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CRITICAL REVIEW

A survey of modeling and control in ball screw feed-drive system

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Abstract

Ball screw feed-drive system (BSFDS) is the precision transmission mechanism widely used in micron-scale positioning or motion trajectory control. Its desired specifications including high acceleration, speed, accuracy, and stability are challenged by vibration, friction, thermal error, uncertainty, etc. Inspired by these challenges, the modeling and control issues have been widely studied and discussed for decades. This paper presents an overview of modeling and control approaches, including identification, linear parameter varying, thermal error modeling and control, nonlinear control, and robust control. In particular, it reviews the emerging control issues and approaches, such as artificial intelligence, learning control, and data-driven control, which have increased in recent years.

Keywords Ball screw · Dynamical modeling · Motion control · Vibration · Thermal error · Nonlinear · Uncertainty

1 Introduction

Ball screw feed-drive system (BSFDS) is a mechanism that converts the rotational motion of a motor into the translational motion of a nut-driven carriage. It is widely used in high-precision positioning or tracking systems of industrial automation equipment because of its relatively low cost, high rigidity, low friction, low sensitivity to external forces and inertia changes [1]. In particular, as a crucial drive/transmission element, BSFDS is moving toward the higher speed and precision, which drive the need to a higher motion accuracy and a closed-loop control bandwidth [2]. Accordingly, the dynamics modeling and control issues of BSFDS have long been a hot area of research in academia and industry [3–5].

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BSFDS exhibits extensive applications in machine tools [1], semiconductor manufacturing equipment [6], aerospace equipment [7], vehicles [8], various elevating mechanisms [9], textile machinery [10], and some other equipment. For instance, BSFDS is the transmission part of machine tool. The motor rotates ball screw when a machine is working, so that the moving part of the machine connected by a nut moves in a straight line. In aerospace equipment, a load capacity of BSFDS is very important to its stiffness and positioning accuracy. In vehicles, BSFDS is often used in the shift mechanism and steering system with the advantages of large loads and high transmission efficiency. In lifting mechanism, BSFDS contributes to solving the problems on uneven running, loud noise, and inaccurate stopping of an elevator.

In the above applications, BSFDS faces the following challenges and issues. Firstly, with control bandwidth increasing, axial and torsional vibrations of ball screw become an intractable problem. The resonant dynamics in control bandwidth directly affect the positioning and tracking accuracy in BSFDS [11, 12]. Secondly, the thermal error problem of ball screw also severely restricts the positioning and tracking accuracy in BSFDS [13]. The thermal error caused by an increasing temperature in BSFDS is a deformation or an expansion of machine elements. Temperature increase is generated by heat sources, like motors, friction, and external radiation. Thirdly, the existence of nonlinear factors in BSFDS complicates the modeling and control design process and reduces the positioning and tracking accuracy [14], such as friction, nonlinear elastic property, and other nonlinear dynamic behaviors. Among nonlinear factors, nonlinear friction is the main factor that leads to the increasingly complex dynamic behavior in BSFDS. Fourthly, uncertainties may deteriorate the stability and other performance of BSFDS [15]. Uncertainties of BSFDS include parameters variations, disturbances, and model errors.

In view of the above issues, the dynamics modeling and control approaches of BSFDS are reviewed. First, the system identification methods of BSFDS are reviewed. System identification is an experimental modeling method that establishes a model conforming to the actual physical system based on the system input and output signals. This modeling method effectively overcomes the limitation of the theoretical modeling of BSFDS and meets the requirements of an actual control system. Next, linear parameter varying (LPV) method in BSFDS has reviewed. Compared with traditional linear time-invariant (LTI) modeling, LPV method exhibits advantages in modeling nonlinear factors. Moreover, LPV method provides a valuable way to solve the dynamic parameters variation problems caused by the flexible structure and load changes of BSFDS. Then, thermal error modeling and compensation of BSFDS have been discussed. Thermal error modeling is problematic due to the fact that it is a complex nonlinear varying process. Thermal error compensation is a process of correcting thermal errors that needs to be based on an accurate thermal error model. After that, nonlinear control methods are reviewed focusing on the nonlinear factors in BSFDS. Nonlinear control methods include friction compensation, sliding mode control, and other nonlinear control approaches. Unfortunately, these methods cannot solve the uncertainty issues. In the end, robust control is reviewed to solve the uncertainties of BSFDS. Robust control can realize a high closed-loop bandwidth, and maintain stability and robustness in the presence of uncertainties, such as external disturbances, parameter variations, and model errors.

Accompanying the boom in artificial intelligence, machine learning, data-driven and other emerging intelligent control methods, new solutions are available for solving BSFDS modeling and control issues. Artificial intelligence methods include intelligent algorithms such as artificial neural network, genetic algorithm, fuzzy control [16]. Their main goal is to enable machines to perform complex tasks that normally require human intelligence. Deep learning, iterative learning, reinforcement learning, and other types of learning-based control methods are collectively referred to as learning control. In the process of learning control, the complex calculation process and parameter estimation of the plant can be simplified or ignored. Only the actual output signals and the desired signals are detected. So it is commonly used in the unmodelable system. Unlike traditional model-based control, data-driven control relies on input, output and processing of data for its analysis and design. That is, data-driven control does not have a modeling process.

This paper, which reviews the researches related to BSFDS modeling and control, is organized as follows. It begins with reviewing the mechanism and several typical applications of BSFDS in Sect. 2 to illustrate the challenges of modeling and control issues. Before presenting specific modeling and control approaches, Sect. 3 will be concerned with the generalized modeling and control issues of BSFDS. In Sect. 4, it is given an overview of the corresponding modeling and control approaches to the mentioned issues in Sect. 3. Separating the issues and approaches of modeling and control into two sections (Sects. 3 and 4, respectively) allows us to classify commonly used control approaches to solve specific issues to BSFDS, such as vibrations, thermal errors, nonlinear factors and uncertainties. Moreover, along with the rise of emerging control technologies such as artificial intelligence, Sect. 5 provides a review of emerging control issues and approaches. Finally, some concluding remarks are given in Sect. 6.

2 Mechanism and applications of BSFDS

2.1 Mechanism

The main work of this paper is to overview the dynamics modeling and control issues of BSFDS, which determined by its mechanical structure. The mechanical structure diagram of ball screw is shown in Fig. 1. It is utilized to convert rotary motion into linear motion, or convert torque into axial repetitive force with high precision, reversibility and high efficiency [1].

2.1.1 Composition of BSFDS

BSFDS can be separated into mechanical transmission system, position measurement system, control system, and

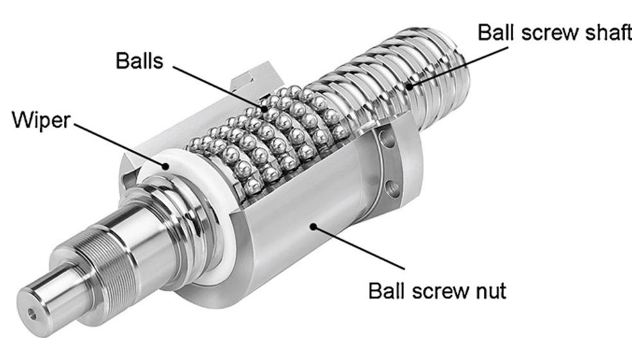


Fig. 1 The mechanical structure diagram of ball screw [1]

electrical drive system, while its structure schematic diagram is shown in Fig. 2.

The mechanical transmission system consists of nut, screw, bearings, coupling, guideways, and carriage, of which the ball screw is composed of screw, nut, and balls. The two ends of the ball screw are supported by bearings, and the one near the motor is connected to the motor spindle by a coupling. The coupling transmits the driving torque generated by the motor to the ball screw. At the same time, it has the function of absorbing the violent pulse shock and overload protection. The nut is rigidly connected to the carriage that slides along the linear guideways. The purpose of a linear guideway is to support the carriage and ensure that it always moves along a straight line. And many performances of BSFDS are affected by the guideway accuracy. The position measurement system usually adopts the linear encoder to measure the linear displacement of the table and the rotary encoder of the servo motor to measure the rotary position of the motor shaft, which constitutes a linear-rotary displacement feedback system. The control system depends on a computer system with software to implement the control algorithms, data sampling, parameter adjustment and monitoring, and other visual interaction operations. The electrical drive system mainly refers to the drive mechanism consisting of motor drive and servo motor. The motor driver converts the control signal from the controller into a voltage or current signal that can drive the motor operation.

2.1.2 The working principle and transmission properties of ball screw

In ball screw, the screw and nut are both machined with a curved thread groove. A spiral raceway is formed when the screw and nut are mounted together, which is filled with balls. The balls roll along the raceway when the ball screw in operation, and then move in a circular motion through the ball return pipe in the nut [17].

According to the working principle of ball screw, BSFDS has the following transmission properties: 1) High transmission efficiency, which can reach 95% to 98% [1]. 2) Low friction, which has advantages of low difference between dynamic and static friction factors, smooth movement, no crawling phenomenon at low speed movement, high positioning and tracking accuracy [17]. 3) Long life, which benefits from the small surface roughness and wear. As ball screw is made of high quality alloy, the surface of the raceway has high hardness [18]. 4) Limitation of the backlash, which is realized by giving proper preload, and can improve the rigidity of the system. 5) Reversibility, which means the rotary motion of BSFDS can be converted to linear motion and vice versa, i.e., both the screw and the nut can be used as active parts.

The mechanism structural characteristics of BSFDS bring many specific issues to the modeling and control, such as vibrations, friction, backlash.

2.2 Applications

BSFDS is widely used in various industrial equipment and precision instruments because of the properties of ball screw [6–9, 19, 20].

2.2.1 Machine tools

Machine tool is the top priority of equipment manufacturing and an important symbol of modernization machining, with the characteristics of high precision, high efficiency and high flexibility. With the development of machine tools to high-speed, high-precision and heavy-duty, BSFDS has become an indispensable transmission element of high-performance machine tools [1, 21]. As the most important transmission part of machine tools, BSFDS directly affects the machining accuracy and performance of machine tools [19].

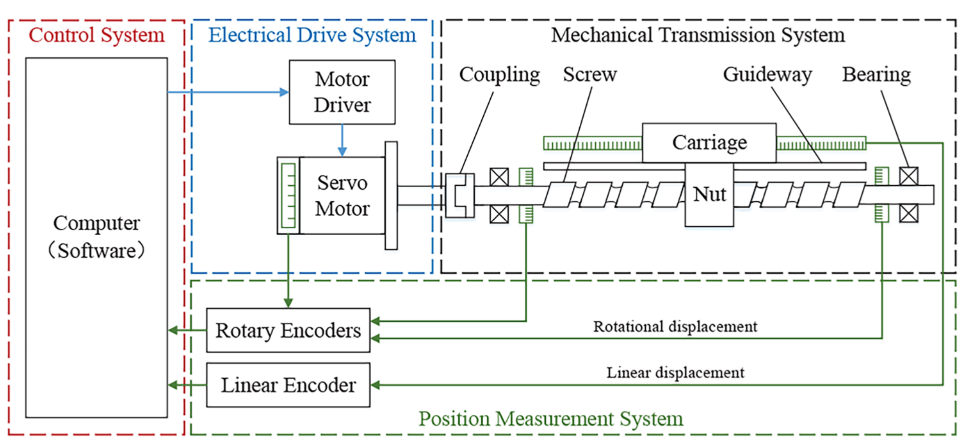


Fig. 2 Composition of BSFDS

2.2.2 Semiconductor manufacturing equipment

Semiconductor manufacturing equipment places extremely high requirements on accuracy and speed of motion control [22]. BSFDS is an important transmission element in semiconductor manufacturing equipment. With the advantages of simple structure, high accuracy, and long life, BSFDS is used in micron-level precision positioning and tracking control of semiconductor manufacturing equipment [6].

2.2.3 Aerospace equipment

Actuator is the actuating component that manipulates the rotation of aircraft rudder (maneuvering surface) in an autopilot. Due to high efficiency, high rigidity, compact structure, and high transmission accuracy, ball screw actuator is the most common drive/transmission mechanism in aerospace equipments [7, 23]. The large cylindrical shells in aerospace is quite difficult to manufacture, because of the long dimensions, heavy weight, and high precision requirements [24]. The large-scale aerospace spinning machine with the double-drive nut rotary ball screw is mainly used to manufacture large cylindrical shells [5].

2.2.4 3D printers

3D printer usually adopts BSFDS as the conversion mechanism of rotary motion and linear motion. It can achieve high mechanical efficiency and printing accuracy by taking advantage of low friction and high transmission efficiency in BSFDS [20].

2.2.5 Vehicles

Automated mechanical transmission (AMT) is an important component of vehicle automatic transmission with simple structure, high transmission efficiency, and low cost [25]. And BSFDS is the main mechanism of AMT to achieve large load, fast and accurate shifting actions in vehicles due to its high precision, fast feed, and high axial rigidity [8].

2.2.6 Elevating mechanisms

Elevators using BSFDS effectively improve the transmission efficiency and accuracy, and run smoothly with low noise [9]. Moreover, BSFDS elevating mechanism is capable of precision elevating motions, which is widely used in radar antennas, rockets, artillery launchers, and medical machines [26].

2.2.7 Other applications

Doffing device of spinning frames is the key mechanism in doffing and spinning process [27]. BSFDS with special nut is an important part of the doffing devices to achieve low backlash, smooth operation, and high transmission accuracy [10].

In summary, BSFDS has been received extensive applications in motion control fields. There is an urgent demand for further improving the performance and efficiency and reducing the hazards of BSFDS, so it is of significant engineering value to research modeling and control issues of BSFDS.

3 Modeling and control issues

BSFDS has a lot inherent physical characteristics, such as structural vibration, friction, and thermal errors. All of these characteristics deteriorate the control performance and poses challenges to the modeling and control of BSFDS. Therefore, this section will comprehensively sort out the issues of BSFDS modeling and control.

3.1 Vibration

Vibration is an inherent property of common non-rigid structures, and all actual structures in physical world are non-rigid or flexible. Thus, vibration is a natural phenomenon that exists universally. In BSFDS, vibration reduces the accuracy, destroys the stability, and limits the close-loop control bandwidth. Recently, plenty of research efforts are devoted to vibration problem of BSFDS [28–31].

BSFDS is composed by multiple components that can be flexibly interconnected. If all the components are seen as rigid body, vibrations only exist in flexible connections. And these flexible connections can be modeled by the lumped mass modeling method [32]. Lumped mass modeling method replaces each component with a mass block. And the flexible connections are represented by massless springs. The structural damping unit is represented by an equivalent damping unit.

However, it is only an ideal assumption that all the components are rigid body. In fact, all components are flexible, of which ball screw has the greatest impact on system performance. Therefore, ball screw is considered as a continuous system in time and space with distributed physical parameters of mass, stiffness and damping. This system is also called distributed parameter system [12]. Mathematically, distributed parameter system is presented as partial differential equation, which is difficult to find its analytical solution. By discretization and reasonable model reduction, distributed parameter system can transform into a finite dimensional discrete model, which is mathematically described as linear differential equations [33]. The discrete model implements a discrete approximation to the continuous model, and its model state vector is the physical coordinate of system. Moreover, modal analysis is utilized to transform the physical coordinates into modal coordinates, so that linear differential equations can be decoupled and become an independent set of equations [34]. It can also be solved numerically using finite element modeling method [35].

With the modal model of BSFDS, the interactions between axial, torsional and lateral dynamics of ball screw can be analyzed. The simulated natural frequencies and mode shapes are shown in Fig. 3. The most dominant mode

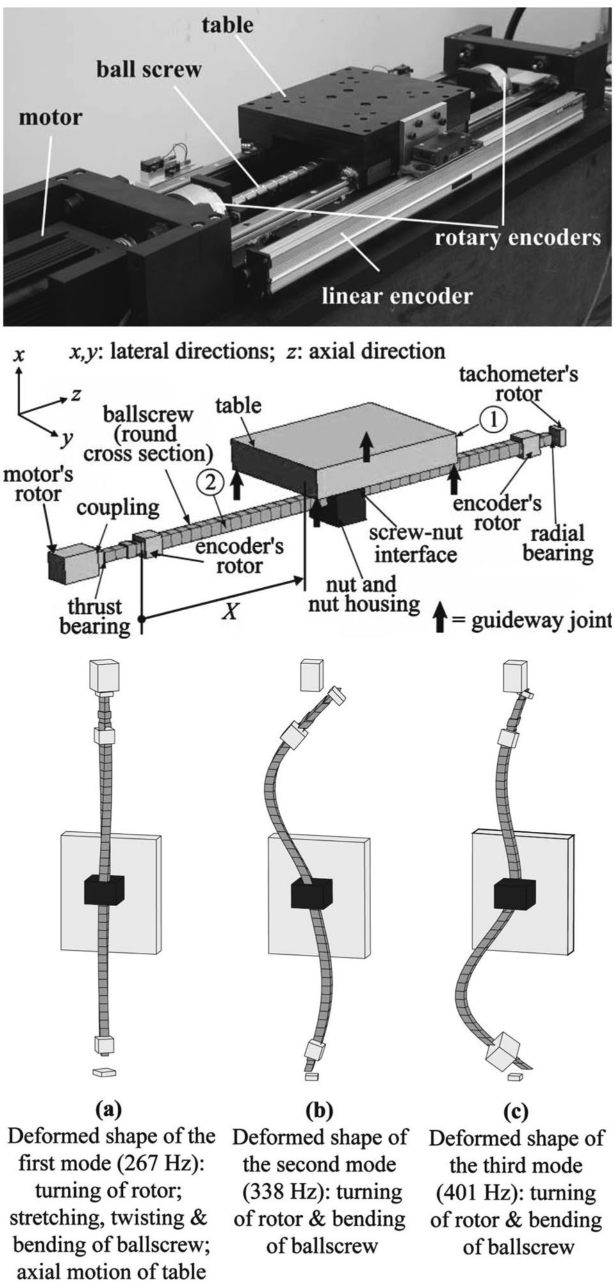


Fig. 3 Simulated deformed shapes of three modes of BSFDS [1, 28]

(first mode, as shown in Fig. 3a) affecting the axial positioning accuracy of the carriage involves the turning of motor (as a result of the torsional coupling connecting it to ball screw), axial, torsional, and lateral vibrations of ball screw and axial vibrations of table. The second and third modes (as shown in Fig. 3b, c) are due to the turning of motor and lateral vibrations of ball screw, and they have little effect on the table position.

With the increasing requirements of BSFDS in speed, acceleration, and precision, its flexible modes will be triggered to generate vibration, affect the accuracy, even seriously damage the machine. These flexible modes limit the system closed-loop control bandwidth, and adversely affect positioning and tracking accuracy [36]. In addition, BSFDS controller should compensate the dynamic changes mainly caused by structural flexibility and load mass varying, due to the nonlinearities and uncertainties in actual system [37]. Consequently, an accurate dynamic model of BSFDS with flexible structures will contribute to solving the problem.

3.2 Thermal error

Precision positioning and tracking control puts forward new requirements on BSFDS. A large number of scholars and engineers dedicate to the research of thermal error [38].

Specially, thermal error occurring on temperature changes constrains the machining accuracy of workpieces in machine tools. The three major types of errors in machine tools are thermal error, geometric error, and cutting-force induced error [39]. It is worth noting that previous studies have shown that thermal error of BSFDS is about 30% ~ 50% of the total error, and reach up to 70% in precision machining [13]. Thermal error is the displacement and angle changes on account of deformation or expansion due to the temperature increase. In BSFDS, the relative motion between various components generates heat in contact area. In general, some of the possible heat sources are [38, 40]: (a) heat generated by bearings; (b) heat generated between the nut and screw; (c) heat generated in motor; (d) heat generated by the guideways; (e) external heat sources including environmental temperature variation, solar and personal radiations. The heat generation and heat transfer mechanism of BSFDS is shown in Fig. 4. The motor and ball screw are connected by a coupling, which limits the heat generated by motor flow to ball screw. Namely, the heat generated by motor can be ignored.

In machine thermal deformation phenomena, the thermal deformation dynamics in response to heat flux is composed of two processes: heat transfer process and thermoelastic process [42]. The heat transfer process is shown in Fig. 4. Different heat sources transferring to BSFDS cause the thermoelastic process. A simply thermoelastic deformation process is shown in Fig. 5a. The heat flux inputs from the left fixed end of the spindle like ball screw, and heat dissipates

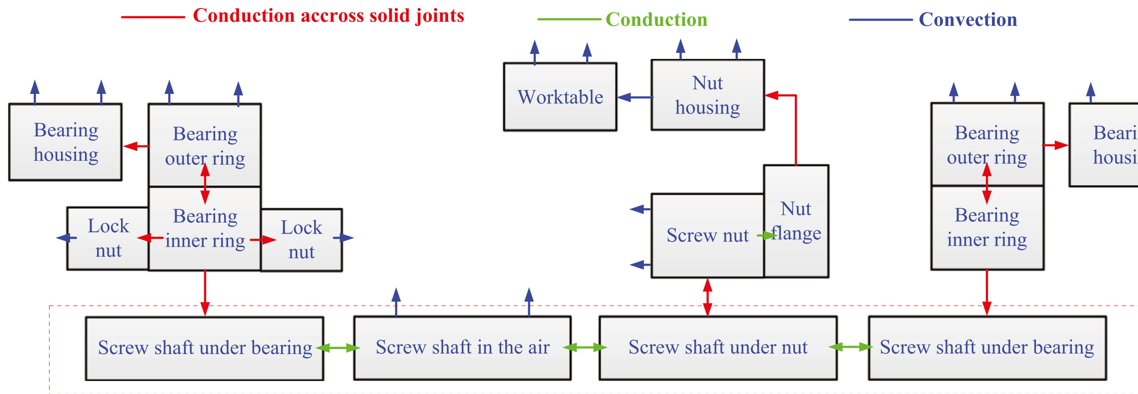
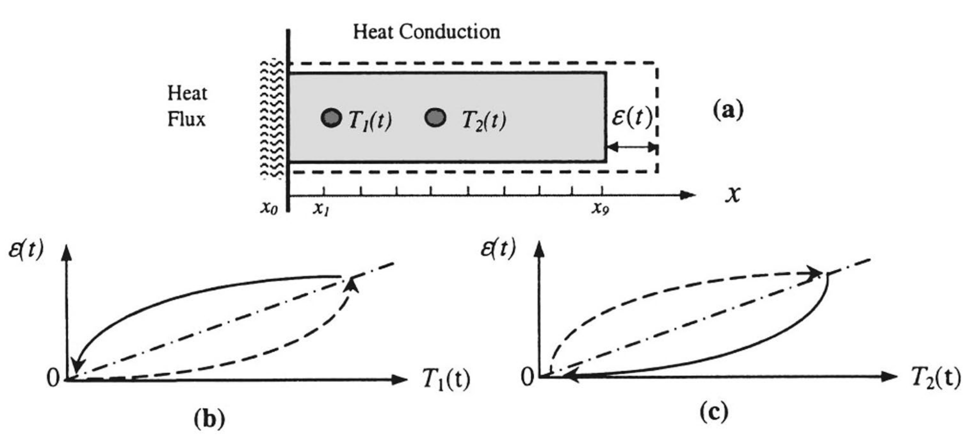


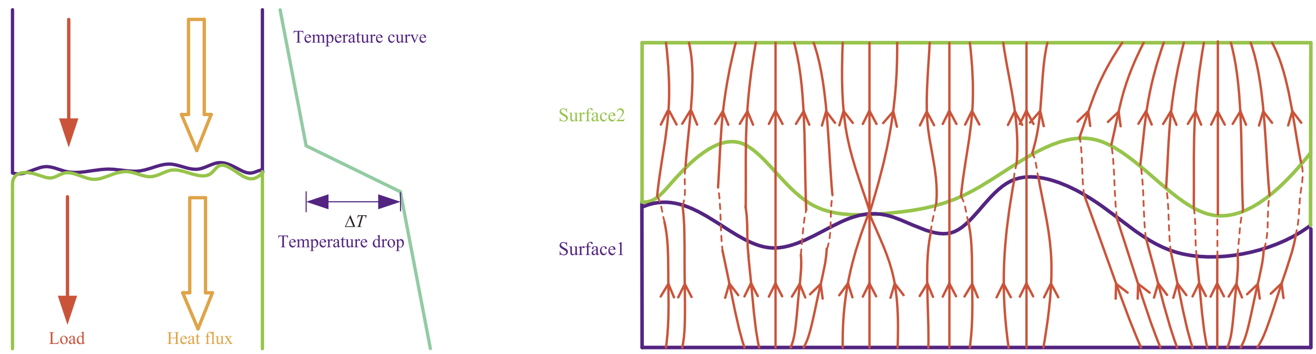
Fig. 4 Heat generation and heat transfer mechanism of BSFDS [41]

around the spindle surface through heat convection and radiation. $T(t)$ is the temperature variation function of time t in response to the heat flux input, and $\epsilon(t)$ is the thermal deformation accumulated at the spindle free end. Because the distance to heat flux input is different, the dynamic response of each temperature measurement has a different time constant. During the heating deformation process, $T(1)$ leads with respect to $T(2)$, $T(2)$ lags with respect to $T(1)$, and the cooling process is the opposite, as shown in Fig. 5b, c. Obviously, the thermal deformation caused by dynamic change of heat source cannot be expressed by the temperature value of a certain point or some discrete points, which has strong timeliness and integrity [42]. Therefore, thermal deformation modeling requires the temperature field of the entire screw rather than a finite number of discrete points on it. For objects with simple shapes (such as plates, cuboids, cylinders and spheres), analytic solutions can be obtained by combining certain initial conditions and boundary conditions. However, the obtained solutions are very complex and usually expressed in the form of infinite series. Moreover, in the case of complex heat transfer, thermal deformation is a thermal-structural coupling process, which is difficult to obtain the analytical solution of temperature field. Under actual operating conditions, parameters such as speed, operating time, and motion range are not constants, which makes it more difficult to estimate the temperature field.

It has been proven that the thermal contact resistance is essential for thermal characteristic analysis of BSFDS [43]. Nevertheless, thermal contact resistance is usually considered a constant and obtained through repeated testing and engineering experience, which is clearly unreasonable at high speeds. The reason is that, there are a large number of solid joints in BSFDS, including the bearing inner ring/shaft journal and the bearing outer ring/bearing housing. A joint in a machine tool represents the contact between elements and machining contacting surfaces, with a certain roughness and waviness [44]. When surfaces are in contact, incomplete contact will occur at the joint due to a rough surface, as shown in Fig. 6a. And heat flux will contract as it passes through the joint surface, as shown in Fig. 6b. Thus, heat flux is restricted by the thermal contact resistance of the solid joints, resulting in a sharp temperature drop at the solid joints, as shown in Fig. 6a. Thermal contact resistance should be defined as a distribution function rather than

Fig. 5 Pseudo-hysteresis effect of thermoelastic deformation. (‘–’ warm up stage; ‘——’cool down stage) [42]





(a) Temperature drop at the solid joint **(b)** Shrink of the heat flux

Fig. 6 Formation mechanism of thermal contact resistance [45]

a constant, because the contact pressure is non-uniformity along the solid joint.

The location and strength of heat sources, the mechanical structures, the material properties and the coefficient of thermal expansion are coupled with each other. And the temperature field of ball screw is non-uniform distribution. All these reasons work together to result in thermal error. In order to minimize the thermal error in BSFDS, various methods have been proposed, which will be presented in Sect. 4.4.

3.3 Nonlinear factors

There are several non-linear factors in BSFDS, such as friction [14, 46] and backlash [47]. They complicate the control design process and reduce the positioning and tracking accuracy.

3.3.1 Frictional behavior

Rolling friction force is much smaller than that of sliding friction, which is the reason ball screw is used instead of sliding screw in precision motion control. However, the friction is still a major nonlinear factor in growing complexity of the dynamic behavior of BSFDS. Friction in BSFDS is a multifaceted phenomenon, incorporating Coulomb and viscous friction, nonlinear friction at low velocities, temporal phenomena and interface elasticity. In particular, BSFDS equipped with rolling contact elements such as ball screw, bearing, and linear motion guideway experiences nonlinear frictional behavior. Friction causes frequent stick-slip motion and limited-cycle oscillations, which severely affect the motion control performance and stability of BSFDS. In order to achieve high precision in motion control of BSFDS, the friction factor cannot be ignored. Nonlinear friction is generally reduced by various friction compensate approaches, which attempt to compensate for the effects of friction. The prerequisite for friction compensation is the modeling of friction force to predict and to compensate friction. Therefore it is also named model-based friction compensation. Friction is a natural phenomenon that is quite hard to model, and it is not yet completely understood. Most of the existing model-based friction compensation approaches use classical friction models. The classical friction models are described by static maps between velocity and friction force. Typical examples are different combinations of Coulomb friction, viscous friction [48], and Stribeck effect [49], such as Stribeck model [48], Dahl model [50] and DeWit model [51]. Stribeck model [52] has been widely used in friction modeling and compensation, and it can describe the complex static performance correctly. A dynamic model describing the spring-like behavior during stiction was proposed by Dahl [50]. Dahl model is essentially Coulomb friction with a lag in friction force change when the direction of motion is changed. DeWit has proposed a new dynamic friction model that combines the stiction behavior, i.e., the Dahl effect, with arbitrary steady-state friction characteristics which can include the Stribeck effect. Based on above friction models, online friction compensation approaches will be reviewed in the next section [14, 53].

3.3.2 Nonlinear elastic property

In micro-scale (within a range of several micrometers), the positioning mechanism using a preloaded ball screw showed nonlinear elastic behavior [54–56]. Under transient conditions, the contact points on the rolling elements have a partial adhered region as shown in Fig. 7. At that moment, the relation between F and displacement x shows the property as a nonlinear spring. This phenomenon is called nonlinear elastic property or nonlinear spring behavior of rolling elements. The nonlinear elastic property of BSFDS is available

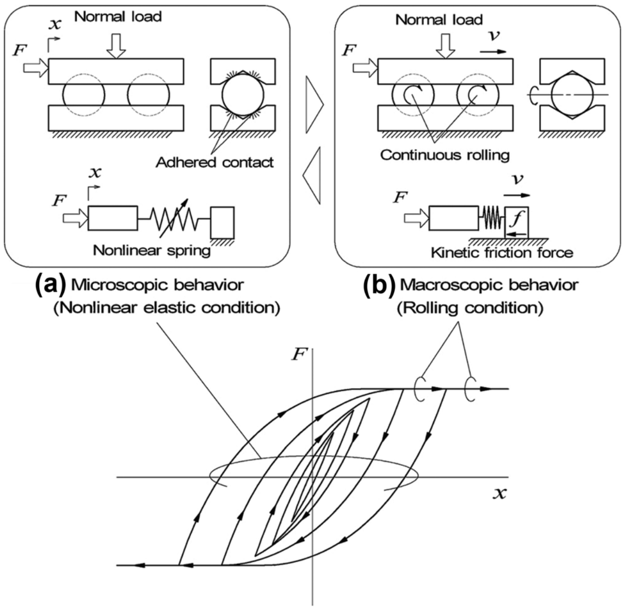


Fig. 7 Nonlinear elastic property [55]

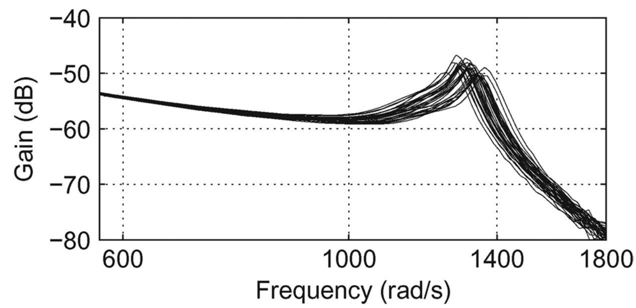


Fig. 8 Uncertainty in frequency response function of BSFDS [37]

for nanometric positioning without the sticking between torque input and displacement [57]. And the property has hysteresis, which causes error motion in continuous-path positioning, such as quadrant glitch error [58]. The nonlinear elastic property is one of the most crucial factors for the determination of the performance in submicron or nanometre level positioning.

3.3.3 Other nonlinear dynamic behaviors

In addition to the above analyzed nonlinear friction and micro-scale elastic properties, BSFDS still has other nonlinear dynamic characteristics, such as nonlinear Hertzian force [59], tooth groove force [60, 61], piecewise restoring force [62], thrust ripples [63], and deflection angle caused by assembly error [15]. The combined effect of above nonlinear factors results in BSFDS having complex nonlinear dynamic characteristics. The nonlinear dynamic behavior is one of the most important factors in determining the motion performance, which leads more and more researchers to pay attention to the nonlinear dynamic characteristics in BSFDS [64–66].

3.4 Uncertainties or model errors

As shown in Fig. 8, there are unavoidable uncertainties in BSFDS model, such as parameter variations, disturbances, model errors caused by unmodeled dynamics [64, 67–69]. These uncertainties may significantly deteriorate the performance of BSFDS.

3.4.1 Parameters variations

Unlike the ideal LTI system with fixed parameters, the parameters of BSFDS dynamical model in actual are constantly varying with time [37, 70]. For example, ball screw wears during use and the preload force gradually decreases. Then, the uncertainty of preload force breeds the uncertainty of axial stiffness and contact angle [71]. Moreover, the model parametric uncertainties are mainly caused by position variation and structural flexibility of BSFDS [72]. That is, the structural vibration parameters also vary with position and operating conditions [37]. If the position varying leads to a variation in the feeding system mechanism, the flexible modal parameters vary accordingly. Similarly in actual operating conditions, the mass of workpieces on table is varying. As a result, BSFDS is a dynamic system with time-varying parametric uncertainties [73, 74]. To achieve high tracking performance, all the parameter variations of viewpoints above should be taken into account.

3.4.2 Disturbances

The influence of disturbance is inevitable during the BSFDS motion, such as measurement noise [75], process noise [76], electromagnetic disturbance [77], cable disturbance [78], temperature disturbance [79]. Disturbances of BSFDS can be divided into internal disturbances generated within the system and external disturbances from outside the system. Specifically, internal disturbances include unmodeled modal mechanical vibration, irregular motor jumps, white noise interference of the encoder, random and irregular errors of the command signal, etc. External disturbances include nonlinear friction, cutting force, cable disturbance, ambient temperature variation, etc. Above disturbances are random, irregular, and difficult to model. These features can affect the tracking accuracy of BSFDS [70]. This problem will be solved using linear/nonlinear disturbance estimation and compensation methods [80], which will be described in detail in the next section.

3.4.3 Model errors

There must be modeling errors with the real physical system in BSFDS dynamics modeling [28]. These modeling errors can be divided into three main types. The first type is inaccurate modeling error [81]. It is easily understood, as the model is a simulation and assumption of the real objective physical world, the model must not accurately describe the real physical system, and there must be errors between them. The second type is modeling error due to simplification and assumptions about the model [82]. To achieve the requirements of calculation, analysis and design, the model must be simplified and assumed, such as the modeling error caused by linearizing the nonlinear factors. The third type is unmodeled dynamics modeling error [83]. It is because a tradeoff should be taken between model accuracy and reduced computational that the model needs to describe real physical systems with the lowest possible model order, which ignores the higher-order dynamics and leads to residual modeling error [84].

In order to improve the performance in trajectory tracking and disturbance rejection for BSFDS with uncertainties, the uncertain modeling and robust control should be considered. Based on uncertainty model, robust controllers are designed to improve the tracking performance with robustness to uncertainties. And disturbance rejection and robust control approaches will be described in detail in next section.

4 Modeling and control approaches

A number of approaches have been proposed over the decades to solve the modeling and control issues that exist in BSFDS. The specific modeling and control approaches include lumped mass modeling, finite element modeling, identification, linear parameter varying, thermal error compensation, nonlinear control, and robust control, which will be overviewed in this section.

4.1 Common modeling methods

The most commonly used modeling methods are lumped mass modeling, finite element modeling, and hybrid modeling.

4.1.1 Lumped mass modeling

Lumped mass modeling is a commonly used modeling method, which replaces the mass units with finite mass blocks, elastic structures with massless springs, and structural damping units with equivalent damping units. The Lumped mass model of BSFDS is shown in Fig. 9. It is a simple model, which is mainly utilized to express low frequency dynamics of BSFDS. However, it does not accurately describe the flexible dynamics of BSFDS.

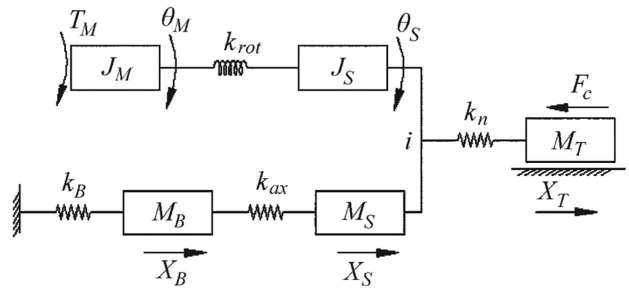


Fig. 9 Lumped mass model of BSFDS [85]

4.1.2 Finite element modeling

Finite element modeling (FEM) method first discretizes BSFDS into finite element units. Then a suitable finite element approximation method is chosen to interpolate each unit. Next, a global stiffness matrix needs to be constructed. This will yield some finite element equations for the entire structure, the computational model of which is shown in Fig. 10. The computational speed of the method is closely related to the size of finite element and the complexity of approximation method. FEM model can show the details of BSFDS dynamics, which can describe not only the static state but also the moving state. However, the model is complex, which needs large scale calculation. Moreover, each downscaling method has specific requirements, and there are many factors to be considered in practical applications.

4.1.3 Hybrid modeling

Hybrid modeling combines the advantages of lumped mass modeling and finite element modeling. Ball screw is treated as flexible structure with finite element modeling method, and the other components in BSFDS are modeled by lumped mass modeling method, as shown in Fig. 11. Compared to lumped mass modeling and finite element modeling, this method is more accurate in flexible dynamics with less calculation.

However, the model parameters obtained by the above methods are inaccurate and need to be updated by experimental methods. The general method is identification.

4.2 Identification

The model-based control of BSFDS need an accurate model for controller design. However, common modeling methods above are the simplification of actual model, which leads to model errors between theoretical model and actual model. Therefore, it is necessary to build a mathematical model by the input and output signals of BSFDS in line

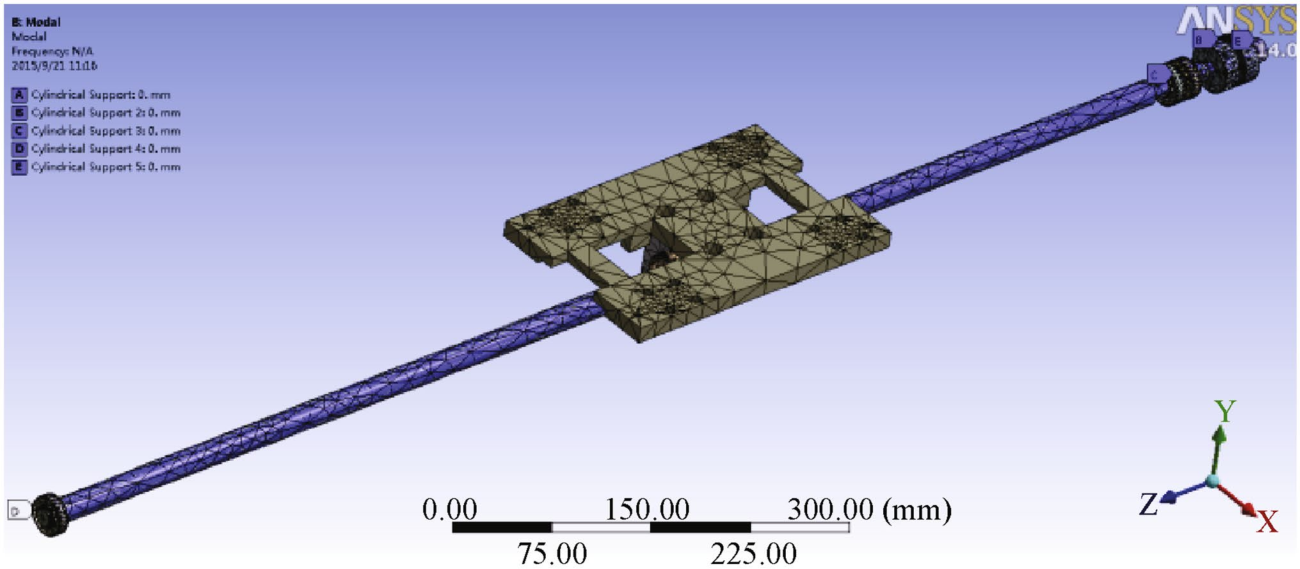


Fig. 10 FEM model of BSFDS [86]

with the actual system [88], i.e., identification. Identification is divided into frequency domain identification and time domain identification.

4.2.1 Frequency domain identification

Frequency domain identification is a non-parametric modeling method based on spectral analysis. The frequency spectrum curve is first achieved and then the transfer function is parameterized by curve fitting. The advantage of frequency domain identification is that it can model continuous-time systems directly from output signals excited by a band-limited input signals [89]. Therefore, it is widely used in BSFDS modeling. For instance, a flexible model is proposed to express the first-order axial vibration of BSFDS. It obtains the mass, damping, and stiffness matrices of BSFDS by the frequency response curve of a sweep experiment [90]. A third-order discrete transfer function model is utilized for BSFDS by applying the frequency domain identification method [91, 92]. A closed-loop frequency domain identification is used to obtain

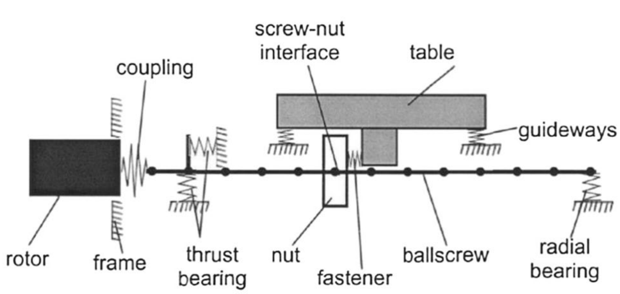


Fig. 11 The hybrid model of BSFDS [87]

a position-dependent and load-dependent LPV model for BSFDS [37, 93]. However, when fitting the non-parametric model obtained from frequency domain identification, it is necessary to set appropriate initial values of parameters. Otherwise, the solution process will fall into local optimum and obtain an inaccurate result.

4.2.2 Time domain identification

Time domain identification, like the subspace identification method, has also made significant progress in the past two decades. Compared with frequency domain identification, it does not need parameterization or iterative optimization, and the realization relies on some simple and reliable linear algebra tools, such as QR decomposition and singular value decomposition [94]. Modern control technology is based on the state space method. Although frequency domain identification can transform the result into state space form, its state coordinates are generally confined to controllable, observable or modal form. Subspace identification method can directly obtain the state space model, and its state coordinates are not bound to any nominal form [95]. Therefore, subspace identification method is increasingly used. For example, subspace identification is used to identify the two-degree-of-freedom BSFDS. And the result shows that subspace model can predict the vibration of XY table more accurately [96]. Similarly, subspace identification is employed to achieve online identification and verification of BSFDS [97]. An adaptive model predictive control for BSFDS is implemented using subspace identification and backward windowing techniques [98].

4.3 Linear parameter varying

The flexible structure of ball screw and the change of table load are two main factors which cause the dynamic varying of BSFDS. Firstly, the parameters of BSFDS motion equations are varying position-dependence, which can be analyzed by Ritz series [29, 99]. Secondly, the load change in motion will also make mode parameters varying of BSFDS [37]. The traditional LTI modeling methods cannot effectively describe the parameters varying of BSFDS. So, a new method of system modeling and control, LPV method, is applied to solve this problem, which has attracted great attention in industry and academia in recent years.

4.3.1 LPV modeling

LPV modeling in BSFDS is reviewed in the following.

The parameters of LPV model are time-varying. Under a certain model structure, parameters are usually expressed as polynomial functions of measurable time-varying signals, which can express the nonlinearity of BSFDS. LPV state space (LPV-SS) and LPV input-output (LPV-IO) are the two main structural forms. As most of feeding systems are controlled by computer systems, the discrete LPV-SS and LPV-IO models are expressed as following:

$$\begin{cases} \boldsymbol{X}(k) = \boldsymbol{A}(\boldsymbol{\theta}(k))\boldsymbol{X}(k-1) + \boldsymbol{B}(\boldsymbol{\theta}(k))\boldsymbol{U}(k-1) \\ \boldsymbol{Y}(k) = \boldsymbol{C}(\boldsymbol{\theta}(k))\boldsymbol{X}(k) + \boldsymbol{D}(\boldsymbol{\theta}(k))\boldsymbol{U}(k) \end{cases} \tag{1}$$

$$\boldsymbol{Y}(k) = \sum_{i=1}^{n_a} a_i(\boldsymbol{\theta}(k))\boldsymbol{Y}(k-i) + \sum_{j=1}^{n_b} b_j(\boldsymbol{\theta}(k))\boldsymbol{U}(k-j) + \boldsymbol{\varepsilon}(k) \tag{2}$$

where $\boldsymbol{X}(k)$ is the state variables at time k, $\boldsymbol{U}(k)$ is the control inputs, $\boldsymbol{Y}(k)$ is the system outputs, $\boldsymbol{\theta}(k)$ is the time-dependent scheduling variables, $\boldsymbol{A}(\boldsymbol{\theta}(k))$, $\boldsymbol{B}(\boldsymbol{\theta}(k))$, $\boldsymbol{C}(\boldsymbol{\theta}(k))$, $\boldsymbol{D}(\boldsymbol{\theta}(k))$ are the state matrixes of the system, n_a and n_b are respectively autoregressive and moving average part of order, and $\boldsymbol{\varepsilon}(k)$ is white noise.

Compared with LPV-IO model, LPV-SS model can express the internal dynamics of BSFDS [100–102].

LPV system modeling can be divided into theoretical modeling and experimental modeling.

For theoretical modeling, there are three methods to transform nonlinear systems into LPV models [103]. The first method is Jacobian linearization, which considers the plant to be a LTI model with scheduling variables in a small range. The second method is state transformation method, which establishes a LPV model by eliminating the nonlinear factors independent of variable parameters using appropriate state transformation. The third method is function substitution, which uses the linear combination of variable parameters and the differential equations dependent on variable parameters as the replacement decomposition equations. The common disadvantage of all three methods is that they all depend on the system equilibrium point. The first two methods depend on system multiple equilibrium, while the last method only depends on a system random equilibrium.

For experimental modeling, many studies are devoted to parameterize model by experimental data. In most of these studies, the LPV model is obtained by using nonlinear functions of scheduling variables, or recursive least square method [104]. For example, the experimental data identification method is adopted to obtain the LPV model of BSFDS by nonlinear square method [93]. An experimental method is proposed to determine the optimal points for experimental data identification methods [105]. BSFDS is expressed as an uncertain linear model with time-varying parameters, which takes structural flexibility, runout effect, and mass variation into account [37].

The challenge of LPV modeling in BSFDS is that the nonlinear description of LPV model is not unique. LPV modeling is the foundation of LPV controller design. The rational choice of marker points in LPV modeling is another challenge. The existing LPV system modeling process are heavily dependent on the marker point of original nonlinear system. But the current selection of maker point is still dependent on experience.

A general LPV modeling approach with small modeling errors is the basis for improving control theory of LPV systems.

4.3.2 LPV control

LPV control in BSFDS is reviewed in the following.

The gain-scheduled control is the most widely used control approach for LPV systems. The performance of LPV system can be improved by gain-scheduled control technique where the controller explicitly depends on varying parameters. For the single-input single-output (SISO) system, LPV control is the single scheduling variable case [106]. A gain-scheduled H_∞ controller is firstly proposed for a mechatronic system with varying dynamics using ad-hoc linear scheduling and analytical LPV controllers separately [107]. A LPV gain-scheduled controller is proposed using interpolating technique to cope with varying dynamics for a pick-place machine in which the dynamic behavior is depending on a single varying parameter [108]. For the multi-input multi-output (MIMO) system, LPV control is the multiple scheduling variables case [109]. The state space model interpolation of local estimates (SMILE) technique is proposed to model the MIMO systems whose dynamics depend on multiple scheduling variables [110]. An interpolation-based approach is extended to design gain-scheduled multi-H_∞ controller for an overhead crane system with a varying cable length [111].

LPV control synthesis is another widely used technique [112], where a parameter-dependent controller is designed with guaranteed stability of the closed loop for all possible time-varying parameter trajectories. A switching LPV controller is proposed to flexible BSFDS with a wide range of operating conditions using analytical LPV model [113]. By using state space model interpolating technique, an interpolating gain-scheduled (IGS) H_∞ loop shaping controller is proposed [73]. The SMILE technique is used to interpolate robust LTI controllers, and then IGS controller can be obtained by the linear least-squares optimization [111]. The present LPV control concerns the high performance tracking controller design for BSFDS with flexible modes and multiple time-varying parameters. Although the LPV control synthesis is attractive as an extension of LTI control methodologies, it appears to be still not widely used in industrial applications, and LPV methods are difficult to apply due to considerable computational burdens [112].

4.4 Thermal error solutions

Thermal error caused by the thermal deformation is one of the most significant factors influencing the accuracy of BSFDS. Therefore, this subsection will review the thermal error solutions.

4.4.1 Thermal error avoidance and control

The two strategies are respectively supposed to avoid the generation of non-uniform temperature distribution or the control of heat flux into BSFDS [38, 44]. In this case, engineers tend to design the structure of machine with thermal symmetry, separate the heat source, rearrange the structure of machine and control room temperature of workshop, etc [114, 115]. With the development of new materials, a variety of low thermal expansion coefficient materials that are not sensitive to temperature have been applied to the temperature control of BSFDS. The coefficient of thermal expansion of carbon fiber is negative [116]. By using high thermal conductivity and emissivity of graphene to enhance heat dissipation, a biomimetic graphene-coated ball screw is fabricated to reduce the thermal deformation of ball screw [117]. FEM method and improved lumped heat capacity method are proposed to analyze the thermal characteristics of a hollow ball screw [118]. It was shown that the hollow design can reduce the temperature rise and obtain thermal balance quickly. But this method reduces the stiffness of ball screw. A liquid cooling system with water, cooling oil, light oil and cutting oil is arranged as coolant in BSFDS, and the heat dissipation effect of various coolant is discussed [119]. The results show that the screw temperature is less varying when using the forced water cooling method, which can make BSFDS reach equilibrium quickly.

4.4.2 Thermal error modeling and compensation

The above methods can only reduce but not eliminate the influence of structure temperature varying. Therefore, thermal error modeling and compensation is an economical and effective method to improve accuracy of BSFDS [120, 121].

Accurate thermal error model and good robustness are the foundation of thermal error compensation [122]. At present, thermal error modeling is divided into theoretical modeling and empirical modeling.

- *Theoretical modeling*

Theoretical modeling is to establish partial differential equations by heat transfer theory in Eq. (3) and solve them with appropriate boundary conditions in Eq. (4). Ball screw is regarded as a one-dimensional component, shown in Fig. 12. A nonlinear partial differential equation model is established to solve the temperature distribution and thermal error of ball screw [123, 124].

$$\frac{k}{c\rho}\frac{\partial^2 T}{\partial x^2} = \frac{\partial T}{\partial t} + \frac{4\alpha_h c_g}{kA}(T - T_a) \tag{3}$$

where k is heat conductivity, ρ is the density of ball screw, c is specific heat capacity, $T(x, t)$ is the temperature field function of position x and time t, α_h is the synthetic heat release coefficient of air, c_g is the perimeter of cross section, A is the cross section of the pole, and T_a is environment temperature. When boundary condition is $x = 0$ and $x = L$,

$$\begin{cases} T(x,0) = T_0 \\ \left.\dfrac{\partial T}{\partial x}\right|_{x=0} = -\dfrac{q}{kA} \\ \left.\dfrac{\partial T}{\partial x}\right|_{x=L} = -\dfrac{h_r}{k}[T(L,t) - T_0] \end{cases} \tag{4}$$

where T_0 is the temperature in $t = 0$, q is heat flux density, h_r is the surface heat transfer coefficient per unit area, and L is the length of the one-dimensional pole.

In more complex cases, the solution of partial differential equation cannot be obtained easily. So the temperature field and thermal deformation are usually obtained by

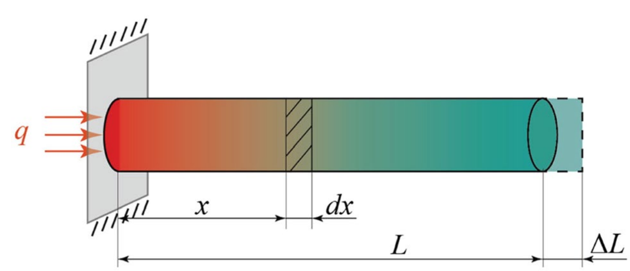


Fig. 12 The simplified one-dimensional model of ball screw [124]

using finite element analysis [40, 125]. The accuracy of finite element modeling method depends on the accuracy of boundary conditions. But accurate heat source intensity and boundary conditions are difficult to obtain due to the nonlinear temperature rise of BSFDS. Moreover, the application of this method is limited, because numerical analysis is time-consuming.

- *Empirical modeling*

The general steps of empirical modeling are as follows: selecting thermal key points, and using some algorithm to establish mapping relationship between thermal key points and thermal errors. Thermal key points of temperature are closely related to thermal errors, and the temperature field of BSFDS could be mainly reflected by the temperature of these points. In general, these points are close to the main heat sources [126]. The selection of key points is crucial to the success of any empirical model [122]. The goal of the selection of thermal key points is to select as few key temperature points as possible and accurately reflect the temperature field. Current selection of thermal key points is often based on experience and statistical knowledge, such as engineering judgment, correlation analysis [127], stepwise regression [128], forward selection and backward elimination [129].

However, above methods ignore the multicollinearity of temperature, and are unable to identify an optimal model according to various selection criteria [122]. Fuzzy clustering method can improve the minimum modeling and compensation efficiency of independent variables, eliminate the multicollinearity between temperature variables, and minimize the number of independent variables in the thermal error model, which is of great significance to the robustness of the thermal error model [130].

In order to establish a correct and effective thermal error model, many modeling strategies have been applied to find the optimized model with high accuracy and robustness.

Some common methods like least squares and regression analysis are proposed to establish thermal error model. For example, multivariate linear regression analysis and time series are used to map relation between the selected key temperature points and thermal errors[131]. A projection pursuit regression model is developed and applied to CNC machine tools [132]. However, above models are difficult to achieve a precise quantitative prediction due to the dynamic change in the thermal behaviors, resulting from complex and volatile working conditions.

With the development of artificial intelligence technology, intelligent methods such as neural networks [133], support vector machine (SVM) [134], genetic algorithm (GA) [135], and particle swarm optimization (PSO) [136] are used for thermal error modeling. However the neural network model of prediction results depends largely on the initial value of the selected.

Single modeling methods often struggle to achieve good performance, so hybrid modeling methods have been proposed to compensate for their respective shortcomings. GA, PSO, and grey theory have been adopted into the neural network for the optimization of initial value, and the increasing of the accuracy, convergence and robustness [130, 137]. Similarly, an ant colony algorithm-based BP neural network is developed to predict the thermal error of a CNC machine tools [138].

In summary, the existing thermal error modeling methods take a long time to analyze, calculate or train. Multisource error and real-time variability are still the modeling challenges.

After developing and verifying the thermal error model, the next step is to use the model to complete the thermal error compensation. Basically, there are two techniques for implementing the thermal error compensation: feedback interception method and origin-shift method [139, 140]. The feedback interruption method is used to achieve real-time compensation of thermal error by inserting the phase signal into the feedback loop of the servo system. First, the thermal error caused by temperature change is converted into equivalent pulse according to the thermal error mathematical model. Then, the pulse equivalent is inserted into the feedback loop of the servo system to automatically increase or decrease the position feedback pulse to achieve thermal error compensation. However, this compensation method is sometimes complicated and can easily interfere the insertion signal with the own feedback signal of the control system. The origin-shift method input the thermal error calculated from the thermal error model to the controller as a compensation signal. The thermal error compensation is achieved by modifying the motion command or reference origin of the servo control system by the controller. The origin-shift method is widely used in machine tools because of its low cost and high accuracy [38].

4.5 Nonlinear control

For nonlinear systems, except in rare cases, there is no set of feasible general methods, and each method can only be effective for a certain class of problems, not universally applicable. For the nonlinear factors of BSFDS raised in the Sect. 3.3, there will give the corresponding nonlinear control strategies as follows.

4.5.1 Friction compensation

Control strategies that attempt to compensate for the effects of friction are called friction compensation techniques, such as low friction machine design or lubricant choice, integral control with deadband, direct force feedback, Coulomb friction or position-dependent friction feedforward [141–144]. These friction compensation techniques are proposed to achieve higher precision in the motion control of BSFDS. According to whether the friction model is used or not, they can be divided into model-based and non-model-based friction compensation methods. The model-based friction compensation techniques require a suitable friction model to effectively predict and compensate the friction force on feeding system motion [46]. In other words, the compensation performance is highly dependent on the accuracy of the friction model. Much work has been done to characterize nonlinear friction behavior to achieve a nonlinear model of friction, as stated in Sect. 3.3.1. The parameters of friction model can be identified by a data gathering experiment, or continuously, on-line estimated as part of operation of the machine. If the parameters are then used in a model-based friction compensation, on-line identification will become adaptive control with the observers to compensate for instantaneous friction force in BSFDS working. In addition, various adaptive friction compensation methods that used observers based on the different friction models have been presented [145].

However, there is no model correctly and over a broad range of conditions predicting the presence of friction of feeding system. Thus, the non-model-based approach does not require a friction model, such as high gain proportional-derivative (PD) [51] and adaptive controls [145]. In these methods, friction has typically been considered a disturbance. For example, a zero phase error tracking controller (ZPETC) is proposed to significantly reduce the tracking error influenced by friction by the elimination of the unstable zero dynamics [146]. A variable structure controller with a Luenberger-type disturbance observer is presented to observe the disturbance, including the friction force [147–149].

4.5.2 Sliding mode control

Sliding mode control (SMC), also called variable structure control, is in essence a special class of discontinuous and nonlinear control [150]. SMC is independent of object parameters and disturbances, with the advantages of fast response, insensitive to parameters varying and disturbances, no needs of online identification, easy implementation and so on. However, due to the existence of inertia and lag factors, it is difficult to slide strictly along the sliding mode facing the equilibrium point. Instead, it crosses the ground back and forth on both sides of the sliding mode surface to reach the equilibrium point, which results in chattering and obstructing application of SMC [151, 152].

Due to the performance of BSFDS is limited by vibration modes, nonlinear factor and uncertainties (parameters perturbation and disturbances), SMC is suitable to provide a reasonable control that is robust against perturbation and invariant to matched uncertainties. For example, adaptive and discrete-time SMCs [153–155] are proposed to control ball screw drives with structural flexibility, which achieves an active damping of the vibrations and a substantial improvement in the bandwidth. But they were designed for nominal plant ignoring the time-varying parametric uncertainties and external disturbances. So, several SMC schemes with backstepping or fuzzy controllers are proposed for systems containing time-varying uncertainties and external disturbances, to accomplishing accurate position performance [70, 156, 157]. Other variants of the SMC include adaptive sliding mode control and nonlinear sliding mode control. They are more flexible and offer higher tracking performance compared to the traditional SMC [158]. An adaptive backstepping sliding mode controller based on the function approximation technique for the single-input multi-output flexible ball screw drive is proposed [70]. A nonlinear SMC with a feedforward compensator for system uncertainties is proposed, which enhances the tracking performance of feed-drive systems. Through Lyapunov stability theory, the system stability was analyzed and confirmed and its convergence to the sliding surface was assured [159].

4.5.3 Other nonlinear control approaches

Other nonlinear control approaches are used in BSFDS for solving nonlinear factors, such as inverse model compensation, nonlinear feedback linearization, active disturbance rejection control. The inverse model compensation method tries to multiply the inverse model with the nonlinear model to get the unitized scalar or matrix, which is often used in the design of feedforward controller. The difficulty of the inverse model compensation method is how to obtain the inverse model of the nonlinear model, which is often not available [160]. The basic idea of the feedback linearization method for nonlinear systems is to compensate the nonlinear controlled object model into a linear system by the method of feedback, and then use the linear system theory for control system design [161]. The active disturbance rejection control adopts observation and compensation to deal with the nonlinearity and uncertainty in the control system, and cooperate with the nonlinear feedback method to improve the dynamic performance of the controller [162, 163].

In summary, a number of nonlinear control methods, such as nonlinear compensation, variable structure control, and feedback linearization, have been proposed for high performance control in response to nonlinear factors, uncertainties, and disturbances in BSFDS.

4.6 Robust control

Many studies point out that model uncertainties (parameters varying, disturbances, and model errors) are the major factors that degrade position tracking performance of BSFDS [68, 70, 164, 165]. Therefore, the robust control should be considered to maintain the robustness of BSFDS. The main robust control strategies used in BSFDS include H_∞, μ-synthesis, and disturbances observer, etc.

4.6.1 H_∞ control

H_∞ control is the most commonly used robust control method in BSFDS, which is the suppression of the maximum gain in the set of transfer functions. Various H_∞ control schemes are proposed to suppress vibration, external disturbance, and model perturbation, etc [166–169]. A dual structure-based H_2/H_∞ control approach is introduced to cope with the examined uncertainties. The improved H_2/H_∞ controller provides an integration performance enhancement by taking BSFDS comprehensive performance index and rude vibration into consideration [170]. With a consideration of the nonlinearities and parametric variations depending on the table position and table mass changes, a synthesized robust gain scheduling controller is proposed [73]. In order to mitigate the undesirable effects of parameter uncertainties and keep the tracking performance, a full-state feedback controller is presented, with poles assignment and smooth position tracking constrains [171].

4.6.2 μ-synthesis

Uncertainties are unstructured in H_∞ control, which actually has strong conservatism. The μ-synthesis reduces the conservatism of the control system through structural uncertainties and improves the control performance while ensuring system stability. The structured uncertainties are introduced to cover the uncertainties in BSFDS and build an uncertain model [68]. With the uncertain model, the μ-synthesis technique is adopted to design the robust controller for overcoming the performance deterioration caused by uncertainties [172–174]. Furthermore, the results show that the μ-synthesis control strategy can improve the performance in trajectory tracking and disturbance rejection for BSFDS in the presence of the structured uncertainties.

4.6.3 Disturbance observer

Another solution to model uncertainties and external disturbances is a disturbance observer (DOB) [158, 175–177]. For example, a DOB outputs the difference between the nominal model and the actual plant, and it can be used to improve the robustness of a controller [178]. A cascade P-PI controller is used with an inverse model-based disturbance observer, which is shown that the proposed controller can effectively suppress external disturbances [179]. Similar control structure has been introduced, which consists of a PI controller, a disturbance observer, and a friction feedforward controller [180]. Furthermore, the disturbance observer is further used to achieve automatic tuning of model parameters. In designing robust feedback loops, the disturbance observer can be applied in model inversion [181], adaptive robust control [182], adaptive sliding mode control [183], and model output-based disturbance cancellation [184]. These were verified to mitigate the effects of external disturbances, parameter variations, and unmodeled dynamics.

In summary, the prevalent principle of robust controller design is to realize a high-bandwidth feedback loop that maintains stability and robustness in the presence of external disturbances, parameter variations, and unmodeled dynamics.

5 Emerging control issues and approaches

The traditional model-based control method has to get an accurate control model. However, in practice engineering, it is unrealistic to achieve an accurate mathematical model due to nonlinearity, uncertainty, external disturbance, parameter time-varying characteristics, etc. Thus, global steady linear control modeling is often a difficult task to accomplish.

With the rise of emerging control approaches, new solutions to above problems have been provided. For instance, intelligent control methods such as neural network can be fitted for nonlinearity factors; data-driven methods skip the modeling process and rely directly on data to design controllers; and learning control method relies on its own learning function to identify the controlled plant, to recognize the characteristic of the external environment, and to change its own characteristics accordingly.

5.1 Artificial intelligence, AI

The definition of artificial intelligence (AI) remains controversial [185]. In mechanical manipulation and control field, AI is a new technical science which studies and develops the theory, method, technology and application system to simulate, extend and expand human intelligence. And its main goal is to enable machines to perform complex tasks that would normally require human intelligence. By combining large amounts of data with rapid iterative processing and intelligent algorithms, AI could learn, decide and control automatically. Therefore, AI methods widely used in the field of intelligent control of mechanical systems. Specifically, AI methods include neural network, fuzzy control, genetic algorithm, etc [16]. The following will introduce several commonly used AI methods in modeling and control for BSFDS.

5.1.1 Artificial neural network, ANN

Artificial Neural Network (ANN), is a research hotspot that has emerged in the field of AI since the 1980s. ANN is a system consisting of a large number of neurons widely interconnected, and this structural feature of it determines that ANN has the ability of high-speed information processing. So it is widely used in dynamic performance optimization, nonlinear and uncertainty, thermal error modeling and compensation, and other fields of BSFDS.

The dynamic performance of BSFDS in machine tools has an important impact on the machining quality and efficiency of the whole machine tools. The optimization of the dynamic performance of BSFDS has always been the focus and difficulty in academic and engineering field. ANN can accurately identify the dynamic parameters of BSFDS, optimize and analyze the dynamic performance of the system, and reduce the influence of motion and vibration on the motion precision of the system [74, 186]. Moreover, the nonlinearities and uncertainties of BSFDS can be well approximated by ANN, giving the system good tracking performance and friction compensation capability [166, 187–189]. The applications of ANN in thermal error modeling and prediction mainly include BP neural network [190], RBF neural network [191, 192], Kohonen neural network [191], Elman neural network [193] and wavelet neural network [194]. The results show that neural network model has better modeling accuracy, fitting performance, and stronger prediction ability, which provide new solutions for thermal error prediction and compensation.

5.1.2 Genetic algorithm

Genetic algorithm (GA) is an efficient stochastic search and optimization method, which is developed based on the principles of biological evolution theory. Compared with the other search and optimization methods, GA do not depend on gradient information or other auxiliary knowledge in the calculation. Its search direction is only determined by the objective function and the corresponding fitness function. Therefore, GA provides a new global optimization search approach for solving complex system problems. It has been widely used in BSFDS, including the identification and optimization of dynamic parameters in modeling, thermal deformation and thermal error problems, etc.

GA is used to solve the dynamics and nonlinear problems of BSFDS, which can ensure the stability, accuracy, rapidity, and reduce the tracking error [195]. GA can solve nonlinear problems well and has high identification accuracy, so it is often used in parameters estimation of BSFDS, including installation parameters, boundary conditions, friction parameters, axial stiffness and damping parameters, etc. [195–198]. GA has strong robustness and universality, and is often used to the thermal error modeling [199] of BSFDS, which can effectively reduce thermal errors.

5.1.3 Other intelligent algorithms

Other intelligent algorithms such as fuzzy control, particle swarm optimization, simulated annealing algorithm are also used in modeling and control of BSFDS.

Fuzzy control does not require an accurate mathematical model of the plant and is insensitive to nonlinearities, coupling parameters and time-varying characteristics. PID control and sliding mode control are usually used in BSFDS. However, PID control requires accurate mathematical model, and sliding mode control has the chattering problem. To mix with fuzzy control, fuzzy PID controller and fuzzy sliding mode controller have faster response speed, higher control accuracy and stronger robustness [200, 201].

Particle swarm optimization is a swarm intelligence method. It is similar to GA, but requires fewer parameters to tune. So it is commonly used to solve nonlinear constrained optimization problems in BSFDS [202].

Simulated annealing algorithm is a stochastic optimization-seeking algorithm based on Monte-Carlo iterative solution strategy [203]. And it is used to solve local optimization problems in BSFDS [204].

5.2 Learning control

In general, learning control is the process of acquiring control strategies for a specific control system and a specific task through iterative trials [205]. It enables the estimation of unknown information as the system proceeds. Optimal control based on learning control can gradually improve the system performance. In the learning control process, only the actual output signal and the desired signal need to be detected, while the complex dynamic computation and parameter estimation of controlled object can be simplified or omitted. Therefore, for the repetitive motion of controlled objects such as industrial robots and CNC machine tools, learning control has a wide range of application prospects.

5.2.1 Machine learning

Machine learning (ML) is a general term for a class of algorithms that attempt to mine large amounts of historical data for implied patterns and use them for prediction or classification.

Deep learning (DL) is a method of representation learning based on data in ML. Compared with ANN, DL adds unsupervised learning process and can overcome the local optimization problem of ANN [206]. It can adaptively mine features from input data and is widely used in fault diagnosis and identification in BSFDS [7, 207–209]. DL can also address the limitations of BSFDS dynamics models, of which difficulty is to obtain unpredictable dynamic characteristics, such as position-dependent frictional and velocity perturbations [210].

Support vector machine (SVM) is also a commonly used ML algorithm. It is a statistical learning method based on the principle of structural risk minimization, and has advantages in dealing with small-sample, nonlinear mapping problems. Moreover, practical engineering is often a small-sample situation, so SVM is widely used for fault diagnosis [211, 212] and preload force prediction [213, 214] in BSFDS.

5.2.2 Iterative learning

Iterative learning control (ILC) is one of the learning-based control methods. It is a very effective tracking control method when the same reference trajectory is repeated. ILC can be applied to the friction compensation of BSFDS.

The traditional friction compensation method is based on the model, which needs to use complex equations to express the rolling friction characteristics [215]. Because parameters of the model are difficult to determine, the rolling friction model is applied not well in practice. ILC does not need the rolling friction model, and the repeatable tracking error will be gradually suppressed with the increase of iteration times [215–217].

5.2.3 Other learning algorithms

Other learning algorithms, such as reinforcement learning (RL), and transfer learning (TL), can also be applied in BSFDS control.

RL is a trial-and-error method of learning by interacting with a controlled environment in order to maximize rewards for the best actions of the object. Feedback control of BSFDS is often realized by PID controller, but it is not a simple matter to adjust PID parameters. Therefore, some researchers explore the use of RL to develop feedback control methods [218, 219]. RL can be used to provide the BSFDS controller with autonomous adaptation and learning. The controller parameters can be randomly searched and optimized with higher control accuracy [220].

In BSFDS, the performance degradation of ball screw has a great influence on the control precision [221]. Degradation identification is of great significance to improve the safety of mechanical operation. For most identification methods, it is important to get a large number of labeled training data. Unfortunately, for some components, such as ball screw, it is difficult to collect a large amount of labeled status data. TL can use knowledge learned from rich labeled data to solve a similar task [222]. In the case of missing or insufficient target domain labeled data, TL is helpful for condition recognition [223, 224]. Therefore, TL is used in the degradation recognition of BSFDS [208].

5.3 Data-driven control

Data-driven control refers to use the input and output data to design the controller without the mathematical model information. Specifically, data-driven control, data-driven learning, data-driven modeling and optimization get rid of the dependence on the mathematical model of the controlled system. Data-driven control has been applicated in BSFDS including model-free adaptive control [225], iterative learning control [217], and data-based PID control techniques [46]. Data-driven modeling is also applied to BSFDS, including dynamics modeling [210], position error modeling [188], thermal error modeling [135], rolling friction modeling [215], etc. In BSFDS, many optimization methods lack mathematical expressions, and even cannot obtain an accurate objective function. As a result, the solution of such problems needs to rely on the indirect system input-output data, that is, the model based on data-driven strategy.

5.4 Hybrid methods

It is difficult to use a single control method to achieve a good system control requirement. In practice, hybrid control methods are often used to achieve better control requirements. For example, GA is employed to optimize the parameters of SVM, which can enhance the accuracy of residual life prediction and fault diagnosis in BSFDS [211, 214, 226]. Fuzzy control and ANN are often used to deal with unknown nonlinearities and disturbances, as well as to identify and control complex systems. Fuzzy neural network (FNN) inherits the reasoning technology of fuzzy control and the learning ability of ANN. In addition, the wavelet fuzzy neural network can converge quickly and achieve a high convergence precision under the condition of reducing the network size [227–229]. ANN can adequately approximate complex nonlinear relationships with a high degree of robustness and fault tolerance. However, it faces the problem of slow convergence and tendency to fall into local extreme value. To solve this problem, GA can be used to obtain the optimal initialization parameters of ANN, so as to accelerate the convergence rate and obtain the global optimal solution [199, 230]. PID control is the most widely used control strategy in industry because of its simplicity, robustness and reliability. However, a suitable selecting of PID parameters is time-consuming and complex, and a fixed PID controller may degrade the control performance. Using GA in multi-objective optimization, the adaptive tuning of nonlinear PID parameters is conveniently realized [231]. In addition, fuzzy PID control combined the advantages of fuzzy control and PID control [200, 232].

6 Conclusion

BSFDS is widely utilized in many precision positioning and tracking control areas like CNC tools. Depended on the structure and properties of ball screw, BSFDS is up against the challenging issues in modeling and control, such as vibrations, thermal errors, nonlinear factors and uncertainties. Motivated by above challenges in modeling and control, various approaches have been proposed to solve these issues, like identification, linear parameter varying, thermal error compensation, nonlinear control, and robust control. With the swift development of intelligent technologies, this paper also presented current and emerging control issues and approaches, such as artificial intelligence, learning control and data-driven control.

Author contribution All the authors contributed to the overall conception of this paper. Tao Huang: Conceptualization, Methodology. Queting Kang: Data curation, Writing- Original draft preparation. Shuangjiang Du: Visualization, Investigation. Qian Zhang: Writing- Original draft preparation. Zhihong Luo: Writing- Original draft preparation. Qian Tang: Writing- Reviewing and Editing. Kaiming Yang: Supervision. All the authors read and approved the final manuscript.

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