to the position near the middle of the screw, and gradually increases when the worktable moves to the both ends.



**Figure 10.9** Influence of worktable position on axial first-order natural frequency

**(2) Influence of worktable weight on axial first-order natural frequency**

By performing simulation in the same way except that the worktable is kept at the center position and changing the worktable weight, the weight-frequency curve can be obtained as shown in Figure 10.10. It can be seen that the axial first-order natural frequency decreases with the increase of worktable weight. Besides, the rate of the axial first-order natural frequency decrease becomes larger when the weight is around the original value of 100 *kg*.



**Figure 10.10** Influence of CNCMTs table weight on axial first-order natural frequency

When the worktable weight is reduced by 10%, the axial first-order natural frequency increases by 4.94%. It can be concluded that the first-order natural frequency of the CNCMTs feed system can be effectively improved by reducing the worktable weight.

### 10.7.3 Results and discussion

With the aim of increasing the first order natural frequency and thus improving the upper limit of spindle speed, the structure of the worktable was optimized with a weight reduction by 5% according to the analysis above. A new generation of three-axis CNCMTs was manufactured based on the optimized parameters, and modal experiments were carried out using modal test equipment including an hammer, a signal conditioners, a data collector and modal testing software.

According to the modal test, the axial first-order natural frequency of the new feed system is 310.35 *HZ*when the worktable is located in the middle of the screw. It is obvious that the axial first-order natural frequency of the feed system has been improved. When machining the plane with a 4-edged end milling cutting tool, the spindle speed can reach 4655 *r/min*, which increases by nearly 22% compared with the value before LD. All the system parameter values before and after LD are shown in Tab.10.3, which reveals the effectiveness of LD.

**Tab.10.3** System parameter values before and after LD

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| System parameters | Before LD | After LD | Amount of change | Rate of change |
| Axial first-order natural frequency | 254.65 *HZ* | 310.35 *HZ* | 350 | ↑22 % |
| Worktable weight | 100 *kg* | 95 *kg* | 5 | ↓5 % |
| Maximum spindle speed | 3820 *r/min* | 4655 *r/min* | 835 | ↑22 % |

## 10.8 summary

In this chapter, a DT-driven LD method for CNCMTs has been proposed for the optimization of CNCMTs performance. The steps for implementing DT-driven LD in digital space are introduced in detail with respect to the workload-DT model design, application of workload data and optimization and evaluation for CNCMTs. Finally, a case study of feed system optimization design using the DT-driven LD method is introduced to verify the feasibility of this method and indicates that the allowable cutting speed turns higher, which can improve the cutting efficiency and support high-speed cutting. This DT-driven LD method can also be applied to other equipment design.

Future work will focus on the lean thinking application in the manufacturing of CNCMTs based on the DT-driven method. In addition, suppliers, designers, manufacturers and other stakeholders can fully collaborate and communicate to realize the optimum combination of LD and lean manufacturing.

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