IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 10, 2019, accepted June 29, 2019, date of publication July 3, 2019, date of current version July 23, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2926509

Soft Computing Techniques for Surface Roughness Prediction in Hard Turning: A Literature Review

KANG HE[1], MENGDI GAO[1], AND ZHUANZHE ZHAO[2]
[1]School of Mechanical and Electronic Engineering, Suzhou University, Suzhou 234000, China
[2]School of Mechanical and Automotive Engineering, Anhui Polytechnic University, Wuhu 241000, China

Corresponding author: Mengdi Gao (mengdgao@163.com)

This work was supported in part by the Natural Science Foundation of Anhui Province under Grant 1708085ME104 and Grant 1808085ME127, in part by the Key Project of Natural Science Foundation of Universities of Anhui Province under Grant KJ2017A439 and Grant KJ2018A0451, in part by the Suzhou Univ. Professor (PhD) Scientific Research Foundation under Grant 2016JB09, in part by the Suzhou College Teacher Application Ability Development Workstation under Grant 2018XJYY01, and in part by the Suzhou Engineering Research Center for Collaborative Innovation of Mechanical Equipment under Grant SZ2017ZX07.

ABSTRACT Hard turning has become an attractive alternative to the more time-consuming and costly grinding technique. Unfortunately, high-quality prediction of the surface roughness generated during hard turning is difficult due to the technical complexities involved. Hence, it is currently receiving much research attention. The objective of this paper is to survey the current state of the soft computing techniques for surface roughness prediction in hard turning. It focuses on three areas: data acquisition, feature selection, and prediction model of surface roughness. First, the characteristics of hard turning and surface roughness are introduced, and a framework of the soft computing techniques is presented. Then, the three key areas are surveyed thoroughly. Finally, the recommendations and challenges faced by industry and academia are discussed, and the conclusions are drawn.

INDEX TERMS Surface roughness prediction, soft computing techniques, hard turning, review.

I. INTRODUCTION

A. HARD TURNING

With the increase in demand for product individuality, manufacturers face increasingly challenging expectations, such as increasing product quality and variability, decreasing product life-cycles and, most importantly, lowering product costs [1], [2]. Significant advances have been seen in the machinability of hard processing materials in recent years. There are many advantages in machining high-hardness materials compared with softer materials, such as significant savings in cost, increased productivity rates, improved surface quality, and elimination of deformities caused by dynamic cutting temperatures [3]. Hard turning is such a processing technology and is defined as a machining process in which materials with a hardness of 45–65 HRC (Rockwell scale. Based on different hardness test scales, the hardness of materials can be expressed as HRC, HRB, and so on.) are turned using single-point cutting tools with high hardness and wear resistance [3]. The cutting tools used are usually made of polycrystalline cubic boron nitride (CBN) and ceramics [4]. Most hard turning applications involve the manufacturing of bearings, shafts, forgings, camshafts, gear-shafts, and cutting tools, due to their high strength and wear resistance requirements [5]. In the fabrication of complex parts, hard turning can reduce manufacturing costs by up to 30 times [6].

Compared with the conventional turning operations used for softer materials, hard turning is unique in several key ways, including the part's hardness, the process parameters, the cutting tool required, and the mechanisms involved during chip formation. In hard turning, hardened steels are usually considered to be difficult-to-cut materials and, therefore, care must be taken to choose suitable process parameters, which usually have a relatively narrow range of acceptable values. If inappropriate process parameters are selected, the workpiece's surface quality will deteriorate and tool life, dimensional accuracy, and/or cutting stability will suffer [5], [7], [8]. In addition, the cutting tools selected should have excellent performance, mainly in terms of high indentation hardness, high hot-hardness, high fatigue resistance, high

The associate editor coordinating the review of this manuscript and approving it for publication was Jinming Wen.

abrasive wear resistance, and high physical and chemical stability [9]. CBN and ceramic tools are favored for the hard turning of hardened steels, which is widely accepted to be superior to grinding, which is costly, for the cutting of various difficult-to-cut materials, such as high-speed steels, hardened steels, die steels, bearing steels, white cast iron, and alloy cast irons [6]. The specific cutting forces encountered in hard turning (force per unit, chip cross-sectional area) are larger than those in conventional turning operations. Experiments have shown that, compared with turning a material with 32 HRC hardness, the turning of AISI 52100 ball bearing steel with 63 HRC hardness requires 50% greater cutting force and 100% greater feed and thrust forces. When machining hardened steel (45-55 HRC) with a CBN insert, experiments have revealed that the radial thrust cutting force is the largest among the three cutting force components [10]. In addition, it is important to rigorously control the workpiece surface quality during hard turning.

Davim and Figueira [11] investigated workpiece surface quality in industrial hard turning practice and argued that surface roughness will be obtained when average surface roughness (Ra) $< 0.8\ \mu$m. This implies that the surface finish produced by hard turning is only equivalent to that obtained by grinding [12]. A potential alternative to traditional grinding methods, hard turning has many distinct characteristics. Hard turning has greater flexibility to produce a variety of superior precision components and has the potential to process complex geometries with the one set-up. The contact area between the cutting tool and the workpiece is usually several times smaller in hard turning than in grinding, which creates lower temperatures. The high temperatures produced in high-speed grinding penetrate deep into the workpiece, risking thermal damage. In addition, hard turning has a higher material removal rate than grinding, making the product figuration more convenient and efficient. The average stress over the entire contact length is greater in hard turning than in grinding and may induce a relatively deep compressive residual stress in the area around individual grain contacts. High levels of compressive residual stress induced by hard turning are beneficial to the contact fatigue strength of the workpiece and can extend the contact fatigue life of bearings and crankshafts [13]. Fig. 1 summarizes the differences between traditional turning and hard turning.

B. SURFACE ROUGHNESS

Surface properties such as roughness play an important role in the functional features of machined components. Understanding hard turning surface roughness generation mechanisms can help improve the workpiece surface quality [14]. *Surface roughness* usually refers to deviations from the centreline of the nominal surface. Workpiece surface morphology is the result of the superimposition of deviations from distinct orders.

As can be seen from Fig. 2, Deviation Type 1 (roughness) is mainly related to the cutting edge shape and chip formation. Deviation Type 2 (waviness) is primarily related to the circularity and waviness of workpiece surface morphology and is mainly caused by workpiece material inhomogeneities. Deviation Type 3 (shape error) is mainly related to flatness and is caused by erroneous setups and workpiece deformation. Based on the abovementioned theoretical surface morphology and structure analysis, the hard turning cutting mechanism mainly depends on numerical simulation [15]–[18]. However, numerical simulation of hard turning are mainly done to analyze certain key issues related to processing performance, such as the influence of cutting tool material, tool nose radius, workpiece material and cutting parameters on the process efficiencies in terms of cutting force, white layer, cutting temperature, surface residual stress and surface integrity [19]. The mechanisms of surface roughness formation are rarely discussed [20] and, therefore, will not be discussed in this article.

Although finite element simulation can easily obtain many parameters that are difficult to observe during actual hard turning, many practical imperfections, such as cutting vibrations, tool breakage, and chip bonding, are not taken into account. Therefore, in some cases, observations do not agree with predictions [21]. Although a lot of literature suggests that process parameters, such as workpiece and cutting tool characteristics, have a decisive influence on the generation of surface roughness [22], [23], their role in surface roughness mechanisms remains unknown. As there are many factors involved that have complex interactions, it is difficult to generate explicit analytical models for hard turning processes.

Therefore, in order to obtain more information related to surface roughness states and effectively analyze it for online surface roughness prediction, soft computing techniques, or called indirect measurement methods in this article, are

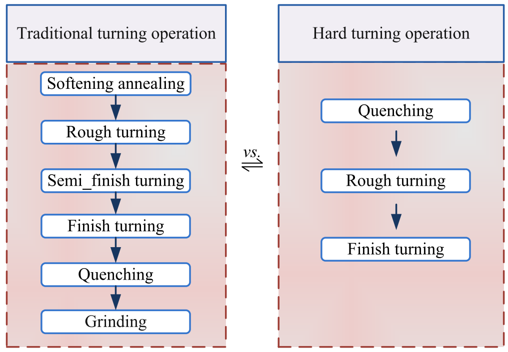

FIGURE 1. Differences between traditional turning and hard turning.

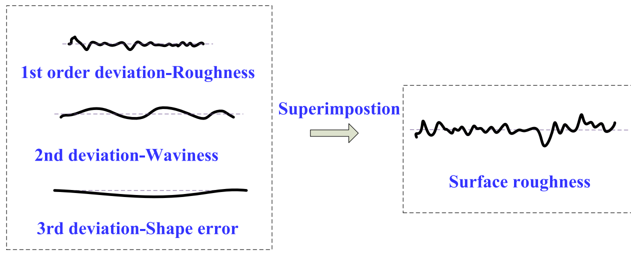

FIGURE 2. Surface form deviations.

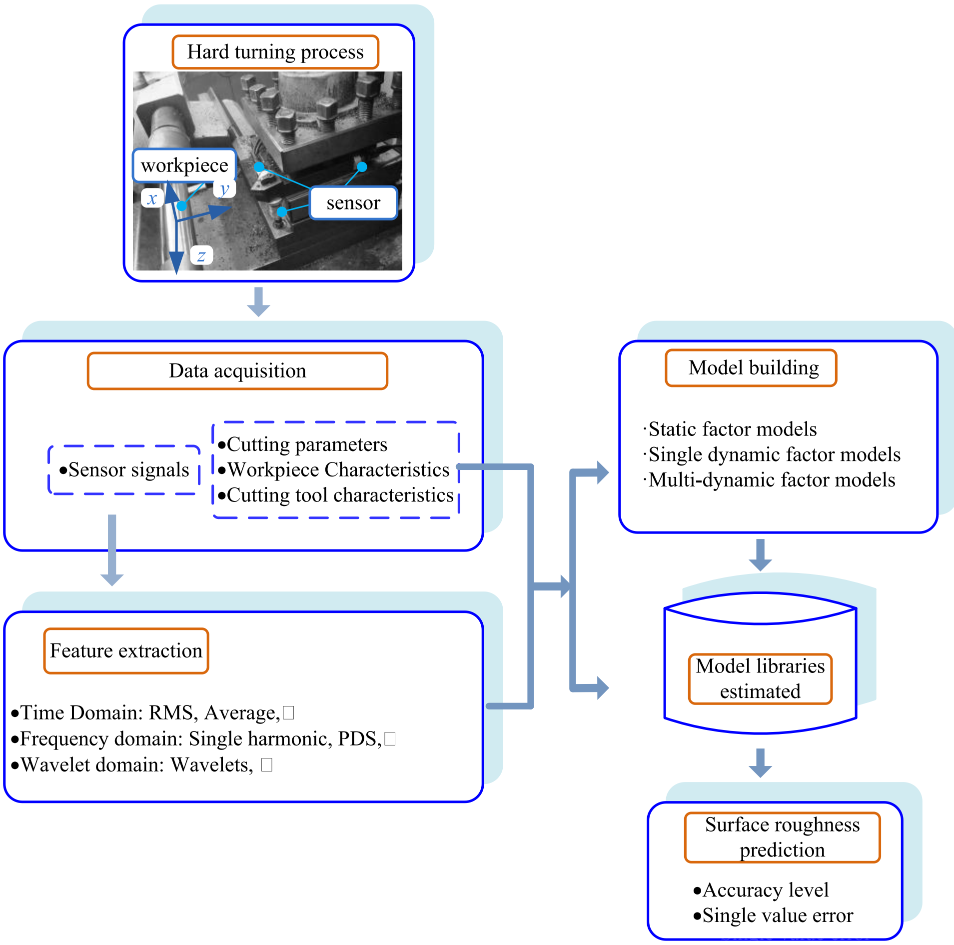

FIGURE 3. Overview of the soft computing techniques for surface roughness prediction.

widely employed in research and development. Such techniques can predict surface roughness without interfering with the hard turning process, thereby increasing efficiency and allowing online adjustments [22]. To achieve this, machining status information such as vibrations, cutting forces, images, electric current, cutting heat, acoustic emissions, sound, and chip formation [23]–[25] can be used to monitor the quality of the machining process. Based on feature extraction from such data, a predictive model can be constructed and trained. After that, the model can be used for surface roughness prediction. Fig. 3 shows an overview of the soft computing techniques relevant to this approach.

In the context of this technical framework, this paper is organized as follows. Section 2 outlines possible data acquisition methods, which include direct and indirect measurement. Section 3 presents the feature extraction methods that can be employed to select or extract the features most meaningful for surface roughness prediction. Section 4 describes the prediction model of surface roughness in hard turning. The challenges and opportunities associated with surface roughness prediction in hard turning are discussed in Section 5, then the key conclusions are presented in Section 6.

II. DATA ACQUISITION

A. CUTTING PARAMETERS

The cutting parameters in hard turning are process factors such as cutting speed, feed rate, and depth of cut. These are crucial to attaining high surface quality [26]–[29] and will yield the desired surface roughness of workpiece (i.e. meet the technical specifications). However, predictive models are largely dependent on the most significant parameters influencing surface roughness and do not include all possible influences. In order to achieve this purpose, a significant number of researchers have employed analysis of variance (ANOVA) to estimate the relative contributions of each process factor [30]. For the remainder of this paper, the term cutting parameters refers to cutting speed (v_c), feed rate (f), and depth of cut (a_p).

Pontes *et al.* [31] employed cutting parameters as controlling variables to predict the surface roughness of turned AISI 52100 hardened steel. A design of experiments (DOE)-based approach to the design of artificial neural networks (ANNs) with a radial basis function (RBF) has been proposed for surface roughness prediction. The varied cutting conditions correspond to the operational limits provided by the toolmaker (Sandvik Coromant, 2009). In their experimental study, training and testing datasets for an ANN with 720 cases were obtained by designing an experiment with 60 runs. Their research shows that the proposed RBF can achieve a mean absolute error of 0.388% after being trained with only 36 examples. Khamel *et al.* [12] investigated the effects of cutting parameters on tool life, surface roughness and cutting forces in the finish hard turning of 60 HRC AISI 52100 bearing steel with a CBN tool. The combined effects of the cutting parameters on performance characteristics (tool life, surface roughness, and cutting forces) were analyzed by ANOVA. The results show that surface roughness and tool life are strongly influenced by feed rate and cutting speed while cutting force is influenced by the depth of cut. Lalwani *et al.* [32] investigated the effect of cutting parameters on cutting forces and surface roughness in finish hard turning of MDN250 steel. The results show that feed rate has a significant effect on surface roughness. Cutting parameters were optimized by Asiltürk and Akkuş [3] to minimize surface roughness (R_a and R_z) based on the Taguchi method in the hard turning of AISI 4140 (51 HRC) with coated carbide cutting tools. Using the statistical methods of signal-to-noise ratio (SNR) and ANOVA, they showed that the feed rate has the most significant effect on surface roughness (R_a and R_z) at a reliability level of 95%. Saini *et al.* [33] investigated the effects of cutting parameters on tool wear and surface roughness. Experimental data were acquired during the hard turning of hardened AISI H-11 steel and ANOVA was utilized to determine statistical significance. Panda *et al.* [9] investigated the optimization of cutting conditions on surface quality characteristics (R_a, R_z and R_t) in the hard turning of EN31 steel. ANOVA was employed to determine which cutting parameters affected the surface quality. Pontes et al.[34] used a dataset containing cutting parameters acquired by DOE as input for RBF networks to predict surface roughness. Agrawal *et al.* [35] performed 39 sets of trials to study the effect of cutting parameters on surface roughness in the hard turning of an AISI 4340 steel workpiece (hardened to 69 HRC) under dry conditions. Cutting parameters were employed by Bouacha *et al.* [36] as input variables for response surface methodology (RSM) estimation of surface roughness and cutting force components (F_a, F_c and F_p) in the hard turning of hardened AISI 52100 bearing steel with a CBN tool. Using the Taguchi method, cutting parameters were employed as input of ANN for surface roughness prediction in the hard turning of AISI H13 steel with minimal cutting fluid application [37]. Fnides *et al.* [38] employed cutting parameters in a multiple regression model. The cutting parameters of cutting speed, feed rate, and depth of cut were optimized by ANOVA. Das *et al.* [29] employed cutting parameters as input to quadratic models of surface roughness during hard turning. ANOVA was employed to optimize the cutting parameters, with the results showing that feed rate is the principal cutting parameter influencing surface roughness, followed by cutting speed.

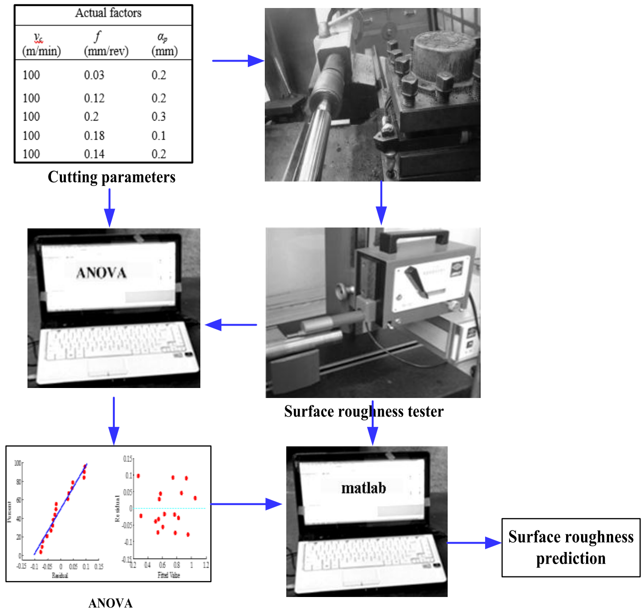

FIGURE 4. The experimental setup and the data flow analysis.

TABLE 1. Analysis of variance for surface roughness(R_A).

Source	DF	Seq. SS	Adj. MS	F	Prob.>F	Cont.%
v_c	1	0.0085	0.1974	31.64	0.000	1.04
f	1	0.1279	0.2295	36.79	0.000	**15.74**
a_p	1	0.0192	0.0431	6.91	0.027	2.36
Cs	1	0.1763	0.1116	17.89	0.002	**21.69**
$f \times a_p$	1	0.0385	0.0372	5.97	0.037	4.74
f^2	1	0.3307	0.3293	52.78	0.000	**40.70**
$Cs \times Cs$	1	0.0555	0.0555	8.90	0.015	6.83
Error	9	0.0562	0.0062			6.91
Total	16	0.8126				100

A schematic representation of the experimental setup and data analysis used in this study are shown in Fig. 4. The cutting parameters and surface roughness are determined by a full factorial design and surface roughness testing, respectively. Then, the experimental results of surface roughness (R_a) and cutting parameters are analyzed by ANOVA to determine the significant factors using Minitab 15 software.

The surface roughness ANOVA is calculated at a significance level (α) of 0.05 (95% confidence). The value (Cont.%) in the last column of the ANOVA table indicates the statistical significance of the corresponding response. For example, as shown in Table 1, the main contributions are for the interaction f^2 (40.70%), while for C_S it is 21.96% and for f it is 15.74%. In Table 1, v_c is the cutting speed, f is the feed rate, a_p is the depth of cut, C_S is the signal feature extracted, and $\times$ denotes interaction terms.

B. WORKPIECE AND CUTTING TOOL CHARACTERISTICS

In order to obtain more comprehensive state information during hard turning processes, many factors other than the cutting parameters can be employed to predict surface roughness more accurately and efficiently. These include the characteristics of the workpiece material and cutting tool.

Aouici *et al.* [6] analyzed the effects of cutting parameters and workpiece hardness on surface roughness and cutting force components in the hard turning of AISI H11 steel hardened to 40, 45 and 50 HRC using CBN 7020 (Sandvik Company). ANOVA was employed for four-factor (cutting speed, feed rate, depth of cut and hardness) and three-level factorial experimental designs. The analysis showed that surface roughness is influenced principally by feed rate and workpiece hardness, while depth of cut and workpiece hardness influence the cutting force components. Chinchanikar and Choudhury [39] investigated the effects of workpiece material hardness and cutting parameters on the performance of coated carbide tools, including their cutting forces, surface roughness, and tool life. ANOVA was employed to determine the most significant parameters, which showed that surface roughness is significantly affected by the feed rate and depth of cut. Mia *et al.* [27] employed cutting speed, feed rate and material hardness as independent variables and surface roughness (R_a) and mean chip-tool interface temperature (θ) as responses. ANOVA was used to determine the effects of control factors. They also used various cutting speeds, feed rates, material hardness, and dry / high pressure lubrication (HPC) as input for an ANN to predict surface roughness in the turning of hardened EN 24T steel [40]. An experiment conducted by Azizi *et al.* [41] investigated the effects of cutting parameters and workpiece hardness on surface roughness and cutting force in the hard turning of AISI 52100 steel. ANOVA was employed to determine the significant parameters, with the results indicating that feed rate, workpiece hardness and cutting speed have significant effects on surface roughness; whereas the depth of cut, workpiece hardness and feed rate have significant impacts on cutting force components. The influence of hardness and spindle speed on surface roughness (R_a) in hard turning was studied by using ANOVA, with the results showing that workpiece hardness has a significant effect on surface roughness [42]. Fig. 5 shows the deeper correlation that workpiece hardness affects surface roughness.

In addition to considering the characteristics of workpiece materials, many studies have also discussed the effects of cutting tool characteristics on workpiece surface roughness [43]. Özel *et al.* [44] and Tang *et al.* [45] investigated the effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and forces in the finish hard turning of AISI H13 steel using CBN. Four-factor (hardness, edge geometry, feed rate and cutting speed) and two-level experiments were conducted and analyzed by ANOVA. Yurtkuran *et al.* [46] employed cutting parameters and coating conditions in a predictive model of R_a in the hard turning of X40CrMoV5-1 steel with CBN tool. An optimization study with analysis of signal-to-noise (S/N) ratios was conducted to reveal their relationships. Manivel and Gandhinathan [47] used the tool nose radius and cutting parameters as independent variables to predict surface roughness and tool wear. ANOVA and S/N ratios were used to optimize the independent variables. Cutting parameters and cutting tool angle were employed by Vishal *et al.* [21] and Meddour *et al.* [48] as input for an ANN that predicted cutting forces and surface roughness. The effects of cutting parameters on cutting forces and surface roughness were evaluated by linear regression. Cutting parameters and tool geometry, were employed by Karpat and Özel [49] as input of ANN for multi-objective prediction. The input parameters were optimized according to the multi-objectives by the dynamic neighborhood particle swarm optimization methodology. Ferreira *et al.* [50] investigated the effects of cutting speed, feed rate, and use of conventional and multi-radius ceramic tools on surface roughness in the hard turning of AISI H13 steel. ANOVA showed that the multi-radius ceramic tool and feed rate had the strongest effects on surface roughness. Singh and Rao [43] employed cutting speed, feed rate, rake angle and nose radius as factors to predict surface roughness based on response surface methodology. These parameters were optimized using ANOVA, with the results indicating that feed rate is the dominant factor affecting surface roughness, followed by nose radius, cutting speed and rake angle. Fig. 6 shows the deeper correlation that tool characteristics affects surface roughness.

C. SENSOR SIGNALS

Although the cutting parameters and workpiece/cutting tool characteristics are more critical and easier to obtain than other factors, they are static parameters that cannot reflect dynamic changes in surface roughness during hard turning processes [51]. In order to effectively capture dynamic information related to surface roughness, sensor signals can be exploited

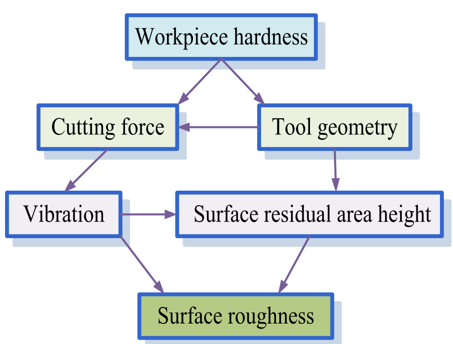

FIGURE 5. Map of the effect of workpiece hardness on surface roughness.

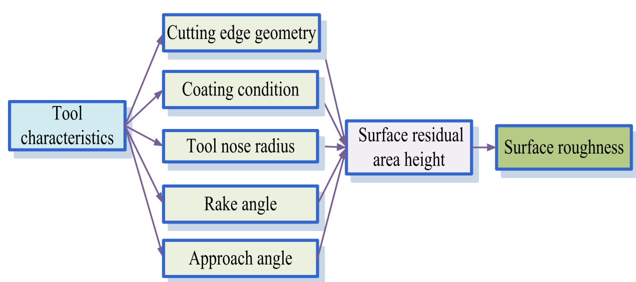

FIGURE 6. Map of effect of tool characteristics on surface roughness.

TABLE 2. Factors affecting the workpiece surface roughness in hard turning.

Factors	Type	Significant Yes √ ;No □	References
cutting speed	cutting parameter	□	24, 38, 31, 36, 3, 12, 33,34, 37, 30, 35, 7
feed rate	cutting parameter	√	24, 38, 31, 36, 3, 12, 33,34, 37, 30, 35, 7
depth of cut	cutting parameter	□	24, 38, 31, 36, 3, 12, 33,34, 37, 30, 35, 7
workpiece hardness	material characteristics	√	24, 42, 6, 1, 41, 39
tool geometry	cutting tool characteristics	√	24, 44, 49, 21, 46, 47
cutting vibration	sensing signal	√	56, 53, 60, 52, 54
cutting force	sensing signal	√	24, 54, 57
audible sound	sensing signal	√	58, 54
cutting temperature	sensing signal	√	56

for surface roughness prediction, such as cutting vibrations, temperatures, and forces etc.

Cutting vibration signals are widely used because they are directly related to surface roughness and are easy to obtain [52]. Hessainia *et al.* [53] employed tool vibration in the radial and tangential directions, and cutting parameters such as cutting speed, feed rate, and depth of cut as the main inputs for surface roughness prediction in the hard turning of 42CrMo4 hardened steel. He *et al.* [52] used cutting parameters and cutting vibration signals to predict surface roughness based on a detailed analysis of the workpiece surface formation mechanism. The ANOVA analysis was carried out for a 5% significance level, i.e., for a 95% confidence level. The results showed that the vibration signal affects surface roughness in a considerable way. Deshpande *et al.* [54] employed cutting vibrations, forces, and sound, along with cutting parameters, to estimate surface roughness in the turning of Inconel 718 on a computer numerical control lathe machine. The cutting forces are measured using piezoelectric dynamometer. The sound generated at the tool-chip interface was measured with a microphone probe. The vibrations were measured using noncontact-type laser doppler vibrometers. Delijaicov *et al.* [55] studied the influence of cutting vibrations on surface roughness. The cutting vibrations were collected by a piezoelectric dynamometer close to the tool and workpiece interface.

An attempt was made by Arulraj *et al.* [56] to combine cutting temperature with cutting parameters as input for an ANN to predict surface roughness in the hard turning of H13 tool steel hardened to 43 HRC. The cutting temperature was measured using an Amprobe (IR750) infrared thermometer and test results showed it to be effective. Process parameters (tool edge geometry, workpiece hardness, cutting speed, feed rate and cutting length) and cutting force were used as inputs for an ANN by Özel and Karpat [24] to predict surface roughness and tool wear during hard turning. ANOVA results showed that workpiece hardness, cutting length, and some interaction terms were less significant effect on surface roughness. Grzesik [57] used a piezoelectric dynamometer to measure cutting forces to determine the plowing energy and friction coefficient and reveal the spring-back effect of surface roughness. The audible sound emitted during hard turning was found by Frigieri *et al.* [58] to be a valuable source of information for surface roughness diagnosis. Sound emissions are collected by a microphone installed close to the cutting tool in the cutting area. Compared with the other monitoring signals used for surface roughness prediction, such as cutting vibration signals, cutting force signals and electric current signals, the sound that comes from the machining process is easily accessible and audio microphones are easy to install. The acoustic signals, however, are vulnerable to interference noise produced by external circumstances, which increases the complexity of signal processing. Mia *et al.* [59] collected the time (t) gap between the minimum quantity coolant lubrication pulsing with the cutting parameters to predict the surface roughness based on a devised least square support vector machines (LS-SVM). Table 2 summarizes the factors that affect workpiece surface roughness.

Although information collected by sensors can be effectively used to monitor dynamic changes in surface roughness, it must be processed by a complex signal processing system involving acquisition, filtering, and feature extraction.

III. FEATURE SELECTION

After data acquisition, feature selection is a critical issue. Signals obtained during hard turning are generally cutting vibrations, cutting forces, audible sounds, and cutting temperatures. The application of these signal features is discussed in the time domain, frequency domain, and time-frequency domain. Hessainia *et al.* [53] employed vibration acceleration amplitudes in the radial and tangential directions and cutting parameters as input to predict surface roughness. Meddour *et al.* [60] used tool vibrations, cutting parameters and the tool nose radius for surface roughness prediction in the hard turning of AISI 52100 steel. A correlation between tool vibrations and surface roughness was revealed. Cutting temperature, as well as cutting parameters, was employed by Arulraj *et al.* [56] as input to an ANN to predict surface roughness in hard turning. The test results showed that an ANN based on cutting temperature made better predictions than one that was not. Özel and Karpat [24] employed the three force components with other cutting parameters to predict surface roughness and tool wear. The amplitude of the cutting force was used as direct input to an ANN to acquire the workpiece surface roughness.

In addition to extracting features from the time domain, many researchers have also extracted features from the frequency and time-frequency domains. Frigieri *et al.* [58] extracted mel-frequency cepstral coefficients (MFCCs) from audible sound emissions for surface roughness diagnosis in hard turning. They separated the sound signal into several frames and calculated the energy spectrum for each frame. Each energy frame was filtered using a triangular filter bank. A discrete cosine transform (DCT) was applied to the natural logarithm of the mel spectrum, which resulted in MFCCs (Eq. 1). Experiments with the turning of AISI 52100 hardened steel verified the validity of this feature.

$$c_k(m) = \sum_{l=0}^{L-1} \log\left(\tilde{s}_k(l)\right) \cos\left(\frac{\pi m}{2L}(2l+1)\right), \quad \forall k = 1, \ldots K \tag{1}$$

where m =1, 2, …, C and C is the number of desired coefficients.

He *et al.* [52] extracted multidirectional fused features from cutting vibration signals acquired during hard turning. The cutting vibration signals were acquired by three PCB acceleration sensors placed close to the tooltip. The cutting vibrations in the x, y, and z directions were processed based on independent component analysis (ICA) and singular spectrum analysis (SSA). The correlation of the cutting vibrations was removed using ICA and the dynamic changes in surface roughness were detected by SSA. The extracted fusion feature C_s can be formulated as follows (Eq. 2).

$$C_s = \frac{\sum_r \eta_r \|E^r\|_2^2}{\sum_r \|E^r\|_2^2} \tag{2}$$

where $E^r \in \{E^x, E^y, E^z\}$ is the elementary matrix that the cutting vibration corresponds to $\eta_r \in \left\{\eta_x, \eta_y, \eta_z\right\}$ is a weight vector obtained by the correlation analyses of E^r and R_a.$r \in \{x,\ y,\ z\}$ denotes the three coordinate directions. Experimental studies show that the proposed combined features are more effective for workpiece surface roughness prediction than single-signal characteristics.

Our recent statistical analysis, obtained by consulting 39 relevant studies in detail (most of them published from 2012–2019), revealed that the cutting parameters currently used for surface roughness prediction in hard turning account for a large proportion of the input data. The cutting parameters are still the most important parameters for surface roughness prediction in hard turning, followed by sensor signals and cutting tool/workpiece characteristics. Most of the features extracted from sensor signals are concentrated in the time domain, followed by the frequency and time-frequency domains. Notably, in the time-frequency domain, fewer features are extracted. The descriptors are shown in Fig. 7.

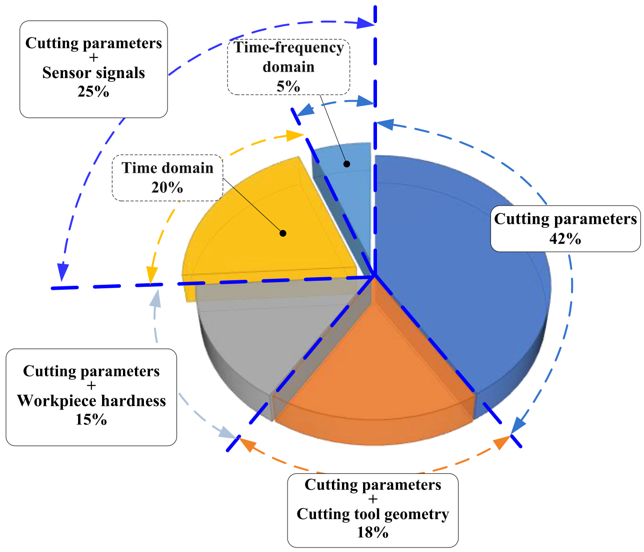

FIGURE 7. Input data selection for surface roughness prediction in hard turning.

IV. PREDICTIVE MODEL

Predictive models of surface roughness are widely employed in the study of hard turning and visual machining processes. Many studies have shown that it is a powerful and efficient tool with which to understand surface generation mechanisms, optimize machining parameters, and identify surface accuracy without costly trial-and-error experiments [14], [43], [53], [61]. In order to effectively implement online monitoring of surface roughness during hard turning, many researchers have focused on developing models that take into account the different factors influencing hard turning, which are governed by the relative movement between the tool-tip and workpiece. Fig. 8 shows the development of surface roughness predictive models.

Compared to dynamic signals, some static factors, such as cutting parameters, workpiece characteristics and cutting tool characteristics, are more accessible. Therefore, some studies on surface roughness prediction take into account static parameters and assume that the geometric surface profile is mainly influenced by cutting speed, feed rate, depth of cut, tool geometry and workpiece hardness. Linear regression models and ANNs are widely used in this field.

Khamel *et al.* [12] proposed a quadratic model of cutting forces (F_a, F_c and F_p), tool life (T) and surface roughness (R_a) using coded variables that correspond to the cutting parameters. After eliminating terms with no significant effect on the responses according to ANOVA, quadratic models were developed to predict the cutting forces, tool life, and surface roughness. Saini *et al.* [33] developed a response surface methodology (RSM) to predict surface roughness and tool wear for various cutting conditions in the finish hard turning of AISI H-11 steel. Aouici *et al.* [6] also developed a RSM to predict surface roughness and cutting force components in the hard turning of AISI H11 steel with 40, 45 and 50 HRC using CBN. Four factors (cutting speed, feed rate, depth of

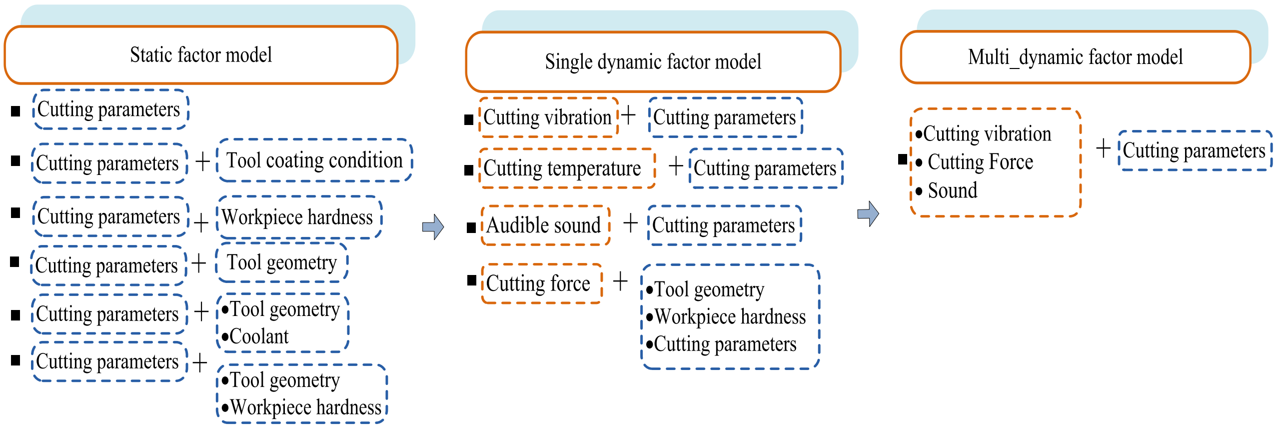

FIGURE 8. Development of surface roughness model considering the different influencing factors.

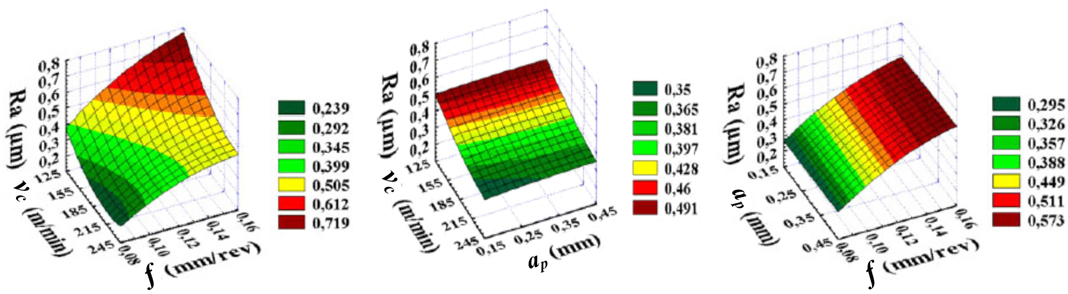

FIGURE 9. Estimated response surface of surface roughness parameters versus *Vc*, *f* and a_p.

cut and hardness) were analyzed by ANOVA and the terms with significant effects on the surface roughness and cutting force components were used in the final quadratic models. Chinchanikar and Choudhury [39] proposed a multiple linear regression model for predicting cutting forces, surface roughness, and tool life by using the workpiece material hardness and cutting parameters as input arguments during the turning of AISI 4340 steel of various levels of hardness.

A multiple linear regression model of surface roughness and cutting force was developed by Azizi *et al.* [41] that used cutting speed, feed rate, depth of cut and workpiece hardness as predictors. The model was validated using ANOVA. Panda *et al.* [9] utilized multiple linear regression analysis to predict surface quality characteristics (R_a, R_z, and R_t) in the hard turning of EN 31 steel hardened to 55 HRC. Yurtkuran *et al.* [46] developed a first-order mathematical model for surface roughness prediction that used multiple regression analysis based on the optimization of hard turning cutting conditions. Manivel and Gandhinathan [47] proposed a full quadratic regression model to predict surface roughness and tool wear, with the optimized parameters acquired by ANOVA and S/N ratio analysis. Fnides *et al.* [38] developed a multiple regression method for surface roughness prediction. The model was based on the dominant cutting parameters acquired by ANOVA. Singh and Rao [43] developed a RSM for surface roughness prediction in the finish hard turning of bearing steel. First- and second-order models were compared, with the former considered adequate for representing the hard turning process.

The RSM was analyzed and modeled by Bouacha *et al.* [36] to predict surface roughness and cutting forces during hard turning. The combined effects of cutting parameters on surface roughness and cutting forces were analyzed by ANOVA. Using the L27 Taguchi orthogonal experiment, a quadratic model of surface roughness and cutting forces is developed as follows:

$$Y = a_0 + \sum_{i=1}^{3} a_i X_i + \sum_{i=1}^{3} a_{ii} X_i^2 + \sum_{i<j}^{3} a_{ij} X_i X_j \tag{3}$$

where Y is the desired response (surface roughness, cutting forces), a_0 is a constant, and a_j, a_{ii} and a_{ij} denote the linear coefficient, quadratic and cross-product terms, respectively. X_i denotes the coded variables corresponding to the cutting parameters. ANOVA was employed to analyze the significance of the regression and the individual model coefficients to verify the goodness-of-fit of the model obtained. A 3D response surface corresponding to each variable is illustrated in Fig. 9 [36].

By eliminating terms with no significant effect on the responses, the final quadratic models in terms of actual factors are as follows [36]:

$$R_a = 0.29 - 0.01 \cdot V_c + 14.41 \cdot f - 33.68 \cdot f^2 - 0.01 \cdot V_c \cdot f \left(R^2 = 99.1\%;\ R^2\ (ajus) = 98.9\%\right) \quad (4)$$

$$F_p = 936 - 4 \cdot V_c - 5068 \cdot f - 778 \cdot a_p + 18718 f^2 + 1932 \cdot a_p^2 + 4480 \cdot f \cdot a_p \left(R^2 = 97.3\%;\ R^2\ (ajus) = 96.3\%\right) \quad (5)$$

In contrast to the multiple linear regression used in most studies, a novel random forest regression was presented and applied by Agrawal *et al.* [35] to predict surface roughness. It employed cutting parameters as independent variables in a machining process for the first time. This model was found to be more accurate than multiple regression models. In addition to linear regression equations, artificial intelligence models have also been employed for workpiece surface roughness prediction in hard turning. ANN models estimate surface roughness with high accuracy, are more stable and converge much faster than multiple linear regression models. In many cases, regression models developed using DOE techniques failed to correctly predict minimal roughness values [62]. Zare Chavoshi and Tajdari [42] developed ANN and regression methods for modeling of surface roughness in hard turning. The input parameters were hardness and spindle speed, and laboratory studies showed that the ANN was preferred for the prediction of surface roughness during hard turning. Pontes *et al.* [31] developed a DOE-based approach for the design of ANNs with an RBF in a systematic way. It was used for surface roughness prediction in the turning of AISI 52100 hardened steel. DOE was employed to select the levels of the factors and optimize the network structure. However, the proposed strategy cannot be extrapolated to other network structures. The impact of the interactions of factors on network performance remains to be investigated. An ANN model was proposed by Beatrice *et al.* [37] to predict surface roughness parameters in the hard turning of H13 tool steel hardened to 45 HRC. Experimental investigation showed that an ANN consisting of three neurons in the input layer, two hidden layers with seven neurons each, and one neuron in the output layer (3-7-7-1) produced the lowest MSE value. Hard turning cutting forces and surface roughness were measured by Sharma *et al.* [21] using an ANN with one hidden layer with 20 neurons and selection of 323 epochs. The validity of the model was tested with experimental data and found to be 76.4% accurate. Karpat and Özel [49] employed an ANN to construct the non-linear relations between machining parameters, including tool geometry and the performance of interest (surface roughness, productivity, and residual stress). The output of the ANN was multi-objective, and the input parameters were optimized by the dynamic neighborhood particle swarm optimization methodology. The results indicate that the methodology is efficient in solving multi-objective optimization problems that have conflicting objectives. Pontes *et al.* [34] proposed a radial base function neural network for R_a prediction in the hard turning of SAE 52100 steel. The cutting speed, feed, and depth of cut were employed as controlling variables. A central composite design (CCD) was conducted using three points: (i) a full factorial design with 23 runs, (ii) six axial points, and (iii) four center points, which resulted in 18 runs. Using three replicates for each run and augmenting the design with six face-centered runs, the entire design comprised 60 runs.

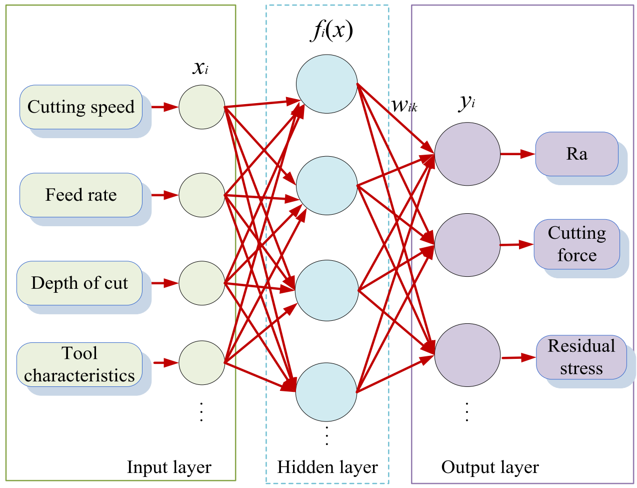

FIGURE 10. A Radial Basis Function (RBF) network.

A typical RBF neural network is composed of three layers: an input layer composed of three radial units, a hidden layer (represented by function $f_i(x)$) and an output layer, as shown in Fig. 10. An RBF network has k radial units in the intermediate layer and one output, as given by:

$$y = \sum_{i=1}^{k} w_i f_i \left(\|x - \mu\|^2\right) + w_0 \quad (6)$$

where x is an input vector, μ the hyper-center of radial units, f_i is the activation function, w_i is the weight value, and w_0 is a constant.

Surface roughness is determined by the cutting parameters and by irregularities, such as cutting tool geometry, tool wear, cutting vibration, workpiece hardness, cutting heat, cutting fluid, and workpiece material properties [49]. The process-dependent nature of roughness formation, as well as the numerous uncontrollable factors that influence it, makes it difficult to predict surface roughness accurately. The most common practice is to select the conservative process parameters as mentioned above. However, this route neither guarantees the desired surface finish nor attains high metal removal rates. Therefore, a single dynamic signal combined with cutting parameters has been considered in the modeling of surface roughness. These dynamic signals are mainly cutting vibrations, cutting temperature, and acoustic signals. Hessainia *et al.* [53] developed a quadratic model associated with a response optimization technique to predict surface roughness based on cutting parameters and tool vibrations. Mia and Dhar [26] proposed a RSM to predict surface roughness and average chip-tool interface temperature based on significant factors obtained by ANOVA. Arulraj *et al.* [56] developed an ANN model to fuse cutting temperature with cutting

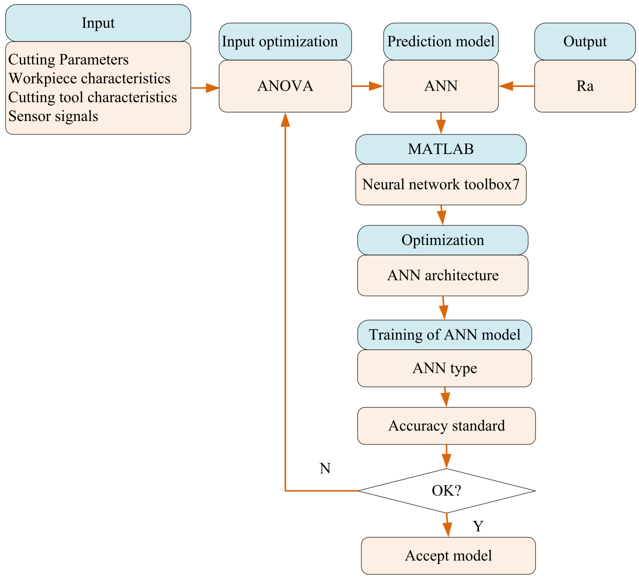

FIGURE 11. Outline of ANN modeling.

parameters to predict surface roughness in hard turning. The ANN model including cutting temperature was superior to that without sensor fusion. ANN architectures are illustrated in Fig. 11.

A Gaussian mixture model (GMM) as developed by Frigieri *et al.* [58] to perform surface roughness diagnosis. Based on the corresponding clustering technology of the underlying sound, the GMM model was parameterized by $\lambda = (w_i, \mu_i, \Sigma_i)$, which are estimated using the expectation-maximization (EM) algorithm. The mixture weights, means, and variances for each iteration of λ were re-estimated ($\bar{\lambda} = (\bar{w}_i, \bar{\mu}_i, \bar{\Sigma}_i)$) using the respective formula:

$$\bar{w}_i = \frac{1}{T}\sum_{t=1}^{T} p\left(i\left|\vec{x}_t, \lambda\right.\right), \quad \bar{\mu}_i = \frac{\sum_{t=1}^{T} p\left(i\left|\vec{x}_t, \lambda\right.\right)\vec{x}_t}{\sum_{t=1}^{T} p\left(i\left|\vec{x}_t, \lambda\right.\right)},,$$
$$\bar{\sigma}_i^2 = \frac{\sum_{t=1}^{T} p\left(i\left|\vec{x}_t, \lambda\right.\right)\vec{x}_t}{\sum_{t=1}^{T} p\left(i\left|\vec{x}_t, \lambda\right.\right)} - \bar{\mu}_i^2 \tag{7}$$

where $\vec{x}_t$ is a D dimensional feature vector, the model was validated and its diagnostic accuracy reached 98.125%.

In view of the surface formation being affected by cutting parameters and irregularities, it is difficult to fully reflect variations in surface roughness using only single dynamic signal that is a low level of imitation of human brain information processing [63]. Multi-sensor data fusion systems can effectively compensate for such shortcomings.

Özel and Karpat [24] utilized an ANN and regression model to predict surface roughness and tool flank wear in finish hard turning. The inputs were workpiece hardness, cutting speed, feed rate, axial cutting length, and mean values of three force components F_x, F_y, F_z (N) measured during finish hard turning, which were optimized by ANOVA. The results show that ANN with cutting force inputs yielded better results than neural networks without cutting force inputs, and compared to the regression models, the neural network models provided better predictive capabilities. He *et al.* [52] proposed a hybrid model to evaluate surface roughness in hard turning using a Bayesian inference-based hidden Markov model and least-squares support vector machine (HMM-SVM). The model inputs are cutting parameters, multidirectional fusion features, which are extracted from three cutting vibration components x, y, z in three-dimensional space and optimized by a proposed five-step iterative algorithm. Experimental studies show that the proposed hybrid model can be used accurately for surface roughness prediction in cases with missing samples. Deshpande *et al.* [54] proposed a regression model to predict surface roughness using cutting parameters along with cutting force, sound, and vibration in turning of Inconel 718. The prediction results of regression models with fusion data input are compared with that developed using only cutting parameters. Fine association of fit between measured and estimated surface roughness is confirmed by the former. He *et al.* [65] also proposed a coupled hidden Markov model to monitor surface roughness accuracy grade by using three cutting vibration components x, y, z in three-dimensional space to analyze the effect of the sensor layout on the monitoring accuracy. The fusion features, extracted by a singular spectrum and wavelet analysis, as well as the cutting parameters, constitute the input information to the system. The case study shows that the coupled hidden Markov model with multi-sensor data fusion inputs yielded better results than that with single sensor data inputs.

Single dynamic signal processing or low-level multi-sensor data processing imitate information processing by the human brain at a low level. However, multi-sensor information fusion systems maximize access to the target detected by the effective use of multi-sensor resources [40], [64], [65]. There is a fundamental difference in the information processing methods required for multi-sensor fusion and single signals. The key is that multi-sensor information fusion is more complex and usually occurs at several levels. A representation of this multi-sensor information fusion architecture is shown in Fig. 12. It can be seen that there are three levels of representation in the multi-sensor information fusion model: the first is the data fusion level, in which the task is to acquire raw data from the environment for data-level fusion; the second is the feature fusion level, which obtains a symbolic level of inference about the data; and the third is the decision fusion level, where possible decisions are assembled according to the information gathered. More often, surface roughness in hard turning is predicted based on the analysis of multiple parameters, either from the same type of sensor or from a completely separate one. Multi-sensor fusion systems can greatly improve the accuracy and reliability of online workpiece surface roughness prediction in hard turning [56]. Since hard turning machining exhibits a unique behavior, which is different than regular turning operations, multi-sensor data fusion model for surface roughness prediction in hard turning is less than that for surface roughness prediction in traditional turning. Table 3 presents the multi-input models applied for surface roughness prediction in hard turning.

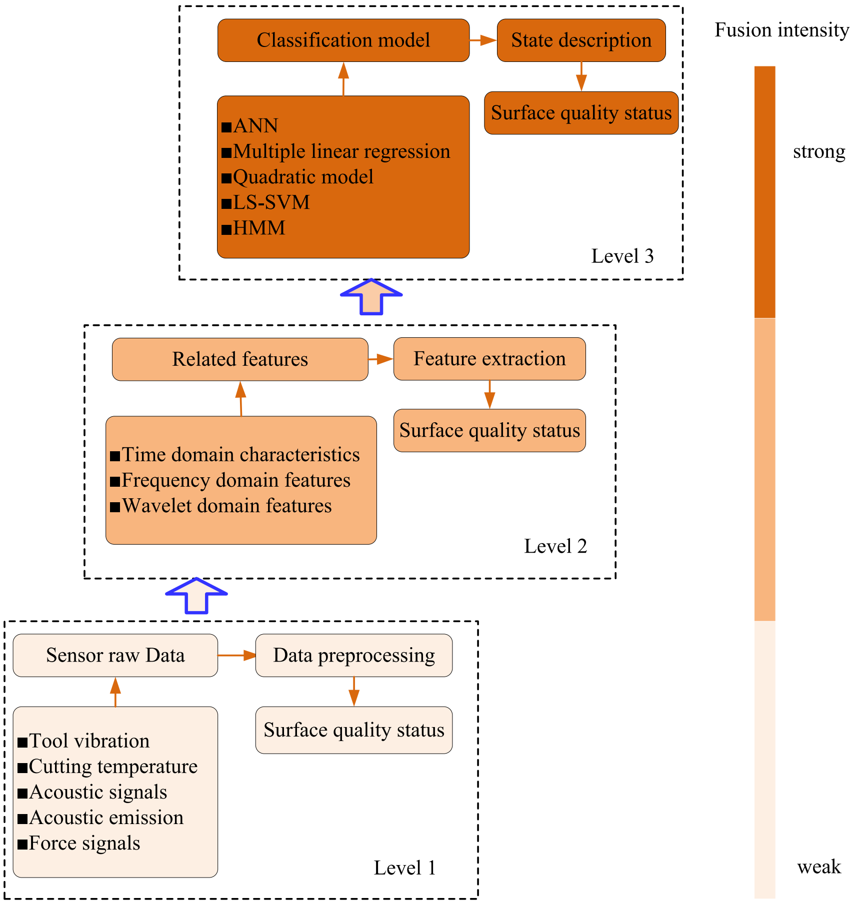

FIGURE 12. Multi-sensor information fusion architecture for surface roughness prediction.

V. RECOMMENDATIONS AND CHALLENGES

Compared with conventional turning, hard turning requires fewer production steps, saves energy, and reduces machining time. The surface roughness is a vital index that must satisfy the technical specifications. Soft computing techniques, being efficient online prediction methods, have been the focus of much research. Although much effort has been made to study the data acquisition, feature selection and modeling of surface roughness, many of these concepts are highly complex and have large numbers of interacting factors, thus preventing high surface quality from being attained. Technological advances in the fields of sensors and signal processing can solve these issues to a certain extent. Accordingly, the main recommendations and challenges in hard turning are summarized as follows.

(1) Cutting parameters are easier to obtain and more critical than other factors. However, more recent studies have shown that workpiece/cutting tool characteristics are also significant factors affecting surface roughness. Therefore, more effort should be made in investigating the inherent causal relationship between workpiece/tool properties and surface roughness to obtain further critical information for surface roughness prediction. Moreover, compared with static factors(cutting parameter, workpiece/cutting tool characteristic), the application of dynamic factor (sensor signal) is currently very limited.

(2) In the current literature, the optimization of cutting conditions for a certain level of surface roughness is mainly based on ANOVA analysis. However, regarding state monitoring in hard turning processes, it is often necessary to optimize multiple goals. Intelligent optimization algorithms, such as genetic algorithms, particle swarm optimization and shuffled frog leaping algorithms, which are mainly employed for multi-objective optimization in engineering problems, could be used in conjunction with the developed models to predict surface roughness and related factors. However, very few similar approaches have been found.

(3) With regard to online surface roughness prediction, feature selection remains a critical issue. Most feature extraction in current literature is focused on the time domain; while in the wavelet domain, fewer features have been extracted. Wavelet-based feature extraction methods are also powerful tools for condition monitoring in manufacturing processes, as demonstrated by many studies. It is critical to further study feature extraction methods in the wavelet domain for surface roughness prediction in hard turning.

(4) Surface roughness predictive models in most studies are static models, using inputs that are static parameters that

TABLE 3. Arguments of Models for Surface Roughness Prediction in Hard Turning.

Independent factors	Models	Responses	References
work material hardness, cutting parameters	response surface methodology	cutting forces, surface roughness	6, 39, 41
cutting parameters	response surface methodology	surface roughness, cutting force	36
cutting parameters	response surface methodology	surface roughness, flank wear	33
cutting parameters	random forest regression	surface roughness	35
cutting parameters	response surface methodology	surface roughness, cutting force, tool wear	12
cutting parameters	ANN	surface roughness	31, 33
cutting parameters	multiple regression model	surface roughness	38
cutting parameters	ANN	surface roughness, cutting force	37
cutting parameters, tool geometry	ANN	surface roughness, cutting force	21, 48
cutting parameters, tool geometry	response surface methodology	surface roughness, tool wear	47
cutting parameters, tool geometry, and cutting vibration	response surface methodology	surface roughness	60
cutting parameters, tool geometry	ANN	surface roughness, productivity, residual stress	49
cutting parameters, cutting temperature	ANN	surface roughness	56
acoustic signals	GMM	surface roughness	58
cutting parameters, cutting vibration	HMM-SVM	surface roughness	52
cutting parameters, force, sound, vibration	multiple regression	surface roughness	54
cutting parameters, cutting vibration	response surface methodology	surface roughness	53, 55
cutting parameters, force	ANN	surface roughness	24

* Cutting parameters refer to cutting speed (v_c), feed rate (f), and depth of cut (a_p).

assume that the geometric surface profile in hard turning is determined by cutting speed, feed rate, depth of cut, cutting tool geometry, and workpiece hardness. Compared with dynamic factors such as cutting vibrations, cutting temperature and acoustic signals, it is difficult for static parameters to reflect dynamic changes in surface roughness and reveal surface formation mechanisms during hard turning processes. Therefore, surface generation models need to be integrated with more dynamic factors.

(5) Most current studies have concentrated on using information fusion models based on multiple linear regression and artificial neural networks. However, other information fusion models, such as hidden Markov models, Bayesian networks, dynamic Bayesian networks, support vector machines, Dempster-Shafer theory, and their combinations, while being employed to deal with dynamic uncertainty by many researchers, have not been further exploited to provide more effective fusion models of hard turning.

VI. CONCLUSIONS

The current work presents a review of the soft computing techniques used for predicting surface roughness in hard turning processes. In recent years, a great deal of research activity has been conducted and many interesting results have been produced. The main information concerning soft measurement techniques for surface roughness prediction in hard turning can be summarized as follows.

(1) Most data employed for surface roughness prediction in hard turning are static factors such as cutting parameters, tool geometry, and workpiece hardness. Dynamic signals picked up by sensors are also employed to some extent, such as cutting vibrations, cutting forces, audible sounds, and cutting temperatures.

(2) As is evident from the references, the optimization of input factors for surface roughness prediction in hard turning depends mainly on ANOVA analysis. ANOVA investigates how important factors affect the response, allowing the development of polynomial models that include the factors under consideration and their statistical significance.

(3) Generally, most of the features extracted from dynamic signals, such as cutting vibrations, cutting forces, audible sounds, and cutting temperatures, are mainly concentrated in the time domain. However, in the time-frequency domain (the wavelet domain, for example), fewer features have been extracted and developed in current literature.

(4) As was revealed by the referenced papers, most of the predictive models of surface roughness in hard turning are static models and single dynamic models, which mainly take into account some static parameters or a single dynamic signal. However, multi-dynamic factor models, which could be ideally used in fusion with more static and dynamic factors, need to be introduced for a more realistic depiction of surface roughness generation. Furthermore, currently, surface roughness prediction in hard turning is more inclined to multi-objective prediction. In addition to the surface roughness of the workpiece, it also includes cutting force, tool wear, tool life, and so on.

REFERENCES

[1] L. Hao, L. Bian, N. Gebraeel, and J. Shi, "Residual life prediction of multistage manufacturing processes with interaction between tool wear and product quality degradation," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 1211–1224, Apr. 2017.

[2] K. Ding, F. T. S. Chan, X. Zhang, G. Zhou, and F. Zhang, "Defining a digital twin-based cyber-physical production system for autonomous manufacturing in smart shop floors," *Int. J. Prod. Res.*, to be published.

[3] I. Asiltürk and H. Akkuş, "Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method," *Measurement*, vol. 44, no. 9, pp. 1697–1704, 2011.

[4] S. Chinchanikar and S. K. Choudhury, "Machining of hardened steel—Experimental investigations, performance modeling and cooling techniques: A review," *Int. J. Mach. Tools Manuf.*, vol. 89, pp. 95–109, Feb. 2015.
[5] M. Dogra, V. S. Sharma, A. Sachdeva, N. M. Suri, and J. S. Dureja, "Tool wear, chip formation and workpiece surface issues in CBN hard turning: A review," *Int. J. Precision Eng. Manuf.*, vol. 11, no. 2, pp. 341–358, 2010.
[6] H. Aouici, M. A. Yallese, K. Chaoui, T. Mabrouki, and J.-F. Rigal, "Analysis of surface roughness and cutting force components in hard turning with CBN tool: Prediction model and cutting conditions optimization," *Measurement*, vol. 45, no. 3, pp. 344–353, 2012.
[7] J. Wen and X.-W. Chang, "On the KZ reduction," *IEEE Trans. Inf. Theory*, vol. 65, no. 3, pp. 1921–1935, Mar. 2019.
[8] J. Wen, J. Wang, and Q. Zhang, "Nearly optimal bounds for orthogonal least squares," *IEEE Trans. Signal Process.*, vol. 65, no. 20, pp. 5347–5356, Oct. 2017.
[9] A. Panda, A. K. Sahoo, and A. K. Rout, "Investigations on surface quality characteristics with multi-response parametric optimization and correlations," *Alexandria Eng. J.*, vol. 55, no. 2, pp. 1625–1633, 2016.
[10] W. Chen, "Cutting forces and surface finish when machining medium hardness steel using CBN tools," *Int. J. Mach. Tools Manuf.*, vol. 40, no. 3, pp. 455–466, 2000.
[11] J. P. Davim and L. Figueira, "Machinability evaluation in hard turning of cold work tool steel (D2) with ceramic tools using statistical techniques," *Mater. Des.*, vol. 28, no. 4, pp. 1186–1191, 2007.
[12] S. Khamel, N. Ouelaa, and K. Bouacha, "Analysis and prediction of tool wear, surface roughness and cutting forces in hard turning with CBN tool," *J. Mech. Sci. Technol.*, vol. 26, no. 11, pp. 3605–3616, 2012.
[13] Y. B. Guo and D. W. Yen, "Hard turning versus grinding—The effect of process-induced residual stress on rolling contact," *Wear*, vol. 256, nos. 3–4, pp. 393–399, 2004.
[14] S. Saini, I. S. Ahuja, and V. S. Sharma, "Residual stresses, surface roughness, and tool wear in hard turning: A comprehensive review," *Mater. Manuf. Processes*, vol. 27, no. 6, pp. 583–598, 2012.
[15] D. M. Kim, V. Bajpai, B. H. Kim, and H. W. Park, "Finite element modeling of hard turning process via a micro-textured tool," *Int. J. Adv. Manuf. Technol.*, vol. 78, nos. 9–12, pp. 1393–1405, 2015.
[16] M. Sadeghifar, R. Sedaghati, W. Jomaa, and V. Songmene, "Finite element analysis and response surface method for robust multi-performance optimization of radial turning of hard 300M steel," *Int. J. Adv. Manuf. Technol.*, vol. 94, nos. 5–8, pp. 2457–2474, 2018.
[17] D. Li, C. Wu, and Z. Zhang, "Linearized Galerkin FEMs for nonlinear time fractional parabolic problems with non-smooth solutions in time direction," *J. Sci. Comput.*, vol. 80, no. 1, pp. 403–419, 2019.
[18] X. Cheng, J. Duan, and D. Li, "A novel compact ADI scheme for two-dimensional Riesz space fractional nonlinear reaction–diffusion equations," *Appl. Math. Comput.*, vol. 346, no. 1, pp. 452–464, 2019.
[19] G. Bartarya and S. K. Choudhury, "State of the art in hard turning," *Int. J. Mach. Tools Manuf.*, vol. 53, no. 1, pp. 1–14, 2012.
[20] C. L. He, W. J. Zong, and J. J. Zhang, "Influencing factors and theoretical modeling methods of surface roughness in turning process: State-of-the-art," *Int. J. Mach. Tools Manuf.*, vol. 129, pp. 15–26, Jun. 2018.
[21] V. S. Sharma, S. Dhiman, R. Sehgal, and S. K. Sharma, "Estimation of cutting forces and surface roughness for hard turning using neural networks," *J. Intel. Manuf.*, vol. 19, no. 4, pp. 473–483, 2008.
[22] V. D. Patel and A. H. Gandhi, "Analysis and modeling of surface roughness based on cutting parameters and tool nose radius in turning of AISI D2 steel using CBN tool," *Measurement*, vol. 138, pp. 34–38, May 2019.
[23] S. S. Sarnobat and H. K. Raval, "Experimental investigation and analysis of the influence of tool edge geometry and work piece hardness on surface residual stresses, surface roughness and work-hardening in hard turning of AISI D2 steel," *Measurement*, vol. 131, pp. 235–260, Jan. 2019.
[24] T. Özel and Y. Karpat, "Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks," *Int. J. Mach. Tools. Manuf.*, vol. 45, nos. 4–5, pp. 467–479, 2005.
[25] D. I. Suyama, A. E. Diniz, and R. Pederiva, "Tool vibration in internal turning of hardened steel using cBN tool," *Int. J. Adv. Manuf. Technol.*, vol. 88, nos. 9–12, pp. 2485–2495, 2017.
[26] M. Mia and N. R. Dhar, "Optimization of surface roughness and cutting temperature in high-pressure coolant-assisted hard turning using Taguchi method," *Int. J. Adv. Manuf. Technol.*, vol. 88, nos. 1–4, pp. 739–753, 2017.
[27] M. Mia, P. R. Dey, M. S. Hossain, M. T. Arafat, M. Asaduzzaman, M. S. Ullah, and S. M. T. Zobaer, "Taguchi S/N based optimization of machining parameters for surface roughness, tool wear and material removal rate in hard turning under MQL cutting condition," *Measurement*, vol. 122, pp. 380–391, Jul. 2018.
[28] R. Kumar, A. K. Sahoo, R. K. Das, A. Panda, and P. C. Mishra, "Modelling of flank wear, surface roughness and cutting temperature in sustainable hard turning of AISI D2 steel," *Procedia Manuf.*, vol. 20, pp. 406–413, Jan. 2018.
[29] S. R. Das, A. Panda, and D. Dhupal, "Hard turning of AISI 4340 steel using coated carbide insert: Surface roughness, tool wear, chip morphology and cost estimation," *Mater. Today Proc.*, vol. 5, no. 2, pp. 6560–6569, 2018.
[30] S. R. Das, D. Dhupal, and A. Kumar, "Study of surface roughness and flank wear in hard turning of AISI 4140 steel with coated ceramic inserts," *J. Mech. Sci. Technol.*, vol. 29, no. 10, pp. 4329–4340, 2015.
[31] F. J. Pontes, M. B. Silva, J. R. Ferreira, A. P. de Paiva, P. P. Balestrassi, and G. B. Schönhorst, "A DOE based approach for the design of RBF artificial neural networks applied to prediction of surface roughness in AISI 52100 hardened steel turning," *J. Braz. Soc. Mech. Sci. Eng.*, vol. 32, pp. 503–510, Dec. 2010.
[32] D. I. Lalwani, N. K. Mehta, and P. K. Jain, "Experimental investigations of cutting parameters influence on cutting forces and surface roughness in finish hard turning of MDN250 steel," *J. Mater. Process. Technol.*, vol. 206, nos. 1–3, pp. 167–179, 2008.
[33] S. Saini, I. S. Ahuja, and V. S. Sharma, "Influence of cutting parameters on tool wear and surface roughness in hard turning of AISI H11 tool steel using ceramic tools," *Int. J. Precis. Eng. Manuf.*, vol. 13, no. 8, pp. 1295–1302, 2012.
[34] F. J. Pontes, A. P. de Paiva, P. P. Balestrassi, J. R. Ferreira, and M. B. da Silva, "Optimization of radial basis function neural network employed for prediction of surface roughness in hard turning process using Taguchi's orthogonal arrays," *Expert Syst. Appl.*, vol. 39, no. 9, pp. 7776–7787, 2012.
[35] A. Agrawal, S. Goel, W. B. Rashid, and M. Price, "Prediction of surface roughness during hard turning of AISI 4340 steel (69 HRC)," *Appl. Soft Comput.*, vol. 30, pp. 279–286, May 2015.
[36] K. Bouacha, M. A. Yallese, T. Mabrouki, and J.-F. Rigal, "Statistical analysis of surface roughness and cutting forces using response surface methodology in hard turning of AISI 52100 bearing steel with CBN tool," *Int. J. Refractory Met. Hard Mater.*, vol. 28, no. 3, pp. 349–361, 2010.
[37] B. A. Beatrice, E. Kirubakaran, P. R. J. Thangaiah, and K. L. D. Wins, "Surface roughness prediction using artificial neural network in hard turning of AISI H13 steel with minimal cutting fluid application," *Procedia Eng.*, vol. 97, pp. 205–211, Jan. 2014.
[38] B. Fnides, M. A. Yallese, T. Mabrouki, and J.-F. Rigal, "Surface roughness model in turning hardened hot work steel using mixed ceramic tool," *Mechanics*, vol. 77, no. 3, pp. 68–73, 2009.
[39] S. Chinchanikar and S. K. Choudhury, "Effect of work material hardness and cutting parameters on performance of coated carbide tool when turning hardened steel: An optimization approach," *Measurement*, vol. 46, no. 4, pp. 1572–1584, 2013.
[40] M. Mia and N. R. Dhar, "Prediction of surface roughness in hard turning under high pressure coolant using artificial neural network," *Measurement*, vol. 92, pp. 464–474, Oct. 2016.
[41] M. W. Azizi, S. Belhadi, M. A. Yallese, T. Mabrouki, and J.-F. Rigal, "Surface roughness and cutting forces modeling for optimization of machining condition in finish hard turning of AISI 52100 steel," *J. Mech. Sci. Technol.*, vol. 26, no. 12, pp. 4105–4114, 2012.
[42] S. Z. Chavoshi and M. Tajdari, "Surface roughness modelling in hard turning operation of AISI 4140 using CBN cutting tool," *Int. J. Mater. Form.*, vol. 3, no. 4, pp. 233–239, 2010.
[43] D. Singh and P. V. Rao, "A surface roughness prediction model for hard turning process," *Int. J. Adv. Manuf. Technol.*, vol. 32, nos. 11–12, pp. 1115–1124, 2007.
[44] T. Özel, T.-K. Hsu, and E. Zeren, "Effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and forces in finish turning of hardened AISI H13 steel," *Int. J. Adv. Manuf. Technol.*, vol. 25, nos. 3–4, pp. 262–269, 2005.
[45] L. Tang, C. Gao, J. Huang, H. Shen, and X. Lin, "Experimental investigation of surface integrity in finish dry hard turning of hardened tool steel at different hardness levels," *Int. J. Adv. Manuf. Technol.*, vol. 77, nos. 9–12, pp. 1655–1669, 2015.

[46] H. Yurtkuran, M. E. Korkmaz, and M. Günay, "Modelling and optimization of the surface roughness in high speed hard turning with coated and uncoated CBN insert," *Gazi Univ. J. Sci.*, vol. 29, no. 4, pp. 987–995, 2016.
[47] D. Manivel and R. Gandhinathan, "Optimization of surface roughness and tool wear in hard turning of austempered ductile iron (grade 3) using Taguchi method," *Measurement*, vol. 93, pp. 108–116, Nov. 2016.
[48] I. Meddour, M. A. Yallese, H. Bensouilah, A. Khellaf, and M. Elbah, "Prediction of surface roughness and cutting forces using RSM, ANN, and NSGA-II in finish turning of AISI 4140 hardened steel with mixed ceramic tool," *Int. J. Adv. Manuf. Technol.*, vol. 97, nos. 5–8, pp. 1931–1949, 2018.
[49] Y. Karpat and T. Özel, "Multi-objective optimization for turning processes using neural network modeling and dynamic-neighborhood particle swarm optimization," *Int. J. Adv. Manuf. Technol.*, vol. 35, nos. 3–4, pp. 234–247, 2007.
[50] R. Ferreira, D. Carou, C. H. Lauro, and J. P. Davim, "Surface roughness investigation in the hard turning of steel using ceramic tools," *Mater. Manuf. Process.*, vol. 31, no. 5, pp. 648–652, 2016.
[51] S. Arfaoui, F. Zemzemi, M. Dakhli, and Z. Tourki, "Optimization of hard turning process parameters using the response surface methodology and finite element simulations," *Int. J. Adv. Manuf. Technol.*, vol. 103, nos. 1–4, pp. 1279–1290, Jul. 2019.
[52] K. He, Q. Xu, and M. Jia, "Modeling and predicting surface roughness in hard turning using a Bayesian inference-based HMM-SVM model," *IEEE Trans. Autom. Sci. Eng.*, vol. 12, no. 3, pp. 1092–1103, Jul. 2015.
[53] Z. Hessainia, A. Belbah, M. A. Yallese, T. Mabrouki, and J.-F. Rigal, "On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations," *Measurement*, vol. 46, no. 5, pp. 1671–1681, 2013.
[54] Y. Deshpande, A. Andhare, and N. K. Sahu, "Estimation of surface roughness using cutting parameters, force, sound, and vibration in turning of Inconel 718," *J. Brazilian Soc. Mech. Sci.*, vol. 39, no. 12, pp. 5087–5096, 2017.
[55] S. Delijaicov, F. Leonardi, E. C. Bordinassi, and G. F. Batalha, "Improved model to predict machined surface roughness based on the cutting vibrations signal during hard turning," *Arch. Mater. Sci. Eng.*, vol. 45, no. 2, pp. 102–107, 2010.
[56] J. G. A. Arulraj, K. L. D. Wins, and A. Raj, "Artificial neural network assisted sensor fusion model for predicting surface roughness during hard turning of H13 steel with minimal cutting fluid application," *Procedia Mater. Sci.*, vol. 5, pp. 2338–2346, Jan. 2014.
[57] W. Grzesik, "Prediction of surface topography in precision hard machining based on modelling of the generation mechanisms resulting from a variable feed rate," *Int. J. Adv. Manuf. Technol.*, vol. 94, nos. 9–12, pp. 4115–4123, 2018.
[58] E. P. Frigieri, P. H. S. Campos, A. P. Paiva, P. P. Balestrassi, J. R. Ferreira, and C. A. Ynoguti, "A mel-frequency cepstral coefficient-based approach for surface roughness diagnosis in hard turning using acoustic signals and Gaussian mixture models," *Appl. Acoust.*, vol. 113, pp. 230–237, Dec. 2016.
[59] M. Mia, M. Morshed, and M. Kharshiduzzaman, "Prediction and optimization of surface roughness in minimum quantity coolant lubrication applied turning of high hardness steel," *Meas.*, vol. 118, pp. 43–51, Dec. 2018.
[60] I. Meddour, M. A. Yallese, and H. Aouici, "Investigation and modeling of surface roughness of hard turned AISI 52100 steel: Tool vibration consideration," in *Proc. Multiphys. Modeling Simulation Syst. Design Conf.*, Sousse, Tunisia, Dec. 2014, pp. 419–431.
[61] G. Bartarya and S. K. Choudhury, "Effect of cutting parameters on cutting force and surface roughness during finish hard turning AISI52100 grade steel," *Procedia CIrP*, vol. 1, pp. 651–656, Jan. 2012.
[62] İ. Asiltürk, "Predicting surface roughness of hardened AISI 1040 based on cutting parameters using neural networks and multiple regression," *Int. J. Adv. Manuf. Technol.*, vol. 63, nos. 1–4, pp. 249–257, 2012.
[63] J. V. Abellan-Nebot and F. R. Subirón, "A review of machining monitoring systems based on artificial intelligence process models," *Int. J. Adv. Manuf. Technol.*, vol. 47, nos. 1–4, pp. 237–257, 2010.
[64] J. J. Clark and A. L. Yuille, *Data Fusion for Sensory Information Processing Systems*. New York, NY, USA: Springer, 2013.
[65] K. He, Z. Zhao, M. Jia, and C. Liu, "Dynamic Bayesian network-based approach by integrating sensor deployment for machining process monitoring," *IEEE Access*, vol. 6, pp. 33362–33375, 2018.

KANG HE received the B.S. degree in mechanical engineering from the Henan University of Science and Technology, Luoyang, China, in 2003, the M.S. degree in mechanical engineering from Nanchang University, Nanchang, China, in 2010, and the Ph.D. degree in mechanical engineering from Southeast University, Nanjing, China, in 2015.

From 2004 to 2007, he served as a Green Belt for the machining of automobile engine in Engine Plant of Jiangling Motors Corporation, Ltd. (the joint ventures with Ford), Nanchang. From 2011 to 2012, he was responsible for the engine assembly as a Principal Engineer in Engine Plant of Jiangling Motors Corporation, Ltd. During this period, he was responsible for the completion of the Φ14 twist drill performance improvement projects, Φ28 oil pump orifice reamer quality improvement projects, and annual savings of processing costs 120 000 yuan. He is currently a Key Member of the Mine Machinery and Electronic Engineering Research Center and a Public Bidding Evaluation Expert with Suzhou University. He has published more than ten academic papers, including the IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, *Journal of Mechanical Engineering* (in Chinese), and *The International Journal of Advanced Manufacturing Technology*. His current research interests include fault diagnosis, manufacturing process condition monitoring, and quality assurance.

Dr. He also serves as a Reviewer for several journals.

MENGDI GAO was born in 1991. She received the Ph.D. degree in mechanical and electronic engineering from the Hefei University of Technology, Hefei, China, in 2017.

She is currently the Head of the 3D Printing Laboratory, School of Mechanical and Electrical Engineering, Suzhou University. She has published more than ten academic papers, including the *Journal of Dynamic Systems, Measurement, and Control* (ASME), IJAMT, and *Energy Conversion and Management*. Her current research interests include the green design and manufacturing and 3D printing technology. Her current research interests include manufacturing process condition monitoring, and low-carbon energy-saving optimization theory and method for stamping forming. She has been invited to be a Reviewer for several SCI/EI journals.

ZHUANZHE ZHAO received the B.S. degree in mechanical manufacture and automation and the M.S. degree in measuring and testing technologies and instruments from the Henan University of Science and Technology, Luoyang, China, in 2002 and 2005, respectively, and the Ph.D. degree in mechanical manufacture and automation from Southeast University, Nanjing, China, in 2016.

He is currently an Associate Professor with the school of Mechanical and Automotive Engineering, Anhui Polytechnic University. He is also a Key Member of the Key Laboratory of Advanced Numerical Control and Servo Drive Technology of Anhui Province. He has published more than ten academic papers, including *Neural Computing and Applications* and *Natural Computing*. His current research interests include the intelligent computing, mechanical condition monitoring, and fault diagnosis. He has been invited to be a Reviewer for several SCI/EI journals.