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An Improved Rapid Power and Energy Prediction Method of Drilling Process for Sustainable Manufacturing

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ABSTRACT Energy modeling and energy-saving have attracted extensive attention in the manufacturing industry. Energy monitoring, modeling, and management issues of grinding, milling, and turning processes have been widely studied. However, special research on drilling power and energy consumption needs to be strengthened. The existing drilling power and energy models have the problems of high computational complexity and low practicability. To address this issue, an improved rapid power and energy prediction method of drilling process is proposed in this study. The motivation of the proposed method is to reduce the computational complexity and improve the practicability without losing the predictive accuracy for drilling power and energy. To verify the effectiveness of the proposed method, experimental and case studies were carried out. The results show that the number of formulas, variables, coefficients of the proposed method are all decreased significantly, therefore, the computational complexity is greatly reduced. Meanwhile, power predictive accuracy is improved by 1.91% instead of decreasing compared with the traditional method. Consequently, the simpler model, lower computational complexity, and higher power accuracy make the proposed method more practical in manufacturing industry.

INDEX TERMS Drilling processes, power prediction, energy prediction, sustainable manufacturing.

I. INTRODUCTION

Sustainable manufacturing is of great significance in manufacturing, mechanical engineering, energy science, environmental science and other fields [1]. The purpose of sustainable manufacturing is to reduce energy and resource consumption while manufacturing products efficiently [2], and bring economical and environmental benefits to the manufacturing industry and human society [1]. Reducing energy consumption in machining processes has been viewed as an effective way to promote sustainable manufacturing [3]. Consequently, energy saving and sustainability improvement have gradually become the research focus of manufacturing [4], [5]. The energy consumption of manufacturing activities accounts for about ninety percent of the total energy consumption of industrial sectors [6]. However, the energy utilization efficiency in manufacturing is not high which indicates that the potential of energy-saving in the manufacturing industry is remarkable [7]. More specifically, the research of the International Energy Agency (IEA) showed that

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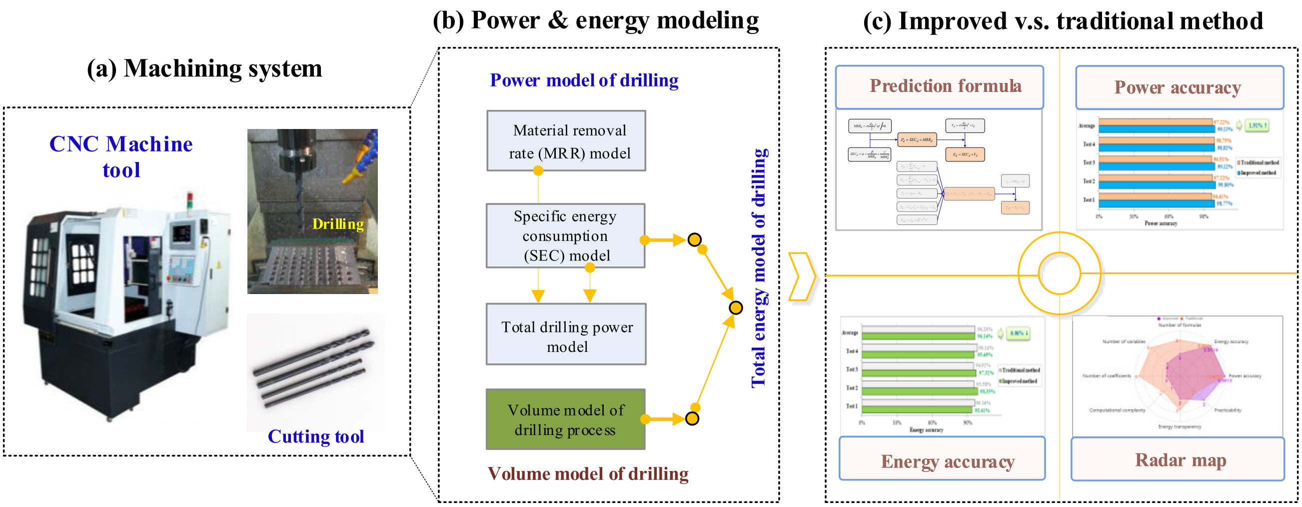

FIGURE 1. Framework of the proposed method: (a) Machining system; (b) Power & energy modeling; (c) Improved vs. traditional method.

energy-saving potential of the manufacturing industry is 25EJ∼37EJ, which accounts for 18%∼26% of the total energy consumption in the industry [8]. As one of the most commonly-used processing technologies in manufacturing, the machining process plays a vital role in energy conservation and emission reduction for manufacturing [9]. Moreover, milling processes, turning processes, grinding processes, and drilling processes are typical and commonly-used machining processes in manufacturing industry [10]. A growing number of researchers are focusing on energy management of milling [11], turning [12], and grinding processes [13]. However, special research on drilling power and energy consumption needs to be strengthened. One type of the existing drilling power and energy models is based on the drilling force or drilling torque models [14], [15]. Due to the high computational complexity of drilling force and torque, the computational complexity of the above drilling power and energy models is very high. The other type of drilling power model is composed of sub-power models, such as standby operating power model, spindle-rotating power model, feeding power model, and so on [16]. Because of the accumulation of prediction errors of each sub-power model, the accuracy of total drilling power prediction needs to be further improved. To fill these gaps, an improved rapid power and energy prediction approach of drilling is proposed in this research. The contribution of this research is that the computational complexity will be reduced while the drilling power prediction accuracy is improved, which makes the proposed method more practical in the manufacturing industry. The method can help managers quickly evaluate the energy consumption of drilling schemes, and provide decision support for energy-saving scheme selection. In addition, the outcomes of this study can provide model and data support for energy optimization of drilling.

Figure 1 demonstrates the framework of the method in this article. First, the energy consumption characteristics of drilling machining system are analyzed (see Fig.1a). Then, an improved rapid power and energy prediction models are proposed based on material removal rate and specific energy consumption (see Fig.1b). Finally, as shown in Fig.1c, the improved rapid power and energy prediction method is compared with the traditional method from the following aspects: computational complexity of prediction model, power accuracy, energy accuracy, etc.

The rest of this article is organized as follows. The literature review is given in Section II. Then, section III demonstrates the proposed method, including the improved rapid power and energy prediction method, and the comparison with the traditional method. Section IV conducts the experimental study to obtain the coefficient values in the proposed method. In Section V, a case study is conducted to verify the proposed method of the paper. The results and discussion of the research are given in Section VI. In Section VII, conclusions are summarized and future work is discussed.

II. LITERATURE REVIEW

More and more literatures have studied the energy-saving and sustainability improvement of manufacturing and remanufacturing processes [17]–[24]. Especially for the manufacturing process, a considerable amount of researches focus on energy monitoring, modeling, and energy-saving methods [25]–[30]. Various previous studies indicate that the energy efficiency of machining is not high enough [31]–[33], which is generally lower than thirty percent [34], [35]. Hence, the potential of energy-saving for machining process is very considerable [36]. Consequently, on the one hand, energy management of machining and the improvement of energy efficiency have a good theoretical research value. On the other hand, it also has good practical significance [37]. In recent years, energy monitoring, modeling, and efficiency improvement of different types of machining processes have been extensively researched. For instance, Asrai et al. [38] proposed a novel mechanistic model of energy consumption for milling processes. Xiao *et al.* [39] proposed a knowledge driven optimization method for energy-efficient turning, which had a high potential for improving energy efficiency of the turning process. Sinha *et al.* [40] attempted to establish a composition model of specific grinding energy for the grinding process. Likewise, drilling is also a typical and broadly employed machining process in the manufacturing industry [41]. However, its energy modeling and energy efficiency enhancement has not been well-studied [16].

Existing energy monitoring and energy modeling related researches of drilling primarily focus on unconventional processes, including micro-drilling process, electrical discharge machining (EDM)-drilling, and laser drilling. Franco *et al.* [42] analyzed energy as a vital performance indicator for micro-drilling processes. Yoon *et al.* [43] established new models and methods to better manage the manufacturing energy and manufacturing costs for the micro-drilling. Pellegrini and Ravasio [44] developed a sustainability index with energy consumption as one of the main indexes, which was applied to the micro-EDM drilling process. Yang *et al.* [45] introduced a modeling method for the energy consumption of EDM drilling process based on material removal rate. Cao *et al.* [46] performed a monopulse EDM ablation drilling experiment on Ti-6Al-4V titanium alloy and the results show that the machining efficiency of EDM drilling is low. Pastras *et al.* [47] developed an analytical and numerical approach of evaporation pulsed laser drilling process and established the energy efficiency of the pulsed laser drilling process dependent on the laser source parameters. Nguyen *et al.* [48] carried out optimization of electrical discharge drilling process by comprehensively considering three objectives, including energy efficiency, product quality, and drilling productivity.

At present, studies regarding the energy modeling of conventional drilling are insufficient. The research on the cutting force of drilling can provide a basis for the power or energy modeling of drilling. Dehghan *et al.* [49] measured and analyzed the temperature, thrust force, and torque of drilling. Li *et al.* [50] carried out research about drilling force, including identified relevant parameters of drilling force, established drilling force model, and verified the proposed model. Glaa *et al.* [51] developed a numerical model for predicting cutting forces and torque of the drilling process for titanium alloy Ti6Al4V and verified the effectiveness of the model by experimental drilling tests on a vertical machine. Naisson *et al.* [52] established an analytical model of thrust force and torque of the drilling process, and experimental studies were conducted in various cutting conditions to validate the modeling approach. However, the modeling of drilling power or energy based on cutting force is generally complex and difficult to calculate. Meral *et al.* [53] indicated that the parameters such as drilling parameters, workpiece material, and cutting tool of drilling, affect performance indicators such as surface roughness, drilling force, drilling energy, etc. Zhang *et al.* [54] conducted multi-objective parameter optimization of peck deep-hole drilling process by considering both the energy consumption and processing time. in addition, experimental studies were carried out to verify the effectiveness of the proposed method. In our previous studies, we proposed a drilling power model, which decomposed into the power of material-drilling, cutting-fluid-spraying, spindle-rotating, feeding, and standby operating [16]. The prediction accuracy of the above power prediction model of drilling is high. However, its computational complexity is also very high and the industrial practicability needs to be improved. To address this issue, an improved rapid power and energy prediction approach of drilling is proposed in this research. The purpose of the proposed method is to reduce the computational complexity and improve the practicability without losing the prediction accuracy of drilling power or energy.

III. METHODOLOGY

The rapid modeling procedure of drilling power and energy is shown in Fig. 2. Total drilling power is calculated with material removal rate (MRR) and specific energy consumption (SEC). MRR represents the material volume of tool cutting

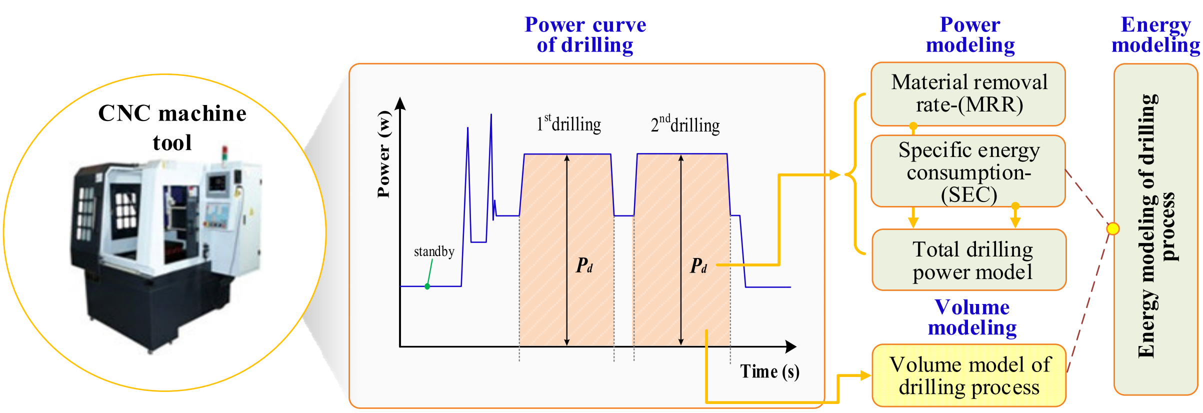

FIGURE 2. Rapid power and energy modeling procedure of drilling.

within unit time (one second or one minute). While SEC indicates machine tool energy consumption to remove unit volume of material (it can be one mm^3 or one mm^3) [32]. Then, total energy consumption of drilling is obtained by multiplying SEC by the volume of material removed during the drilling process.

A. IMPROVED RAPID POWER AND ENERGY PREDICTION METHOD OF DRILLING

1) RAPID POWER PREDICTION MODEL OF DRILLING

As mentioned above, the total power of drilling can be calculated with MRR and SEC. Therefore, it is necessary to model MRR firstly to establish the total drilling power mode. According to the definition, MRR can be calculated as:

$$MRR_d = \frac{V_d}{t_d} \tag{1}$$

where MRR_d stands for the material removal rate of drilling process, mm^3/s; V_d represents the volume of material removed by cutting tool during drilling, mm^3; t_d is the material drilling duration, s.

According to the characteristics of drilling movement, the material volume of the cutting tool (V_d) can further be expressed as:

$$V_d = \pi(\frac{d_T}{2})^2 \times l_d \tag{2}$$

where V_d indicates the volume of material removed by the cutting tool, mm^3; d_T is cutting tool diameter, mm; l_d stands for the depth of drilling, mm.

For the drilling process, the material drilling duration (t_d) is expressed as:

$$t_d = \frac{l_d}{v_d} = \frac{l_d}{nf/60} \tag{3}$$

where t_d is the material drilling duration, s; l_d is the depth of drilling, mm; v_d is the feeding velocity of drilling, mm/min; f represents the feed rate of drilling, mm/r; n means the spindle rotating speed, r/min.

By substituting Eq.(2) and Eq. (3) into Eq. (1), the material removal rate can further be expressed as:

$$MRR_d = \pi(\frac{d_T}{2})^2 nf/60 \tag{4}$$

where MRR_d indicates the material removal rate of drilling process, mm^3/s; d_T is the diameter of cutting tool, mm; f indicates the feed rate of cutting tool, mm/r; n represents the spindle rotating speed, r/min.

Similarly, establishing the SEC model is another important basis for obtaining the total drilling power mode. In this article, SEC of drilling indicates energy consumed by machine tool for drilling one mm^3 of material, the unit of SEC is J/mm^3. Based on our previous experimental research and data analysis of the drilling process, the SEC of the drilling process can be expressed as [55]:

$$SEC_d = \alpha + \frac{\beta}{MRR_d} + \frac{\gamma}{MRR_d^2} \tag{5}$$

where SEC_d represents the specific energy consumption of drilling process, J/mm^3; α is a constant value; MRR_d indicates the material removal rate of drilling process, mm^3/s; β is a coefficient of $\frac{1}{MRR_d}$; γ represents a coefficient of $\frac{1}{MRR_d^2}$. The values of the constant α and coefficient β, γ can be obtained through curve fitting with experimental data.

With the established models of MRR and SEC of the drilling process, the total drilling power can be obtained and the corresponding formula is written as:

$$P_d = SEC_d \times MRR_d \tag{6}$$

where P_d indicates the total power of drilling process, W; SEC_d is the specific energy consumption of drilling, J/mm^3; MRR_d represents the material removal rate, mm^3/s.

By substituting Eq.(5) into Eq. (6), the total drilling power prediction model of drilling can further be written as:

$$P_d = \alpha MRR_d + \beta + \frac{\gamma}{MRR_d} \tag{7}$$

where P_d indicates the total power of drilling process, W; MRR_d represents the material removal rate, mm^3/s; α, β and γ are the coefficients of the formula.

2) RAPID ENERGY PREDICTION MODEL OF DRILLING

In section 3.1.1, the model of specific energy consumption (SEC) of drilling process (Eq.5) and the model of the volume of material removed by cutting tool (Eq.2) have been established. Therefore, the energy prediction model of drilling can be built rapidly and conveniently.

$$E_d = SEC_d \times V_d \tag{8}$$

where E_d indicates the energy consumption of drilling, J; SEC_d is the specific energy consumption for drilling, J/mm^3; V_d represents the volume of material removed by cutting tool, mm^3.

By substituting Eq.(5) and Eq. (2) into Eq. (8), the energy prediction model of drilling can further be expressed as:

$$E_d = (\alpha + \frac{\beta}{MRR_d} + \frac{\gamma}{MRR_d^2}) \times \pi(\frac{d_T}{2})^2 \times l_d \tag{9}$$

where α is a constant value; MRR_d indicates the material removal rate of drilling, mm^3/s; β is the coefficient of $\frac{1}{MRR_d}$; γ represents the coefficient of $\frac{1}{MRR_d^2}$; d_T stands for the cutting tool diameter, mm; l_d indicates the depth of drilling, mm.

B. IMPROVED METHOD V.S. TRADITIONAL METHOD

As depicted in Fig.3a and Fig.3b, the improved rapid prediction method is compared with traditional method. In the traditonal method, the total drilling power is divided into five parts: (1) standby-operating power (P_{so}), (2) cutting-fluid-spraying power (P_{cfs}), (3) spindle-rotating power (P_{sr}), (4) z-axis-feeding power (P_{zf}), and (5) material-drilling power (P_{md}). The total drilling power model is established

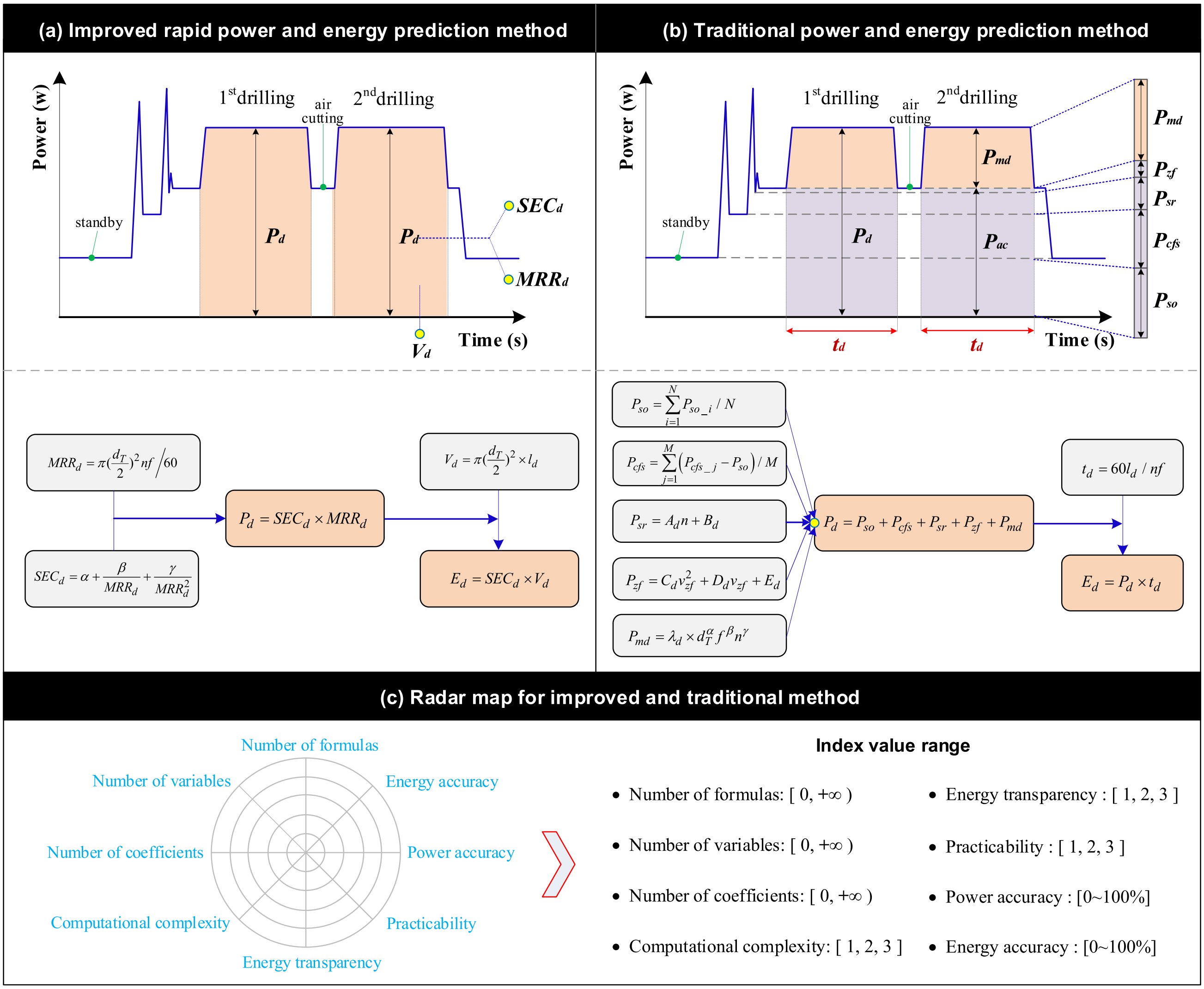

FIGURE 3. Improved rapid prediction method compared with traditional method: (a) Improved prediction method; (b) Traditional prediction method; (c) Radar map for improved and traditional method.

through building the power model of the above five parts. Then, the drilling energy is obtained by multiplying the drilling power by cutting duration [56].

As shown in the radar map of Fig.3c, the comparison between the improved and traditional method is conducted from eight aspects: number of formulas, number of variables, number of coefficients, computational complexity, energy transparency, practicability, power accuracy, and energy accuracy. The specific meanings and index value ranges of the above eight aspects are listed in Table 1.

For the index of number of formulas, the index value can be an integer value range from zero to positive infinity. The smaller the number of formulas is, to some extent, reflects the simpler the calculation process will be. When it comes to the index of number of variables, the index value can also be an integer value range from zero to positive infinity. Moreover, the smaller number of variables indicates a smaller input workload of the calculation process. Similarly, a smaller number of coefficients represents a better availability of the formula. Computational complexity can be divided into three levels: small (the value is '1'), general (the value is '2'), and large (the value is '3'). It is obvious that the smaller the computational complexity, the better. Energy transparency is also divided into three levels: poor (the value is '1'); general (the value is '2'); good (the value is '3'). The higher the energy transparency, the better. The practicability is divided into three levels: poor (the value is '1'); general (the value is '2'); good (the value is '3'). The higher the practicability, the better. When it comes to the power accuracy and the energy accuracy, the closer predictive value to 100% demonstrates a better model was established.

IV. EXPERIMENTAL STUDY

A. EXPERIMENTAL INFORMATION

To obtain the values of the constant α and coefficients β and γ in Eq.(5), an experimental study was performed on

TABLE 1. Specific meanings and index value ranges of the eight comparison aspects.

No.	Index	Meaning	Value range	Target
1	Number of formulas	the number of formulas involved in the calculation of drilling power and drilling energy	[0, +∞)	↓
2	Number of variables	the number of variables involved in the calculation of drilling power and drilling energy	[0, +∞)	↓
3	Number of coefficients	the number of coefficients to be fitted in the calculation formulas of drilling power and energy	[0, +∞)	↓
4	Computational complexity	the complexity of calculation to acquire the drilling power and energy	[1,2,3]	↓
5	Energy transparency	the degree of availability of sub-power and the degree of support for energy visualization	[1,2,3]	↑
6	Practicability	the practicality of the method applied in actual production environment	[1,2,3]	↑
7	Power accuracy	the predictive accuracy of total drilling power	[0-100%]	↑
8	Energy accuracy.	the predictive accuracy of total drilling energy	[0-100%]	↑

Note: ↓ indicates the smaller the better, ↑ indicates the bigger the better.

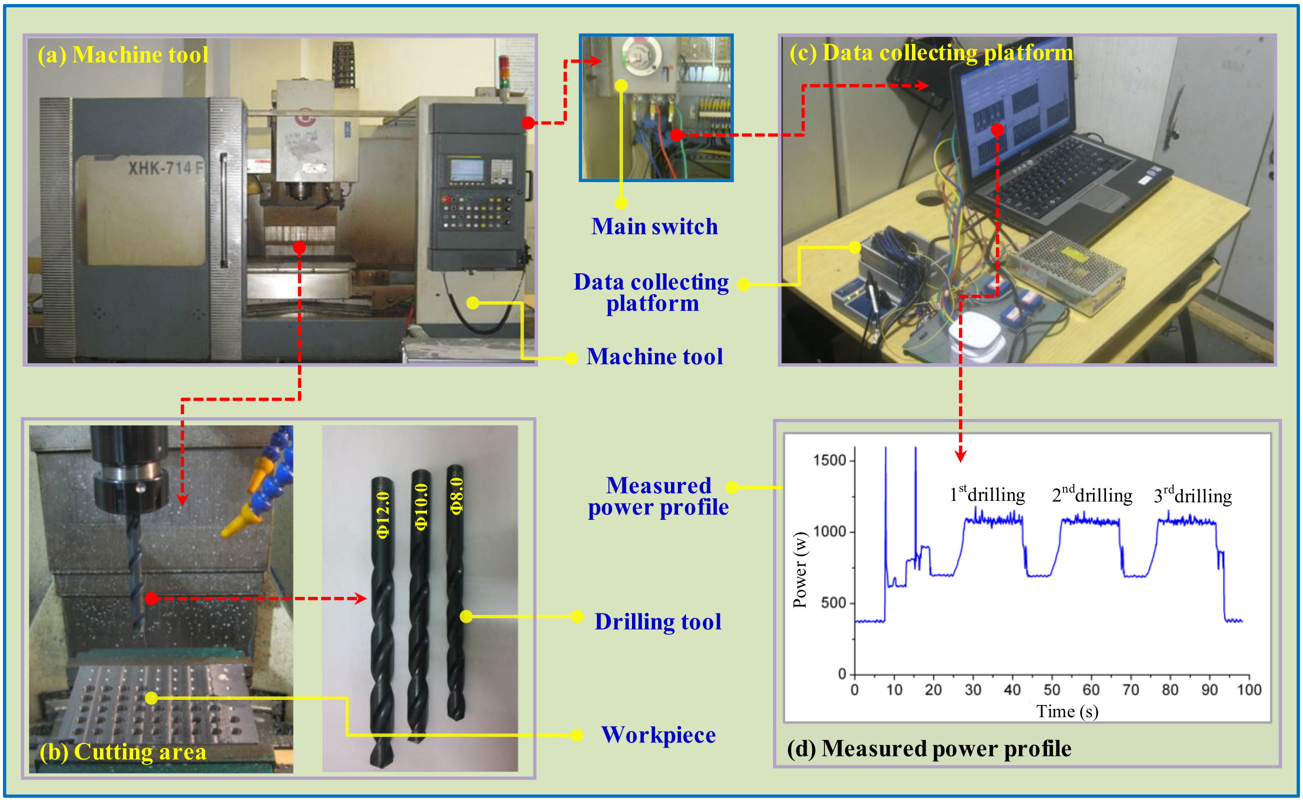

FIGURE 4. Drilling experimental related information: (a) Machine tool; (b) Cutting area; (c) data collecting platform; (d) Measured power profile.

a CNC machine tool (XHK-714F machining center, see Fig.4a). For the studied machine, the maximum feed speeds of X-/Y-/Z- axes are 12/12/10 m/min and the rated-power of the spindle motor is 7500W. The drilling tool used for the experiments was parallel shank twist drill. The diameters of the drilling tools were 8mm, 10mm and 12mm according to the experimental design, and the drill point angle of all drilling tools was 118°, as shown in Fig.4b. The workpiece material used for drilling experiments is AISI 1045 steel. The dimension of the workpiece is 150 × 150 × 30 mm. According to the recommended parameter values for cutting tool, machine tool performance, and manual of machining process [57], [58], values of drilling parameters for experimental study were selected, as listed in Tab. 2.

The drilling experiments were designed by orthogonal array, during drilling experiments, values of drilling power

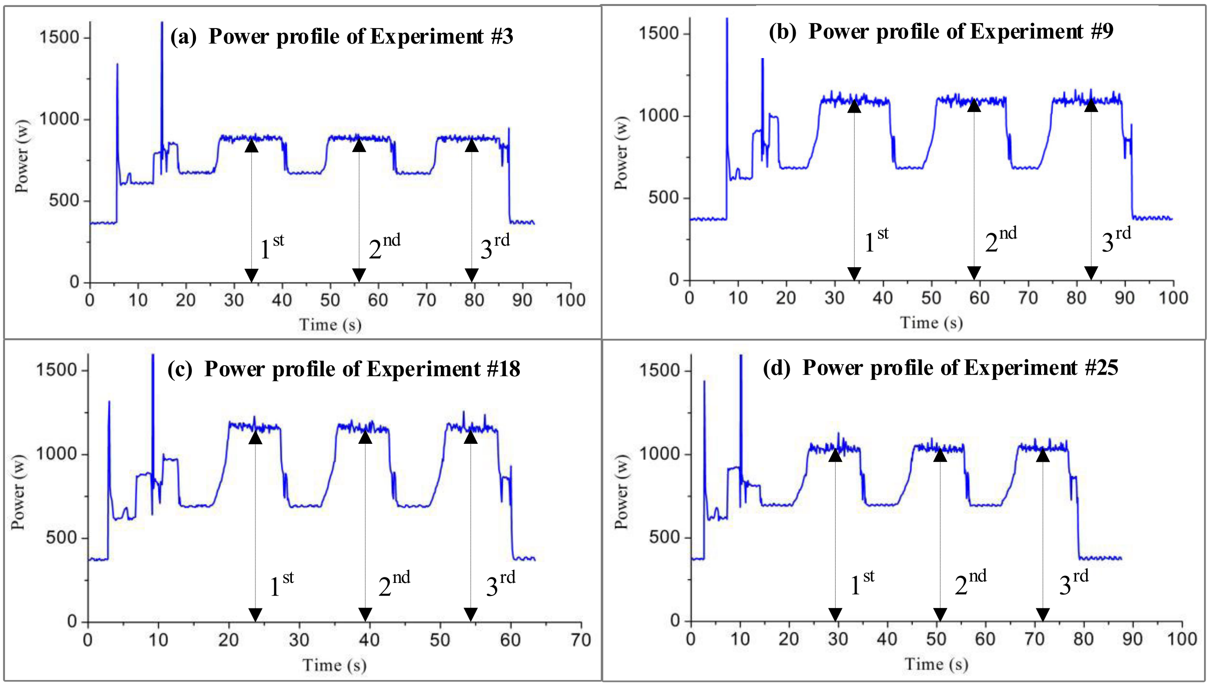

FIGURE 5. Acquired power profiles of drilling experiments: (a) Power profile of experiment #3; (b) Power profile of experiment #9; (c) Power profile of experiment #18; (d) Power profile of experiment #25.

TABLE 2. Designed levels of drilling parameters for orthogonal experiments.

Parameters	Diameter of drilling tool (mm)	Feed rate (mm/r)	Rotating speed of spindle (r/min)
Level 1	8.0	450	0.06
Level 2	10.0	550	0.08
Level 3	12.0	650	0.10

and drilling energy were gathered with an energy acquisition platform (see Fig.4c), which was built up by our research group. The sampling frequency of the platform was set to 0.1 seconds. For detailed information on the energy acquisition platform, please refer to literature [16]. The measure power profile for the experimental study is shown in Fig.4d.

According to the L27 (3^{13}) orthogonal table, 27 groups of drilling experiments were performed on the researched machining center (XHK-714F). For one group of drilling experiment, the drilling processes were repeated three times with the same drilling parameters. The measured total drilling power for the experiment was obtained by averaging the three measurements. The acquired power curves of four drilling experiments (experiment #3, #9, #18, #25) are shown in Figure 5.

B. PARAMETER ACQUISITION

Based on the designed parameter levers and the L27 (3^{13}) orthogonal table, the specific drilling parameter values of 27 groups of experiments are listed in the second to fourth columns of Table 3. According to formula (4), the material removal rate can be calculated as: $MRR_d = \pi(\frac{d_T}{2})^2 nf/60$. Combined with the information in Table 3, the MRR can also be expressed as: $MRR_d = \pi(\frac{②}{2})^2 \times ④ \times ③/60$. For the experiment#1, the used drilling parameters are $d_T = 8.0$ mm, $f = 0.06$ mm/r, $n = 450$ r/min. Then, the material removal rate of this experiment can be obtained: $MRR_d = \pi(\frac{d_T}{2})^2 nf/60 = \pi(\frac{8}{2})^2 \times 450 \times 0.06/60 = 22.619$ mm^3/s. Similarly, material removal rates of all 27 groups of experiments can be obtained, as listed in column ⑤ of Table 3.

As mentioned above, during the drilling processes of the experiments, drilling power and drilling energy values were gathered with the data acquisition platform in Figure 8. Moreover, the measured total drilling power values of 27 groups of experiments are shown in column ⑥ of Tab. 3. According to Equation (6), the total drilling power is computed as: $P_d = SEC_d \times MRR_d$. Moreover, the SEC of drilling can be calculated as: $SEC_d = P_d/MRR_d$. Combined with the information in Table 3, the SEC can also be calculated as: $SEC_d = ⑥/⑤$. For the experiment#1, the measured total drilling power $P_d = 803.692$ W, material removal rate $MRR_d = 22.619$ mm^3/s. Therefore, the SEC_d of this experiment can be calculated: $SEC_d = P_d/MRR_d = 803.692/22.619 = 35.531$ J/mm^3. By using the same method, SEC_d values of all 27 groups of experiments can be obtained, as listed in column ⑦ of Table 3.

According to formula (5), the SEC_d can be expressed as a polynomial function of MRR_d: $SEC_d = \alpha + \frac{\beta}{MRR_d} + \frac{\gamma}{MRR_d^2}$. With the obtained values of MRR_d and SEC_d in Table 3,

TABLE 3. Orthogonal experiment sequence and MRR, measured total drilling power and SEC values of each experiment.

① Exp. No.	② d_T Diameter of cutting tool (mm)	③ f Feed rate of cutting tool (mm/r)	④ n Spindle rotating speed (r/min)	⑤ MRR_d Material removal rate (mm^3/s)	⑥ P_d Measured total drilling power (W)	⑦ SEC_d Specific energy consumption (J/mm^3))
1	8.0	0.06	450	22.619	803.692	35.531
2	8.0	0.08	450	30.159	846.185	28.057
3	8.0	0.10	450	37.699	884.830	23.471
4	10.0	0.06	450	35.343	890.365	25.192
5	10.0	0.08	450	47.124	944.013	20.033
6	10.0	0.10	450	58.905	999.564	16.969
7	12.0	0.06	450	50.894	950.238	18.671
8	12.0	0.08	450	67.858	1023.253	15.079
9	12.0	0.10	450	84.823	1094.179	12.900
10	8.0	0.06	550	27.646	835.682	30.228
11	8.0	0.08	550	36.861	875.295	23.746
12	8.0	0.10	550	46.077	918.151	19.927
13	10.0	0.06	550	43.197	923.618	21.382
14	10.0	0.08	550	57.596	987.516	17.146
15	10.0	0.10	550	71.995	1045.487	14.522
16	12.0	0.06	550	62.204	997.313	16.033
17	12.0	0.08	550	82.938	1079.229	13.012
18	12.0	0.10	550	103.672	1160.719	11.196
19	8.0	0.06	650	32.673	855.518	26.185
20	8.0	0.08	650	43.563	906.964	20.819
21	8.0	0.10	650	54.454	952.143	17.485
22	10.0	0.06	650	51.051	954.583	18.699
23	10.0	0.08	650	68.068	1023.460	15.036
24	10.0	0.10	650	85.085	1089.614	12.806
25	12.0	0.06	650	73.513	1037.892	14.118
26	12.0	0.08	650	98.018	1129.292	11.521
27	12.0	0.10	650	122.522	1230.180	10.040

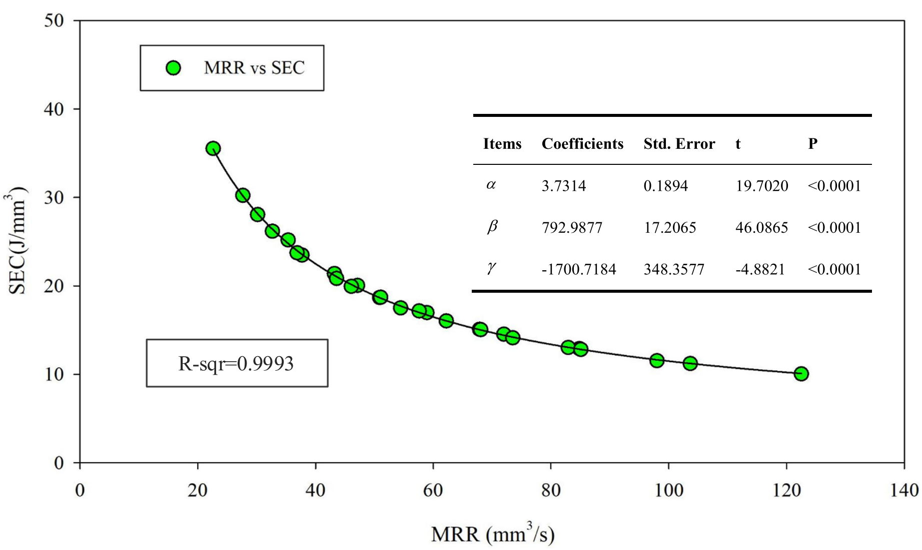

FIGURE 6. Nonlinear regression results of specific energy consumption.

the nonlinear regression model was developed according to Eq. 5 by using SigmaPlot 14.0® Software. The nonlinear regression results for specific energy consumption of the researched machine tool are depicted in Figure 6.

According to the nonlinear regression results in Figure 6, the values of the constant α and coefficients β, γ are obtained as follows: $\alpha = 3.7314$, and $\gamma = -1700.7184$. Consequently, the specific energy consumption model of the machining tool (XHK-714F machining center) is expressed as:

$$SEC_d = 3.731 + \frac{792.988}{MRR_d} - \frac{1700.718}{MRR_d^2} \tag{10}$$

The nonlinear regression results show that the R-Square value is 0.9993 and is very close to "1", which demonstrates that the above established SEC model can well describe the SEC under different material removal rates.

V. CASE STUDY

To verify the proposed improved method, a case study was further performed on a machining center (XHK-714F). The material of workpiece is AISI 1045 steel and the drilling tool is parallel shank twist drill. The detailed parameter values of four cases are given in Tab. 4. The drilling power and drilling energy values of the cases were measured simultaneously with the data acquisition platform.

A. RAPID POWER PREDICTION OF DRILLING CASES

According to formula (4), the material removal rate can be calculated as: $MRR_d = \pi(\frac{d_T}{2})^2 nf/60$. Combined with the drilling parameter values of the cases in Tab.4, the $\mathrm{MRR_d}$ for the drilling case 1 is calculated as: $MRR_d = \pi(\frac{d_T}{2})^2 nf/60 = \pi(\frac{12}{2})^2 \times 460 \times 0.07/60 = 60.696\ \mathrm{mm^3/s}$. For the researched machine tool, the specific energy consumption model has been established as: $SEC_d = 3.731 + \frac{792.988}{MRR_d} - \frac{1700.718}{MRR_d^2}$. Then, the $\mathrm{SEC_d}$ for the drilling case 1 can be obtained $SEC_d = 3.731 + \frac{792.988}{60.696} - \frac{1700.718}{60.696^2} = 16.334\ \mathrm{J/mm^3}$. Hence, the drilling power of case 1 can be easily predicted with Equation (6): $P_d = SEC_d \times MRR_d = 60.696 \times 16.334 = 991.41$ W. Similarly, predicted drilling power values of the drilling case 2∼4 were all obtained, as shown in Table 5.

B. RAPID ENERGY PREDICTION OF DRILLING CASES

According to formula (2), the material volume of removed by cutting tool is computed as: $V_d = \pi(\frac{d_T}{2})^2 \times l_d$. The drilling parameters of drilling case 1 can be obtained from Table 4: diameter of cutting tool $d_T = 12$ mm and drilling depth $l_d = 10$ mm. Then, the material volume removed by the cutting tool for case #1 can be calculated as: $V_d = \pi(\frac{12}{2})^2 \times 10 = 1130.973\ \mathrm{mm^3}$. In addition, the $\mathrm{SEC_d}$ for drilling case #1 has been obtained in Table 5: $SEC_d = 16.334\ \mathrm{J/mm^3}$. Consequently, the drilling energy of the case #1 can be easily predicted with Equation (8): $E_d = SEC_d \times V_d = 16.334 \times 1130.973 = 18473.31$ J. Similarly, predicted energy values of the drilling case #2∼#4 were all obtained, as shown in Table 6.

VI. RESULTS AND DISCUSSION

A. RESULTS

With the energy acquisition platform, acquired power values of four drilling cases were obtained, which are listed in Tab. 7. The prediction accuracies of drilling power for the researched cases with traditional and improved models were acquired, which are shown in Table 6. It can be seen that the power predictive accuracies for the drilling cases with the traditional model are 96.41%, 97.22%, 96.51%, and 98.75%, respectively. In addition, the predictive accuracies of the drilling cases with the improved model are 98.77%, 99.80%, 99.12%, and 98.82%, respectively.

Similarly, collected energy values for drilling cases can be obtained using the power and energy collecting platform,

TABLE 4. Drilling parameters of four drilling cases.

Parameters	Case #1	Case #2	Case #3	Case #4
Diameter of cutting tool (d_T), mm	12.0	10.0	10.0	8.0
Feed rate (f), mm/r	0.07	0.08	0.07	0.09
Spindle rotating speed (n), r/min	460	580	540	640
Drilling depth (l_d), mm	10.0	10.0	10.0	10.0

TABLE 5. Predicted drilling power with the improved rapid power predictive model.

Parameters	Case #1	Case # 2	Case # 3	Case #4
Material removal rate MRR_d ($\mathrm{mm^3/s}$)	60.696	60.737	49.480	48.255
Specific energy consumption SEC_d ($\mathrm{J/mm^3}$)	16.334	16.326	19.063	19.434
Predicted drilling power (W)	991.41	991.59	943.24	937.79

Note: Predicted drilling power with Eq.(6): $P_d = SEC_d \times MRR_d$.

TABLE 6. Predicted drilling energy with the improved rapid energy predictive model.

Parameters	Case #1	Case #2	Case #3	Case # 4
Specific energy consumption SEC_d (J/mm^3)	16.334	16.326	19.063	19.434
Material volume removed by cutter V_d (J/mm^3)	1130.973	785.398	785.398	502.655
Predicted drilling energy (J)	18473.31	12822.41	14972.04	9768.60

Note: Predicted drilling energy with Eq.(8): $E_d = SEC_d \times V_d$.

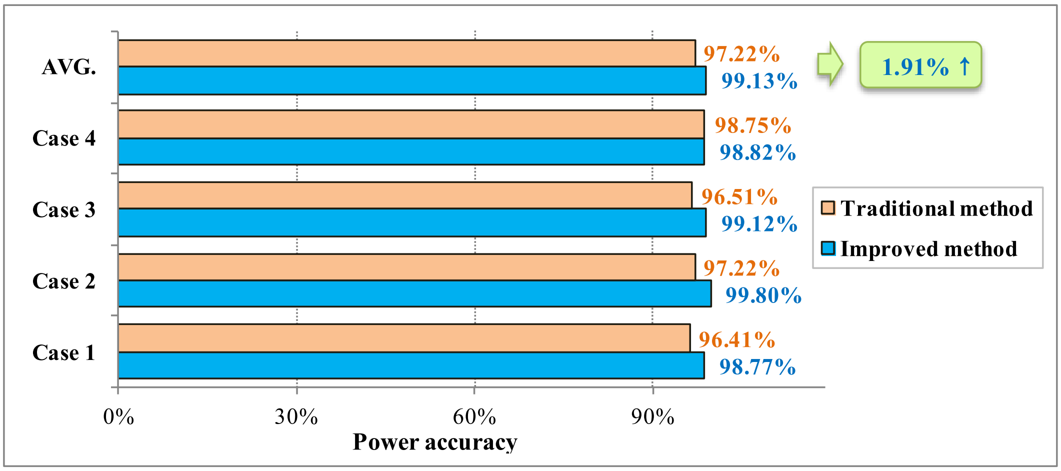

FIGURE 7. Predictive accuracy comparison of drilling power between traditional and improved method.

TABLE 7. Predictive accuracies of drilling power models.

Parameters	Case #1	Case # 2	Case #3	Case # 4
Measured drilling power (W)	1003.72	993.62	951.60	926.85
Predicted power with model A[a] (W)	967.70	966.01	918.38	915.25
Predicted power with model B[b] (W)	991.41	991.59	943.24	937.79
Accuracy of model A (%)	96.41	97.22	96.51	98.75
Accuracy of model B (%)	98.77	99.80	99.12	98.82

Note: [a] Traditional power predictive model with equation $P_d = P_{so} + P_{cfs} + P_{sr} + P_{zf} + P_{md}$. [b] Improved rapid power predictive model with equation $P_d = SEC_d \times MRR_d$.

which are listed in Tab.8. The predictive energy accuracies for the drilling cases with traditional and improved models were acquired, which are shown in Table 8. It can be seen that the energy predictive accuracies for the drilling cases with the traditional model are 96.14%, 95.58%, 94.92%, and 98.16%, respectively. In addition, the predictive accuracies of the drilling cases with the improved model are 93.41%, 98.35%, 97.32%, and 95.49%, respectively.

B. DISCUSSION

The prediction accuracy comparison of drilling power between traditional and improved methods is depicted in Fig. 7. It is indicated that the prediction accuracies of cutting power for drilling cases by using the improved method are all above 98%. The average predictive accuracy with the improved method is up to 99.13%, which is 1.91% higher than the traditional method. The reason is that the traditional power model is composed of several sub-power models, and the prediction errors of each sub-power model will be accumulated when calculating the total drilling power. The proposed rapid power prediction model is obtained directly by multiplying specific energy consumption (SEC_d) and material removal rate (MRR_d). Because the error accumulation is avoided, the power prediction accuracy is higher than the traditional method. In addition, because there is no need to calculate the sub-powers, the computational complexity of the proposed method is also significantly reduced, which makes the industrial practicability better.

Except the sub-power based model, the proposed model is also compared with the cutting force-based model, which is shown in Table 9. The comparison results indicate that

TABLE 8. Predictive accuracies of different energy models.

Parameters	Case #1	Case #2	Case #3	Case #4
Measured drilling energy (J)	17330.89	13038.14	15383.56	9346.68
Predicted energy with model A[a] (J)	17999.22	12461.53	14602.24	9518.60
Predicted energy with model B[b] (J)	18473.31	12822.41	14972.04	9768.60
Accuracy of model A (%)	96.14	95.58	94.92	98.16
Accuracy of model B (%)	93.41	98.35	97.32	95.49

Note: [a] Traditional energy predictive model with equation $E_d = P_d \times t_d$. [b] Improved rapid energy predictive model with equation $E_d = SEC_d \times V_d$.

TABLE 9. Comparison of different models.

Items	Reference	Accuracy	Complexity	Model [a]
Cutting force-based model	Wang et al [14]	98.87%	Large	$P = P_{idle} + P_{cutting} + f(P_{cutting})$ $P_{cutting} = f / 6000 \cdot \int dF_z(z) + \int V(z) \cdot dF_t(z)$, etc
Sub-power-based model	Jia et al [16]	97.22%	General	$P_d = P_{so} + P_{cfs} + P_{sr} + P_{zf} + P_{md}$ $P_{md} = \lambda_d \times d^{\alpha} f^{\beta} n^{\gamma}$, $P_{zf} = C_d v_{zf}^2 + D_d v_{zf} + E_d$, etc
This article's model	Proposed model	99.13%	Small	$P_d = SEC_d \times MRR_d$

Note: [a] Only the main calculation models are shown

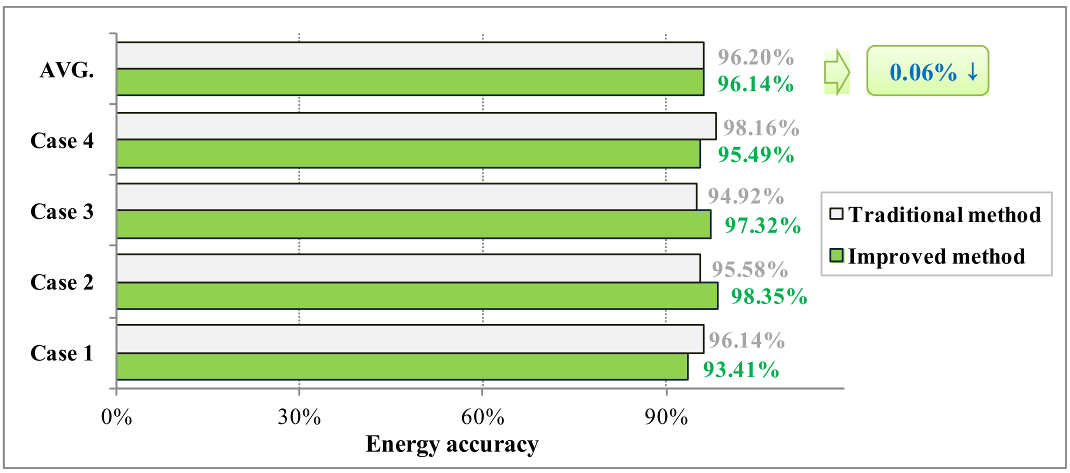

FIGURE 8. Predictive accuracy comparison of drilling energy between traditional and improved method.

the power predictive accuracy of the proposed method is the highest, which is 0.26% higher than that of cutting force-based model and 1.91% higher than that of sub-power-based method. Due to the complexity of cutting force model, the computational complexity of cutting force-based method is the largest. The computational complexity of the proposed method is significantly reduced compared with the cutting force-based method and the sub-power-based method. It can be seen that the proposed method is superior to the traditional methods in terms of power prediction accuracy and computational complexity.

Moreover, the predictive accuracy comparison of drilling energy between traditional and improved methods is shown in Figure 8. It is demonstrated that the average prediction accuracy of the improved method and the traditional method is basically the same, with a difference of only 0.06%. For drilling case 2 and case 3, the predictive accuracies with the improved method are 2.77% and 2.40% higher than that of

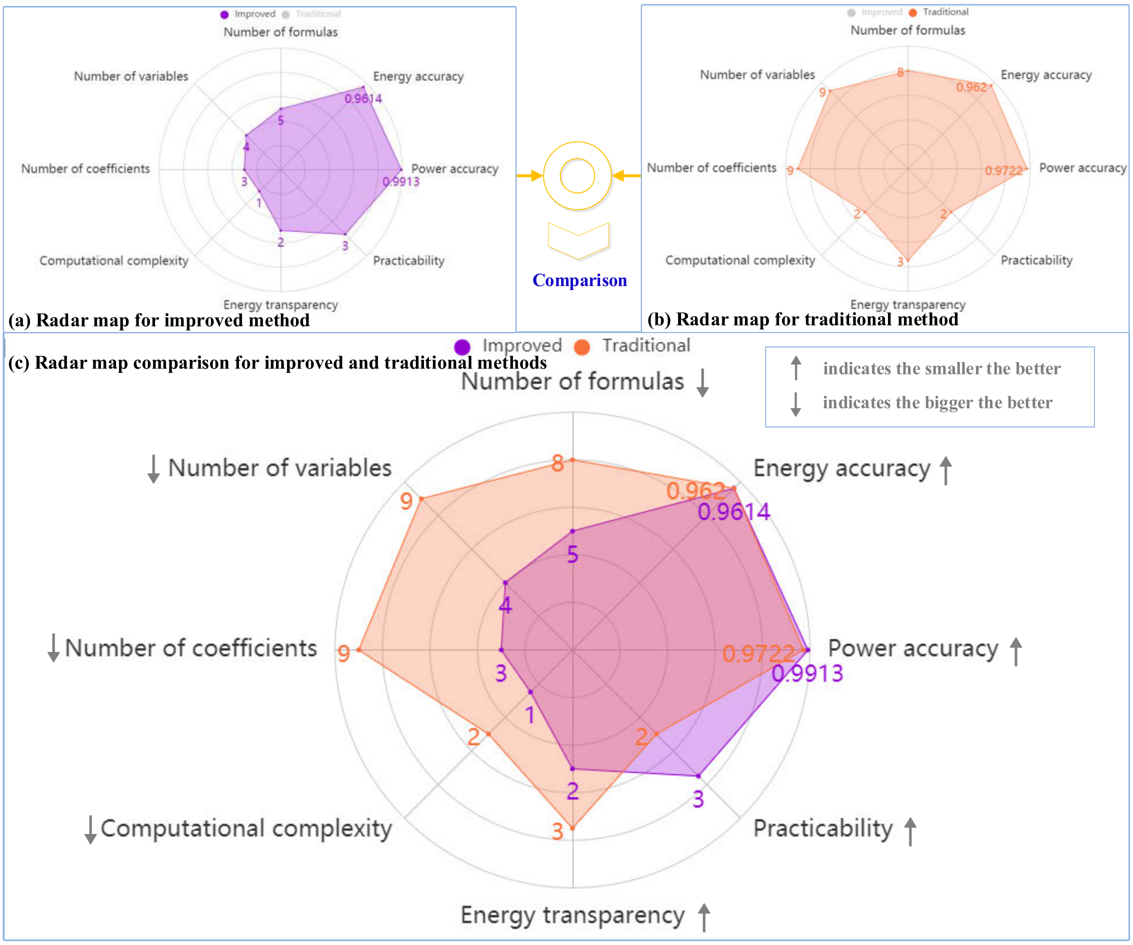

FIGURE 9. Radar map comparison: (a) Radar map for improved method; (b) Radar map for traditional method; (c) Radar map comparison for improved and traditional method.

the traditional method, respectively. It is necessary to point out that the improved prediction method involves only four variables, and only three coefficients need to be fitted. However, in order to predict energy consumption, the traditional method involves nine variables, and nine coefficients need to be fitted. That is to say, the computational complexity of the proposed method is greatly reduced when the energy predictive accuracy is basically the same as that of the traditional method, which makes the proposed method more practical in the manufacturing industry.

According to Figure 3 in Section3.2, five calculation formulas are needed in the improved method. However, in the traditional method, because of the need to calculate each sub-power value of drilling process, a total of eight formulas are needed. Therefore, the corresponding values can be marked in the radar map, as shown in Figure 9. In addition, there are four variables in the improved method: d_T-diameter of cutting tool, n-rotating speed of spindle, f-feed rate, and l_d-drilling depth. It means that once the improved model is built, only four variable values are needed to obtain the drilling power and energy consumption. When it comes to the traditional method, the number of variables is nine. Moreover, values of the other six indexes for the improved and traditional method can be obtained and the corresponding values are marked in the radar map (see Figure 9).

It can be seen from the radar map that the number of formulas, variables and coefficients of the improved rapid power and energy prediction method in this paper are all less than those of the traditional method. Consequently, it makes the computational complexity of the improved method lower than that of the traditional method. Due to the simplicity and convenience of computation, the improved method pays more attention to total drilling power and does not calculate each sub-power value, which makes the energy transparency of the improved method inferior to the traditional method. However, it should be pointed out that the drilling power and energy still can be obtained with the improved method, which can meet the demand in most conditions. Moreover, the simpler model with lower computational complexity and easily acquired parameters make the practicability of the improved method better than the traditional one. For predictive power accuracy, the proposed method is 1.91% higher than the traditional

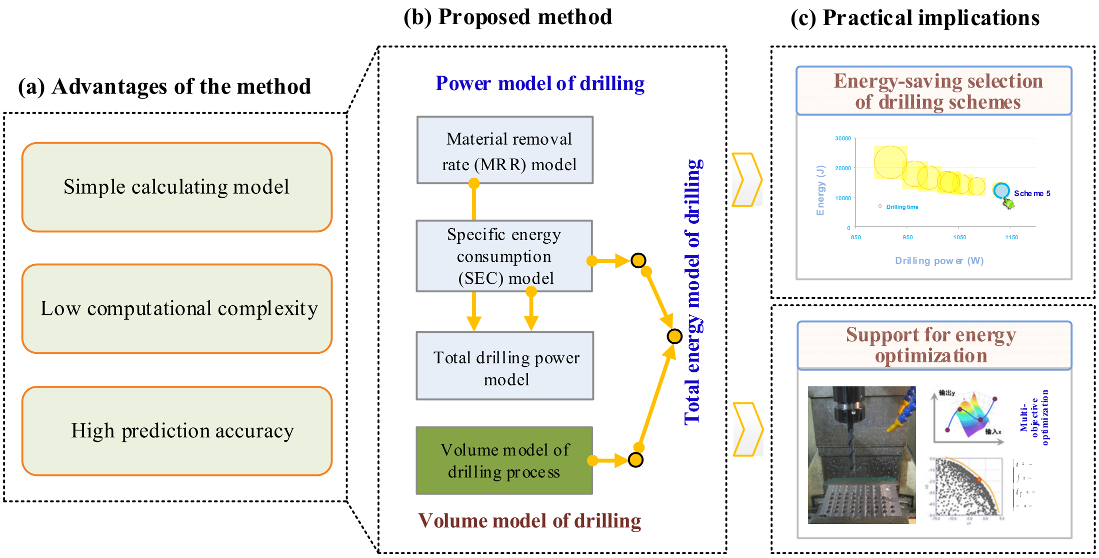

FIGURE 10. **Practical implications of the proposed method.**

method. The reason is that the improved method is to directly predict the total drilling power instead of accumulating by sub-power values, so that the error accumulation in the process of sub-power value accumulation can be avoided. When it comes to the energy accuracy, the average predictive accuracies of drilling energy with the improved and traditional method are both above 96% and the difference is only 0.06%. It can be seen that in addition to transparency and energy accuracy, the improved method performs better in the other six aspects than the traditional method. More specifically, the improved method can obtain a simpler calculating model, lower computational complexity, higher power accuracy and better practicability by sacrificing a certain degree of energy transparency.

As shown in Fig.10a and Fig.10b, The proposed method establishes a simple model with low computational complexity and high prediction accuracy, which makes the prediction of power and energy more convenient and practical in the manufacturing industry. More specifically, this method can help workshop managers or operators quickly evaluate the power and energy consumption of drilling schemes, and provide decision support for energy-saving selection of drilling schemes and scientific planning of technological process. In addition, the outcomes of this study can provide model and data support for energy optimization of drilling processes, as depicted in Fig.10c.

The main limitation of the proposed method is that when the established model is directly applied to different type of drilling machines or drilling other materials, the accuracy of the model would decline. To obtain high prediction accuracy, the coefficients in the model need to be rebuilt again by using the same modeling method. To deal with this problem and make the proposed method more convenient to be used by operators and managers in manufacturing industry, the following studies will be carried out in our future work. On the one hand, preliminary experimental researches will be conducted to obtain the coefficient values in power and energy consumption models for typical types of drilling machine tools and workpiece materials in advance. On the other hand, a supporting software will be developed to realize the calculation processes of the method and the obtained coefficient values for the method will be stored in the database of the supporting software. Users only need to select information of machine tools, workpiece materials and so on, so that the power and energy consumption could be rapidly predicted.

VII. CONCLUSION

A. SUMMARY OF THE RESEARCH AND PRACTICAL IMPLICATIONS

Drilling process, as a common machining technology in manufacturing industry, its energy modeling and optimization has not been studied very well. The existing power and energy modeling approaches of the drilling process based on the drilling force model or based on the sub-power models, such as standby operating power model, spindle-rotating power model, etc. However, the following aspects still need further improvement: the power and energy model are too complex, the calculation complexity is very high, and the industrial practicability needs to be improved. To address these issues, an improved rapid power and energy prediction approach for drilling is developed in this research. Moreover, experimental study and case study were performed on a XHK-714F machining center. The research results showed that the power and energy predictive accuracies are 99.13% and 96.14%, respectively, which illustrated the feasibility of the improved modeling method in this paper.

Additionally, the power and energy models are simpler and the computational complexity is lower compared with the traditional approach. As a result, the industrial practicability of the proposed method is significantly improved. The advantages of the proposed improvement method are summarized as follows: (i) an improvement of 1.91% power predictive accuracy is achieved compared with the traditional approach, which can provide more accurate power model support for energy optimization of drilling; (ii) the number of formulas, variables and coefficients are significantly reduced without losing the energy accuracy of drilling. More specifically, the number of formulas is reduced from 8 to 5; The number of variables is reduced from 9 to 3; When it comes to the number of coefficients, it is changed from 9 to 3. Consequently, the computational complexity of the proposed method is greatly reduced compared with the traditional method; (iii) the simpler model, lower computational complexity and higher power prediction accuracy make the proposed method more practical in industry.

As mentioned above, the proposed method establishes a simple model with low computational complexity and high prediction accuracy, which makes the prediction of power and energy more convenient and practical in the manufacturing industry. More specifically, the method can help workshop managers quickly evaluate the energy consumption of drilling schemes, and provide decision support for energy-saving selection and scientific planning of technological process. In addition, the outcomes of this study can provide model and data support for energy optimization of drilling.

B. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Drilling power and energy consumption are influenced by drilling parameters, machine tools and workpiece materials. Consequently, the established rapid power and energy model has good accuracy for predicting power and energy of the XHK-714F machining center when drilling AISI 1045 steel. However, the main limitation of the proposed method is that when the established model is directly applied to other type of drilling machines or drilling other materials, the accuracy of the model would decline. In order to obtain high prediction accuracy, the coefficients in the model need to be rebuilt again by using the same modeling method. It is necessary to point out that although a specific model could not be applied to all situations, the rapid modeling method for building drilling power and energy model is universal. Based on the modeling method proposed in this article, the power and energy model for any type of materials using any drilling machine tools could be rapidly established. In order to make the proposed method more convenient to be used by operators and managers in manufacturing industry, the following studies will be carried out in our future work. On the one hand, preliminary experimental researches will be conducted to obtain the coefficient values in the power and energy consumption models for typical types of drilling machine tools and workpiece materials in advance. On the other hand, a supporting software will be developed to realize the calculation processes of the method and the obtained coefficient values for the method will be stored in the database of the supporting software. Users only need to select information of machine tools, workpiece materials and so on, so that the power and energy consumption could be rapidly predicted.

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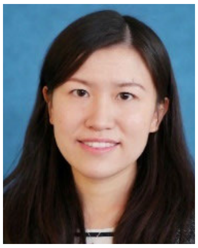

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