Application of vibration singularity analysis, stochastic tool wear, and GPR-MOPSO hybrid algorithm to monitor and optimise power consumption in high-speed milling

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Received: 17 January 2022 / Accepted: 8 May 2022

Abstract. Power consumption in manufacturing direct affects production costs and the environment. Therefore, the process of evaluating and researching power consumption in the machining process is very important. During high-speed milling, the power consumption varies due to tool wear and radial deviation. Therefore, a new model power consumption optimization is proposed based on cutting mode factors taking into account tool wear and radial deviation. In the existing power consumption models, studies on the effects of radial deviation and tool wear have not been thoroughly investigated. Stochastic tool wears established during high-speed milling is established in combination with the cutting force analysis model and wavelet singularity vibration point analysis. The nonlinear processes due to stochastic tool wear and cutting edge geometry were considered in the model. To optimize power consumption and establish a model for the real-time prediction of power consumption, a new GPR-MOPSO hybrid algorithm was developed based on Gaussian process regression (GPR) and multi-objective particle swarm optimizations (MOPSO). In order to verify the feasibility proposed monitoring and optimization model, experimental processes high-speed milling have been established. Results showed that the presented improvement model will reduce power consumption by 20.38% compared with manufacturer manuals chosen process parameters.

Keywords: Singularity vibration / GPR-MOPSO / stochastic tool wear / power consumption / holder exponent / high-speed milling

1 Introduction

Power consumption (PC) is of great concern to manufacturers because it has a direct impact on product costs and the environment. Studies by Rigacci et al. [1] shown that in the life of the machine tool operating costs account for more than 20% of PC. Bigot et al. [2] concluded that in the US, the electricity used for machine tools is up to 80% produced from fossil fuels, this process will generate a significant amount of CO₂. Aggarwal et al. [3] showed that the PC in the machining process is greatly influenced by the cutting mode parameters. Therefore, the reduction of PC is an urgent issue that must be addressed to establish a sustainable production process and avoid environmental protection problems.

With the capability of machining an extensive variety of shapes and materials, therefore, milling is one of the most commonly used metalworking methods. Zhou et al. [4] showed that in recent years, high-speed milling (HSM) has become more and more popular and widely used. HSM has high applicability in many different industries such as automotive, marine, aerospace, mold, defense industry, and many more. According to Zheng et al. [5] considers that HSM has a significantly higher cutting speed than conventional machining and therefore higher machining efficiency. The chip and material morphology in HSM is different due to the large fracture behavior and strain rate so PC tends to vary more than conventional milling parameters.

Stochastic tool wear (STW) always exists in HSM, however, the influence of STW is often ignored in previous PC research models. Wang et al. [6] introduced a model to monitoring PC by investigating the cutting tool conditions and flank wear of the drilling process. Liu et al. [7] studied the effect of different levels of tool wear during hard milling to PC. Recent studies are mainly interested in the indirect tool wear assessment process with conventional milling processes. Hoang et al. [8] presented a novel monitoring model based on the independent force component model established based on cutting mode parameters by the
milling method. Ma et al. [9] proposed the parameter estimation procedure according to the machining conditions combined with the particle filtering algorithm in the STW prediction model. So far, studies on STW applied to HSM are still limited and need to be further studied. Jeyakumar et al. [10] gave experimental methods combined with finite element analysis in analyzing the influence of different types of tool wear on the force cutting. During PC monitoring and optimization, problems related to HSM have not been paid enough attention, some works are currently only investigating for conventional or micro-milling processes.

Ki et al. [11] commented that singularities analysis is applied early in image processing, in which a sudden change in the pixel is usually expressed through a singularity change so singularity point is used to define boundaries in the images. The study by Su et al. [12] report that during machining under the supervision of sensors, tool wear is easily recognized through singularity analysis. Wavelet analyzes together with the Fourier transforms are the commonly used tools in singularity point analysis from the received signals, these tools can provide better local frequency characteristics over the time domain. Zhu et al. [13] proposed a model to predicting tool wear from the probability density functions of the singularity points, thereby giving the sensitivity and the relationship corresponding to the different conditions of the cutting tool such as cutting speed, depth of cut, feed rate and workpiece material is determined through the experimental process. According to Zhang et al. [14] research, in recent years, the process of single point analysis in cutting tool monitoring has focused on the experimental analysis of vibration, shear force, and acoustic emission signals during milling, turning, or micro-milling. Meanwhile, research on differences and systematic singularity point analysis in HSM is limited.

Overview studies by Barbieri et al. [15] shown that the particle swarm optimization (PSO) algorithm is a swarm-based intelligence optimization method that simulates the behavior swarm of birds. Xu et al. [16] commented that it is an efficient algorithm for solving single-objective optimization problems and achieving satisfactory results. However, in numerical optimization problems and practical engineering applications, multiple objectives should be met simultaneously. To fix this problem, Pan et al. [17] introduced the multi-objective particle swarm optimization (MOPSO) algorithm established by improving the conventional PSO algorithm, which is used as a reliable and flexible technique to optimize a target function. However, with PSO or MOPSO algorithms, the ability to predict the output parameters is not flexible and powerful. To overcome this limitation, the Gaussian process regression (GPR) model is a flexible and powerful tool, besides this model also provides a reliable space for the prediction method [18]. When these two algorithms combine, it creates an efficient multi-objective optimization model with strong predictive power. This goal is directly related to the problems of prediction and optimisation for high performance in PC during HSM. Accordingly, a hybrid MOPSO method and the GPR algorithm are combined, and the combination is called hybrid GPR–MOPSO algorithm. The two algorithms are combined to overcome each other’s limitations and offer a robust optimization, prediction model. Caserta and Voš [19] argue that this approach belongs to mathematics, that is, effectively combines hyper-simulation diagrams and mathematical programs. According to this approach, solutions are refined based on the starting points of the local search process obtained from the global search results. Studies by Nguyen et al. [20] shown that these solutions give high accuracy in predicting and optimizing continuous parameter domains.

To address the above-mentioned challenges, the present study introduces an improved PC model for HSM. The proposed model considers the nonlinear process caused by tool wear and radial deviation and cutting trajectory of the cutting edge and combines it with the singularity analysis of wavelet vibration. A new hybrid algorithm GPR-MOPSO is established to predict and optimize PC by combining GPR and MOPSO algorithms. The accuracy of the optimization and the prediction of the PC proposed model is verified through experimental processes. The proposed model for HSM will serve as a useful reference base for operators, planners, and manufacturers.

2 PC model in HSM when considering STW

2.1 Considering tool wear and radial deviation effect to cutting force component models

In HSM, calculating the cutting force from the tool wear geometry models to the machining trajectory belongs to the class of the most difficult problems to solve. Accordingly, a prerequisite in the computational model of force components is to determine the instantaneous uncut chip thickness (UCT) as the geometric trajectory functions of the chip. According to this property, the cutting force model in HSM is established from the tool wear micro geometry equation. Description in Figure 1 shown that the HSM geometrical parameters process with tool tip is origin placed, the axial direction corresponding z-axis, feed rate direction corresponding x-axis.

With fixed Cartesian coordinates \( O, y_t \), the tool coordinates at the time of machining are determined by \( O, x_0 y_0 z_0 \). The coordinates of the survey point \( P(x_P, y_P, O) \) on the cutting tool blade are determined by:

\[
\begin{align*}
  x_P &= f_t \times t + R\sin\theta(t) \\
  y_P &= R\cos\theta(t)
\end{align*}
\]  

(1)

Research by Kline and DeVor [21] shows that cutting tool radial deviation often occurs during HSM and needs to be controlled. The tool radial deviation includes tilt and offsets as shown in Figure 2. The setting process from the machining area to the cutting tool geometry model is determined through the main coordinate system \( O_0 x_0 y_0 z_0 \), the machining coordinate system \( O x_0 y_0 z_0 \) and the offset coordinate system \( O_0 x_0 y_0 z_0 \). The machining area trajectory is represented by:
\[ x_r = \left( R^* - R \right) \times \sin \left[ \alpha_o + \omega t - \frac{z \times \tan \beta}{R} + \frac{2\pi j}{N_z} \right] \]
\[ y_r = \left( R^* - R \right) \times \cos \left[ \alpha_o + \omega t - \frac{z \times \tan \beta}{R} + \frac{2\pi j}{N_z} \right] \quad \text{(2)} \]

The cutting tool radius affected by tool wear and radial deviation are determined by.

**See equation (3) below.**

where \( \chi = \varphi - \lambda + \frac{2\pi j}{N_z}, \delta = \phi + \varphi - \lambda + \frac{2\pi j}{N_z}. \)

Krishnakumar et al. [22] pointed out that with measurement models in nonlinear systems when considering the condition of the cutting tool, it can be represented as described below:

\[ x_i = f(x_{i-1}, \sigma_i, \zeta). \quad \text{(4)} \]

The relationships between vibration, cutting force and tool wear during HSM are determined by:

\[ y_i = h(x_i, v_i, \zeta). \quad \text{(5)} \]

Study by Zhou et al. [23] shown that the following states can be obtained from update steps and recursive predictions from the Bayesian \( \xi \) algorithm. The process parameters \( \zeta \) and the output parameters \( y_i \) will give the following probability density function \( P(x_i|y_i, \zeta): \)

\[ P(x_i|y_i, \zeta) = P(x_i|y_{i-1}, \zeta) \times P(x_i)|y_{i-1}, \zeta| \quad \text{(6)} \]

where

\[ P(x_i|y_{i-1}, \zeta) = \int (P(x_{i-1}|y_{i-1}, \zeta) \times P(x_i)|x_{i-1}, \zeta)dx_{i-1} \quad \text{(7)} \]

\[ P(y_i|y_{i-1}, \zeta) = \int (P(x_i)|y_{i-1}, \zeta) \times P(y_i)|x_i, \zeta)dx_i. \quad \text{(8)} \]

According to Pulido and van Leeuwen [24], basis on the Monte Carlo sequential method and the probability distribution function Particle filtering algorithm \( P(x_i|y_i, \zeta) \) approximated by random objects and limiting weights \( x^k_{i-1}, \zeta, k = 1, 2, ..., K \), \( \sigma^k_{i-1} \) as determined by

\[ P(x_{i-1}|y_{i-1}, \zeta) \propto \sum_{k=1}^{N} \sigma^k_{i-1} \delta(x_{i-1} - x^k_{i-1}). \quad \text{(9)} \]

\[ R^* = \sqrt{R^2 + \rho^2 + (L - z^2 \sin^2 \tau + 2R \cos \chi + 2(L - z) \rho \cos \phi + R \cos \delta) \sin \tau} \quad \text{(3)} \]
The relationship between the points $E$, $G$ and $O_t$ is shown by

$$\tan(\theta(t)) = \frac{x_G - x_E}{y_G - y_E}. \quad (13)$$

When the uncut chip thickness instantaneously $GE$ taking into account tool wear and radial deviation is determined by:

$$h_c = \sqrt{(x_G - x_E)^2 + (y_G - y_E)^2}. \quad (14)$$

Altintas and Lee [25] shown that in the machining zone, the elastic deformation of the workpiece will occur when IUCT less than minimum value, then differential cutting force components are determined by:

$$\begin{align*}
    [dF_{xp}] &= \begin{bmatrix} \cos(\theta(t)) & \sin(\theta(t)) & 0 \\ -\sin(\theta(t)) & \cos(\theta(t)) & 0 \\ 0 & 0 & 1 \end{bmatrix} \\
    [dF_{yp}] &= \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \\
    [dF_{zp}] &= \begin{bmatrix} (K_{tp}.A_p + K_{tr}.dz) \\ (K_{sp}.A_p + K_{sr}.dz) \\ (K_{up}.A_p + K_{ur}.dz) \end{bmatrix}, \quad h_c \leq h_{\text{min}}.
\end{align*} \quad (15)$$

Research by Zhang et al. [26] suggests that the $A_p$ plow area is the intersection of the plow material with the IUCT in the cutting zone. Differential cutting force components when IUCT greater than minimum chip thickness determined by:

$$\begin{align*}
    [dF_{xs}] &= \begin{bmatrix} \cos(\theta(t)) & \sin(\theta(t)) & 0 \\ -\sin(\theta(t)) & \cos(\theta(t)) & 0 \\ 0 & 0 & 1 \end{bmatrix} \\
    [dF_{ys}] &= \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \\
    [dF_{zs}] &= \begin{bmatrix} (K_{tx}.h_c + K_{tr}.dz) \\ (K_{sx}.h_c + K_{sr}.dz) \\ (K_{ux}.h_c + K_{ur}.dz) \end{bmatrix}, \quad h_c > h_{\text{min}}.
\end{align*} \quad (16)$$

From equations (15) and (16) the cutting force components are given.

### 2.2 Apply singularity vibration point analysis in cutting tool monitoring

The tool conditions are directly related to the variation of the vibration wavelet as depicted in Figure 4. New cutting
tools corresponding to the initial period, the resulting waveform profile is relatively messy and produces large singularities. When the cutting tool is in the steady wear stage, stable waveforms and fewer singularities are obtained. This process shows that tool wears for different stages, stable waveforms and fewer singularities are received signals.

The exponential function $f(t)$ with $A > 0$ when $t = v$ and $(\alpha \geq 0)$ if $A > 0$; $p_v$ degree polynomial $m$ with

$$f(t) = p_v(t) + \nu_v(t).$$

$$|\nu_v(t)| = |p_v(t) - f(t)| \leq A \times |t - v|^{\alpha}.$$  \hspace{1cm} (17)

where $A$: constant. Equation (18) has an upper bound determined by the exponent $\alpha$, which is the exponent of the function $f(t)$.

The holder exponent determined through the corresponding largest wavelet transform modulus in the time domain. The first scale value received is determined by $WTf(u, s)$ signal wavelet transform $f(t)$ with position $u = 0$

$$\frac{\partial WTf(u, s)}{\partial u} = 0.$$  \hspace{1cm} (19)

The wavelet coefficients in the vicinity of the maximum current value are determined by:

$$A \times |WTf(u, s)| \leq s^{(\alpha+1)}. \hspace{1cm} (20)$$

where $\alpha$: holder exponent. The wavelet coefficient by discrete scaling $s = 2^k$ along the maximum modules will be expressed as follows:

$$\log_2|WTf(u, s)| \leq \log_2A + j\left(\frac{2\alpha + 1}{2}\right). \hspace{1cm} (21)$$

The relationship between the maximum wavelet transform modulus and the $j$-scale is shown by equation (21). Parameters with a high $\alpha$ value show that the function $f(t)$ works more stably and often. Study by Wang and Liang [27] indicate that the process of determining the holder exponent with wavelet transform modules is used to machine diagnostics, tool, and equipment condition monitoring.

Because noise produces negative HE values, this process can be distinguished by maximum wavelet transform module through considering the development of their values along with scales. These maximum wavelet transform module $s$ are primarily dominated by noise, so they need to be removed. The results analysed by Figures 5a and b shows the original raw signal obtained from the machining process influenced by noise. When machining at 12,000 rpm (spindle speed), thirty spindle revolutions the number of sampling is 11,580 points. According to Mallat and Hwang [28] stated that noisy signals are received corresponding to high frequencies while the effective signals are obtained with low frequencies. Aim to take advantage of the noise reduction features, researchers and experts often use wavelet filters, low pass filters, etc. From Figures 5b and c, it can be seen that the maximum wavelet transform module noise reduction algorithm can greatly improve the noise reduction effect and achieve smoother curves. From Figures 5c and d, it can be seen that the noise reduction signal by wavelet is much smoother. This process preserves more real signal points and eliminates more noise for smoother curves. To further evaluate the noise reduction effect, a frequency spectrum analysis process for the signal was conducted. The energy of the vibration signal should be distributed at integer multiples of the tooth pass frequency ($f_{tooth}$).

2.3 PC pattern in HSM when considers tool radial deviation and wears

The study by Kunpeng et al. [29] shown that the total PC in HSM can be determined by:

$$P = P_c + P_i + P_a.$$  \hspace{1cm} (22)

In HSM, $P_i$ determined through speed $P_i = \phi(n)$, whereas $P_a$ can be thought of as a linear function of $P_c$.

The cutting power in HSM is related to the ability to remove the workpiece residue generated by the
spindle speed and feed direction. The differential cutting power component in the feed direction is created by the radial component \(dP_{fr}\) and the tangential \(dP_{ft}\) is determined by

\[
dP_{ft} = \frac{dF_t \cos(\theta(t)) \times f_t}{60000},
\]

\[
dP_{fr} = \frac{dF_r \sin(\theta(t)) \times f_t}{60000}. \tag{24}
\]

The differential cutting power components relative to the feed direction are determined by

\[
dP_f = dP_{ft} + dP_{fr} = \frac{[dF_{t}\cos(\theta(t)) + dF_r\sin(\theta(t))] \times f_t}{60000} = \frac{dF_x \times f_t}{60000}. \tag{25}
\]

The differential cutting power components related to spindle speed include the differential cutting forces of radial \(dF_r\) and tangential \(dF_t\) defined by

\[
dP_r = dP_{rz} = \frac{2\pi n R}{60} dF_z. \tag{26}
\]

From equations (25) and (26) the cutting power is determined by

\[
P_c = P_f + P_r = \int dP_f + \int dP_r = \frac{f_t}{60000} \int dF_x + \frac{2\pi n R}{60} \int dF_z. \tag{27}
\]

The total cutting power in the HSM is determined by

\[
P = (1 + C_0 \left[\frac{f_t}{60000} \int dF_x + \frac{2\pi n R}{60} \int dF_z\right] + g(n) + C_1 \left[\frac{f_t}{60000} \int dF_x + \frac{2\pi n R}{60} \int dF_z\right]^2. \tag{28}
\]
3 Monitoring and optimization model of PC

The process of monitoring and optimizing PC belongs to the class of experimental problems, so an empirical approach is required. This approach will meet the rigorous technical requirements in the future. Stemming from this feature, with experimental processes being conducted on specific equipment, materials, and technology systems and the hybrid GPR-MOPSO algorithm was developed to provide optimal machining parameters for HSM while accurately predicting the tooling conditions as described in Figure 6, on that basis can be applied to similar fields.

The GPR-MOPSO matching algorithm described by steps:

Step 1. Establishment experimental design. The experiments are designed based on the principle of similar appearance factors and depend on each factor is assessed on levels.

Step 2. Execution of the experiments and collection of data. Experimental processes are conducted on HSM machines, and the relevant data, including flank wear, cutting force, vibration, machining surface quality and PC level, are collected.

Step 3–1. Calculate the theoretical value and establish the empirical relationship. The theoretical tool wear value is calculated, the empirical relationship involving the cutting force is established, the network topology is determined and the swarm population at a random rate and position is initialized using GPR and MOPSO.

Step 3–2. Analysis of the experimental parameters. The purpose of this process is to evaluate the capability to predict the influence of the cutting mode factors and machining time on tool wear, cutting forces, PC and noise. The decision to repeat the experiment under improved conditions or to continue the test can be evaluated using the test results affected by the noise.

Step 4–1. The problem of predicting flank wear, cutting force and PC is introduced to help the decision-making process for technicians. The target function under the required technical conditions is then optimized to produce the optimal parameters in accordance with the machining conditions.

Step 4–2. The largest and smallest influencing factors of the power optimization problem are determined through empirical analysis. The input variable for the power

Fig. 6. GPR–MOPSO hybrid algorithm diagram.
optimization problem of HSM is selected amongst these factors. This process aims to show the economy of participating in the control of technological parameters.

Step 5. Identification tool wear and PC. The GPR algorithm is used so that the prediction process for flank wear, cutting force and PC is close to the experiment.

Step 6. The flank wear, cutting force, PC and confidence intervals are predicted through GPR.

Step 7. The prediction and optimization PC then against the maximum value compared with the maximum value (threshold value). Execution will return to step 3 if the predicted parameter less than the limited value. Otherwise, step 8 is executed.

Step 8. A warning is given when predicted values are close to the threshold value. The machine is stopped when the parameters are equal to or larger than the threshold parameters.

The prediction and optimization approach of the GPR–MOPSO hybrid algorithm, along with the empirical analysis in mechanical processing, overcomes the disadvantages of the traditional model and adds a new phase.

Overcoming disadvantages: Establishing an empirical relationship when the GPR–MOPSO application solves the prediction problem and optimizes the machining process that the GPR algorithm increases predictive accuracy and flexibility.

Add a new stage: Use experimental design to show the influence of machining parameters on output parameters and noise levels, verify confidence intervals for testing, and collect process data.

4 Experimental setup when HSM in PC monitoring and optimization

Experiment processes were performed on AISI 1043 Steel by CNC machining center MC500 as shown in Figure 7. Constraints and limited range for CNC machining center MC500 are described as on Table 1. The tool is an end mill, TiAlN coated high-speed steel material, manufactured by Sandvik Coromant. The tool parameters are listed in Table 2. PC was measured with a Panasonic KW9M three-phase AC meter. The measurement of cutting force and vibration during the experiment was performed on the Kisler 9257B and Brul & Kjaer equipment respectively. Tool flank wear was measured with a Nikon V12B digital gauge.

From the established technological parameters, experiment processes are performed in three data sets, two are used for training and one is used in the cutting force prediction tool wear, PC, and confirm prediction accuracy method. In which, tool wear is measured and replaced with a new tool after each experiment run.

During HSM, there are many factors that affect surface quality, PC, tool life and wear. In this study, only controllable factors are investigated, other factors are considered as boundary conditions or signal noise. In order to create a database for PC monitoring and optimization, two experimental steps were established. The first experiment aims to verify tool wear monitoring ability with technological parameters shown in Table 3. The second experimental process with the parameters and sequences described in Table 4, these experiments aim to show the relationship between the output parameters from the cutting mode parameters, thereby verifying the predictive ability of the proposed models.

5 Results and discussion

5.1 Holder exponent parameter analysis

Figure 8 shows the mean holder exponent and singularities that are very sensitive to different wear states of the tool. Through the flank wear rate change, the transition points will be determined. When the cutting tool transitions from steady-state operation to accelerate wear, the tool rapidly transitions to fracture and failure. This is a signal that predicts the tool’s life end.
The mean value of the holding exponent increases as the tool enters the tool break phase. At this time, many new cutting edges are formed in the cutting area creating a completely new cutting tool. Experiments to investigate the change in flank wear of the tool are performed on the same cutting tool and the technology mode according to different time states as shown in Figure 8. The results show that the tool wear curve consists of three domains: domain (A): the initial wear area, domain (B): the stable wear zone, domain (C): the accelerate wear. This process shows that wear follows the pattern of typical tool wear as shown by the study of Mallat and Hwang [28].
5.2 Verified predictive model of tool wear, cutting forces component and PC

The proposed model for predicted tool wear and force under the experimental conditions in Tables 1 and 2 is shown in Figure 9. The experimental results show the high accuracy of the proposed prediction model. This model, which considers the tool wear and cutting force, PC predictive models in HSM when surveying to tool wear are confirmed through experimental processes. The HSM experimental parameters are as described in Table 2 to investigate the feasibility and effectiveness of the proposed PC model. The description in Figure 10 shows the PC results between the experimental model and the proposed theoretical model when surveying with and without tool wear.

Figure 10 indicates that the error between the test result and the mean PC value when taking into account tool wear is less than 5.92%, whereas that between the predicted PC without tool wear effect and test result are less than 16.65%. Therefore, the proposed PC prediction model that considers the effect of tool wears more accurately than the model that does not include such effect. Findings indicate the efficacy of the PC identification model established. Analysis results show that the force components when referring to tool wear give results closer to the true value without mentioning tool wear. The PC model is built based on established force components. When tool wear is ignored, the PC prediction error is larger than it would be otherwise. The proposed PC model is unlike traditional models only in terms of spindle speed and the ability to remove machining residues, this model combines the cutting mode parameters and tool wear, generating predictions with high accuracy on PC during HSM.

5.3 Optimization PC

The PC optimization model is set with minimum on the basis of total power. The proposed GPR-MOPSO algorithm is combined with stochastic tool wear in PC optimization when HSM. Equation (29) uses the PC optimization model to give optimal parameters.

\[ F_m(n, f_1, a_p) = \min(P) \]  \tag{29}  

where \( 1 \leq a_p \leq 30 \).
PC should not exceed the allowable value for the safe operation of the machine and spindle motor as shown by equation (30).

\[ P \leq P_{\text{max}}. \]  

(30)

Based on the optimization model considering the singular wavelet and STW analysis, the hybrid GPR–MOPSO algorithm is used as an optimization method to minimize the PC in the HSM process. Constraints on cutting mode and cutting power are determined by the CNC machining center as described in Table 1.

The analysis results by the hybrid algorithm GPR–MOPSO give a set of optimal cutting mode parameters, including spindle speed, radial and axial depth of cut, feed rate of 12950 rpm; 0.12 mm; 10 mm; 0.11 mm/tooth, respectively. Comparison results from optimal cutting parameters between the proposed model and the processes according to PSO and manufacturer manuals chosen process are presented in Table 5. The total PC with the optimized cutting parameters by using GPR–MOPSO and PSO is 2.562 and 2.887 kW, respectively. By contrast, the total PC with the preferred cutting parameters is 3.218 kW. The PC reduction of 20.38 % and 11.25 % when the optimized cutting parameters by using the hybrid GPR–MOPSO algorithm are adopted compared with that of the manufacturer manuals chosen process and PSO selection, respectively. The results show that values for radial depth of cut, feed rate, and cutting speed when selected according to the manufacturer’s instructions can cause faster tool wear leading to reduced

![Fig. 9. Predicted tool wear, force components by using the proposed model.](image-url)
life and increased costs. Thus, with the proposed method applied to HSM, it is possible to be flexible and reliable in minimizing PC. Figure 11 depicts a cognitive decision-making model for the online optimization and monitoring of PC. When the predicted parameters get close to the threshold parameter or exceed the threshold value, the device will issue a warning or stop the machine, returning the cutting tool to the original position. During HSM machining processes, the input data is always added to the database through which the output data is always updated and retrained.

### 6 Conclusions

A new PC optimization and monitoring method based on STW and singularity analysis in vibrational signals for HSM is proposed. The main conclusions made based on the obtained results are shown below:

- A probabilistic model for determining the cutting force components in HSM is established on the basis of the Particle filtering algorithm in estimating the tool trajectory when surveying the STW.

### Table 5. Priority and optimized cutting parameters.

| Properties                  | Cutting parameters | Experimental results |
|-----------------------------|--------------------|----------------------|
| Preferred cutting parameters| $n$ (rpm)          | $f_t$ (mm/tooth)     | $a_v$ (mm) | $a_p$ (mm) | $P$ (kW) |
| Optimised by PSO            | 13500              | 0.15                 | 0.15       | 10         | 3.218 kW |
| Optimised by GPR–MOPSO      | 12950              | 0.11                 | 0.12       | 10         | 2.562 kW |

Fig. 10. Predictive and error models of PC with and without the effect of tool wear.
The holding exponents have the characteristic of being very sensitive in determining transition points when monitoring tool wear with different states, including the transition from steady wear to accelerated wear. Another important feature of this exponent is that the sensitivity does not depend on tool wear values, tool type, technological parameters, or workpiece material so the holder exponent very advantageous when monitoring tool conditions.

Experimental processes with the proposed model show that the predictive PC results, cutting force, tool wear are easy to observe and very close to the measurement results.

A new innovative GPR–MOPSO hybrid algorithm is proposed to monitor and optimize PC. Technological parameters for HSM are optimized according to the proposed algorithm to reduce PC by 20.38% and 11.25% compared optimal cutting modes from the manufacturer’s instructions and the PSO algorithm, respectively. The high applicability and feasibility of the proposed model are demonstrated through successful testing processes applied for PC model monitoring and optimization.

With the proposed approach, in future studies, the authors will apply multi-objective optimization of output parameters such as PC, the surface quality, the tool life, and the material removed rate when used in high-speed processing of difficult-to-machine materials and complex surfaces by using different cutting tools.

**Disclosure statement**

The authors have nothing to disclose and no conflict of interests regarding the publication of this paper.

**Nomenclature**

| Symbol | Description |
|--------|-------------|
| $f_{t}$ | Feed rate |
| $n$ | Spindle speed |
| $R$ | Tool radius |
| $f_{t}$ | Contact angle |
| $\tau$ | Tilts angle |
| $\rho$ | Offset angle |
| $\lambda$ | Offset direction |
| $\beta$ | Helix angle |
| $\phi$ | Deviation position angle |
| $x_{o}$ | Initial offset |
| $z$ | Height of survey point at the time $t$ (s) |
| $\omega$ | Spindle angular velocity (rad/s) |
| $N_{e}$ | Number of cutting edges |
| $R^{*}$ | Cutting tool radius when tool wear |
| $L$ | The length of the tool protrusion after the tool is installed |
| $R$ | Milling cutter radius |
| $j$ | Number of teeth |
| $\phi$ | Angle of inclination of the cutting edge along the $z$-direction |
| $i$ | Discrete-time index |
| $x_{i}$ | Tool wear according to time index $i$ |
| $f$ | State change function ($x_{i-1}$ to state $x_{i}$) |
| $\xi$ | Constants do not change during machining |
| $\omega$ | The randomness of tool wear when noise is taken into account |
| $h$ | Measurement function |
| $y_{i}$ | Output parameter |
| $v_{i}$ | Noise when measuring |
| $K_{te}, K_{re}, K_{ac}$ | Boundary force factors |

**Fig. 11.** PC online monitoring and optimization model in HSM.
$K_{tp}$, $K_{rp}$, $K_{ap}$: Ploughing force factor
$P_e$: Residual work material removal capacity power
$P_a$: Auxiliary power
$P_i$: Spindle power
$P_{max}$: Maximum allowable power

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Cite this article as: Dung Hoang Tien, Tran Duc Quy, Thoa Pham Thi Thieu, Nguyen Duy Trinh, Application of vibration singularity analysis, stochastic tool wear, and GPR-MOPSO hybrid algorithm to monitor and optimise power consumption in high-speed milling, Manufacturing Rev. 9, 14 (2022)