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Condition Monitoring of Machine Tool Feed Drives: A Review

The innovations propelling the manufacturing industry towards Industry 4.0 have begun to maneuver into machine tools. Machine tool maintenance primarily concerns the feed drives used for workpiece and tool positioning. Condition monitoring of feed drives is the intermediate step between smart data acquisition and evaluating machine health through diagnostics and prognostics. This review outlines the techniques and methods that recent research presents for feed drive condition monitoring, diagnostics and prognostics. The methods are distinguished between being sensorless and sensor-based, as well as between signal-, model-, and machine learning-based techniques. Close attention is given to the components of feed drives (ball screws, linear guideways, and rotary axes) and the most notable parameters used for monitoring. Commercial and industry solutions to Industry 4.0 condition monitoring are described and detailed. The review is concluded with a brief summary and the observed research gaps. [DOI: 10.1115/1.4054516]

Keywords: machine tool dynamics, machining processes, sensing, monitoring and diagnostics

1 Introduction

The manufacturing industry is rapidly adopting intelligent methods and principles to optimize productivity. This is driven by the advancements in information and manufacturing technologies and is leading the way to a paradigm shift in manufacturing called Industry 4.0. One of the primary aspects of this revolution is the digitalization and networking of factories. Due to the strong demands for improvements in quality, efficiency, and quick market response, the manufacturing industry is in need of a revolutionary upgrade in the form of cyber-physical systems [1]. The purpose is to connect people to physical systems while sharing in-depth information about those systems which is aided by the use of artificial intelligence among other advanced technologies.

Industry 4.0 demands that machine tools keep up with the innovation by employing a digital twin that can, for example, apply advanced algorithms for prognostics and health management (PHM), machining optimization, and augmented reality process visualization [2]. Such innovations are being recognized in the maintenance of machine tools as the industry moves away from the dominant preventive maintenance (PM) strategies to predictive maintenance and beyond.

The goal of maintenance is to improve the longevity of production equipment and operations by repairing, replacing, or maintaining equipment components. A timeline of the maintenance strategies used throughout the various industrial revolutions is shown in Fig. 1. The predominant maintenance strategies include corrective maintenance and PM. Corrective maintenance, otherwise known as run-to-failure or reactive maintenance, is when maintenance decisions are based on the occurrence of failures of equipment. Policies under this type of maintenance tend to result in high maintenance related costs and lost production [4]. Preventive maintenance aims to conduct maintenance actions before equipment failure occurs thereby reducing equipment failure rates. This improves the availability and reliability of equipment while contributing to minimizing failure costs and downtime [5]. PM is generally based on scientific methods applied through experience or original equipment manufacturer (OEM) recommendations [6]. PM includes comprehensive strategies, such as reliability-centered maintenance and total-productive maintenance, as well as the strategies of time-based maintenance (TBM) and condition-based maintenance (CBM).

Time-based maintenance is a strategy that relies on periodic maintenance actions. These actions aim to avoid equipment failures by replacing components before they fail. The success of TBM is based on its foundation of predicting component reliability based on analyses of failure data [7]. Though TBM has been the dominant maintenance policy for decades, this strategy has limitations. Replacing equipment at regular intervals ignores the current health of the equipment. This leads to unnecessary downtime and additional costs due to unnecessary maintenance actions. Another limitation is that TBM assumes equipment failure characteristics are predictable [6]. This lends to the so-called bathtub curves that define three stages of failure. These being wear-in, useful life, and wear-out. However, as noted by Hashemian [8], failures can occur at seemingly random times and many failures are attributed to infant mortality (i.e., premature failure).

The shortcomings of TBM have led to a maintenance strategy that questions the health condition of equipment. By determining the relative condition of machine components, an optimal time for maintenance or component replacement can be determined. Condition-based maintenance relies on the acquisition of real-time and historic data representative of machine health to make these informed decisions. The core foundation of CBM is thus condition monitoring (CM). Developments in information and communication technologies (ICTs) have improved the prospects of CBM. However, the conversion from TBM to CBM includes judging whether the relative benefits of CBM outweigh the additional costs [9]. These costs include the monitoring equipment and the means of measuring, storing, and analyzing data.

Though some definitions put CBM under a PM paradigm, some consider it to be either synonymous with predictive maintenance

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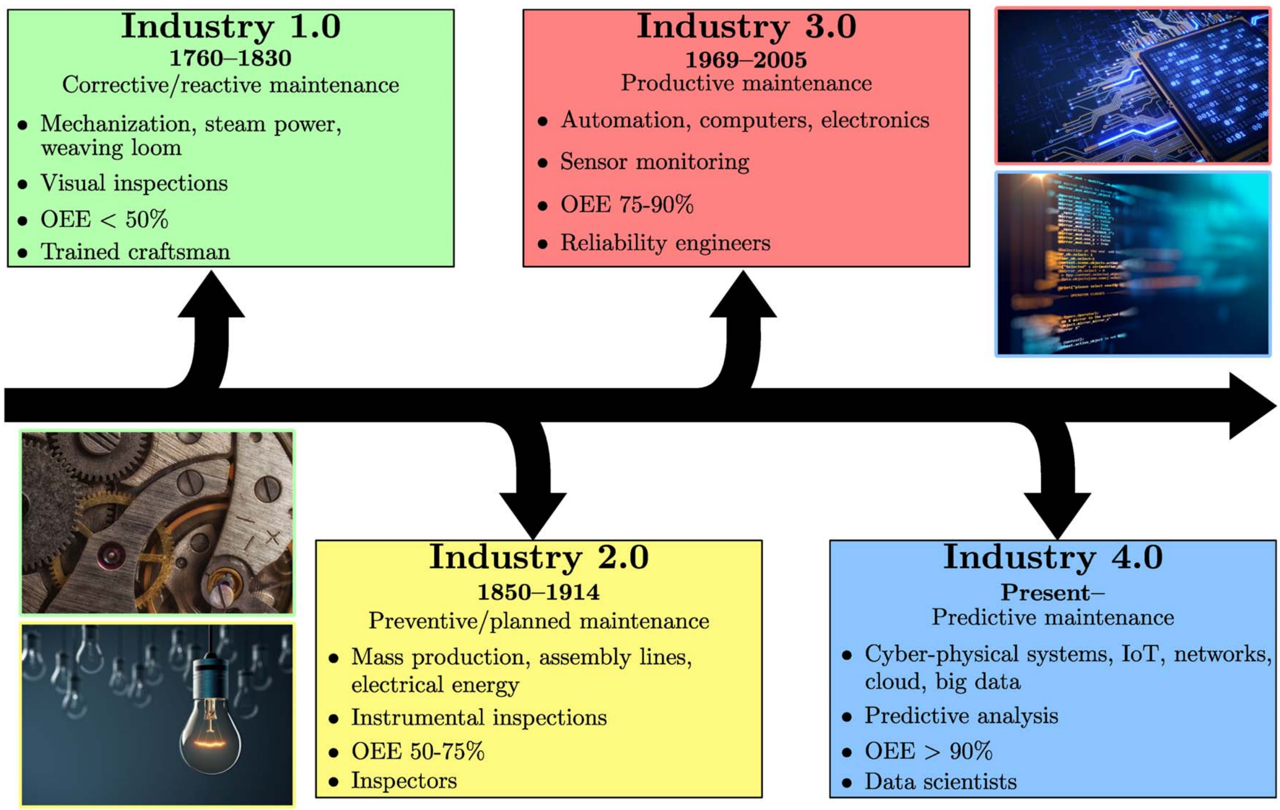

Fig. 1 The four industrial revolutions including their predominant maintenance strategy, characteristics, inspection method, overall equipment effectiveness, and the specialized personnel that aided the maintenance teams of the era. This timeline was inspired by the work of Poór et al. [3].

(PdM) [8,10] or a classification of PdM [11]. The purpose of PdM policy is in the name: to *predict* faults or failures of a system such that maintenance decisions and actions can be optimized. It is a right-on-time maintenance strategy that involves evaluating the state of a deteriorating system [10,11]. The evaluation of the state, or "health," of a system is performed via diagnostics and prognostics, terms adopted from the healthcare industry. Diagnostics involve the detection, isolation, and identification of faults. Fault detection notifies that a problem has occurred, fault isolation locates the faulty component or equipment, and fault identification seeks to determine the nature of the fault [12]. Prognostics aim to predict the future condition or health state of components or equipment based on measured and available data. Both tasks can provide valuable information for maintenance decisions, but successful prognosis can prove to be superior in utility.

Diagnostics and prognostics require the intermediate step of condition monitoring. Condition monitoring bridges the gap between raw, complicated machine data and the useful information obtained through health evaluation. The relationships between CM and diagnostics and prognostics is shown in Fig. 2. CM involves the analysis of measured signals and data to detect changes that can reflect the health of the system. Such analysis can include the calculation of various features and model parameters. Diagnostics and prognostics can further use these features and parameters for fault detection and remaining useful life (RUL) calculation. The health evaluation can then be monitored for significant changes that indicate a fault/failure or to notify that a maintenance action is imminent.

Machine tools can be considered as the backbone of modern manufacturing due to their complex machining capabilities. These include production and computer numerical control (CNC) machine tools. Production machine tools are composed of automated part transfer systems that move workpieces between groups of simpler tools. Examples are rotary and conventional (or in-line) transfer machines. CNC machine tools are among the most common tools found in manufacturing. They provide the precision and speed of computers to machine intricate parts while maintaining close tolerances. CNC machines include turning centers that perform turning, boring, facing, threading, profiling, and cutoff operations, and machining centers that are used for milling, boring, drilling, and tapping [13]. Multi-axis machining centers include horizontal, vertical, and universal spindle configurations. Vertical gantry and bridge machine tool structures are used for large workpieces as they yield improved stability of the spindle. Horizontal machines are more versatile with the capability to machine four sides of a workpiece when used with a rotary indexing table. Universal machining centers have spindle heads that can rotate and effectively act as both horizontal and vertical machines. Turning centers include CNC lathes and automatics which use live tooling and can have multiple slides and spindles.

Common to nearly all machine tools are the systems and subsystems that comprise the machine. The feed drives, guideways, spindle and tooling systems, tool changer, hydraulic circuits, pneumatic circuits, and electrical hardware are all subject to degradation and abrupt failures. As machine tools gain complexity, so do their maintenance requirements. The maintenance of these systems can be both expensive and time consuming. To maximize economic profitability, the maintenance actions needed for these machines and their systems need to be optimized. However, close attention should be made to the critical systems that are the most costly to maintain. These include feed drive systems that are composed of either linear or rotary actuators and guideways or slides. Linear feed drives typically use servo motors, ball screws, and linear guideways to drive a worktable or tool to a position or follow a contour as directed by the numerical controller (NC). Rotary axes commonly use direct drives or worm drives to orient tooling and the worktable. The control of these systems is made possible through sensors that measure feedback signals. These components undergo natural wear that affect the positioning accuracy and can lead to breakdowns and

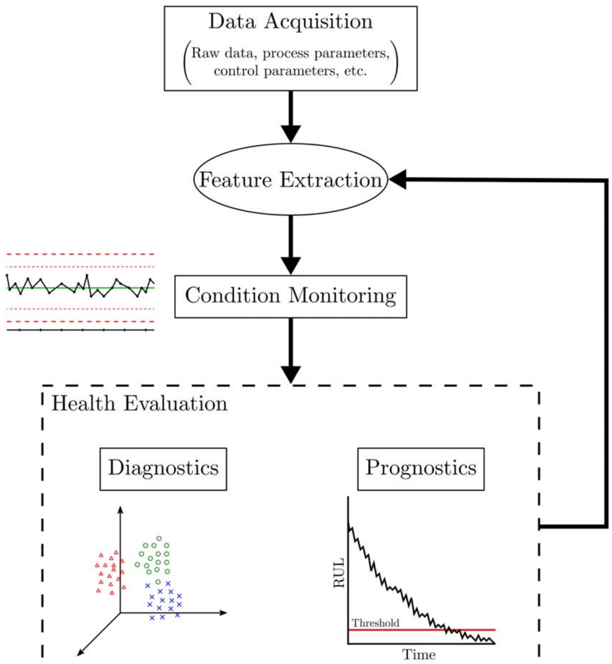

Fig. 2 The relationship between condition monitoring, diagnostics and prognostics. The feedback from the health evaluation box shows that diagnostic and prognostic characteristics can be extracted and monitored, much like the raw data.

lost production. Monitoring the health condition of feed drives can prove useful in optimizing maintenance actions. This is made possible by the rich amount of data being measured by the sensor systems through which the health condition of the feed drive can be estimated.

Due to the cost and downtime associated with feed drive deterioration and failure, many CM methods have been developed over the past two decades in an attempt to mitigate these factors. Previous review articles that have covered machine tool feed drive monitoring include Refs. [14–17]. These articles provide well-organized information on this field of research but have their shortcomings. The advancements in sensor technology and data analysis have outdated the review by Martin [14]. Goyal and Pabla [16] provide detailed information on machine tool vibration monitoring but exclude modern data analysis techniques such as machine/deep learning. Teti et al. [15] and Baur et al. [17] lack a detailed and comprehensive approach to feed drive condition monitoring. This review attempts to address these shortcomings by providing a comprehensive review of machine tool feed drive condition monitoring.

This paper presents a state-of-the-art review of condition-based monitoring of machine tool feed drives. Due to the close relationship with diagnostics and prognostics, these methods are also included. The subject matter is dealt with by first observing condition monitoring applications and their challenges in Sec. 2. Thereafter, an overview of machine tool feed drives is given in Sec. 3. Condition monitoring, the sensors used, and computational methods are described in Sec. 4. Condition monitoring of machine tool feed drives is reviewed in Sec. 5. Commercial and industry solutions to condition monitoring are given in Sec. 6. Lastly, a summary of the reviewed research and the future outlook of the field are presented in Sec. 7.

2 Applications and Challenges of Condition Monitoring

Condition monitoring is an area of research with many applications beyond machine tools. These applications include the monitoring of wind turbines, trains, and railways [18–20]. This section explores the condition monitoring of two areas closely related to machine tools: rotating machines and machine/structure health. Afterwards, background literature and information on the CM of machine tools and machining processes are given.

2.1 Condition Monitoring of Rotating Machines.

The condition monitoring of electrical motors has seen a breadth of research. The 2005 article by Nandi et al. [21] reviews the common faults and symptoms of electrical motors as well as the monitoring strategies developed to mitigate them. This work surveys the signals used and the frequency contents of each. Alternative methods such as thermal measurements and chemical analyses are also explored. The authors recognize the slow replacement of human involvement in the monitoring process, and automated artificial intelligence (AI)-based techniques such as neural networks, fuzzy logic systems, and expert systems are investigated.

Singh and Ahmed Saleh Al Kazzaz [22] see that an ongoing problem with diagnostic techniques of induction motors is the requirement for constant human interpretation. This suggests that the logical progression is to automate the diagnostic process of induction machines. Also noted is the need for real industrial solutions as most solutions do not consider the non-ideality of environment variables on the measured parameters. Zhang et al. [23] review medium-voltage induction motors stating that their breakdowns lead to high repair costs and financial losses due to the subsequent downtime. Condition monitoring and fault detection in the stator, bearing, rotor, and air gap eccentricity are prevalent, as are the monitoring of thermal protection and temperature estimation. The effectiveness, robustness, accuracy, and complexity of induction motor monitoring features are analyzed as well.

Kande et al. [24] consider the CM of electrical machines on a plant-wide scale. The investment requirements and the complexity of larger-scale monitoring strategies increase with the number of measurements needed. This leads to only the most severe circumstances influencing the implementation of such monitoring strategies. An inhibiting factor is the ratio of CM cost to equipment cost which deters the use of monitoring to guide maintenance teams over a large number of machines. With the development of low-cost technology, a solution to plant-wide monitoring arises with the use of integrated smart sensors embedded in the machines (see Fig. 3). These sensors can monitor more variables than what could otherwise be monitored, but likely with reduced accuracy and precision. However, they offer a monitoring solution at the plant scale.

A more narrow monitoring scope of electrical motors applies to bearings [25]. This overview details that bearing faults count for

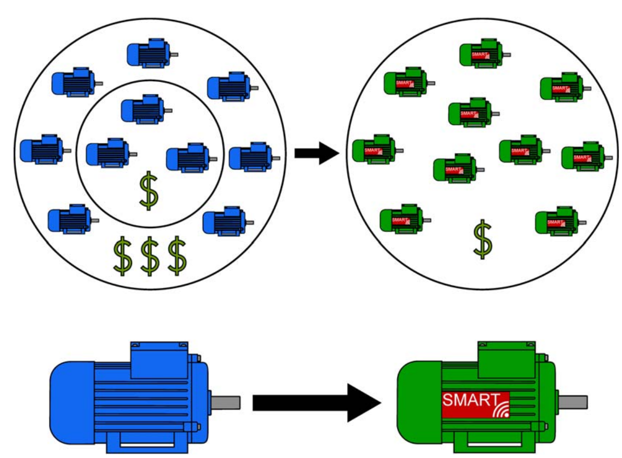

Fig. 3 The required investment into CM commissioning and installation leads to only a subset of an entire plant being monitored, often with less variables being monitored. New integrated smart sensors embedded into machines can offer greater monitoring capacity at more affordable prices.

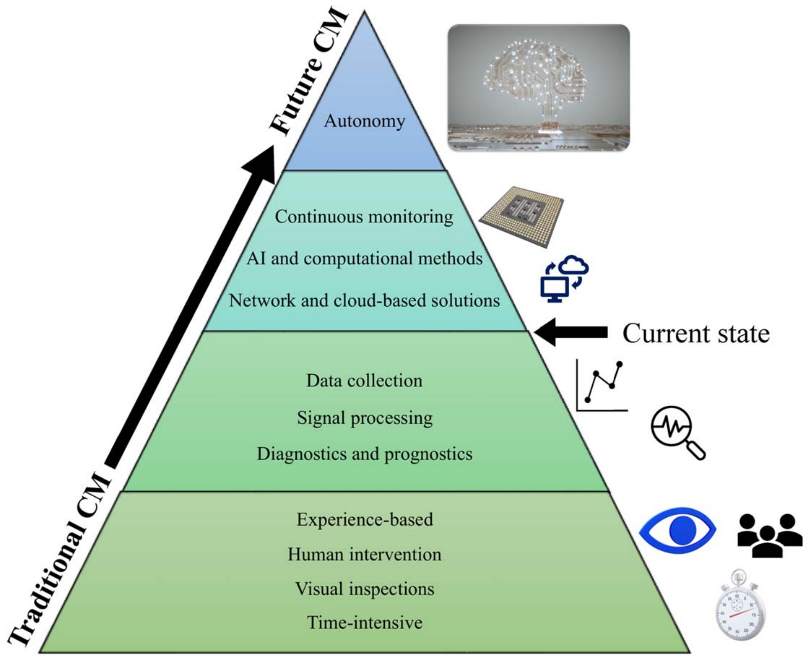

Fig. 4 The progression from traditional condition monitoring to the future of condition monitoring uses more autonomous methods. The current state of condition monitoring falls between using collected data for diagnostic/prognostic purposes and utilizing artificial intelligence and network or cloud-based solutions to continually monitor systems. Condition monitoring in general is on a trajectory to attain completely autonomous monitoring capabilities.

about half of all electric machine failures. Seven different monitoring schemes are shared with a focus on their implementation. The fault modeling and predictive health monitoring of rolling element bearings have been investigated extensively in general as well [26].

2.2 Health Monitoring of Structures and Machines.

In structural health monitoring, vibrations are the chief data type for analysis. In situ and non-destructive sensing methods and analyses are used to detect damage and degradation of structures. Carden and Fanning [27] review the methods in monitoring the vibrations of structures. At the time of its publication, the majority of the literature had focused on modal analysis due to historical reasons and the easily interpreted results.

Aside from rigid structures, Randall's book [28] on condition monitoring teaches the vibration analysis methods applied to machines. Jardine et al. [12] explore machinery diagnostics and prognostics. This article presents the monitoring of machines through three main steps of CBM, namely, data acquisition, signal processing, and maintenance decision-making. CBM is recognized to be the superior choice over the traditional maintenance strategies of run-to-failure and preventive maintenance policies. Despite this, CBM has not been widely implemented due to inadequate data collection and improper communication between theorists and practitioners, among other reasons. The review hypothesizes that future diagnostics and prognostics will focus on continuous monitoring and automatic diagnosis/prognosis. A recent review on machine health monitoring shows that hypothesis may be correct. Zhao et al. [29] review deep learning and its applications to machine health monitoring. The authors state that deep learning-based strategies require less human intervention and expert knowledge, which would provide a solution that is not just applicable to specific machines, but machines as a whole. However, such methods have yet to be demonstrated under real manufacturing variation. The progression of condition monitoring from traditional methods to the methods of the future is depicted in Fig. 4. The end-goal for CM is the complete autonomy of the process which alerts for abnormal events and suggests the correct maintenance action. As of today, we stand between the methods that use signal characteristics and machine learning (ML).

2.3 Condition Monitoring in Machine Tools.

The condition monitoring of machine tools can generally be categorized as *process* health monitoring or *equipment* health monitoring. The former involves the monitoring of the cutting tool, part quality, and process stability. The latter monitors the health condition of the various systems of machine tools. However, these forms of monitoring are not completely independent as the wear of equipment can affect process stability, workpiece quality, etc., but a distinction is made to highlight their differences. A comparison between the two methods is given in Fig. 5.

2.3.1 Process Health Monitoring.

The early research in tool condition monitoring (TCM) shows the usefulness of sensor systems employed in machining. Byrne et al. [30] encapsulate the adoption of these systems in industry in a 1995 review. Important aspects of TCM are the development of multiple sensors for increased reliability, intelligent sensors with better processing and decision-making actions, and the integration of open architecture NCs using these sensor systems. The developments aim towards producing more stable processes, allowing to detect tool breakage and optimizing tool usage.

Teti et al. [15] compiled a comprehensive review that captures the state-of-the-art in advanced monitoring of machining operations. Modern sensor systems are much more reliable and cost less than they did in the past. Signal processing algorithms and decision-making strategies have also been progressing quickly. However, it is observed that few of these advanced methods have been brought into the limelight of industrial application, regardless of the amount of industry data available. This is attributed to the complex implementation requirements which need an abundance of human attention. If the goal going forward is to improve

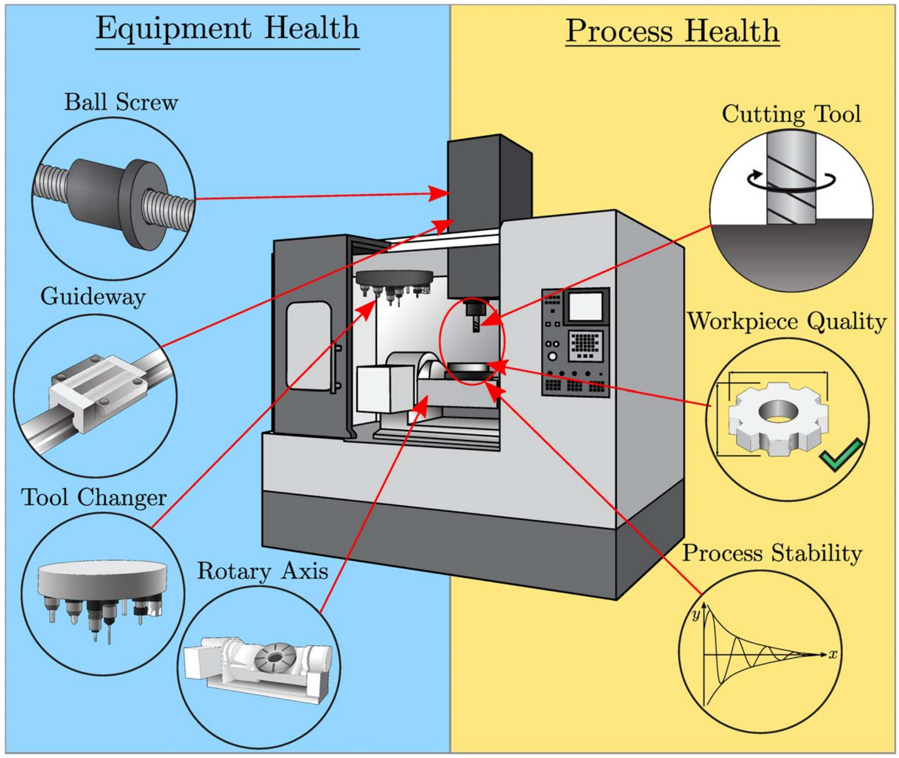

Fig. 5 A comparison between equipment and process health monitoring of machine tools. Equipment health monitoring includes the monitoring of feed axis components such as ball screws and guideways. Process health monitoring involves the cutting tool, cutting process, workpiece quality, and process stability.

autonomy and reduce machine tool operators from the monitoring process, then the problems of sensor robustness and false positives need to be addressed.

The specific application of TCM in milling operations shows its implementation to be complicated. The general involvement of TCM acceptable for all milling processes has been a reluctant achievement. Zhou and Xue [31] describe that the challenges of developing inexpensive TCM models for specific conditions, optimizing multi-sensor/feature configurations, use of monitoring models for prognosis rather than diagnosis, and the application of more advanced AI-based monitoring methods are preventing wider implementation of TCM in milling. More recently, Patil et al. [32] note that deep learning can meet some of these challenges, thus bringing the field of TCM closer to complete Industry 4.0 implementation.

2.3.2 Equipment Health Monitoring. The 1994 review of condition monitoring and fault diagnosis in machine tools by Martin [14] outlines the activity and excitement concerning condition monitoring and its applications to CBM. This work focuses on equipment health monitoring and distinguishes between soft faults, i.e., slowly developing faults, and hard faults. The former shows to be a better candidate for condition monitoring while the latter can be more easily diagnosed. Online and offline monitoring is discussed as well as autonomous monitoring. This leads to decisions about the parameters to be monitored and the method of data acquisition. The research of condition monitoring is foreseen to be of increasing importance and a request for more information on how faults arise is asked.

Vibrations can give key insight into the health of machine tools. Goyal and Pabla [16] review the research on the tools used for vibration analysis concerning the CM of machine tools. These tools include the sensors and signal processing algorithms needed to extract meaningful quantities that represent the health of the machine tool. The common signal processing techniques include wavelet transforms (WTs), time series models, the Hilbert–Huang transform (HHT), and combinations of these methods as well. Contact type sensors are found to be the most prevalent in measuring vibrations in machine tools. However, non-contact sensors provide measurements with reduced mass-loading effects as they are isolated from the machine dynamics. These sensors allow for quicker and more accurate comparisons with theoretical models. Concluding the review is the hypothesis that research may focus on capitalizing on new information communication technologies. Smartphone devices can be used for better access to the health condition of the machine, improving maintenance decision-making.

PHM is noted to be the next maintenance strategy beyond CBM. Baur et al. [17] give a survey on PHM applied to machine tools. Much attention is given to prognostics and the different approaches available including their shortcomings. These methods are described for each of the main subsystems of machine tools, those being the feed axis, spindle, cutting tool, and hydraulic system. Similar to Ref. [16], limitations on current methods include the need for improved information collection systems as ICT becomes more prevalent in manufacturing. Another limitation is the need for methodologies that can adapt prognostic models through online data in order to remain relevant.

With the increasing implementation of smart sensors systems and the use of artificial intelligence and machine learning algorithms, manufacturing industries are moving towards the next generation of manufacturing. Industry 4.0 and the digital realm of manufacturing involve the integration of ICT and automation to improve efficiency and decision-making. As will be seen in this article, much research is conducted in laboratory settings where smart systems and machine learning are used to monitor the condition of machine tools. Some studies include the analysis and implementation of these methods on industrial equipment used in actual manufacturing environments. This begins to pave the way for industrial applications of CM. However, the complete merging of Industry 4.0 and ICT in industry is still yet to be seen in this area.

3 Machine Tool Feed Drives

The machine tools considered in this review generally consist of CNC machining systems. Machine tool feed drives are the axes that provide movement and positioning of a table and workpiece or the spindle and cutting tool. An overview of machine tool feed drives is given in this section.

Traditionally, CNC machine tools are categorized as machining or turning centers, although multi-functional (mill-turn machines) tools are becoming more common. Modern machine tools can operate with five or more axes where each axis is composed of either a linear or rotary drive. However, three-axis CNCs are not uncommon. For example, a five-axis vertical machining center can have three linear axes (*x, y, and z*) and two rotary axes (*a* and *b*). The most common linear feed drive in machine tools is the ball screw drive [33]. As such, linear motor drives are not considered here.

3.1 Ball Screw Drives. Ball screw drives translate the rotational motion of a drive motor into the linear motion of the table. The motor can drive the ball screw directly or through a gear reducer or gearbox. The components of a ball screw drive include the ball screw, ball nut, AC or DC drive motor, support bearings, guideway or slide, the table, and encoder sensors as shown in Fig. 6. AC permanent magnet synchronous motors are the most common to drive ball screw axes in machine tools. A preload in the screw nut is usually needed to eliminate backlash and increase stiffness. Preload can be applied by the use of double-nut designs, oversized balls, or shifting the pitch of the nut relative to the ball screw.

3.1.1 Ball Screw Models. Ball screw drives deflect torsionally due to the ball screw shaft, the screw nut, and the motor–shaft coupling. Damping characteristics are also seen due to friction in the motor, support bearings, and the screw nut. A dynamic model that ignores the torsional flexibility (i.e., a rigid body model) can be represented by the transfer function, $G(s)$, relating the motor position, θ_m, to the motor torque, T_m,

$$G(s) = \frac{\theta_m}{T_m} = \frac{K}{s(J_e s + B)} \tag{1}$$

where K is a gain factor, J_e is the equivalent inertia reflected onto the motor, and B is the viscous damping coefficient.

When considering the inertial and cutting forces exerted on the ball screw drive, a lumped mass model, such as that shown in Fig. 7, can give more insight into the structural vibrations. In such a model, the inertia of the drive motor, J_m, is connected to the inertia of the ball screw, J_l, by the stiffness and damping elements K_t and C_t, respectively. The transfer function, $\boldsymbol{G}(s)$, of this system is given as

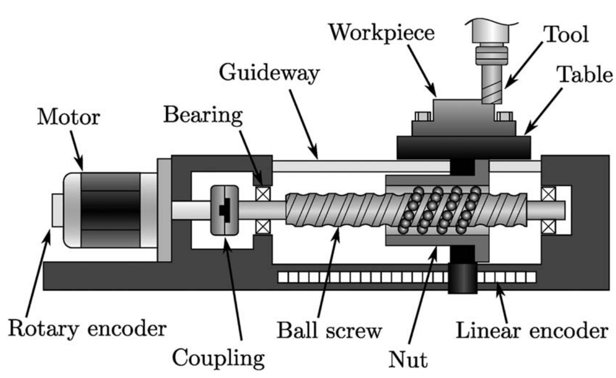

Fig. 6 Components of a ball screw drive

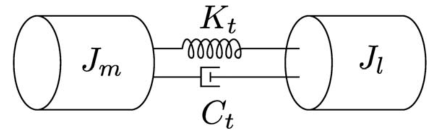

Fig. 7 Ball screw lumped mass model

$$\boldsymbol{G}(s) = \frac{\begin{pmatrix} J_l s^2 + C_t s + K_t & C_t s + K_t \\ C_t s + K_t & J_m s^2 + C_t s + K_t \end{pmatrix}}{s^2\left(J_l J_m s^2 + C_t(J_l + J_m)s + K_t(J_l + J_m)\right)} \tag{2}$$

This then gives the following dynamic equation:

$$\begin{pmatrix} \theta_m \\ \theta_l \end{pmatrix} = \boldsymbol{G}(s)\begin{pmatrix} T_m \\ T_l \end{pmatrix} \tag{3}$$

where θ_l is the angular position of the ball screw and T_l is the applied torque seen by the ball screw. The linear position of the table, x_t, can be obtained by multiplying the angular position of the ball screw by the transmission ratio, R,

$$x_t = \theta_l R \tag{4}$$

For ball screws, the transmission ratio is $R = l/2\pi$, where l is the lead of the ball screw. More complex dynamic models can include the stiffness and damping seen between the table and the screw. See Refs. [34,35] for applications of these models.

Finite element methods (FEMs) have also been used to model the complexities of ball screw drives. An overview of FEM models with respect to ball screw drives is given by Altintas et al. [33].

3.1.2 Control of Ball Screw Drives. A NC generates a trajectory profile from a part program and provides the control algorithms used for axis positioning. The trajectory profile consists of position, velocity, acceleration, and jerk commands that are sent to the axis controllers. The controllers in turn receive position feedback signals from rotary and linear encoders. Such signals may be used in combination with mathematical feed drive models to provide a means of condition monitoring.

The general control method used in modern feed drives is cascaded proportional position and proportional-integral velocity control, or P-PI control. In this control scheme, the reference position, velocity, and acceleration are calculated by the NC and sent to the controller via a field bus. The P-PI control method can be implemented with the use of adaptive gains, online parameter estimation, and feedforward compensation. Control laws may also use acceleration and jerk feedback signals. This control scheme is used to ensure stability against uncertain disturbances and changes in the dynamics due to wear and increased friction. On a deeper level, the motor drive current is also controlled via a PI control law. However, this can often be modeled as unity or as a gain since the bandwidth of the current control loop is much greater than that of the velocity control loop. For instance, the bandwidth of a current controller is typically 1 kHz while the bandwidth of the velocity control loop is usually less than 10% of the current control loop (i.e., 100 Hz). The bandwidth of the position loop is even smaller than that of the velocity loop being approximately 30% of the bandwidth [33]. An example of a control architecture is given in Fig. 8. Feedback filters are also implemented to remove noise from measured encoder signals.

The goal of rigid body controllers is to expand the positioning bandwidth of the feed drive as much as possible [33]. However, this can result in exciting the structural modes of the feed drive axis. These classical control schemes may use lowpass or notch filters in order to remove unwanted exciting frequencies in the control signal. Lowpass filters provide good attenuation of problematic high-frequency signals. However, the structural dynamics must be known with certainty to properly implement notch filters.

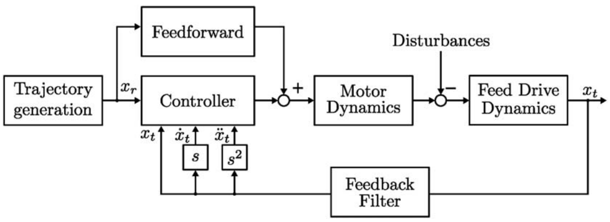

Fig. 8 The general control scheme for a feed drive

Control architectures that do account for the flexibility of the drive can implement several methods to mitigate the resulting vibrations. These include trajectory generation algorithms and active damping. More information on this type of control can be found in Ref. [33].

In condition monitoring, controller data (NC data) are often used in physical, signal-based, and data-driven models. These include encoder feedback signals, motor currents, and torques. More information on the sensors and signals used in machine tools is given in Sec. 4.

3.2 Rotary Axis Drives. Rotary axis drives include the *a*, *b*, and *c* axes of machine tools. They can be driven directly or through a gearbox, much like ball screw drives. Rotary axes can be driven by AC servo motors or DC torque motors. The typical construction of a rotary drive includes the motor, housing, bearings, and position encoder(s). Drives that use torque motors are considered to be direct drives as the load is directly connected to the rotor. Servo-driven axes can often include the use of worm and gear mechanisms.

Rotary drives have similar dynamics to ball screw drives; however, there is no conversion from rotary to linear motion. Likewise, the control of rotary drives is identical as a P-PI controller is implemented for position and speed control. For the condition monitoring of rotary axes, see Sec. 5.4.

3.3 Linear Guideways and Slides. Slides and guideways are linear mechanisms that provide a path for which a table or tool may travel. These mechanisms usually consist of one or more carriages and linear rails on which the carriage(s) are mounted. Slides and guideways can be driven by mechanical, hydraulic, or electrical drives.

Different bearing systems are integrated into the carriages. Friction type bearings include sliding contact bearings (or hydrodynamic bearings) and are the most common [13]. Friction bearings can sometimes experience stick-slip or stiction phenomena, which may occur when static friction is greater than the dynamic friction. Friction is reduced on these guideways by coating the rails in a low-friction material. Rolling element bearings are used in linear guides which are another common guideway system. These bearings include recirculating balls or rollers, or non-recirculating variants. Hydrostatic and aerostatic bearings are used on precision machine tools. The elements of these bearing mechanisms experience no physical contact as they are supported by thin films of oil or continuously flowing air providing low-friction travel. These bearing systems require routine lubrication, among other maintenance actions, to increase component longevity.

The monitoring of guideways typically includes identification of degradation, preload, internal or external forces, and lubrication states. Fault diagnosis can also be performed by recognizing patterns from these monitoring parameters. More on guideway monitoring and diagnosis can be found in Sec. 5.2.

4 Condition Monitoring

Various definitions and descriptions of CM are proposed. Jardine et al. [12] describe CM data as "measurements related to the health condition/state of the physical asset." Campos [36] details CM as a process that "involves data acquisition, processing, analysis, interpretation, and extracting useful information." Ahmad and Kamaruddin [6] report CM as two-fold: "First, it collects the condition data (information) of the equipment. Second, it increases knowledge of the failure causes and effects and the deterioration patterns of equipment." In a review on CBM of machine tools, Goyal and Pabla [16] define CM as the continuous monitoring of parameters for the prediction of component failures.

Common among these definitions is the notion of measuring data. This section begins with the tools needed for data acquisition; those tools being sensors. Next, the methods for processing and analysis are given for signal-based, model-based, and data-driven methods. All of these methods aim to extract useful information about the health state of the machine.

4.1 Sensors and Signals. Sensors are an integral part of machine tools that allow them to operate at the precision required by modern manufacturing. Internal sensors are those that are built into the machine tool by the OEM for positioning and control purposes. The CM methods solely using internal sensors are described as sensorless methods in this work. The methods using external sensors are described as sensor-based. Note that methods using both internal and external sensors are still deemed to be sensor-based. Figure 9 depicts the similarities and differences between sensorless and sensor-based signals.

4.1.1 Internal Sensors and Signals. The most important internal sensors are presented here. However, the sensors described are not exhaustive in the application of machine tools.

Position measurement is needed for the precise machining operations conducted by machine tools. Linear encoders capture the position of the table and workpiece and generally consist of optical encoders. Position feedback signals measured by linear encoders are also used within the position control loop. Rotary encoders measure the angular position of servo motor shafts and provide an indirect measurement of the table position.

The speed and acceleration of the feed drive are commonly measured using the first and second derivatives of measured position signals, respectively. This is usually accompanied by lowpass filtering to reduce the noise introduced by discrete differentiation. These signals can also be measured directly, with tachogenerators and eddy current sensors measuring speed, and pizeo-based sensors measuring acceleration [13,33]. The velocity signal is used in the speed control loop of the drive, while the acceleration is typically used for the suppression of structural dynamics.

Motor drive current can be measured using shunt resistors. Current feedback signals are used in the current control loop of the drive and can be useful for compensating friction and cutting force disturbances [33]. Related to the drive current is the drive torque. In general, the drive torque, T, can be calculated by

$$T = K_t i \tag{5}$$

where K_t is the motor torque constant and i is the drive current. In actuality, the NC and drive controller compute the torque using dynamic values of the torque constant.

The temperature of various components of machine tools, such as drive motors, is measured. Temperature can be used in condition monitoring to give insight into the friction and heating characteristics of machine tool components.

Sensorless machine tool data are captured via the NC. This is generally achieved through electric circuitry, the programmable logic controller (PLC), and various communication interfaces. Modern machine tools have more open NCs where OEMs provide development application programming interface (API) packages and tools [37]. Popular communication protocols include OPC UA and MTConnect. However, condition monitoring research efforts sometimes use external data acquisition devices and

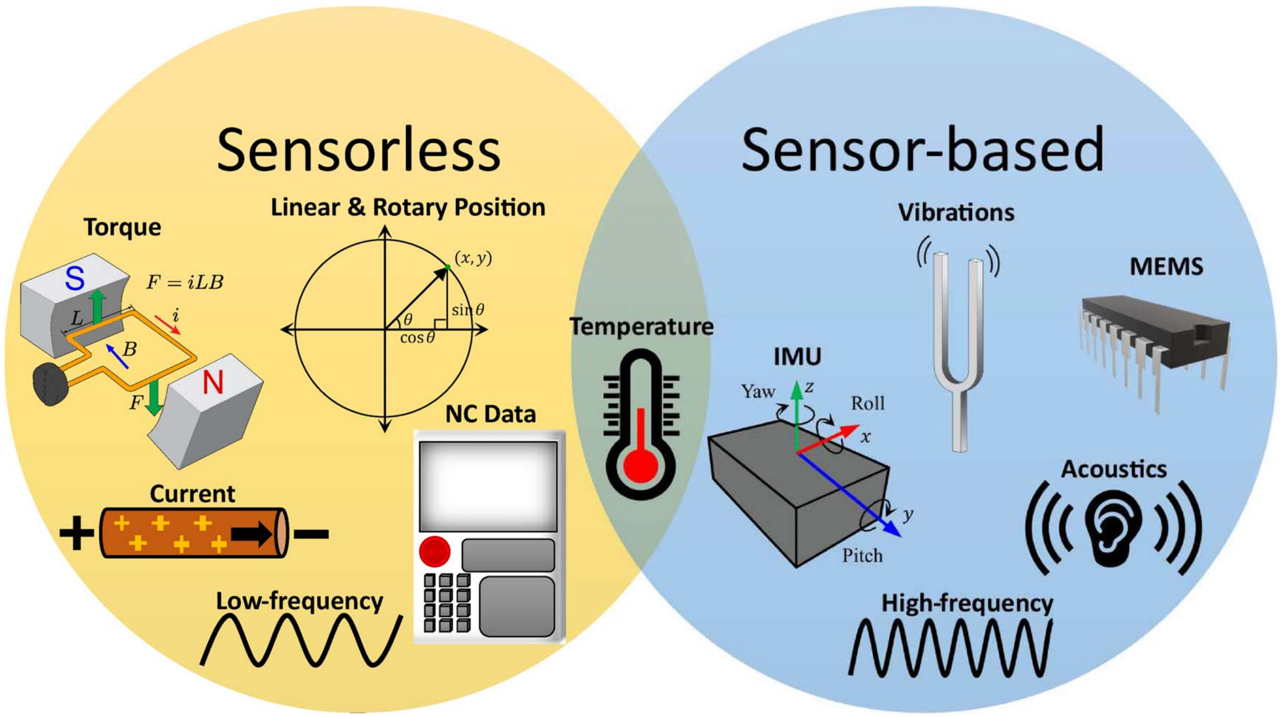

Fig. 9 Comparison of sensorless and sensor-based signals, sensors, and data. Sensorless data are obtained from built-in sensors and signals (torque, current, position, etc.) while sensor-based data are measured from external sensors (accelerometers, acoustic sensors, etc.). Temperature data may be regard as either sensorless or sensor-based given the manner in which the data are measured.

counter cards as OPC UA and MTConnect are generally limited (less than 1000 Hz) in their data sampling rates.

4.1.2 External Sensors and Signals. External sensors are widely used in CM. They are capable of measuring quantities of interest directly, such as vibrations, whereas internal sensors provide more indirect measurements. In this sense, external sensors are more useful than internal sensors. However, external sensors are not easily installed onto production machine tools. For instance, measuring the vibrations of a ball screw nut via an accelerometer can be difficult and is typically left to experimental work. Data collection from external sensors is achieved through a data acquisition device or a personal computer which can make data collection during production hours difficult. For large manufacturers, the installation of hundreds or even thousands of external sensors can be time consuming and extremely expensive as well.

The most commonly used external sensor is the accelerometer which provides measurements of vibrations in machine tool structures and components [16]. Accelerometers contain piezoelectric materials that produce voltage signals when experiencing mechanical stresses. Vibrations can also be measured using displacement transducers, proximity sensors or switches, capacitive sensors, and velocity transducers. Micro-electromechanical system (MEMS) sensors are also becoming more popular in the literature [38–42]. These are outfitted with accelerometers and thermocouples to measure vibrations and temperature. For machine tool feed drives, the common mounting locations for accelerometers include the ball screw support bearings, the screw nut, and the table.

External thermocouples and temperature sensors are used quite extensively in machine tool CM [40,43–47]. These are usually mounted onto support bearings and motor housings. Acoustic emission sensors are used to monitor linear guideways [48] and to detect defects of ball screws [49]. The state of wear of a ball screw is monitored using external current sensors [50]. Likewise, single-phase spindle currents are measured to monitor the health state of a feed drive [51]. Alternative sensing methods include the use of Hall effect sensors [52], cameras [53], an inertial measurement unit (IMU) [54–58], piezoresistive materials [59–62], strain gauges [61,63,64], and tactile load cells [65].

4.2 Signal Processing Methods. Signal processing is the next step after data acquisition. This step in the monitoring process aims to condition signals or extract signal features such that they better represent the information contained in the data. This section outlines the signal processing methods most often used in the research of machine tool CM. The most common signals used for the monitoring of machine tools are encoder positions, drive motor currents or torques and vibrations. These signals are typically pre-processed before more advanced signal processing techniques are used; however, this is not always the case. Signal pre-processing can include filtering, analog-to-digital conversion, re-sampling, de-trending, and segmenting the data. Signal processing techniques are categorized into time domain, frequency domain, and time–frequency domain analyses. It should be noted that sometimes a spatio-temporal or a spatial frequency domain is used for analysis.

A summary of the signal processing methods described below and their applications to machine tool CM literature are shown in Table 1.

4.2.1 Time Domain Analysis. Statistical analysis is frequently used to monitor signals. Parameters such as maximum, minimum, peak-to-peak amplitude, mean, root-mean-square, variance, kurtosis, skewness, and other higher order moments are used. These parameters can be determined during a machine's healthy state to represent threshold values. Continually monitoring these statistical parameters can uncover potential faulty machine states. Furthermore, the parameters are also used as input features for machine learning algorithms with the aim of condition monitoring, diagnostics, or the prognostics of faults and failures.

Time series modeling is used in other condition monitoring scopes [12,15]. This includes autoregressive and autoregressive

Table 1 Summary of signal processing methods

Monitoring area	Sensors and signals: Sensorless	Sensor-based	Signal analysis method
Ball screw			
Wear/performance degradation	Rotary encoder [44,66–68], linear encoder [66,67,69], current [50,69], torque [70]	Vibration [44,71], temperature [44]	Statistical [69], FFT [44,68,70], PSD [50,66,67], WT [70,71], WPT [50,68]
Preload loss	Current [72,73], torque [73]	Vibration [38,40,74,75]	PSD [40], OT [75], STFT [38,40], HHT [74,72,73], MSE [74,72,73]
Backlash	–	Vibration [76], camera [53]	Statistical [53], FFT [76]
Fault detection/ diagnosis	–	Vibration [77]	PCT [77]
Prognosis/RUL	–	–	
Sensing methods/ technologies	–	Wireless vibration [78], hybrid sensor [46]	FFT [78], OT [46]
Other methods	Linear encoder [79,80], torque [80,81]	–	Statistical [81], FFT [79,80]
Linear guide/slide			
Wear/degradation	Rotary encoder [82], linear encoder [82], current [82,83]	IMU [56–58], ball-end probe [83]	Statistical [56,58,83], EMD [82], filtering [57]
Preload and force	–	Vibration [42], optical [65], force [65]	FFT [42], comparative analysis [65]
Lubrication	–	Temperature [47]	Limit analysis [47]
Fault diagnosis	–	Vibration [48], acoustic [48]	FFT [48]
Positioning accuracy and error			
	Linear encoder [84]	Vibration [85]	SSA [84], FFT [85]
Rotary axis			
	Rotary encoder [86], current [87,88]	Ball-bar [89]	FFT [89], EEMD [87], WT [86,88]

moving average models. However, these models are not been frequently observed in the literature of machine tool CM.

Multi-scale entropy (MSE), first proposed by Costa et al. [90], is a time series method that sees use in machine tool CM. MSE is a quantity among many measures of complexity (or entropy) of a finite time series signal. It is popular in the analysis of biological and physiological signals, such as cardiac rhythms [91]. To calculate the MSE of a one-dimensional discrete time series, $\{x_1, \ldots, x_i, \ldots, x_N\}$, one must first construct a coarse-grained time series $\{y^\tau\}$ with scale factor τ as defined in Eq. (6):

$$y^\tau = \frac{1}{\tau}\sum_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \leq j \leq \frac{N}{\tau} \tag{6}$$

This process divides the original time series into non-overlapping segments of length τ and then calculates the average of the data in each segment. For $\tau = 1$ (scale one), the constructed time series $\{y^{(1)}\}$ is the original time series. After this procedure, an entropy measure S_E is calculated for each coarse-grained time series. The entropy measure is then plotted versus the scale factor τ. For monitoring applications, MSE is used to calculate the complexity of vibration signals and drive motor currents in Refs. [72,74], respectively. Motor torque signals are also analyzed using MSE in Ref. [73]. Another uncommon time domain method is singular spectrum analysis (SSA). This method is used to detect position fluctuations caused by defects in a feed drive [84]. More information on SSA can be found in the book by Elsner and Tsonis [92].

4.2.2 Frequency Domain Analysis. Frequency domain analysis gives insight into the useful information contained in the frequency components of signals. Among the most common frequency domain transformations, the fast Fourier transform (FFT) is the most popular. The FFT is an efficient algorithm that calculates the discrete Fourier transform. Windowing functions are typically used in conjunction with the FFT to reduce spectral leakage caused by the finite-length sampling of signals.

Related to the frequency, content of signals is the autospectral density or power spectral density (PSD). The PSD is a measure of the spectral energy content of a signal per unit time. This quantity can yield informative characteristics of time series signals. Some CM research has used a vibration energy parameter, P, defined as

$$P = \sum_{i=0}^{i_{\max}} \sqrt{(S_{xx}(f_i) - S_{0xx}(f_i))^2} \tag{7}$$

where $S_{0xx}(f_i)$ is the PSD of an initial measurement and $S_{xx}(f_i)$ is the PSD of the current measurement. This quantity is used by Verl et al. to study the relationship between positioning errors and ball screw wear [66]. Maier and Heisel also use this parameter to monitor ball screw drives [67].

Additional frequency domain methods include envelope analysis, which is used extensively in rolling element bearing condition monitoring and order tracking (OT). Order tracking involves the study of the fundamental frequencies of a mechanical system that correspond to rotating shaft speeds. These fundamental frequencies are called *orders*. An order spectrum can characterize the energy-intensive components of measured signals over certain frequencies related to the primary rotating speed [93]. In machine tool condition monitoring, OT is used to monitor the ball pass frequency (BPF) of ball screws in Refs. [46,75].

4.2.3 Time–Frequency Domain Analysis. Advanced signal processing techniques include time–frequency analysis. These methods address the fact that regular frequency analysis cannot properly handle non-stationary signals. Thus, methods such as the short-time Fourier transform (STFT) and the WT are proposed. The STFT divides a signal into segments corresponding to a short time-frame windowing function. The Fourier transform is then applied to each segment. Wavelet analysis has emerged as a useful time–frequency method as well. Unlike the STFT, the wavelet transform can be used for multi-scale analysis of a signal [94]. This allows the WT to effectively extract time–frequency features from a signal. However, the WT can experience low resolution at higher frequencies. The wavelet packet transform (WPT) was introduced to overcome this obstacle, allowing for an arbitrary time–frequency resolution [95]. Similar to the WT is the chirplet transform, and a more recent extension, the polynomial chirplet transform (PCT) [96]. The PCT is used to identify faults in a ball screw drive in Ref. [77].

Table 2 Summary of model-based methods

Monitoring area	Sensors and signals: Sensorless	Sensors and signals: Sensor-based	Model
Ball screw			
Wear/performance degradation	Rotary encoder [67], linear encoder [67,100]	Vibration [51,71,101,100], current [51]	BPF [67,71], OMA [51,101,100]
Preload loss	–	Vibration [52,102,103], force [104], Hall sensor [52]	EMA [102,103], OMA [52], analytic [104]
Backlash	Rotary encoder [76,83,105–107], linear encoder [76,108,109,105,106], NC data [105,110]	–	Error [83,108,109,105], EMA [110], algorithm [107], analytic [76,105], adaptive estimation [106]
Fault detection/ diagnosis	Linear encoder [111]	–	KF [111]
Prognosis/RUL	–	Vibration [112–114]	Exponential [112,113], PF [112–114]
Sensing methods/ technologies	–	Vibration [115]	KF [115]
Other methods	Rotary encoder [116], linear encoder [116], torque [116], NC data [117]	–	Adaptive estimation [116], parameter estimation [117]
Linear guide/slide			
Wear/degradation	Current [118]	Vibration [119], strain [64], capacitance [119]	Analytic [62,64,118,119]
Preload and force	–	Vibration [102,120], strain [63], piezoresistive [62]	EMA [102], OMA [120], empirical [63], analytic [62]
Lubrication	–	–	–
Fault diagnosis	–	Ball-bar [121]	Analytic [121]
Positioning accuracy and error			
	Rotary encoder [122–124], linear encoder [123,124], torque [122]	Ball probe [125]	Analytic [123–125], dynamics [122]
Rotary axis			
	Rotary encoder [109,126]	Custom [127], various [128], ball-bar [129]	Error [109,127], analytic [126,129]

The time–frequency method introduced by Huang et al. [97], the HHT, is a very useful contribution used in CM. The utility of the HHT can be attributed to its use of empirical mode decomposition (EMD). EMD is based on the local time scale of the data and further decomposes complex data into finite intrinsic mode functions (IMFs) which produce well-behaved Hilbert transforms. The Hilbert transform of the IMFs yields instantaneous frequencies that are functions of time. These instantaneous frequencies contain useful information and are shown to detect the deterioration in roller bearings among other monitored machine components [98]. Wu and Huang [99] further built upon the deficiencies of EMD, such as mode mixing that causes aliasing in time–frequency distributions, with the advent of ensemble empirical mode decomposition (EEMD). EEMD is used to diagnose faults in the rotary axis of a machine tool in Ref. [87].

4.3 Model-Based Methods. Model-based methods are based on physical assumptions to describe processes and systems. Empirical or phenomenological models can also be built through correlating measured data and observations. Model-based methods generally include deterministic and stochastic models as described below.

The model-based methods used in the CM of machine tool feed drives are summarized in Table 2.

4.3.1 Deterministic Models. Deterministic models assume that the observed process or system has no stochastic, or random, variation in the parameters or observations.

In condition monitoring research, many works use analytical models to monitor quantities of interest. These include derived relations from the feed drive dynamics. The leveling and misalignment of a machine tool are monitored from the drive current through a dynamic model [118]. In Ref. [122], the position reversal of a ball screw drive is monitored using analytical descriptions of vibration amplitudes. Coordinate transformations are applied to machine tool dynamics to monitor position and geometric errors in Refs. [123,124]. Volumetric errors (VEs) are monitored in Ref. [125] using the scale and master balls artifact method [130].

The BPF was adopted from roller bearing theory and applied to the ball nut of ball screws. The BPF can be estimated using analytical equations [71]. This model is usually accompanied by frequency analysis. The frequency of vibration of a machine tool feed drive is also estimated using a derived relationship in Ref. [76].

Force and stress analyses are used to examine the relationship between feed velocity and preload in ball screws [104] and the use of piezoresistive films in linear guides [62].

Models of the backlash seen in feed drives are typically simplistic and consist of measured errors [83,108,109,105]. However, some works employ nonlinear models in their analysis such as in Ref. [106]. An algorithm developed by Chandrasekar and Srinivasan measures backlash error using torque-limited positions [107]. Transient backlash error (TBE) models are also derived for both linear and rotational machine trajectories [105].

4.3.2 Stochastic Models. Unlike deterministic models, stochastic models incorporate randomness or can be described by probability distributions. The Kalman filter (KF) and its variants (extended KF and unscented KF) are popular state estimation algorithms that compute an efficient solution to the least-squares method [131]. In condition monitoring of machine tools, the KF is used for fault detection of ball screw drives [111,115]. The KF algorithm inherently involves Gaussian distribution assumptions. For non-Gaussian problems, sequential Monte-Carlo methods, or particle filters (PFs), are proposed [132]. From a machine tool perspective, PFs are used for the prognosis and RUL calculation of ball screws [112–114].

Exponential models are developed to monitor the RUL of ball screws. In Ref. [113], the degradation process of a ball screw is fit to an exponential model using a Weibull distribution shape parameter [113]. Likewise, an exponential Wiener process is used to predict the RUL [112].

Table 3 Summary of data-driven methods

	Sensors and signals		
Monitoring area	Sensorless	Sensor-based	Models and methods
Ball screw			
Wear/ performance degradation	Rotary encoder [142,143], current [143], torque [142]	Vibration [101,135,139,140,145,152]	MD [140,142,143], CD [101], AE [101], VAE [145], LE [142,143], PCA [139], KPCA [140], DFNN [139], DBSCAN [140], LSTM-GRU [140], MCS [152], BPNN [101,152], DBN [135]
Preload loss	Rotary encoder [136,151,153], linear encoder [136,151,153], current [136,153], torque [151]	Vibration [40,45,103,148,151,153], temperature [40,45]	MD [45], SOM [45], GMM [45], SVM [40,136,151,153], GPR [103,151], GA/KNN [153], GPC [103], CNN [148]
Backlash	Rotary encoder [149,157], linear encoder [149,157], torque [157]	–	ANN [149], DBN [157]
Fault detection/ diagnosis	Rotary encoder [43], linear encoder [43], torque [43,147], NC data [154]	Vibration [43,49,154,158,159], acoustic [49], temperature [43]	MD [158], PCA [154], SOM [43,154], CNN [147,158], BPNN [159], custom [49]
Prognosis/RUL	–	Vibration [114,156]	Gray model [156], GRU-PF [114]
Sensing methods/ technologies	–	Vibration [40], temperature [40]	SVM [40]
Other methods	–	–	–
Linear guide/slide			
Wear/degradation		Vibration [160]	DFNN [160]
Preload and force	–	–	–
Lubrication	–	Vibration [161]	BPNN [161]
Fault diagnosis	–	Vibration [162], micrograph [155]	CNN [162], SMMC [155]
Positioning accuracy and error	–	–	–
Rotary axis	–	Various [150]	ANN [150]

To accurately model a process or system, the model parameters must be estimated with precision. This can be done using measured data and a least-squares fit, as in the machine tool friction model of Reuss et al. [117]. However, for general machine tool models, the external excitation must be chosen carefully to adequately capture the dynamics of the machine. This lends itself to the study of system identification and frequency response functions (FRFs) [133]. Identification of mass, inertia, damping/friction coefficients, and stiffness is possible with system identification methods. More often the modal parameters are estimated directly. Two prominent methods for modal parameter estimation include operational modal analysis (OMA) [134] and experimental modal analysis (EMA). Both of these methods are often used in conjunction with FEM to estimate the natural frequencies of the machine and subsequently measure them. OMA has the benefit of estimating parameters during the actual working conditions of the machine and sees the use in condition monitoring of machine tools [51,52,67,120,101,100].

The online estimation of parameters in nonlinearly parameterized systems can be challenging. Papageorgiou et al. [106] designed online adaptive estimators to estimate the backlash and friction parameters [116] in ball screw drives.

4.4 Data-Driven Methods. In general, data-driven methods cover a wide area that includes the analysis and collection of data. The scope of this section is primarily on statistical learning methods, otherwise known as ML. ML models can be categorized as supervised or unsupervised learning. Broadly speaking, unsupervised learning deals with model training that uses unlabeled data, while supervised learning uses labeled data. There do exist methods that use both labeled and unlabeled data, and these are deemed to be semi-supervised learning.

The models and methods outlined in this section are summarized in Table 3.

4.4.1 Feature Extraction and Feature Learning. Much like signal processing methods, ML begins with data pre-processing. This may include data fusion, or the combining of measured data. For example, in Ref. [135], frequency spectra measured from different vibration sensor signals are combined using parallel superposition. After data pre-processing, features are extracted and selected. It is also possible that features are learned through the ML algorithm.

Feature extraction is used to provide meaningful representations of data such that ML algorithms can identify commonalities and relationships among the features. Feature engineering is the process of using specific domain knowledge to create features. This is usually performed using the signal processing methods presented in Sec. 4.2, with the addition of statistical moments of frequency spectra often included. All of the computed features may be used in the ML method, or a select few can be chosen using various criteria. For example, the Fisher criterion can be used to select the features most representative of the data as in Ref. [136].

ML algorithms are often better suited to work with lower dimensional data. The high-dimensional data that are measured can be sparse which lead to undesirable computation times. Dimensionality reduction is a method used to represent high-dimensional data on a low-dimensional space such that meaningful representations are maintained in the data. A widely known reduction method is principal component analysis (PCA) [137]. An extended method is kernel PCA (KPCA) [138]. These methods are used for the health assessment of ball screws [139,140]. A common reduction technique in machine tool CM includes the calculation of the Mahalanobis distance (MD) [141]. MD is also used for the health assessment of ball screws [45,140,142,143]. Similar to the MD, the cosine distance (CD) is used to detect early faults in machine tools [101].

Beyond regular dimensionality reduction techniques, feature learning, otherwise known as *representation learning* or *deep learning*, is the subject of significant interest in ML research. Feature learning is an unsupervised method where the ML algorithm extracts important features from the data. Such methods include autoencoders (AEs), manifold learning, and deep networks [144]. AEs and the variational AE (VAE) are used to monitor faults and the health of ball screws in Refs. [101,145], respectively.

Manifold learning aims to learn representations of data lying on a low-dimensional manifold embedded in a high-dimensional space. The method of Laplacian Eigenmaps (LEs) proposed by Belkin and Niyogi [146] achieves this task. LE are used for the health assessment of ball screws [142,143]. Deep learning methods that represent feature learning include stacked restricted Boltzmann machines, called deep belief networks (DBNs), and convolution neural networks (CNNs). The degradation of ball screws is monitored using a DBN in Ref. [135]. Ball screw faults are identified using CNNs in Refs. [147,148].

4.4.2 Machine Learning Models. A number of ML models are used in machine tool CM. Regression techniques are often used for continuous parameter monitoring, such as RUL and backlash values. These include the use of artificial neural networks (ANNs) for the estimation of backlash [108,149]. ANNs are also used for the classification of hydrostatic turntable performance [150]. Recurrent neural network structures, such as long short-term memory (LSTM) networks with the use of gated recurrent units (GRUs), called a LSTM-GRU network, are used to estimate the degradation trends of a ball screw [140]. An ensemble gated recurrent unit particle filter (GRU-PF) method is also used to study the prognostics of ball screws [114]. A regression method, called Gaussian process regression (GPR), is used to study the prognostics of ball screws in Refs. [103,151]. Ball screw performance degradation is evaluated using a dynamic fuzzy neural network (DFNN) [139]. The modal parameters of a ball screw drive are assessed with the supplementation of Bayesian ridge regression in Ref. [100].

Classification models are used to identify faults and classify degradation levels in machine tools. A back-propagation neural network (BPNN) along with a multiple classifier system (MCS) is used to diagnose the level of degradation of ball screws [152]. A BPNN is used to detect early faults caused by worn ball screws in Ref. [101]. Gaussian process classification (GPC) is used to classify the wear states of a ball screw based on the identified natural frequencies of the drive [103]. The preload of a hollow ball screw is diagnosed using a genetic algorithm/k-nearest neighbor (GA/KNN) method [153]. A support vector machine (SVM) model is used to diagnose the health of a hollow ball screw drive [136]. Softmax classification is used with a DBN model to monitor the degradation trend of a ball screw [135]. Likewise, a CNN architecture with a Softmax classifier is used to identify faults in a ball screw drive [147].

Several unsupervised clustering methods are used in the literature. Self-organizing maps (SOMs) are used for anomaly detection and diagnosis in machine tools [43,154] as well as for ball screw health assessment in Ref. [45] where a Gaussian mixture model (GMM) is also used. The health status of a ball screw is evaluated using density-based spatial clustering of applications with noise (DBSCAN) in Ref. [140]. In Ref. [155], surface micrographs of linear guideways are monitored using spectral multiple-manifold clustering (SMMC). Beyond clustering, kernel density estimation is used in Ref. [145] for the degradation assessment of a ball screw.

In addition to the above methods, some authors have devised their own self-implemented classification algorithms, such as the fault detection model presented in Ref. [49]. Another method is the use of a multi-variable gray model to predict the RUL of ball screws [156].

5 Condition Monitoring of Machine Tool Feed Drives

Machine tool feed drives are composed of components and subsystems that require frequent maintenance, repair, or replacement. Identifying anomalous events or trends in wear patterns through CM is integral to optimizing maintenance and spare parts scheduling. This section focuses on four primary areas of feed drive condition monitoring research: ball screw axes, linear guidance systems, positioning accuracy/error monitoring, and rotary axes.

5.1 Ball Screw Condition Monitoring. In many manufacturing environments, the downtime due feed drive maintenance can be very expensive and time consuming. Ball screws in particular are critical components of feed drive systems that can be costly and time-intensive to replace or repair. As noted by Yang et al. [163], screw and guide systems require a long time to repair when failures occur. However, these costs are not just incurred once components fail. As the working condition of a ball screw begins to deteriorate, the costs of out-of-spec and scrapped workpieces are accrued as these positioning systems are directly responsible for the quality of the machined workpiece. Thus, it is beneficial to monitor the health of the ball screw to optimize the purchase of spare parts and the scheduling of maintenance actions.

The phenomenon of wear-in ball screws is a tribological process. This entails the friction, lubrication, and characteristics of the sliding surfaces in the ball screw mechanism. The wear seen by a ball screw also affects the dynamics of the feed drive. Thus, the dynamic characteristics of the drive give insight into the health state of the ball screw. Many of the CM solutions presented in this section attempt to monitor wear through direct or indirect characteristics through analyses related to the wear, friction, or lubrication state or through the dynamics of the feed drive.

The deterioration and wear of ball screws is often correlated to the loss of preload in the nut. The preload effectively eliminates the axial backlash seen in ball screws by the use of double-nut designs with an adjustable spacer, lead/pitch offsets, or oversized balls as shown in Fig. 10. However, the preload of the nut increases the friction between the balls and the raceways of the screw and nut resulting in increased wear [164]. The two modes of friction seen in ball screw drives are the rolling and sliding of the balls relative to the raceway. It is the sliding action that leads to adhesive wear between the balls and the raceway and is a major factor attributing to the loss of precision and performance degradation of ball screws [165]. The wear pattern typically seen on ball screws is shown in Fig. 11. A clear connection can be recognized between the ball screw wear and both backlash and preload. The occurrence of

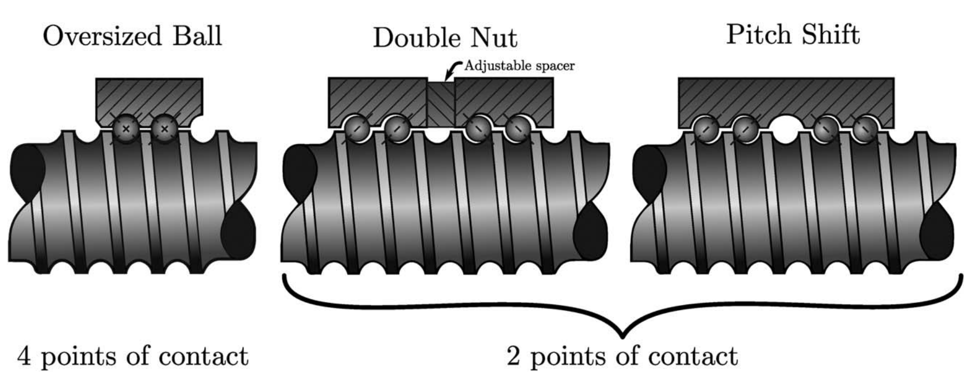

Fig. 10 Ball screw preload mechanisms and the contact points of the ball elements

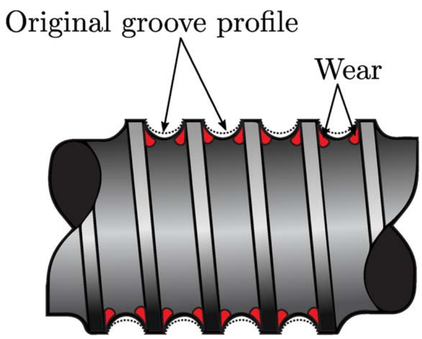

Fig. 11 Wear pattern seen on ball screws that leads to backlash

wear along the raceways leads to a loss of preload in the nut which further increases the backlash of the feed drive. Therefore, monitoring the wear, preload loss, or backlash can give insight into the health condition of the ball screw.

General wear and performance degradation, preload loss, and backlash monitoring are presented next. Afterwards, fault detection and diagnostics are considered, as is remaining useful life and the prognosis of ball screws. Then novel sensing methods and technologies used for health monitoring are explored. This section then concludes with specialized condition monitoring methods such as friction monitoring and the development of unique spatial domain features.

5.1.1 Wear and Performance Degradation Monitoring. The wear of a ball screw can be monitored by correlating various features and data that are indicative of the wear of the screw. The methods used to measure wear can be categorized as sensorless and sensor-based, where both can be considered as indirect methods since wear is typically a phenomenon that must be quantified directly. Sensorless methods typically use drive motor current or torque and linear or rotary encoder data to make correlations or derive features that are representative of the wear. Sensor-based methods employ external sensors, to measure acceleration, temperature, etc., that may be more closely linked with the wear of the ball screw, but at a higher cost to implement. For manufacturers, sensorless methods are very attractive as little to no additional costs are needed to employ these methods if the required computing architectures are present.

Early sensorless methods in monitoring the wear of ball screw drives include those by Verl et al. [66] and Uhlmann et al. [69]. The frequency and spatial domain characteristics of positioning error, reversal error, and a vibration energy parameter using rotary and linear encoders are proposed by Verl et al. [66]. The characteristics reveal a relationship between the positioning errors and wear of the ball screw. Three effects are analyzed with spectral analysis and include: damage that causes impulse-like excitation; resonant frequencies moving due to increased wear; and interference of excitation and resonance can occur due to phase shifts. This work further recognizes that the positioning accuracy of the feed drive is a crucial factor in maintenance decisions. In Ref. [69], a decentralized data management system is used to measure trends in statistical features of feed drive motor current. Bidirectional constant feed rate tests are performed to detect changes in the dynamic behavior of the feed drive. Trends of slowly progressing changes in the feed drive system are seen attributing to the wear of the drive on a centerless grinding machine.

Maier and Heisel [67] compare signal-based and a model-based approaches to the monitoring of ball screw feed drive wear on a lab setup. The study uses a testbed with a region of accelerated wear on a ball screw. Two signal characteristics are derived including the difference between the encoder signals and a vibration energy parameter calculated using linear encoder data. It is observed that the consideration of a single characteristic alone is not useful and one must also consider the sensitivities and standard deviations of the characteristics. For the model-based approach, it is noted that the occurrence of wear (or reduction in contact stiffness used in this work) does not proceed at a constant rate, as in their computed simulations. The authors conclude that there are many difficulties in estimating the lifespan of the ball screw from a model-based approach due to the varying measurements and model inputs. Lastly, the authors explore the ball pass frequency of the screw nut with conclusions that the re-circulation of the balls is an important aspect in the ball screw behavior.

Li et al. [68] analyze the instantaneous angular acceleration (IAA) of a ball screw via the wavelet packet transform. The IAA signals reflect the torsional behavior of the feed axis and its components. Experimental results suggest that computed IAA features are sensitive to the degradation of the feed axis, namely the wear on the ball screw for this study. Another study uses wavelet bicoherence-based quadratic nonlinearity to measure quadratic phase coupling (QPC) in ball screw drives which occurs due to nonlinear behavior in the system [70]. Experiments performed on a vertical machining center show the robustness of the proposed feature compared with commonly used time and frequency domain features. The merits of this feature include its ability to exploit the QPC of a signal at different frequencies, which is useful for detecting the quadratic nonlinear behavior often caused by mechanical faults.

Zhang et al. [81] use NC-measured motor torque to monitor the performance condition of rack and pinion and two different ball screw feed drives. The data are analyzed for transient impacts, long-term trends, and short-term fluctuations using least-squares. The transient impacts represent mechanical clearances or hydraulic stability. The long-term trends represent the structural changes while the short-term fluctuations reflect the dynamic performance of the feed drives. Results show that this signal decomposition method can monitor the long- and short-term performance of the drives.

Deep learning methods using Laplacian Eigenmaps and Mahalanobis distance are used to study ball screw wear. Shuai et al. [142] use LE and MD to determine the nonlinear relationship between the characteristics of speed and torque signals and the health of a ball screw. The model shows to be more accurate and robust compared to other dimensionality reduction techniques, such as PCA and KPCA. Zhao et al. [143] propose a Laplacian Mahalanobis-Taguchi system (LMTS). Speed and drive current signals are used for analysis as they correlate to feed drive performance. Speed signals in particular reflect issues with the lubrication of the drive as this induces more fluctuations in the signal. High-dimensional features are extracted from the speed and drive current signals via the wavelet transform. The dimensionality of these features is subsequently reduced using LE. Results show that the calculated health value from the LMTS method follows the degradation trend better than PCA and locally linear embedding techniques. However, an arbitrary health threshold value is chosen.

The monitoring of ball screw wear using sensor-based methods is also investigated. An offline method of monitoring the wear of the nut balls is proposed in Ref. [166]. This method provides a correlation between ball wear and the surface roughness of machined workpieces and an empirical equation is derived to explain the process. Results show that ball wear causes an increase in the surface roughness of the machined workpieces. Liu et al. [50] investigate the use of drive motor currents (measured via external current sensors) in monitoring the wear of a ball screw. Wavelet packet and energy analysis of three-phase feed currents follows four stages of wear. These being the initial wear-in, a general wear period, an accelerated wear period, and then a final severe wear period. The wavelet and energy analysis shows that increased wear causes an increase in frequency band energy. Qualitative results from Ref. [78] show that worn ball screw vibrations exhibit high amplitudes around frequencies of 180–200 Hz. Health monitoring criteria are determined based on the specific process at hand; however, this is subject to process norms. Overall, this sensor-based method is capable of monitoring ball screws in an online fashion.

A hybrid model- and signal-based method for monitoring the frequencies of defects and their positions on a ball screw test bench are given by Lee et al. [71]. A model of the defect frequencies is derived from the ball pass frequency of the shaft (BPFS) using modified ball pitch diameters and an effective number of balls. The BPFS is obtained by

$$\mathrm{BPFS} = \frac{1}{120} z n \left(1 + \frac{D_w}{d_m} \cos \alpha \right) \tag{8}$$

where z is the number of balls, n is the rotational speed of the shaft, D_w is the diameter of each ball, d_m is the pitch diameter of the balls, and α is the contact angle between the ball, nut, and screw shaft. Modified ball pitch diameter, d_m', and an effective number of balls, z', are used to estimate the defect frequency:

$$\text{defect frequency} = \frac{1}{120} z' n \left(1 + \frac{D_w}{d_m'} \cos \alpha \right) \tag{9}$$

The defect frequencies are easily distinguished from the rotational speed of the ball screw, as is predicted by the model in (9). As defects worsen, the amplitude of the defect frequency is seen to increase. A defect position detection method is achieved by observing abrupt changes in measured vibrations. It is observed that the shocks introduced by defects occur within high frequency ranges. The proposed diagnosis system uses the WT as a bandpass filter over the defect frequencies allowing for the detection of the defects.

Some researchers opt to study the natural frequencies of a feed drive which can give insight into the health state of the machine. However, regular changes in the operating conditions can affect the natural frequencies which can hide the changes due to damage and wear of the ball screw. A Bayesian ridge regression model proposed by Li et al. [100] seeks to reduce the effects of different table positions and feed velocities on the natural frequencies. Two criteria are created as damage indicators with the aim of reducing false alarms. These include the ratio of estimated mean values between a reference state and a subsequent state and the percentage of residual natural frequencies lying outside a defined limit of three standard deviations. The health parameter investigated is the reduction in contact stiffness of the ball screw (due to increased backlash/decreased preload) which affects the natural frequency of the drive. Using vibration measurements, the two damage indicators are then calculated and monitored for abnormalities. Jia et al. [51] provide an analysis of long-term modal parameters and statistical characteristics of a feed drive. By monitoring spindle current and vibration data over the lifetime of the ball screw, it is shown that the standard deviations of both the natural frequencies and the damping ratios of two modes increase due to wear of the ball screw. An increase in the dispersion of the measured parameters is seen at the onset of wear.

Data-driven approaches include that of Zhang et al. [139] where ball screw performance degradation is monitored using a dynamic fuzzy neural network which is initialized by a quantum genetic algorithm (QGA). Vibration data are used as it is recognized that the vibrations of a ball screw increase over its service life. Time and frequency domain features are extracted from vibrations and reduced through PCA. The ball screw performance degradation trend is then obtained from the DFNN. Compared to a BPNN, a radial basis function neural network, and an unoptimized DFNN (no QGA), the proposed model outperforms the alternatives.

A ball screw degradation process can follow a decrease–increase–decrease trend. This makes it difficult for a single model to accurately predict the degradation of the ball screw. The work by Wang et al. [140] splits the degradation process into different trend regions whereby a state-wise deep learning method, consisting of an LSTM-GRU structure, is used to predict the performance state of the ball screw. Different health indicators and trends are obtained using KPCA and MD on vibration signals that reflect the health of the ball screw. After which a density-based spatial clustering of applications with noise process divides the MD data into different states. These states and the corresponding data provide the labeled data used to train the LSTM-GRU model. The method is then compared to regular LSTM and GRU techniques where it shows to have a mean accuracy of 93.5% on test data compared to 91.5% and 92.6% for the LSTM and GRU methods, respectively.

A multiple classifier system with dynamic classifier selection (DCS) is used to detect the severity of ball screw wear in Ref. [152]. The performance of DCS is improved through a novel local class accuracy (N-LCA) technique.

An experimental testbed is used to conduct accelerated life tests of three ball screw states: healthy, having slight deterioration, or having severe deterioration. Machine vibrations are measured for model input as they correlate to the mechanical structure and dynamics. A classifier pool of 10 BPNNs is generated via the Adaboost algorithm. The DCS chooses the classifier based on vibration data features. Results show that the N-LCA method achieves a classification accuracy of 96.78% over 86.64% and 93.09% for Adaboost and LCA alone, respectively.

A method for early fault detection under time-varying conditions is proposed by Luo et al. [101]. Impulse responses are extracted from vibrations by a deep learning sparse autoencoder and a BPNN. State transition matrices are identified yielding the natural frequencies and the damping ratios of the machine tool. It is seen that the natural frequencies are insensitive to time-varying conditions, unlike the damping ratio. Lastly, a health index is developed based on the similarity of the natural frequencies via the cosine distance between feature vectors and is subsequently used to monitor the health of the machine tool.

Three ball screw wear indicators are developed using a signal-based and data-driven approach by Pichler et al. [44]. The three indicators related to abrasion are the ball screw, friction, and motor drive power. Abrasion is detected from the spectral energy of screw nut vibrations. The friction in the ball screw is indirectly detected using the nut temperature. The drive power indicator is also related to the presence of friction as increased friction leads to an increase in the drive power. A combined damage indicator is defined as a weighted sum of the three previous indicators. The method is tested on seven different ball screws with varying health states. For slowly deteriorating wear conditions, the indicators work as expected. Under abrupt failures, the indicators are not able to detect the failure, although the indicators are not designed to detect abrupt failures.

The issues associated with degradation assessment of ball screws include the prior knowledge needed and manual construction of health indicators and their sensitivity to external factors. In addition, a large amount of failure data is usually needed for a reliable degradation model. Wen and Gao [145] address these problems through a model that operates on healthy ball screw data. A variational autoencoder is trained offline using operational data. Online data are then fed into the VAE that constructs health indicators through the reconstruction error. The probability distribution of the health indicators is estimated by kernel density estimation which allows for quantitative measures of the wear. Run-to-failure tests of a ball screw lab setup show that the VAE reconstruction error is a suitable measure of the health indicators. The classification accuracies for healthy, slight deterioration, and severe deterioration states are 96%, 85.5%, and 100%, respectively. It is noted that incipient faults are easily mixed with the healthy state, thus reducing the accuracy of the slight deterioration classification.

Multi-sensor data fusion is implemented by Zhang et al. [135] in combination with a deep belief network to detect the degradation of a ball screw. The method fuses the frequency spectra of vibration signals through parallel superposition. The fused spectrum is used to train the DBN in unsupervised and supervised stages where it then estimates ball screw health using vibration inputs. Results show that the classification accuracy of the DBN method is to be 99.53% where comparisons to a BPNN and the DBN with unfused data achieve accuracies of 92.01% and 85.69%, respectively.

5.1.2 Preload Loss Monitoring. The loss of preload can indicate that the ball screw has undergone wear. Experimentally, preload can be changed using different sized balls in the nut assembly, by constructing specialized adjustable ball screw nuts or by testing ball screws with different preload as designed by the manufacturer. In actual manufacturing environments, preload loss mainly occurs due to abrasion of the ball screw raceway, but the nut or the balls can experience wear as well.

Chang et al. [73] compare ball screws with 2% and 4% preload using a sensorless strategy. Torque signals are seen to be correlated with the preload level of the ball screw. At constant speed, the ball screw with a 4% preload requires more torque. However, the starting torques for each screw maintain a linear relationship across the motor speed range. Torque signals are processed via EMD where preload features are extracted using the HHT and MSE. A distinction between the MSE of the 4% and 2% preload ball screws is observed. A similar comparison of 2%, 4%, and 6% preload of hollow, oil-cooled ball screws is conducted by Huang et al. [72]. Patterns in the motor current representative of preload loss are detected through the HHT and MSE methods. Results also show that the method can determine the prognostic state of the machine when in operation.

Another sensorless hollow ball screw study using encoder and motor current data is developed for condition diagnosis [136]. Feature engineering using Fisher's criterion is constructed to discriminate features from raw data for SVM classification. The conditions examined include faulty ball screw preload and pretension, faulty cooling system, and changing table loads. In terms of the preload classification, motor current is seen to be affected by the ball screw preload and thus varies when preload is lost. The changes in preload and pretension levels are easily seen in the motor current signal and thus more easily classified as compared to the cooling system and table load.

Two studies compare sensorless and sensor-based strategies in monitoring ball screw preload, both on experimental platforms. Li et al. [151] investigate sensor-based and sensorless strategies for the prognosis of preload. The sensorless strategy uses speed and torque signals. The sensor-based method uses data from both the NC and external accelerometers. The torque signal proves to be valuable for fault diagnosis and failure identification. Results indicate that the sensor-based method is less sensitive and more robust than the sensorless method. However, the sensorless method outperforms the sensor-based method in the feature selection criteria, possibly warranting further analysis into its use in monitoring. Huang et al. [153] devise a machine learning approach for diagnosing preload levels where feature extraction is based on NC and vibration signals. Features based on motor current and encoder signals are classified using SVM. Using the motor peak current, the SVM method achieves 100% classification accuracy. Features based on vibration signals are classified using a GA/KNN method which also achieves 100% classification. However, using the SVM method, the vibration features yield a low classification rate. With more sensory information, the SVM method may achieve a higher classification rate.

Verl and Frey [104] investigate a linear correlation between feed velocity and effective ball screw preload. A preliminary force analysis shows that the life of the ball screw is affected by the applied loads on the screw, including the preload which is expressed by the drag torque. An experimental testbed that measures the drag torque and preload forces during tests is used. Preload is measured using a sensor system installed within the screw nut. Tests reveal that the effective preload (as opposed to the static preload measured at rest) is proportional to the feed velocity. It is seen that as the rotational speed increases, so does the effective preload and forces inside the nut, perhaps providing a unique preload monitoring strategy.

Huang and Shin [74] use a sensor-based method to diagnose preload loss using the HHT and MSE of vibrations. Signal patterns from 2%, 4%, and 6% preload ball screws are distinguished using EMD with the Hilbert spectrum while preload features are extracted using the HHT. Experimental results show that preload loss is identified by an increased MSE value, showing that preload can be monitored through comparative analysis of MSE. It should be noted that the research efforts that compare ball screws with predefined preload as per the manufacturer (e.g., 2%, 4%, and 6% preload) may not be very practical. For health monitoring and diagnosis applications, these methods have limitations in that they are implemented on healthy ball screws that do not exhibit wear or degradation characteristics. The practical value of these methods is thus reduced when implemented in real industrial settings.

Tsai et al. [75] monitor the ball pass frequency order (BPO) of varying preload ball screws using angular velocity Vold–Kalman filter order tracking. The BPO in effect analyzes the change in the ball pass frequency or the rate at which the balls pass through the return tube of the nut. This method is less susceptible to noise from other vibration sources in the machine tool. Preload loss increases the ball pass frequency and introduces a side band around that frequency. The onset of preload loss can also be detected based on the level of BPO decrease and the appearance of the side bands.

Several novel sensing methods are proposed to monitor preload. Ehrmann and Herder [59] describe that a piezoelectric self-sensing actuator can be used to control the preload in a ball screw. They propose the use of a power amplifier and signal processing system to transmit high fidelity signals to the actuator, which are then used for diagnosing preload faults in ball screws. Biehl et al. [60] measure preload forces using piezoresistive films on sensor pins mounted in a double-nut ball screw. Preload is measured during installation and changes in the dynamic loads during feed drive movement are detected. Similarly, Möhring and Bertram [61] use strain gauges and piezoresistive thin films in a double-nut system to measure the preload of the nut. The strain gauges measure the preload forces while the thin film sensors measure force and temperature profiles. In addition, sensory electronics are developed as a means for energy harvesting and hybrid energy supply. During experimental tests, noticeable decreases in the measured preload forces are seen.

The preload of a ball screw directly influences the stiffness of the nut which further affects the natural frequencies, and thus the dynamics, of the ball screw drive. Thus, several studies propose to monitor preload loss through vibration analysis. Feng and Pan [38] show validation in using vibrations for monitoring preload by studying a preload-adjustable ball screw drive with a MEMS sensor [39]. Their dynamic model of the ball screw axis uses a manufacturer's empirical model that relates the nut stiffness to the preload. Simulations show that a reduction in preload reduced all three of the natural frequencies of the drive. The nut stiffness and mass of the ball screw are also varied, showing that the second resonant frequency is most affected. Experiments show that the second resonant frequency decreases with decreasing preload. The frequency shift and variation in magnitude of the second resonant frequency are proposed for monitoring preload.

FEM simulations by Ellinger et al. [102] reveal that decreased ball screw and linear guide stiffness also reduces the natural frequencies of the feed drive. The loss in stiffness of the ball screw and linear guides each have more influence on the frequency response over separate, independent frequency ranges. Thus, feed drive wear can be monitored globally through changes in the dynamics of the feed drive. Natural frequencies and their amplitudes are extracted from the modal parameters of a ball screw testbed with varying preload states. An analysis of variance shows that the preload of the ball screw and the linear guides have significant dependencies on these extracted features.

Nguyen et al. [52] propose real-time preload monitoring on a lab setup. Motor currents and vibrations measured during operational states are used to construct an FRF. Preload is monitored using the natural frequency of the screw nut and the mass and position of the table via the model given in Eq. (10).

$$P = \frac{0.1C_a}{\left\{0.8K\left[-(4x_t/\pi d_{\text{minor}}^2 E) - (32R^2L/\pi d_{\text{minor}}^4 G) - (1/k_{\text{bearing}}) - (1/k_{\text{bracket}}) + (1/(2\pi f)^2 \sum M)\right]\right\}^3} \tag{10}$$

In the model, C_a is the dynamic load rating of the screw, K is the nut stiffness (from the manufacturer), x_t is the table position, d_{minor} is the minor diameter of the screw, E is Young's modulus, G is the shear modulus, L is the screw length, $R = l/2\pi$ is the transmission ratio with l being the screw lead, k_{bearing} and k_{bracket} are the stiffness of the bearing and bracket, f is the approximated natural frequency, and $\sum M = m_{\mathrm{table}} + m_{\mathrm{screw}} + m_{\mathrm{nut}} + m_{\mathrm{bracket}}$ is the sum of the masses.

Benker et al. [103] develop a hybrid data-driven and model-based approach. Eigenfrequencies are extracted from an FRF from which Gaussian process classification classifies ball screws with new and degraded preload. In addition, the RUL is predicted by extending the GPC into Gaussian process regression. The GPR model can estimate the RUL of the ball screw very well, even up to the accepted threshold of the RUL.

A data-driven diagnostic approach by Feng and Pan [40] uses vibration and temperature to achieve 100% classification accuracy with an SVM. A prototype sensing unit is developed and installed on a preload-adjustable feed axis. It is found that the PSD of the vibrations and the rising temperature clearly detect differing preload levels.

One of the challenges of monitoring ball screw drives using sensor-based methods is the placement of the sensors themselves. Pandhare et al. [148] address the issue by presenting a deep learning diagnostic model of ball screw preload using domain adaptation across five accelerometer mounting positions. The method attempts to map the relationship between fault critical and feasible sensor locations while training the diagnostic model. A CNN extracts features from data obtained through a healthy preload level of 4% and naturally degraded ball screws. The trained network predicts the labels of unlabeled target domain data using a Softmax classifier. The proposed model achieves high accuracy (98.25%) with validation on 33 transfer tasks, although this was achieved on a lab feed drive.

Jin et al. [45] devise a multi-failure classification system for ball screw health. Failure modes include preload loss and a lack of lubrication. Self-organizing map-minimum quantization error (SOM-MQE) and MD are used to assign health values for lubrication failures while a Gaussian mixture model is used to identify preload levels. The SOM-MQE method shows distinctive "tails" in the health value that are comparable to a failed specimen with backlash. These tails can be an indicator of backlash.

5.1.3 Backlash Monitoring. Traditionally, backlash (depicted in Fig. 12) and other machine tool motion errors are measured by circular profile tests with positional data being measured using a telescopic transducer bar. This method was developed by Kakino et al. [167] and became to be known as the double-ball-bar

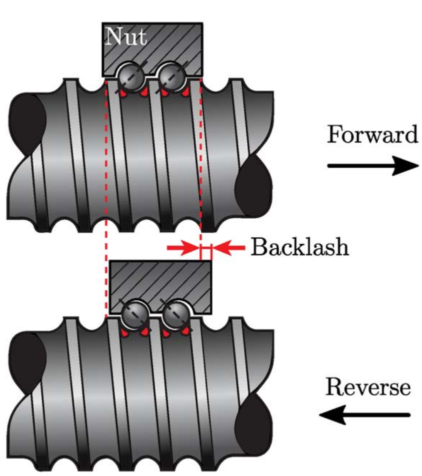

Fig. 12 Backlash in a ball screw due to wear. The effect of backlash is seen when the motion of the screw reverses.

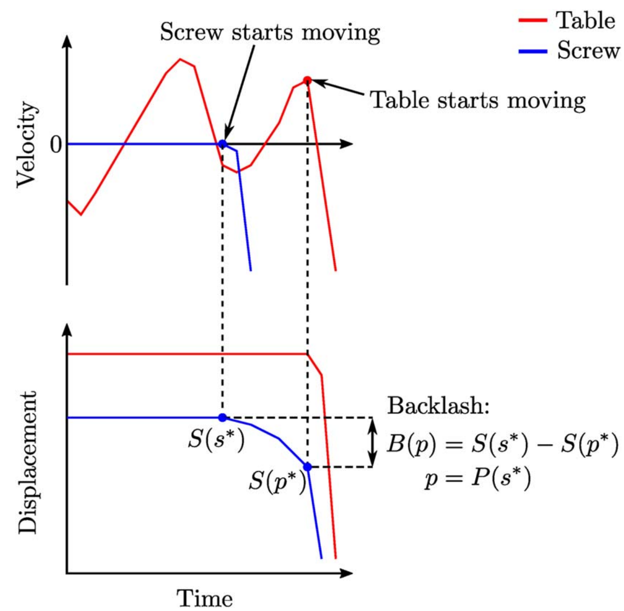

Fig. 13 Backlash measurement used in Refs. [149,157]. Backlash is measured as the difference between the screw's position at the time when the screw begins to move and its position when the table begins to move.

method. Many methods are proposed to measure the motion errors of machine tools, including backlash. However, most of these methods are developed with the intention to compensate motion errors to improve machining precision and accuracy. For condition monitoring applications, the goal is to detect, measure, or correlate backlash in order to optimize the maintenance actions required to rectify the current issue or potential future issues. Sensorless methods to monitor backlash are presented first followed by sensor-based methods.

The models used to calculate backlash in the literature tend to involve the difference between the following:

(1) Rotary encoder and linear encoder measurements [83].
(2) Position command and linear encoder (position error) [108,109].
(3) Torque-limiting positions [107].
(4) Forward and reverse linear encoder positions (position reversal) [105].
(5) The position of the screw when it begins to move and the position of the screw when the table begins to move (see Fig. 13) [149,157].

Figure 14 also shows a common feed drive model that uses backlash within the position control loop. The backlash calculated by these models includes more than just the backlash of the ball screw. These models include the backlash seen by gear trains or other loose components, which in effect is measuring lost motion or the sum of backlash phenomena seen by the feed drive. This lost motion diminishes the usefulness of backlash measurements in monitoring the health of the ball screw directly.

Sensorless backlash monitoring methods extensively use linear and rotary encoders. Plapper and Weck [83] monitor the backlash injected into a feed drive by measuring the difference between the

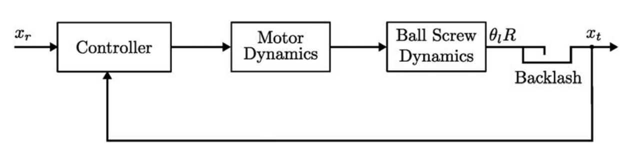

Fig. 14 Ball screw feed drive with backlash included in the position control loop

rotary and linear encoders during movement reversals. With more backlash in the feed drive, there is likely to be a larger discrepancy between the encoder measurements. Results show that the encoder signals can reveal backlash of less than 10 μm. Liu et al. [108] monitor backlash through the difference between forward and reverse position errors along the axes of a three-axis machining center. The position errors are calculated as the difference between the NC command and linear encoder positions. Results show that backlash has a significant effect on the position error of the machine axis. This work uses both ANN and polynomial models to fit the backlash error profile for movement compensation. The ANN performs better; however, it is only capable of offline compensation while the polynomial models can be implemented in an online fashion at the expense of accuracy. Zhou et al. [109] performed multiple circular tests at discrete points along a ball screw axis to measure backlash. The backlash is calculated as

$$B(t) = x_s(t) - x_{\mathrm{cmd}}(t) \tag{11}$$

where $B(t)$ is the backlash at the ith feed axis position measured by the linear encoder, $x_{\mathrm{cmd}}(t)$ is the command position under semi-closed-loop position control, and $x_s(t)$ is the feedback value of the linear encoder. Data collected over a span of 12 months show that backlash worsens over time, suggesting that backlash can be used as an indicator of ball screw wear. Torque-limiting positions are used to monitor backlash in a prototype feed drive by Chandrasekar and Srinivasan [107]. An iterative algorithm that takes the difference between the torque-limited positions, measured by a rotary encoder, quantifies the backlash in the feed drive.

Sliding-mode and adaptive estimation principles are used by Papageorgiou et al. [106] for online sensorless backlash estimation in a lab setup. The method includes two estimation stages: the first for estimating the load-side perturbation torque using a super-twisting sliding-mode observer and the second for estimating the deadzone angle via an adaptive estimator. Simulations show excellent performance from both estimators. The algorithm is tested on a testbed with a modified coupling that introduced backlash. The estimated backlash errors do not exceed 4×10^{-3} rad. The estimation of backlash is definitely a vital tool in monitoring the wear of a feed axis. Thus, this work shows a promising method in backlash monitoring; however, drive model parameters are needed to use this method.

In a sensorless, but offline fashion, Xi et al. [110] monitor the effects of backlash on the first resonant frequency of the speed control loop measured by the NC. Axial screw nut stiffness was reduced and backlash added by the implementation of a custom built sleeve mounted next to the nut. The monitoring strategy includes using the first resonant frequency as a wear indicator. Some drawbacks of this approach are the effects of changing mass, such as tools and workpieces, on the dynamics of the feed axis. Maintenance actions on the ball screw may also affect the measured dynamics as well.

Sato [122] uses frequency responses to estimate backlash or deadband. This work reasons that when the vibration amplitude of the motor torque is larger than the backlash, then the motor torque depends on the dynamics of the table. Conversely, when the vibration amplitude of the motor torque is less than the backlash, the motor torque does not depend on the dynamics of the table and thus the input vibrations will not move the table when sufficiently small. The estimation principle compares the frequency responses relating the command position to the linear encoder position and that relating the command position to the motor torque. The backlash is taken to be the vibration amplitude of the encoder response at the frequency with minimum motor torque amplitude. The methodology provides estimates of the deadband within 5 μm.

TBEs are errors that persist after closed-loop compensation of general backlash error. Shi et al. [105] derive analytical equations for TBE for both straight line and circular trajectories. These equations are calculated using closed-loop control parameters and backlash widths. The backlash width is calculated as the difference between the reverse and forward table positions, x_{t-} and x_{t+}, respectively. Experiments show that measured TBEs are smaller than predicted TBEs, perhaps due to additional control elements not considered in the feed drive model. However, this analytical approach shows potential for the monitoring of TBEs in machine tools.

Wang et al. [149] predict backlash errors using a back-propagation ANN. The backlash errors are calculated as

$$\begin{aligned} B(p) &= S(s^*) - S(p^*) \\ p &= P(s^*) \end{aligned} \tag{12}$$

where $B(p)$ is the backlash at table position p, s^* is the position where the screw begins to move, and p^* is the position where the table begins to move. $S(s^*)$ and $S(p^*)$ are the displacements of the screw in positions s^* and p^*, respectively, and $P(s^*)$ is the displacement of the table at position s^*. The training targets are the backlash errors and the training inputs are linear encoder positions. The ANN model predicts the backlash at a given table position which can be used for compensation or monitored for increased levels of backlash.

Several sensor-based methods exist for backlash monitoring, detection, and prognosis. Moosavian and MohammadiAsl [76] estimate the bandwidth of vibration frequencies due to backlash. Experimentally obtained vibration frequencies of five different machining centers are compared with simulations. Results show that the frequency of vibration in a servo axis is not affected by the magnitude of the backlash. The important factor with respect to the frequency is the position control loop gain. Xing et al. [53] present a low-cost monitoring solution that can be implemented in small and medium-sized enterprises. A camera mounted on a machining center captures pictures of NC compensation parameters, such as backlash, pitch, and straightness error compensation. The parameters are tracked over time and various statistical features are calculated to aid in the maintenance decision process. A recognized drawback of this method is that it does not show the real-time state of the machine tool or the ball screw.

Li et al. [157] develop a diagnostic and prognostic system for backlash error detection and prediction in machining centers. The backlash is estimated using linear and rotary encoder measurements as per Eq. (13):

$$B(p) = \left[x_1(t') - x_1(t^0)\right] - \left[x_2(t') - x_2(t^0)\right] \tag{13}$$

where $x_1(t^0)$ and $x_1(t')$ are the position of the nut at an initial time of measurement t^0 and final time of measurement t', respectively. $x_2(t^0)$ and $x_2(t')$ are the positions of the ball screw at their respective times and p is a discrete point of measurement along the axis. A prognostic layer is used to predict future backlash errors using a DBN with temperature, torque, and machine working time as inputs. Comparatively, this method outperforms a BPNN and SVM regression. The method achieves very low errors, although the DBN was trained for over 14,000 epochs. Thus, overfitting is likely an issue with a practical implementation of this method.

5.1.4 Fault Detection and Diagnosis. Fault detection and diagnostics concern the identification of anomalous behavior and are usually a classification problem. These anomalies can be attributed to changes in operating conditions, such as wear or hard faults. Diagnosing faults is also performed by identifying the faulty component and the type of fault. Few model- and signal-based methods are used for diagnostics. This area of ball screw condition monitoring is more populated with machine and deep learning.

The model-based method by Huang et al. [111] detects and diagnoses unsynchronized motion and encoder reading failures in a prototype gantry stage. Two Kalman filters are designed to accommodate each of the failure modes based on the multiple observer method. Additionally, a fault-tolerant control scheme is proposed. Upon a detected fault, this control method augments the control law with the estimated fault. Under a mechanical failure, it is seen that the filter estimation and tracking error degrade which cause a failure decision function to alert a failure in this case. Similar results are seen with the sensor failure.

The signal-based work by Guo et al. [77] achieves adequate fault identification and prediction of fault locations on an experimental platform. The strategy uses nut vibrations and allows for estimating the time of the fault. Fault locations are calculated using the estimated fault time and the instantaneous rotational frequency (IRF) of the ball screw. The IRF is calculated using a parameterized time–frequency transform, called the polynomial chirplet transform. This technique is shown to perform better than wavelet transforms in terms of estimating the IRF. Once the fault time and IRF are known, the fault location is identified using an integral operation.

Shan et al. [158] attempt to solve the problem of recognizing multiple faults occurring at different positions on a lab feed axis with high accuracy. Data collected from multiple vibration sensors along a ball screw are weighted based on the Mahalanobis distance and a sensitivity index that weighs the significance of each sensor. The weighted data are then fed into a one-dimensional CNN for classification. The method outperforms popular machine learning and deep learning methods, achieving 100% and 97.04% classification accuracy on two datasets.

D'Emilia et al. [49] develop self-implemented classification and pattern recognition algorithms to detect and locate ball screw faults. The algorithms operate on vibration and acoustic emission signals. The pattern recognition algorithm includes calculating time and frequency domain features for all damage classes/states. A feature matrix is then built and suitable features that separate the damage classes within the feature space are chosen and used for classification. Results show that the feature selection algorithm is not able to select adequate features from the acoustic sensor as the features severely overlap in the feature space. The classification algorithm shows similar performance to Bayes and nearest-neighbour classifiers. However, each classifier shows poor classification accuracy, except for one damage class, due to aforementioned inadequate feature selection.

Liao and Pavel [154] propose a strategy to better use operational data obtained from the machine NC and external sensors. This is done to tackle the problems arising when machine usage patterns and operating conditions have changed. Data collected from the NC of a lab test bench are used to label datasets corresponding to different operating conditions. PCA is used to identify sensors that provide the most meaningful information. Anomaly detection and diagnosis are performed using SOMs which convert the complex data into readable health information for operators. Several methods are compared and the proposed strategy shows a higher false positive rate and less accuracy than the method without dimensionality reduction. However, the use of operational data is shown to improve the performance of the diagnostic method.

Liao and Pavel [43] and Siemens AG propose a plug-and-prognose (PnP) technology that uses NC and external sensor data to determine a machine's normal operating characteristics and to identify faulty operating conditions. PnP attempts to improve upon conventional data-driven approaches to machine health by supplying automated and customizable data-driven algorithms that identify the best model parameters and adapt to different machines. The methodology uses SOM with minimum quantization error for anomaly detection and diagnosis. Results determine that temperature measurements of the ball screw support bearings prove to be critical features for monitoring.

Huang et al. [159] diagnose normal and faulty states of a ball screw drive using vibration measurements. A BPNN with additional data clustering is used to process the vibration data. The method is tested with 25 groups of both normal and faulty state signals. The proposed BPNN is capable of correctly classifying the normal and faulty states.

Azamfar et al. [147] develop a deep learning architecture with domain adaptation for cross-domain fault diagnosis of a laboratory ball screw drive. This work seeks to improve fault detection when changes in the ball screw drive are seen. A deep CNN is used for feature extraction and health state classification using raw torque signals. The ball screw underwent natural degradation and wear for the collection of the data. The method achieves high accuracy on unlabeled data when one set of labeled data is used for training and results indicate that the method can effectively extract generalized features for cross-domain fault diagnosis. This method also maintains a higher testing accuracy than comparable techniques.

5.1.5 Prognosis and Remaining Useful Life. Remaining useful life is the common prognostic parameter when concerned with ball screws. To accurately predict the end-of-life of a ball screw would prove very valuable to manufacturers and could save excessive maintenance costs. However, the reliability of these estimates has not been established. The study of ball screw prognosis, in addition to the diagnostics mentioned previously, is still very immature. Only few model-based and data-drive methods exist for ball screw RUL prediction and prognosis.

Zhang et al. [113] present an exponential model of a ball screw degradation process that attempts to quantify the amount of wear. The model uses the wear volume of the ball screw which is derived as a function of the axial load and stroke number. The actual level of degradation is measured using a degradation index calculated using the Weibull distribution shape parameter for measured vibration signal envelopes. RUL is predicted using experimental data and a PF algorithm while a comparison is made with a linear model.

Wen and Gao [112] design a novel weighted Mahalanobis distance (WDMD) health indicator used with an exponential Wiener process to map ball screw degradation. A PF is used for state estimation and RUL prediction. Results show that the WDMD performs better than the traditional MD and the exponential Wiener process model provides better performance than a linear and nonlinear Wiener process model. Despite that the method shows to be more sensitive to the degradation process of a ball screw drive than the traditional MD, the limitations of this approach are the poor prediction in the early stages of degradation. However, the model converges onto the actual degradation path much earlier than the compared models. The method was also implemented on a lab testbed.

Deng et al. [114] develop a hybrid data-driven and model-based method to predict the RUL of a ball screw in real-time. An ensemble GRU-PF model is designed such that the PF provides state measurements beyond the available analytical measurements. Figure 15 shows an overview of the hybrid method. Experiments on a test platform show that the model is superior in predicting RUL compared to other hybrid models over different time scales.

Li et al. [151] use Gaussian process regression to predict the RUL of a ball screw. Optimal features are selected based on a criterion involving the signal-to-noise ratio of calculated health values. Measured vibrations are shown to be more valuable over all other NC and external signals for degradation monitoring. The model predicts the lifespan of the tested ball screw to be 780 h, close to the actual 800-h lifespan.

Zhao et al. [156] develop an online method to predict RUL using a multi-variable gray model. Accelerometers are used to monitor changes in ball screw performance under different machining conditions. EMD is used to extract features. The multi-variable gray model is used to establish the nonlinear relationship between the life of the ball screw, the extracted features, and cutting parameters.

5.1.6 Sensing Methods and Technologies. The integration of accelerometers and other external sensors with ball screw drives can be difficult. For example, the long-range movement of ball screws can interfere with wired sensor technology that attempts to measure the characteristics of the screw nut. This leads to the design and development of alternative sensing method and technology.

One solution to the wired sensor issue is to implement wireless sensors and wireless sensor networks (WSNs). Sudhawiyangkul and Isarakorn [78] design a wireless data transmission sensor

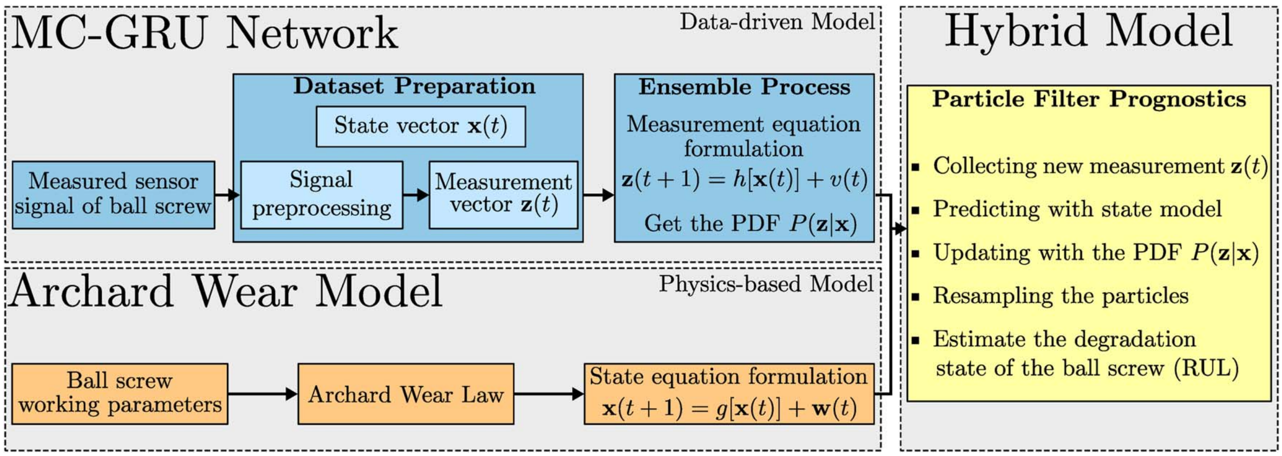

Fig. 15 Hybrid data-driven and physics-based model used by Deng et al. [114]

with energy harvesting and storage. The sensor harvests energy from the linear motion of the feed drive while also measuring vibrations. Uhlmann et al. [41] develop a smart WSN that uses Raspberry Pi computers and MEMS vibration sensors. The aim is to create a highly scalable CM approach using simple and cost-effective electronics. Chang et al. [46] propose a hybrid temperature and vibration sensor with wireless transceiver modules for data transmission. Five of the hybrid sensors are mounted at various locations including the nut, support bearings, the slides, and the drive motor. Lee et al. [168] develop a wireless sensor that measures operational data indicative of ball screw wear. The method emphasizes low-cost and low-power hardware design while focusing on complete data transmission to a server with minimal data. The sensor itself collects vibration, temperature, and preload pressure signals. Zheng et al. [115] show that a wireless ad hoc network protocol, based on the internet of things (IoT), can monitor vibration faults of a machine tool. Wireless acquisition nodes, capable of measuring vibrations, send data from the ball screw to a sink node. The sink node processes the data and further transmits to both a local CNC system and to a remote fault diagnosis system. Schmid et al. [169] develop a WSN that consists of a low-power microcontroller, a transceiver, and an accelerometer. Vibration data are collected and analyzed in a decentralized fashion by the end-device. In addition to the data processing, minimum and maximum values are also recorded. The data are then compared to previously recorded datasets in order to estimate the deterioration status.

As mentioned in Sec. 5.1.2, ball screw nut-embedded sensor technologies are developed to measure, monitor, and diagnose preload forces. Ehrmann and Herder [59] develop a piezoelectric self-sensing actuator to control and monitor preload faults in ball screws. Biehl et al. [60] and Möhring and Bertram [61] both measure preload forces using piezoresistive thin films applied to pins embedded in the screw nut. The work in Ref. [61] also uses strain gauges.

Several alternative sensing methods and technologies include the use of MEMS sensors for monitoring preload and machine tool health [38–41] and the use of a camera for monitoring NC parameters related to the health of a ball screw [53].

5.1.7 Other Condition Monitoring Methods. Specialized CM methods include the development of unique features that represent fault patterns, analyses on parameters such as efficiency, and friction monitoring.

Huang et al. [79] suggest that typical signal features represented in both time and frequency domains do not represent any physical significance. A pre-processing method that uses the linear encoder position to re-sample the position error into a spatial domain is proposed with the aim to provide the physical significance for fault or failure patterns. Both frequency and spatial frequency domain FFT analyses are compared on a lab test bench. For the frequency-based analysis, it is difficult to determine a relationship among the frequency components. However, in the spatial domain-based FFT analysis, the frequency components are more easily recognized as a defect in the ball screw or its harmonics.

Several friction-based monitoring approaches are seen in the literature. Chen et al. [80] estimate friction by analyzing the fluctuations of encoder and motor torque signals. A polynomial fitting algorithm is used to determine the instantaneous average friction value (IAFV) and a fluctuating friction signal (FFS). IAFV is used to represent the effects of the table position and the ball screw pitch errors on the level of friction. Experiments on a CNC lathe show that the characteristics of the FFS frequency spectrum are described by the estimated friction. Non-conventional Stribeck behavior is seen in the mean value of the IAFV for varying feed rates at a given table position. However, the Stribeck effect cannot describe the variations in the estimated friction with the table position.

Offline identification of static friction parameters is generally needed to develop accurate dynamic models for friction estimation. Papageorgiou et al. [116] present an online adaptive estimation method. The method describes the quasi-discontinuous characteristics of friction while sustaining the required level of smoothness needed for online estimation. The estimation strategy can be implemented under normal working conditions of the machine tool. The varying frictional phenomena that are seen in the different operating regimes of the feed axis are segregated by the use of two parallel adaptive estimators where smooth approximations account for stiction, viscous friction, and bidirectional Coulomb friction. The method implements a parameterization that connects the model coefficients to the real properties of friction. In experiments, the estimation algorithms perform exceedingly well with errors as low as 1%.

Friction seen by feed drives is estimated using a friction model by Reuss et al. [117]. From these estimates, certain conditions of the feed axis are monitored. NC signals are measured during operating regimes at rapid feed rates. The friction force, F_R, is estimated as

$$F_R = F_C + f_v v + f_s e^{-(|v|/v_s)} + f_w |v|^k \tag{14}$$

where F_C is the constant Coulomb friction, f_v is the viscous friction coefficient, f_s is the mixed friction coefficient, f_w is the rolling friction coefficient, and v, v_s, and k are the feed velocity, the Stribeck velocity, and a constant, respectively. Results show that new machines show higher levels of friction as compared to 4- and 7-year-old machines. This is attributed to the wear and natural degradation of the machine tools.

5.2 Linear Guide Condition Monitoring. Wear and degradation of guideways is an inevitable phenomenon. The condition monitoring of linear guideway degradation is presented first. Preload and force are monitored to indicate the degree of wear and misalignment of guideways and are introduced next. Following this is lubrication monitoring, which is an important parameter as proper lubrication benefits the performance and lifetime of guideway systems. Lastly, fault diagnosis methods for linear guideways are given.

5.2.1 Wear and Degradation Monitoring. Degradation and wear of linear guideways and slides can occur on the linear rails (e.g., spalling and pitting). For rolling guideways specifically, the bearings of the guides may experience flaking and cracking among other damage (see Fig. 16). Slides also experience changes in their level or inclination angle due to wear.

Extensive research into the use of IMU and similar sensing systems is conducted for linear feed axis guideway degradation. The early work by Vogl et al. [170] uses a multi-sensor-based method to measure changes in linear and angular errors caused by feed axis degradation. Measurements from inclinometers, accelerometers, and rate gyroscopes are able to discern straightness and angular errors with regard to reference measurements. IMU sensors are used to measure geometric errors caused by artificial damage and wear [54,56–58]. These works use a lab setup and include the implementation of data fusion, statistical analyses, and other signal-based methods.

Plapper and Weck [83] analyze changes in the axis drive current due to the effects of pitting on linear guideways. Guideway surface measurements and drive currents are correlated during slow speed tests. A correlation of 0.56 is calculated, suggesting that special care must be taken to use these signals reliably.

Zhao [119] examines the use of accelerometers and a capacitance probe for monitoring wear on an experimental platform. The capacitance probe is capable of measuring deviations in the table position as it traverses the linear rails.

Dumstorff et al. [64] integrate strain gauges to measure deformations in linear rails. By measuring the varying resistance across the strain gauges, it is possible to monitor deformations in the linear rails.

An important aspect of machine tool installation is leveling which can influence the accuracy of the machine tool and its lifespan. The degradation of the machine tool slide level can also reduce machining precision by introducing torsional vibrations in the feed axis. Hun Jeong et al. [118] develop a sensorless method to monitor the slide level by estimating the inclination angle based on a dynamic model. Measured drive motor currents are used to calculate the inclination angle with less than 3.0% error using Eq. (15)

$$|i_+| - |i_-| = \frac{\rho}{\pi\eta K_t} M_t g \sin\theta \approx \frac{\rho}{\pi\eta K_t} M_t g\theta \tag{15}$$

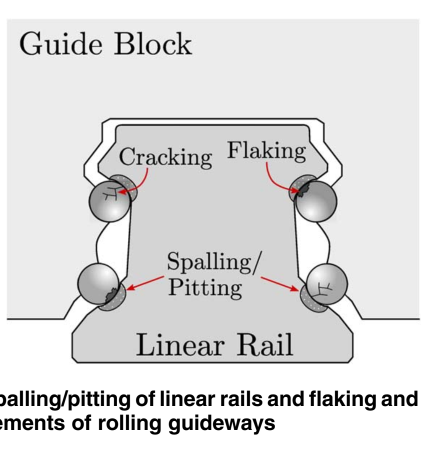

Fig. 16 Spalling/pitting of linear rails and flaking and cracking of the ball elements of rolling guideways

where the difference between the absolute value of the motor current i, when the table moves in the positive (+) and negative (−) directions, is related to the screw pitch ρ, screw efficiency η, motor torque constant K_t, table mass M_t, acceleration due to gravity g, and the inclination angle θ. Zhou et al. [82] also monitor the slide level by estimating the inclination angle and using EMD to filter vibrations from encoder signals. The sensorless method is shown to accurately measure the slide level inclination angle with little to no vibrations affecting the measurement. A similar model to that of Ref. [118] was used with the exception that the motor torque in the positive and negative directions was considered:

$$T_+ + T_- = -\frac{\rho}{\pi} M_t g \sin\theta \approx -\frac{\rho}{\pi} M_t g\theta \tag{16}$$

Huang et al. [160] estimate the RUL of linear rolling guides. A DFNN is trained on empirical RUL estimates and extracts features to provide a nonlinear mapping between measured vibration signals and the RUL of the linear guides. The proposed RUL estimation shows to be very precise.

5.2.2 Preload and Force Monitoring. Much like ball screws, guideways require a preload to reduce play in the guidance system. The work by Tsai et al. [120] monitors the preload loss of a lab test bench and its effects on linear guideways using OMA supplemented with modal assurance criteria (MAC). The yawing mode of the table is found to be sensitive to preload loss. MAC allows for extracting the natural frequencies of the yawing mode despite the occurrence of mode switching due to preload loss over time. Ellinger et al. [102] also determine that decreases in linear guide stiffness reduced the natural frequencies of the feed drive. The preload state of ball screw linear guideways is monitored through its dependency on the amplitudes of the natural frequencies.

Feng and Wang [42] monitor the alignment of linear guide rails enduring varying preload on an experimental setup. Using a MEMS vibration detection module, characteristic frequencies are determined which shows decreasing trends when misalignment deviation is less than 40 μm while increasing trends are seen for deviations between 40 μm and 120 μm. With the use of the MEMS modules and signal processing techniques, the misalignment of linear guideways can be monitored.

Integrated force and strain sensors are used to monitor preload forces as well, albeit on laboratory setups. Denkena et al. [63] apply strain gauge sensors to the side faces of guide carriages to detect longitudinal and transverse forces. The sensitivity of the approach is capable of measuring misalignment of the linear rails. Disturbances such as constraint forces, preload, and roller circulation have posed challenges for this method. However, signal processing can be useful in attaining reliable force measurements. Cheng et al. [65] use an optical mouse sensor and a tactile load cell to monitor forces seen from the guideway. The straightness of the guideway can be determined and the onset of preload loss of the guide can be detected. Krampert et al. [62] apply a piezoresistive diamond-like-carbon (DiaForce®) coating to monitor the stresses imparted on the contact side of the carriage runner block. Measurements compared to FEM and analytical simulations show good agreement.

5.2.3 Lubrication Monitoring. The lubrication of linear guides can dramatically affect the performance of guideway systems and is important for the longevity and efficiency of the machine. Monitoring the condition of the lubricant in guideways can help optimize and schedule maintenance actions. However, the opportunity for missed maintenance actions or careless application of lubricant can lead to non-ideal lubrication. An automatic lubrication system proposed by Sparham et al. [47] seeks the goal of being a cost-effective, less wasteful and flexible solution. Temperature signals measured from the linear guideways are monitored to determine failure thresholds. The temperature signals contain information that relates to the state of friction, wear, and loading conditions on the guideway. A lubrication control unit (LCU) uses these signals to inject lubricant at the appropriate times. A control diagram of the LCU is given in Fig. 17. An optimum oil injection time that minimizes oil consumption is found to be 15 s for the application.

Feng et al. [161] investigate the relationship between "poor," "medium," and "good" lubricant states and measured vibration signals in a lab environment. Wavelet packet decomposition is used to analyze vibration signals in the time–frequency domain. The energy distribution of the vibration signals is then extracted and used as features for classifying the condition of the lubricant. Measured data of the lubrication states is analyzed and their energy distributions extracted and fed into a feedforward BPNN for classification. Greater than 95% average classification accuracy using the energy distribution as input is achieved. Thus, the energy distribution can be a useful feature for fault diagnosis of linear guides.

5.2.4 Fault Diagnosis. Fault diagnosis of linear guideways is quite limited in the literature. The early work by Lai et al. [121] identifies and diagnoses nonlinear geometric errors in machine tool guideways using higher order Taylor series approximations of the guideway roll, yaw, and pitch motion errors. Using measured motion data, the Taylor series model is fit using least-squares to attain the errors in the guideway. Estimated errors are then compared with double-ball-bar measurements. It is determined that lower-order Taylor approximations may be suitable for a given application; however, high-order approximations are more appropriate for high-precision machines despite being much more complex.

Fault patterns of linear guideways are identified through the vibration analysis of Hung et al. [48]. Changing preload is measured through vibration and acoustic characteristics and is attributed to variations in the structural stiffness, or contact stiffness, of the linear guides. The analysis of vibration and acoustic spectra shows that these signals can be used as fault indices and for monitoring fault states of the linear guides. However, the analysis of the acoustic spectra shows that the acoustic characteristics prove to be very distinct and unambiguous as compared to the vibration analysis. This concludes that the acoustic analysis can prove to be more useful in fault diagnosis than vibration analysis.

Kim et al. [162] develop a deep learning fault diagnosis model composed of a one-dimensional CNN. The model is trained on time domain vibrations; however, frequency data are maintained during the learning process and classification is performed using the frequency domain features. The classification method analyzes frequency domain characteristics and is visualized using a frequency-based gradient-weighted class activation mapping. The method shows that the characteristic frequency of higher order harmonics is more useful as the classification criteria for the normal and fault states.

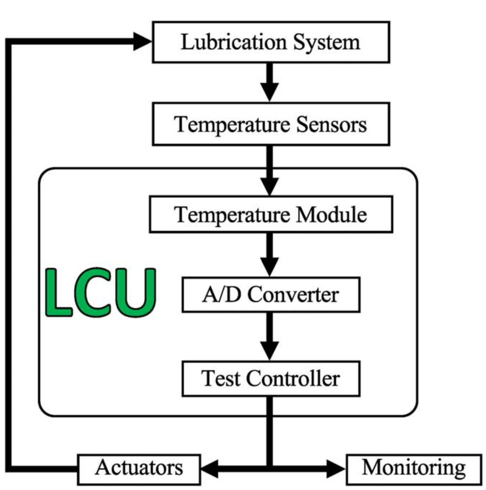

Fig. 17 Lubrication control unit as proposed in Ref. [47]

Zhou et al. [155] use an offline image processing method that detects surface defects of linear guide rails. An adaptive clustering method is developed that is based on multiple-manifolds and local density peaks. The local tangent space for the individual pixels of the images is calculated using mixtures of probabilistic principal component analyzers. Furthermore, similarity matrices are calculated between the local tangent spaces. The proposed clustering method is then improved based on the similarity matrices to determine the clustering center point.

5.3 Positioning Accuracy and Error Monitoring. The accuracy and precision of feed axis positioning depends on the state of both the ball screw and the linear guideways/slide. Wear and damage experienced by the ball screw or guideway system result in motion errors. Monitoring these errors and the positioning accuracy of machine tool feed drives lead to informed decisions about their maintenance.

Workpiece machining error can be monitored based on homogeneous coordinate transformations and sensorless signal measurements as shown by Zhao et al. [123]. This work establishes relationships between motor current, disturbances, and friction. The difference between the rotary and linear encoder measurements are taken to be the machining error. Under perfect conditions, ball screw feedback signals are essentially the same as the motor position with $R\theta_m = x_t$. However, with deviations we get the error

$$E = R\theta_m - x_t \tag{17}$$

The components of the error E are mainly caused by errors in the control, dynamics, and geometry

$$E = \Delta_c + \Delta_d + \Delta_g \tag{18}$$

where Δ_c is the control error, Δ_d is the error in the dynamic characteristics, and Δ_g is the mechanical error. By using a coordinate transformation from the machine coordinate system (MCS) and the tool coordinate system to the absolute coordinate system, the workpiece space error is obtained. Load and no-load data from a five-axis gear grinding machine are transformed according to the coordinate transformations. The space error is determined and used to diagnose issues in the tooth alignment error of a grinding process.

Xu et al. [124] present a sensorless approach to monitor machining error and source tracing using a similar method as in Ref. [123]. A coordinate transformation matrix is derived that relates the cutting tool motion to the workpiece and is used to relate the positioning of the axes to the cutting path of the tool and workpiece. Machining error is then modeled as the difference between the real cutting tool path and the ideal cutting tool path.

Detecting position fluctuations caused by mechanical defects gives insight into the health condition of the feed drive. Xu et al. [84] decompose linear encoder signals via SSA yielding position fluctuations. Comparisons are made with EMD, but SSA shows improved performance and higher accuracy when large trends in the encoder data are present. Experiments on a vertical machining center show that the position fluctuations are mainly caused by the ball screw and are constant at different feed rates.

Xing et al. [125] monitor the accuracy of a machine tool using VEs, vector similarity measures, and an exponentially weighted moving average control chart. It is found that the Euclidean distance and the angle between two consecutive VE vectors provide adequate performance for monitoring the faults and changes in the system. The method can be used to detect accuracy changes induced by machine errors including linear positioning, axis straightness, and c-axis errors.

Wang et al. [85] investigate the alignment error of a ball screw test bench due to vibrations caused by the rotational frequency of the screw. The effect of the alignment error on the ball screw contact angle, the deformation between balls and screw, and the contact force is developed. Results show that the vibration magnitude of the ball screw frequency increases with increasing alignment error. This study also shows a method of monitoring ball screw bending deflection and a potential method in measuring the squareness error between the ball screw and the linear guides.

Vogl et al. [55] use an IMU sensor to measure changes in the linear and angular errors of a linear feed drive. The measured errors are shown in Fig. 18. Compared to a commercial laser-based measurement system, this method is capable of measuring linear and rotary units at the microscale. Thus, it is possible to measure linear axis degradation while revealing the locations and degree of wear with the use of an IMU.

5.4 Rotary Axis Condition Monitoring.

Machine tools with rotary axes are generally more complex and less rigid than linear, three-axis machine tools. The additional rotary axes introduce geometric errors and has warranted much research into quantifying these errors [171–175]. Most of these methods have the purpose to compensate the errors. This section focuses on the work that aims to use these error measurements in a condition monitoring capacity. Methods that do not involve geometric error monitoring are also presented.

A lumped parameter model of a *c*-axis drive is derived by Sztendel et al. [126]. Real-time data acquisition is performed using dSpace and a strategy for monitoring machine tools during operational states is described. One monitoring solution includes comparing the axis dynamics to historical data. The backlash seen by rotary axes is monitored in a sensorless fashion by Zhou et al. [109]. Small angle tests, as shown in Fig. 19, are used to develop a backlash profile of the rotary axis by measuring the difference between the encoder data.

Zhao et al. [86] deploy a sensorless signal-based method to monitor the transmission error and vibrations of a rotary indexing table. The transmission errors are localized via discrete wavelet transform (DWT) analysis and calculated instantaneous angular acceleration signals are used to identify the sources of vibration. DWT analysis is also used by Zhou et al. [88] to monitor servo current signals. A dynamic model is derived that relates incipient faults to the servo current. Experiments show that the servo current is useful in monitoring and diagnosing the fault state of the rotary axis. The location of the fault is apparent from a polar plot of the lower frequency band from the DWT. In Ref. [87], EEMD is used to extract fault information from the servo current in the worm mechanism of a rotary axis. A dynamic model establishes the relationship between the fault state of the axis and the servo current. Results show that the servo current contains valuable information to detect the faults of the rotary axis.

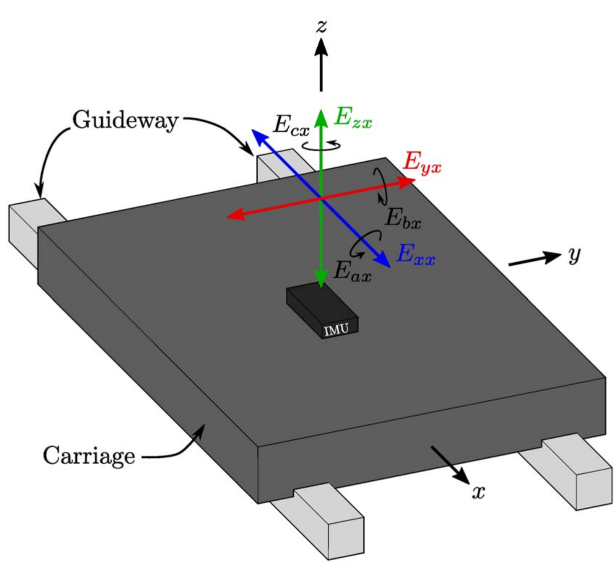

Fig. 18 Linear and angular motion errors measured by an IMU sensor in Ref. [55]

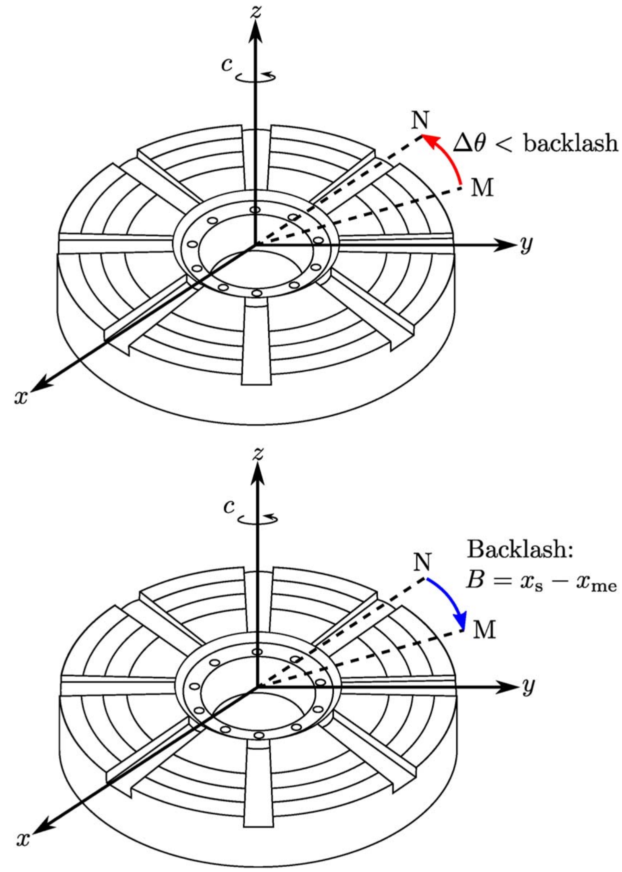

Fig. 19 Testing and measurement procedure for rotary axis backlash in Ref. [109]. The axis is rotated over a short path, M-N, that is less than the backlash (top). The axis is then rotated in the opposite direction until the grid scale value has changed, indicating that the length of backlash has been traverse (bottom). The backlash is measured by the difference between the grid scale, x_s, and motor encoder, x_{me}.

Wang et al. [128] develop an intelligent monitoring system based on multi-source data. Hydrostatic turntable service performance is monitored through analyzing static, dynamic, and thermal characteristics via analytical equations. In Ref. [150], Wang et al. also proposed a performance monitoring solution using an ANN with over-determined nonlinear equation training. Input parameters remain the same as in the previous study and comparisons are made with back-propagation and particle swarm optimization.

Geometric errors are unavoidable. Lou et al. [127] introduce a real-time sensor system to monitor radial, tilt, and angular indexing errors of a lab setup. The sensor system uses a rotary encoder with multiple scanning heads and a miniature autocollimator to measure the motion errors. A model to monitor the radial errors is also proposed. Results show that the model can predict the errors with less than a 2μm deviation from linear variable differential transformer (LVDT) measurements.

Zargarbashi and Mayer [129] develop a double-ball-bar method to measure trunnion (*a*-axis) motion errors. The method examines the radial errors projected onto the bearings of the axis. Five rotational motion errors are measured. Using rigid body and small displacement assumptions, the motion errors are reflected onto the bearings via a transformation matrix. Root-mean-square and kurtosis are used as health indices and compared to baseline values to identify gradually growing errors. In Ref. [89], Zargarbashi and Angeles detail a predictive maintenance strategy using the frequency spectrum of double-ball-bar measurements. Experiments on the trunnion axis show that the rollers and the bearing cage have the greatest influence on the errors. The authors propose that a threshold on the amplitude of the monitored frequencies can help recognize defective parts.

6 Commercial and Industry Solutions

With the advancement of computing technology and optimized signal processing and machine learning algorithms, machine tool OEMs are beginning to integrate Industry 4.0 principles into their products and solutions. These systems can be categorized as system-based and product-based solutions. System-based solutions include hardware and software integration in machine tools with the purpose of condition monitoring. Product-based solutions are components manufactured with integrated sensor systems with the purpose of providing users the data required for monitoring the component.

6.1 System-Based Solutions. Siemens AG is one of the most prominent providers of system-based CM solutions for machine tools. The SINUMERIK CNC Automation System provides hardware and software solutions for many manufacturing industries. The Siemens Industrial Edge [176] for machine tools contains applications through the SINUMERIK CNC SHOPFLOOR MANAGEMENT Software [177]. One such application is Analyze MyMachine/Condition (AMM/C) [178] which is used to monitor the condition of CNC machine tools that use the SINUMERIK 840D sl controller. AMM/C creates a mechanical fingerprint by analyzing and tracking machine axis characteristics such as stiffness, backlash, friction, signature, quadrant errors, and frequency response. These characteristics are measured via programs run by the application and are compared to reference measurements to detect deviations and potential faults.

FANUC has developed a monitoring solution using their MT-LINKI software [179]. MT-LINKI can connect to CNCs and PLCs via OPC UA or MTConnect protocols. The software has the potential to collect and monitor alarm history, signal history, servo and spindle motor currents and temperatures and more. FANUC has also partnered with Preferred Networks Inc. (PFN) to develop a servo and feed axis monitoring solution, called AI Servo Monitor [180]. AI Servo Monitor measures controller data from feed and spindle axes and applies deep learning algorithms to measure anomalies in the machine components. The models use operational torque data as inputs and calculate an anomaly score based on extracted features. As of Aug. 2019, FANUC and PFN have provided AI Servo Monitor as a proof of concept.

Bosch Rexroth's Industry 4.0 solution includes their Online Diagnostic Network (ODiN) [181]. This machine learning solution uses operational data collected through application oriented sensor packages. These data are used to train a machine learning model in an unsupervised manner and compares reference data patterns with new input operational data to detect and learn anomalous behavior.

Montronix® offers solutions for process monitoring and real-time detection of machine tool collisions, tool breakage, overloading, abnormal vibration of the spindle, and machine structure. These solutions are offered for ball screws, linear guides, and spindles. The machine diagnostic software PULSENG-DIAG [182] operates on data from a PulseNG sensor and/or a WiFi BoxNG that measure vibrations. PulseNG-Diag analyzes the signals to diagnose linear axes and offers predictive maintenance information.

DTect-IT [183] is a condition monitoring sensor and software suite by CARON Engineering that uses vibration, strain, power, and analog sensors to monitor working limits, spindle bearing health, barfeeder vibration, tool wear/breakage, etc. DTect-IT allows users to monitor their CNC machine tools through various modes. These include limit analysis, spindle bearing analysis, fault detection, frequency analysis, and sensor data collection analysis.

Artis Marposs (MARPOSS Monitoring Solutions GmbH) provides a line of monitoring hardware and applications. C-Thru4.0 [184] is a database management system that integrates with the GENIOR™ MODULAR [185], an autonomous tool and process monitoring system, and provides predictive maintenance information about a process. Data collected by the GENIOR™ MODULAR is analyzed and show variations in vibration and torque. This module also interfaces with the intelligent sensor system GEMVM [186]. GEMVM measures vibrations and allows for FFT analysis used for CM of drive axes.

Injection molding machines are subject to critical component failures, much like machine tools. Two critical components include the plasticizing screw and the ball screw. ENGEL Austria GmbH provides a smart services platform, e-connect, and e-connect.monitor, for monitoring the condition of these components in addition to hydraulic oil and servo pumps [187]. Wear is monitored during operational states through state-of-the-art sensor technology. Sensor data are analyzed through mathematical models and algorithms. The RUL is predicted for both the plasticizing screw and the ball screw when conditions are measured periodically. Sensors used on the plasticizing screw include an ultrasound sensor, and for the ball screw, temperatures, frequencies, and other performance data are measured. To measure the RUL of the ball screw, a damage indicator is created through a clustering algorithm [188]. These systems also allow maintenance personnel to be notified when components reach a critical condition based on the damage indicator.

6.2 Product-Based Solutions. In addition to system-based solutions, component manufacturers have developed sensor-integrated solutions that enable users to monitor the conditions of, for example, ball screws and linear guides.

August Steinmeyer GmbH partnered with ifm electronic GmbH to develop a preload-sensing system, called Guard Plus [189]. The sensor system is built into the nut of Steinmeyer's ball screws and interfaces with ifm VSE150 modules for vibration monitoring. Measured sensor signals are correlated with torque measurements to reveal characteristics about the level of preload. The signals are monitored over time to indicate preload loss and wear. This technology is applicable to precision ball screws with shaft diameters within 40–80 mm and ball diameters of at least 6 mm.

Schaeffler DuraSense [190] monitors the tribological conditions of linear guidance systems based on vibration signals. DuraSense uses a pre-processing unit that analyzes the sensor signals as carriage lubricants age/deteriorate and the level of lubricant is lost over time.

Bosch Rexroth has also developed an integrated linear guide sensor system, the Integrated Measuring System (IMS) [191]. The IMS provides linear feedback position using a contactless measuring principle, comparable to glass scale encoders. The IMS-A variant of the sensor system has additional temperature sensors and accelerometers that form the foundation for Industry 4.0 applications such as linear guide condition monitoring [192].

The few system- and product-based monitoring solutions described give insight into the state of condition monitoring in industry. There is also a large body of work for the monitoring of system performance, however that falls outside the scope of this review.

The monitoring of rotary and direct drive axes is closely related to the monitoring of rotating machines, but manufacturers have yet to even begin assessing the health condition of these axes. No industry solutions exist for the monitoring of rotary axes which may stem from the lack of research into this area, more work concerning rotary axis monitoring is needed. Besides Siemens and FANUC, all other solutions are sensor-based and require the installation of external sensors and hardware. If manufacturers have the necessary edge and cloud computing network architectures, then sensorless methods may be implemented with ease. However, if they do not

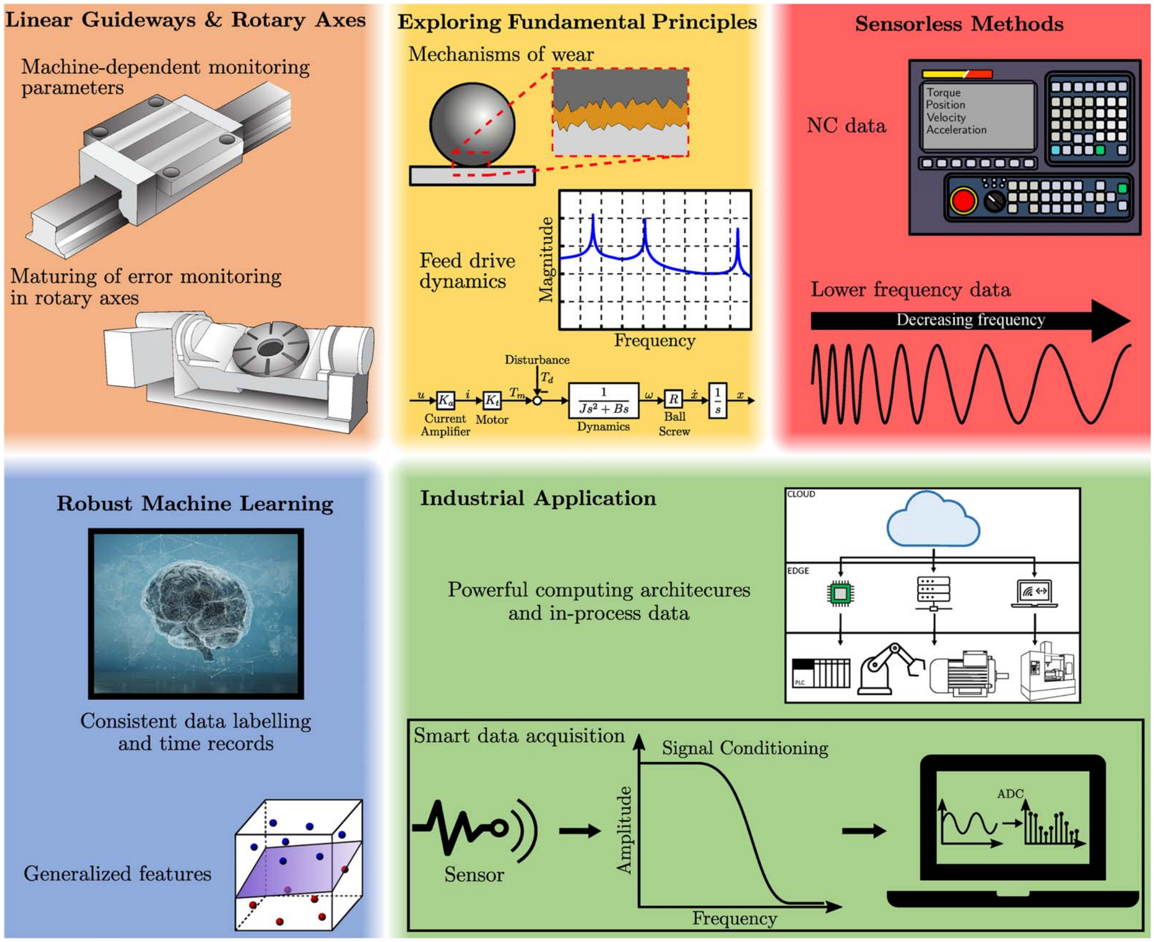

Fig. 20 The future outlook on machine tool feed drive condition monitoring consists of more research in the CM of linear guideways and rotary axes, developing CM methods that capitalize on fundamental principles and sensorless methods, improving the robustness of ML methods and investigating the use of in-process data and smarter data acquisition to facilitate industrial application

have these computing architectures, then sensor-based methods can be more desirable.

7 Summary and Future Outlook

7.1 Summary. Condition monitoring of machine tool feed drives is an expanding area of research that strives to analyze and evaluate machine health. Ball screws, linear guideways, and rotary axes are critical components in machine tools which require accurate monitoring to optimize maintenance actions and reduce operating costs. The methods available include signal processing, model-based theory, and ML algorithms. These are performed on sensorless or sensor-based data as defined by the use of built-in sensors for the former and external sensors for the latter. The most popular parameters to be monitored are wear and degradation or those that are closely related, e.g., preload and backlash. Some CM methods have begun to be introduced in industrial applications as described in Sec. 6. However, there still remain significant gaps in the literature preventing the full adoption of Industry 4.0 principles in modern manufacturing as shown in Fig. 20.

7.2 Key Feed Drive Components for Monitoring. Condition monitoring of ball screws has received more research efforts than those of linear guideways or rotary axes. This is due to the fact that ball screws are a frequently replaced maintenance item that require the longest repair times among other machine tool components and systems. Ball screw CM mainly consists of sensor-based methods that detect changes in wear/deterioration, preload, and backlash. Fault detection and diagnosis, as well as prognostic techniques, have also been explored but require more validation for their adoption in industry. The costs of downtime and poor quality arising from worn or damaged ball screws can be expensive for both small and large manufacturers; the former may not have the operating resources and the latter may have hundreds or thousands of machines to maintain. The attention given to CM research of ball screw drives is thus reflected onto the interests of these manufacturers as a worthwhile investment. In a research setting, ball screws are capable of general, machine independent work. Thus, performing research activities related to ball screw drives is made easier when experimental or prototype testbeds are available. This allows for performing accelerated life tests under no machining loads. Due to the frequency and cost of replacement and the availability for research, ball screws are given the most effort for CM applications.

Conversely, linear guides and rotary axes have received much less attention. For linear guides, this is due to the lower replacement rates. Furthermore, the condition monitoring parameters of linear guides, such as vibration and deflection, are dependent on the specific machine structure. This makes the CM of linear guideways more difficult to generalize as the proposed methods may not be expandable to all machines, even those of the same make and model. The monitoring of linear guideways is composed of wear/degradation, preload/force, lubrication, and positioning accuracy/error monitoring, in addition to fault diagnosis. Like ball screw monitoring, sensor-based approach remains the most popular among the cited works. Rotary axis and drive research have mostly consisted of geometric error measurements used for drive compensation. Little of this research has carried over to CM. As the research of these errors matures, it may begin to find its way into CM of rotary drives.

7.3 Adoption of Condition Monitoring in Industry. The reviewed CM methods seldom reach industrial settings. Those that are used for industrial applications consist of either vibration and FFT analysis or ML diagnostic methods. A good proportion of the reviewed works is implemented on industrial machines, but many are constrained to laboratory setups, test benches, and tailored datasets. Those methods that are used on industrial machine tools are highly tuned to a specific machine and application and are not yet able to be scaled generally. One of the obstacles to successful industrial adoption is the computing power needed for advanced signal processing and machine learning algorithms. However, with the wider implementation of higher level computing architectures, such as edge and cloud computing, this road block may overcome in the near future. In addition, the availability of industry data is also a limiting factor as more data are either not accessible nor collected for analysis and development of industrial CM solutions.

Another road block of industrial machine tool CM is the need to handle varying working conditions. The conditions of industrial manufacturing are chaotic and contrast the controlled environments of machine tools in a laboratory setting. For example, experimental setups often use accelerometers installed on the ball screw nut or table, a sensing method that is difficult to achieve in industry. A growing amount of machine tool CM research has begun to use operational data or data collected during machine traverse periods to mitigate the issue. Operational data contain the non-ideal aspects of industrial environments, but it conveys the real conditions of machine tool feed drives. Collecting data during machine traverse periods, or periods of constant feed rate under no load, allows to eliminate the more complex dynamics of the machine drive, such as the inertia. These data acquisition methods can provide solutions for CM methods to handle various working conditions. However, many CM methods require specific test cycles to be run on the machine to collect such data. Industrial solutions, such as Siemens' Analyze MyMachine/Condition application, require this. Condition monitoring methods that can work off in-process data that do not require test cycles can be highly sought after. Lastly, condition monitoring systems implemented in industry can show false alarms. Methods will need to be developed to reduce the occurrence of false positives which is a major deterrent to the adoption of CM in the industry.

7.4 Sensorless Condition Monitoring. Some researchers have recognized the utility of sensorless CM. Sensorless methods can provide users, who have the required computing technology and hardware, the means to implement CM with ease as no external sensors need to be installed. However, it is recognized that some of the reviewed sensorless methods have used external data acquisition devices and counter cards to measure high-frequency data (>10, 000 Hz). The future of sensorless methods will require CM to use true NC data. This will require methods that concern lower frequency data of less than 1000 Hz as limited by communication protocols.

Sensorless methods also have the benefit of improved reliability when it comes to installing sensors. In industrial settings, sensors can be highly unreliable due to environment conditions and ultimately reduce the reliability of the overall machine tool. Sensor-based CM solutions may be accurate and precise, but when more sensors are installed for monitoring purposes, the robustness of the method may be diminished.

7.5 Advanced Analysis and Modeling Techniques. Data-driven or machine learning methods are most widely explored throughout CM, but more work is needed on the robustness of ML. Much of the data collected for ML monitoring is sparse and incomplete by nature, especially those that require manual input and labeling. ML methods can also yield false positive results and few of the reviewed methods have dealt with this issue. Avoiding false positives will likely grow more complex as more data are used in diagnostic and prognostic models. Methods that use data fusion and hybrid techniques may allow for reduced false positive rates. Other concerns include the lack of a consistent time record between different components and equipment in feed drives and a lack of confidence if ML algorithms suggest actions that are well out of normal practice. It is difficult to discern if such suggested actions are real insights or errors in the ML method. Lastly, the use and appropriate selection of engineered features make ML application highly specific to a given machine tool.

The challenges facing the condition monitoring of machine tool feed drives are complex. However, some studies focus on engineering solutions that do not address the fundamental principles that govern the specific issue. For instance, the wear and degradation monitoring of both ball screws and linear guides is governed by tribological effects and feed drive dynamics. Statistical and other data analysis approaches have been implemented, but attention should be made to methods that attempt to reveal the mechanisms of wear or its effects on feed drive dynamics, and thus aim to monitor the problem more directly. This is no doubt challenging, but it will grant accurate and reliable feed drive condition monitoring.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The data and information that support the findings of this article are freely available. No data, models, or code were generated or used for this paper.

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