

TOOL DESIGN METHOD, APPARATUS, COMPUTER DEVICE AND STORAGE

MEDIUM

FIELD

[0001] The subject matter herein generally relates to a field of designing tool, and in particular to a tool design method, an apparatus, a computer device, and a storage medium.

BACKGROUND

[0002] Geometric shape of a tool is a key factor in improving tool life. Traditional tool design primarily relies on various design schemes proposed by a tool engineer. Tools are then manufactured according to the design schemes, and cutting life of different tools is determined through standard testing, ultimately selecting geometric design of the tool with the longest life. The entire process, from design to manufacturing to experimental verification, is time-consuming and costly. Moreover, due to a dispersion in experimentally obtained tool life results, it is easy to mis-select an optimal geometric design, which is not conducive to the rapid production of tools.

BRIEF DESCRIPTION OF THE DRAWINGS

[0003] The above and/or additional aspects and advantages of the present disclosure will become apparent and easily understood from the description of the embodiments below in conjunction with the accompanying drawings.

[0004] FIG. 1 is a schematic diagram of an application scenario of a certificate management method according to some embodiments of the present application.

[0005] FIG. 2 is a flowchart of a tool design method provided in an embodiment of the present disclosure.

[0006] FIG. 3 is a schematic diagram of a tool surrogate model provided in an embodiment

of the present disclosure.

[0007] FIG. 4 is a detailed flowchart of S03 in the tool design method provided in an embodiment of the present disclosure.

5 [0008] FIG. 5 is a detailed flowchart of S101 in the tool design method provided in an embodiment of the present disclosure.

[0009] FIG. 6 is a schematic diagram illustrating iterative results provided in an embodiment of the present disclosure.

[0010] FIG. 7 is a functional block diagram of a tool design apparatus provided by an embodiment of the present disclosure.

10 SUMMARY

[0011] Embodiments of the present application disclose a tool design method, an apparatus, a computer device, and a storage medium, which may improve the efficiency and accuracy of tool design.

15 [0012] In a first aspect, an embodiment of the present application provides a tool design method. The method includes: obtaining a group of simulation service life parameters by simulating a plurality of sets of geometric feature parameters of a tool on a simulation software; using a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of simulation service life parameters to get a tool surrogate model; optimizing a target geometric feature parameter with an optimal service life parameter by integrating a Particle
20 Swarm Optimization (PSO) algorithm and the tool surrogate model; and designing the tool according to the target geometric feature parameter.

[0013] In some embodiments of the present application, the step of using a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of the service life parameters to get the tool surrogate model comprises: constructing a training dataset

based on the plurality of sets of the geometric feature parameters and the service life parameter; and using neural network algorithm to get the tool surrogate model based on the training dataset, by using the geometric feature parameters as input data of the tool surrogate model and using the service life parameter as output data of the tool surrogate model.

5 **[0014]** In some embodiments of the present application, the step of optimizing the target geometric feature parameter with the optimal service life parameter by integrating the PSO algorithm based on the model to get the tool surrogate model comprises: outputting the optimal service life parameter by adjusting the input data of the tool surrogate model through the PSO algorithm; and determining the target geometric feature parameter according to the optimal
10 service life parameter.

[0015] In some embodiments of the present application, the step of outputting the optimal service life parameter through the tool surrogate model by adjusting the input data of the tool surrogate model through the PSO algorithm comprises: initializing a group of parameters of the PSO algorithm, wherein the group of parameters comprises learning factors C_1 and C_2 , an
15 inertia weight ω , and a number of iterations t ; initializing a position and a velocity of all particles in a particle swarm; updating the initialized position and the initialized velocity of all particles in the particle swarm according to a preset formula, calculating a fitness value of each particle using the tool surrogate model and a preset optimal service life parameter, and updating the position and the velocity of all particles based on the fitness value until a preset condition is
20 satisfied, and determining the target position of the corresponding particle; and obtaining the optimal service life parameter by verifying the preset optimal service life parameter based on the target position.

[0016] In some embodiments of the present application, the preset formula is as follows: $V_i^{t+1} = wV_i^t + C_1 \text{random}(0,1)(P_i^b - X_i^t) + C_2 \text{random}(0,1)(P_g^b - X_i^t)$,

$$X_i^{t+1} = X_i^t + V_i^{t+1},$$

Wherein P_i^b is an optimal position of ai-th particle at a b-th iteration, P_g^b is a global optimal position of all particles at the b-th iteration, w is the inertia weight, C_1 and C_2 are the learning factors. $random(0,1)$ is a random number between (0,1), X_i^{t+1} is current position of the i-th particle at the (t+1)-th iteration, and t is the number of iterations.

[0017] In some embodiments of the present application, the preset condition comprises a condition that the fitness value is less than or equal to a fitness threshold, or a condition that the number of iterations reaches a maximum number.

[0018] In some embodiments of the present application, the geometric feature parameters comprise a radial rake angle and a radial relief angle of an end mill of the tool, the service life parameter comprises a contact stress of the tool.

[0019] In a second aspect, the present application provides a tool design apparatus comprising: a processing module, configured to obtain a group of simulation service life parameters by simulating a plurality of sets of geometric feature parameters of a tool on a simulation software; a training module, configured to use a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of simulations service life parameters to get a tool surrogate model; the processing module, further configured to optimize a target geometric feature parameter with an optimal service life parameter by integrating a Particle Swarm Optimization (PSO) algorithm and the tool surrogate model model; and the processing module, further configured to design the tool according to the target geometric feature parameter.

[0020] In a third aspect, the present application provides a computer device comprising a storage device, at least one processor, and the storage device storing one or more programs that, when executed by the at least one processor, cause the at least one processor to execute a tool

design method.

[0021] In a fourth aspect, the present application provides a non-transitory storage medium having instructions stored thereon, when the instructions are executed by a processor of a computer device, the processor is caused to perform a tool design method.

5 **[0022]** The tool design method provided by the present application may obtain a group of simulation service life parameters by simulating a plurality of sets of geometric feature parameters of a tool on a simulation software, use a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of simulation service life parameters to get a tool surrogate model; optimize a target geometric feature parameter with an optimal
10 service life parameter by integrating a Particle Swarm Optimization (PSO) algorithm and the tool surrogate model; and design the tool according to the target geometric feature parameter. It is not necessary to use actual testing experiments to obtain the optimal geometric feature parameter corresponding to the designed tool, avoiding the time and cost consumption caused by actual testing experiments, and improving the efficiency and accuracy of tool production.

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DETAILED DESCRIPTION

[0023] For ease of understanding, some concepts related to embodiments of the present disclosure are exemplarily provided for reference.

[0024] It should be noted that “at least one” in the disclosure refers to one or more, and
20 “multiple” refers to two or more than two. “And/or” describes an association relationship of associated objects, indicating that there can be three relationships, for example, A and/or B may mean: A alone, both A and B, or B alone, where A and B may be singular or plural. The terms “first,” “second,” “third,” “fourth,” etc. (if present) in the description, claims, and drawings of the present disclosure are used to distinguish similar objects and not to describe a specific order

or sequence.

[0025] In the embodiments of the present disclosure, words such as “exemplary” or “for example” are used to indicate examples, illustrations, or explanations. Any embodiment or design solution described as “exemplary” or “for example” in the embodiments of the present disclosure should not be construed as more preferred or advantageous than other embodiments or design solutions. Rather, the use of words such as “exemplary” or “for example” is intended to present related concepts in a specific manner. In the absence of conflict, the embodiments described below and the features in the embodiments may be combined with each other.

[0026] As shown in FIG. 1, it is a schematic diagram of an application scenario of a certificate management method according to some embodiments of the present application. The tool design method is applied in a computer device1, the computer device 1 may be a server, such as a central server, an edge server, or a local server in a local data center. The computer device 1 may include a communication module 101, a storage device 102, a processor 103, an input/output (I/O) interface 104, and a bus 105. The processor 103 is coupled to the communication module 101, the storage device 102, and the I/O interface 104 via the bus 105.

[0027] The communication module 101 may include a wired communication module and/or a wireless communication module. The wired communication module may provide one or more solutions such as Universal Serial Bus (USB), Controller Area Network (CAN), etc. The wireless communication module may provide one or more wireless communication solutions such as Wireless Fidelity (Wi-Fi), Bluetooth (BT), mobile communication network, Frequency Modulation (FM), Near Field Communication (NFC), Infrared (IR), etc.

[0028] The storage device 102 may include one or more Random Access Memories (RAM) and one or more Non-Volatile Memories (NVM). RAM can be directly read and written by the processor 103 and is used to store executable programs for the operating system or other running

programs (e.g., machine instructions) and may also be used to store user and application data. RAM may include Static RAM (SRAM), Dynamic RAM (DRAM), Synchronous DRAM (SDRAM), Double Data Rate SDRAM (DDR SDRAM), etc.

[0029] NVM may also store executable programs and user/application data, may be loaded into RAM in advance for direct reading and writing by the processor 103. The NVM may include a disk storage device, or a flash memory.

[0030] The storage device 102 is used to store one or more computer programs. The one or more computer programs are configured to be executed by the processor 103. The one or more computer programs include a plurality of instructions which, when executed by the processor 103, implement the tool design method executed on the computer device 1.

[0031] In other embodiments, the computer device 1 also includes an external memory interface for connecting external memory to expand the storage capacity of the computer device 1.

[0032] The processor 103 may include one or more processing units, for example, an Application Processor (AP), a modem processor, a Graphics Processing Unit (GPU), an Image Signal Processor (ISP), a controller, a video codec, a Digital Signal Processor (DSP), a baseband processor, and/or a Neural-Network Processing Unit (NPU). Different processing units may be independent devices or integrated into one or more processors.

[0033] The processor 103 provides computing and control capabilities, for example, the processor 103 is used to execute computer programs stored in the storage device 102.

[0034] The I/O interface 104 is used to provide channels for user input or output. For example, the I/O interface 104 may be used to connect various input/output devices, such as a mice, a keyboard, a touch device, a display, etc., allowing users to input information or visualize information.

[0035] The bus 105 is used to provide communication channels at least between the communication module 101, the storage device 102, the processor 103, and the I/O interface 104 within the computer device 1.

[0036] It is understandable that the structure shown in the embodiments of the present disclosure does not constitute a specific limitation on the computer device 1. In other embodiments of the present disclosure, the computer device 1 may include more or fewer components than shown, or combine certain components, or split certain components, or have different component arrangements. The illustrated components may be implemented in hardware, software, or a combination of software and hardware.

[0037] As shown in FIG. 2, it is a flowchart of a tool design method provided by an embodiment of the present disclosure.

[0038] In one embodiment of the present disclosure, the tool design method is applied to a computer device, such as the computer device 1 shown in FIG. 1. Depending on specific requirements, the order of steps in the flowchart may be changed, and some steps may be omitted.

[0039] S01: a group of service life parameters is obtained by simulating multiple sets of geometric feature parameters of a tool on a simulation software.

[0040] In some embodiments of the present disclosure, an end mill tool is described as an example applied on a Computer Numerical Control (CNC) milling machine, a machining center, and an ordinary milling machine. The end mill tool is used for removing material from a workpiece through rotational motion to machine various shapes of planes, grooves, steps, contour surfaces, cavities, and complex 3D surfaces. The end cutting edge (e.g., bottom cutting edge) of the end mill tool directly participates in axial feed machining (such as milling cavities, drilling, step surfaces). The design for radial rake angle (γ) and radial relief angle (α) of the end mill tool are crucial for tool life, cutting force, and chip evacuation performance. The tool life,

the cutting force, and the chip evacuation performance are relevant to the service life of the end mill tool. For example, the tool life of the end mill tool is equal to the service life of the end mill tool.

[0041] In some embodiments of the present disclosure, the geometric feature parameters include a radial rake angle and a radial relief angle corresponding to the cutting edge of the tool.

[0042] Generally, tool wear mainly depends on stress at the tool tip (e.g., contact stress).

The greater the contact stress of the tool, the shorter the service life of the tool. If the radial rake angle and radial relief angle corresponding to the cutting edge of the tool are suitable for the cutting angle of material to be processed, the energy required will be relatively low. Heat generated during the machining process is less, and temperature corresponding to the cutting edge is lower. Physical property of the tool (such as hardness) will remain high, and the service life of the tool will be longer. If the tool requires more energy during the machining process, the heat generated also increases accordingly. The temperature corresponding to the cutting edge of the tool is higher. The physical property of the tool (such as hardness) will decrease, and the service life of the tool will be shorter. Therefore, the group of service life parameters of the tool at least include the contact stress and the temperature corresponding to the cutting edge.

[0043] In some embodiments of the present disclosure, a preset simulation software may perform simulation calculations on multiple sets of geometric feature parameters of the tool to obtain each group of service life parameters corresponding to each set of the geometric feature parameters. In the field of tool engineering, Design of Experiments (DOE) is a systematic parameter optimization method used to efficiently explore influence patterns of multiple variables on tool performance (such as service life, cutting force, temperature).

[0044] In the process of designing a tool through DOE, a tool engineer may obtain the service life parameter corresponding to each set of geometric feature parameters by performing

DOE simulation calculations based on multiple sets of the geometric feature parameters of the tool. For example, when designing the radial rake angle (γ) and the radial relief angle (α) of an end mill tool, the tool engineer obtains multiple geometric designs, each including the radial rake angle (γ) and the radial relief angle (α). For instance, multiple geometric designs include

5 Geometric Design 1 (DOE1), Geometric Design 2 (DOE2), ..., Geometric Design n (DOEn). Simulating these multiple designs yields corresponding tool life simulation results. For example, simulating based on DOE1 yields Tool Life Simulation Result 1; simulating based on DOE2 yields Tool Life Simulation Result 2; and so on, simulating based on DOEn yields Tool Life Simulation Result n. Each tool life simulation result includes the service life parameter (e.g.,

10 contact stress) corresponding to the respective set of geometric feature parameters. As shown in Table 1 below, simulation datum were performed on 12 tool geometric designs to obtain corresponding simulation results.

[0045] Table 1

DOE	radial rake angle (γ)	radial relief angle (α)	contact stress(Mpa)
1	4°	8°	865.98
2	4°	10°	1071.79
3	4°	12°	1058.34
4	8°	10°	1093.131
5	8°	12°	1091.95
6	8°	14°	1338.16
7	12°	8°	930.323
8	12°	10°	1046.72
9	12°	14°	807.033
10	15°	8°	1219.51

11	15°	10°	1428.69
12	15°	14°	845.64

[0046] In some embodiments of the present disclosure, the preset simulation software includes a Computer-Aided Engineering (CAE) software, such as Ansys, Abaqus, and AdvantEdge.

[0047] S02: a neural network algorithm is used with the multiple sets of the geometric
5 feature parameters and the group of simulation service life parameters to get a tool surrogate model.

[0048] In some embodiments of the present disclosure, the tool surrogate model is trained based on the multiple sets of the geometric feature parameters and the group of simulation service life parameters by constructing a training dataset based on the multiple sets of the geometric
10 feature parameters and the service life parameter and training the tool surrogate model based on the training dataset by using the neural network algorithm, where the geometric feature parameters serve as input data for the tool surrogate model and the service life parameter serve as output data for the tool surrogate model.

[0049] As shown in FIG. 3, the tool surrogate model includes an input layer, a hidden layer,
15 and an output layer. The input layer is used to input multiple sets of geometric feature parameters. The output layer is used to output the service life parameter corresponding to each set of the geometric feature parameters. Specifically, construct a training dataset based on the multiple sets of the geometric feature parameters and the service life parameters, where the training dataset includes m sets of sample data. Each set of sample data includes a geometric feature parameter
20 vector of the tool $X = (x_1, x_2, \dots, x_n)$, and its corresponding service life parameter vector $\check{C} = (\check{c}_1, \check{c}_2, \dots, \check{c}_k)$. Divide the m sets of sample data into a training set and a validation set, where the training set is used for model weight optimization and the validation set is used to evaluate

generalization performance. The input layer of the neural network model receives the n-dimensional geometric feature parameter vector X . The hidden layer includes p neural units $B_j (j = 1, 2, \dots, p)$, each unit calculated as follows:

[0050]
$$B_j = \sigma(\sum_{i=1}^n (w_{ij} \cdot x_i) + b_j)$$

5 [0051] Where w_{ij} is the weight parameter from the input layer to the hidden layer, b_j is a bias parameter of the neural unit of the hidden layer, and $\sigma(\cdot)$ is a nonlinear activation function (such as ReLU or Sigmoid). The output layer generates the k-dimensional service life parameter vector $C = (c_1, c_2, \dots, c_k)$, calculated as follows:

[0052]
$$c_k = \sum_{j=1}^p (w_{jk} \cdot B_j) + c'_k$$

10 [0053] Where w_{jk} is the weight parameter from the hidden layer to the output layer, and c'_k is the bias parameter of the output layer. For an input sample X , the predicted service life C is obtained through layer-by-layer calculation. Define the Mean Squared Error (MSE) as the objective function for training the neural network, measuring a difference between the predicted value C and the true value $\tilde{C}$:

15 [0054]
$$MSE = \frac{1}{m} \sum_{k=1}^k \sum_{s=1}^m (C_k - \tilde{C}_k)^2 = \frac{1}{m} \sum_{k=1}^k \sum_{s=1}^m (c_k^{(s)} - \check{c}_k^{(s)})^2$$

[0055] Where s is the sample index and m is a total number of samples. A gradient descent method is used to backpropagate the error, iteratively optimizing until the MSE converges or a preset number of training epochs is reached. Here, the predicted value C is the contact stress output by the tool surrogate model, and the true value $\tilde{C}$ is the contact stress
20 obtained from simulation. According to the 12 tool geometric designs shown in Table 1, the results obtained through the tool surrogate model are shown in Table 2 below.

[0056] Table 2

DOE	radial rake angle (γ)	radial relief angle (α)	Simulated Contact Stress (Mpa)	neural network model output contact
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				stress (Mpa)
1	4°	8°	865.98	869.73
2	4°	10°	1071.79	775.29
3	4°	12°	1058.34	1067.39
4	8°	10°	1093.131	801.22
5	8°	12°	1091.95	1099
6	8°	14°	1338.16	1327
7	12°	8°	930.323	937.71
8	12°	10°	1046.72	1043.079
9	12°	14°	807.033	644.82
10	15°	8°	1219.51	1158.7
11	15°	10°	1428.69	841.62
12	15°	14°	845.64	801.23

[0057] S03: a target geometric feature parameter with an optimal service life parameter is optimized by integrating a Particle Swarm Optimization (PSO) algorithm and the toolsurrogate model.

5 **[0058]** In this embodiment of the present disclosure, the PSO algorithm simulates swarm intelligence search mechanisms to find the target geometric feature parameter in a solution space that makes the toolsurrogate model output the optimal service life parameter. After training the toolsurrogate model with the multiple sets of the geometric feature parameters and corresponding service life parameters, the PSO algorithm is used to optimize the input layer to make the

10 toolsurrogate model output the optimal service life parameter. Specifically, by treating the toolsurrogate model as a fixed mapping function $C = f(X)$, where X is the geometric feature

parameter and C is the service life parameter. The optimal service life parameter C^* is set at the output layer of the tool surrogate model, and the PSO algorithm is used to inversely search for the target geometric feature parameter that satisfy $f(X) \approx C^*$. Refer to the description of FIG. 3 below for details.

5 [0059] S04: the tool is designed according to the target geometric feature parameter.

[0060] In this embodiment of the present disclosure, by setting the optimal service life parameter output by the output layer of the tool surrogate model, for example, C^* is the minimum contact stress. This minimum contact stress indicates the longest tool life. The PSO algorithm inversely searches for the input data that satisfies $f(X) \approx C^*$, for example, the target
10 geometric feature parameter of the tool. The tool is then designed according to the target geometric feature parameter.

[0061] The tool design method provided by the present disclosure may simulate the service life parameter based on designed multiple sets of the geometric feature parameters. A tool surrogate model is trained by using a neural network algorithm with the multiple sets of the
15 geometric feature parameters and the group of simulation service life parameters. Then, target geometric feature parameter corresponding to the optimal service life parameter is calculated using a PSO algorithm based on the tool surrogate model, and the tool is designed according to the target geometric feature parameter. It is not necessary to use actual testing experiments to obtain the optimal geometric feature parameters corresponding to the designed tool, avoiding the
20 time and cost consumption caused by actual testing experiments, and improving the efficiency and accuracy of tool design.

[0062] As shown in FIG. 4, it is a detailed flowchart of S03 in the tool design method provided by an embodiment of the present disclosure. Depending on requirements, the sequence of steps in the detailed flowchart may be changed, and some steps may be omitted.

[0063] S101: the optimal service life parameter is output through the tool surrogate model by adjusting the input data of the tool surrogate model through the PSO algorithm.

[0064] In this embodiment of the present disclosure, as the geometric feature parameters of the tool serving as the input data to the tool surrogate model constitute a high-dimensional design space and the tool surrogate model as a mapping function has highly nonlinear characteristics, The PSO algorithm employs a guided random search strategy through swarm collaboration, leveraging dual guidance from individual historical optima and the global optimum of the population. This approach efficiently solves the inverse problem of neural networks to obtain optimal service life parameters while ensuring guaranteed global convergence. The specific description of adjusting the input data of tool surrogate model through the PSO algorithm to achieve optimal service life parameter outputs may be found in the subsequent explanation of FIG. 4.

[0065] S102: the target geometric feature parameter is determined according to the optimal service life parameter.

[0066] In this embodiment of the present disclosure, the target geometric feature parameter corresponding to the optimal service life parameter obtained through the PSO algorithm is determined. During the process of solving for the optimal service life parameter using the PSO algorithm, the input data corresponding to that optimal output, i.e., the target geometric feature parameter, is simultaneously determined. For example, by setting the output layer of the through model to output the minimum contact stress of the tool using the PSO algorithm, and directly obtaining the radial rake angle and radial relief angle of the tool's cutting edge corresponding to the input layer of the through model as the target geometric feature parameter during the search process.

[0067] As shown in FIG. 5, it is a detailed flowchart of S101 in the tool design method

provided by an embodiment of the present disclosure. Depending on requirements, the sequence of steps in the detailed flowchart may be changed, and some steps may be omitted.

[0068] S1011: a parameter of the PSO algorithm is initialized.

[0069] In this embodiment of the present disclosure, the parameter of the PSO algorithm
5 includes learning factors C_1 and C_2 , an inertia weight ω , and the number of iterations t . The PSO algorithm randomly generates multiple particles $P_i (i = 1, 2, \dots, n)$. In some embodiments, the parameters of the PSO algorithm also include the number of particles n .

[0070] S1012: a position and a velocity of all particles in a particle swarm are initialized.

[0071] In this embodiment of the present disclosure, it is necessary to initialize the position
10 and the velocity of all particles in the particle swarm and determine the individual best historical position P_i^b and global best position P_g^b of the particle swarm. Specifically, the position of the i -th particle is obtained using a uniform distribution random function: $X_i^{(0)} = \{x_{i1}, x_{i2}, \dots, x_{in}\}$, and the velocity of all particles in the particle swarm is initialized as $V_i^{(0)} = \{v_{i1}, v_{i2}, \dots, v_{in}\}$. The position represents a candidate solution set of geometric feature parameters, where the
15 uniform distribution random function is:

[0072] $x_{ij}^{(0)} = rand(L_j, U_j)$, Where L_j is design lower limits of the j -th dimensional geometric parameter, U_j is the design upper limits of the j -th dimensional geometric parameter, and $rand$ is the uniform distribution random function.

[0073] S1013: an initialized position and an initialized velocity of all particles are updated
20 in the particle swarm according to a preset formula, a fitness value of each particle is calculated using the tool surrogate model and a preset optimal service life parameter, and the velocity and the position of each particles of all particles are updated according to the fitness value until a preset condition is satisfied, and the target position of the corresponding particle is determined.

[0074] In this embodiment of the present disclosure, the velocities and positions of all

particles in the particle swarm are updated based on the preset formula. A fitness evaluation function is determined using the tool surrogate model and the optimal service life parameter, and the fitness value for each particle in all particles is calculated according to this fitness evaluation function. For example, the mean squared error between the neural network output and the optimal service life parameter C^* is used as the fitness evaluation function, and the fitness value for each particle is calculated based on this function.

[0075] In this embodiment of the present disclosure, the preset formula is as follows:

[0076]
$$V_i^{t+1} = wV_i^t + C_1 random(0,1)(P_i^b - X_i^t) + C_2 random(0,1)(P_g^b - X_i^t),$$

[0077]
$$X_i^{t+1} = X_i^t + V_i^{t+1},$$

10 [0078] Where P_i^b is the optimal position of the i-th particle at the b-th iteration, P_g^b is a global optimal position of all particles at the b-th iteration, w is the inertia weight, C_1 and C_2 are the learning factors. $random(0,1)$ is a random number between (0,1), X_i^{t+1} is the current position of the i-th particle at the (t+1)-th iteration, and t is the number of iterations.

[0079] The fitness evaluation function is:

15 [0080]
$$(X) = \frac{1}{k} \sum_{k=1}^k (f_k(X) - C_k^*)^2,$$

[0081] Where $f_k(X)$ is the k-th dimensional output value of the tool surrogate model, and k is the dimension of the service life parameter.

[0082] In this embodiment of the present disclosure, after calculating the fitness value for each particle according to the fitness evaluation function, the velocity and position of all particles in the particle swarm are updated according to the fitness value until the preset condition is satisfied, then the target position of the corresponding particle is determined. The preset condition includes the fitness value being less than or equal to a fitness threshold, or the number of iterations reaching a maximum number.

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[0083] In some embodiments of the present disclosure, after calculating the fitness value for

each particle, if the fitness value is less than a first fitness value corresponding to a first particle at the individual historical best position, update the position corresponding to the particle to the position of the first particle. If the updated fitness value of the first particle is less than a second fitness value corresponding to a second particle at the global historical best position, update the individual historical best position to the global historical best position. Iterative updates proceed in this manner until the preset condition is satisfied, determining the target position of the corresponding particle.

[0084] S1014: the optimal service life parameter is obtained by verifying the preset optimal service life parameter based on the target position.

[0085] In this embodiment of the present disclosure, when the PSO algorithm iteration update satisfies the preset condition, the target position (i.e., the optimal geometric feature parameter) is input into the tool surrogate model to obtain a predicted value of the service life. The predicted value is used to verify its consistency with the preset optimal service life parameter. If an error between the predicted value and the preset optimal service life parameter is less than or equal to an error threshold, the preset optimal service life parameter is used as the optimal service life parameter. If the error is greater than the error threshold, the predicted value is used as a new preset optimal service life parameter, and the PSO algorithm continues the calculation until the error is less than or equal to the error threshold.

[0086] As shown in FIG. 6, the target geometric feature parameter obtained using the tool design method provided by the present disclosure based on the data shown in Table 2 are: radial rake angle of 5.4°, radial relief angle of 10°, corresponding to a contact stress of 761 MPa. According to FIG. 6, the tool design method provided by the present disclosure may find the target geometric feature parameter more quickly. Using the method provided here, the target geometric feature parameter is determined when the number of the iterations reaches

approximately 25. In contrast, using an average value calculation method determines the target geometric feature parameter when the number of the iterations reaches approximately 55. This shows that the tool design method provided by the present disclosure may improve the efficiency of tool design.

5 [0087] As shown in FIG. 7, it is a functional block diagram of a tool design apparatus provided by an embodiment of the present disclosure. The tool design apparatus 10 runs on the computer device 1. The tool design apparatus 10 includes a processing module 101 and a training module 102. The modules/units referred to in the present disclosure refer to a series of computer-readable instruction segments that may be acquired by a processor and perform fixed functions,
10 stored in a storage device.

[0088] The processing module 101 is configured to obtain a group of simulation service life parameters by simulating a plurality of sets of geometric feature parameters of a tool on simulation software. The training module 102 is configured to use a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of simulation service
15 life parameters to get a tool surrogate model. The processing module 101 is further configured to optimize a target geometric feature parameter with an optimal service life parameter by integrating a Particle Swarm Optimization (PSO) algorithm and the tool surrogate model model. The processing module 101 is configured to design a tool according to the target geometric feature parameters.

20 [0089] In some embodiments of the present disclosure, the processing module 101 is further configured to construct a training dataset based on the multiple sets of the geometric feature parameters and the service life parameter; train the tool surrogate model based on the training dataset, by using the geometric feature parameters as input data of the tool surrogate model and using the service life parameter as output data of the tool surrogate model.

[0090] In some embodiments of the present disclosure, the processing module 101 is further configured to output the optimal service life parameter through the tool surrogate model by adjusting the input data of the tool surrogate model through the PSO algorithm; and determine the target geometric feature parameter according to the optimal service life parameter.

5 **[0091]** In some embodiments of the present disclosure, the processing module 101 is further configured to initialize a parameter of the PSO algorithm, wherein the parameter comprises learning factors C_1 and C_2 , an inertia weight ω , and the number of iterations t ; initialize a position and a velocity of all particles in a particle swarm; update the initial position and the initial velocity of all particles in the particle swarm according to a preset formula, calculate a
10 fitness value of each particle using the tool surrogate model and a preset optimal service life parameter, and update velocity and position of all particles based on the fitness value until a preset condition is satisfied, and determining the target position of the corresponding particle; and obtain the optimal service life parameter by verifying the preset optimal service life parameter based on the target position.

15 **[0092]** Embodiments of the present disclosure also provide a computer-readable storage medium. The computer-readable storage medium stores a computer program. The computer program includes program instructions. The method implemented when the program instructions are executed can refer to the methods in the various embodiments of the present disclosure described above.

20 **[0093]** The computer-readable storage medium may be the internal memory of the electronic device described in the above embodiments, such as the hard disk or memory of the electronic device. The computer-readable storage medium may also be an external storage device of the electronic device, such as a plug-in hard disk equipped on the electronic device, a Smart Media Card (SMC), a Secure Digital (SD) card, a Flash Card, etc.

[0094] In some embodiments, the computer-readable storage medium may include a program storage area and a data storage area. The program storage area may store an operating system, applications required for at least one function, etc. The data storage area may store data created according to the use of the electronic device, etc.

5 **[0095]** In the above embodiments, the descriptions of the various embodiments have their own emphasis. For parts not detailed or recorded in a certain embodiment, refer to the relevant descriptions in other embodiments.

[0096] Those of ordinary skill in the art can appreciate that the units and algorithm steps described in the examples combined with the embodiments disclosed herein can be implemented
10 in electronic hardware, or a combination of computer software and electronic hardware. Whether these functions are performed by hardware or software depends on the specific application and design constraints of the technical solution. Professionals can use different methods for each specific application to implement the described functions, but such implementation should not be considered beyond the scope of this application.

15 **[0097]** In the embodiments provided in this application, it should be understood that the disclosed apparatus/terminal device and method may be implemented in other ways. For example, the apparatus/terminal device embodiments described above are merely illustrative. For instance, the division of modules or units is only a logical functional division. In actual implementation, there may be other division methods, for example, multiple units or components
20 may be combined or integrated into another system, or some features may be ignored or not executed. Additionally, the displayed or discussed mutual couplings or direct couplings or communication connections may be indirect couplings or communication connections through some interfaces, devices, or units, which may be electrical, mechanical, or other forms.

[0098] The units described as separate components may or may not be physically separate.

Components displayed as units may or may not be physical units; they may be located in one place or distributed across multiple network units. Some or all of the units may be selected according to actual needs to achieve the objectives of the solutions of the embodiments.

[0099] The above-described embodiments are only used to illustrate the technical solutions of the present disclosure and are not intended to limit them. Although the present disclosure has been described in detail with reference to the foregoing embodiments, those of ordinary skill in the art should understand that they may still modify the technical solutions described in the foregoing embodiments or equivalently replace some of the technical features. However, these modifications or replacements do not cause the essence of the corresponding technical solutions to deviate from the spirit and scope of the technical solutions of the embodiments of the present disclosure, and should be included within the protection scope of the present disclosure.

[00100] The above description is only a partial implementation method of the present disclosure. It should be pointed out that for ordinary technicians in this technical field, several improvements and modifications may be made without departing from the principles of the present disclosure. These improvements and modifications should also be regarded as the scope of protection of the present disclosure.

CLAIMS

What is claimed is:

1. A tool design method, comprising:

obtaining a group of simulation service life parameters by simulating a plurality of sets of

5 geometric feature parameters of a tool on a simulation software;

using a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of simulation service life parameters to get a tool surrogate model;

optimizing a target geometric feature parameter with an optimal service life parameter by integrating a Particle Swarm Optimization (PSO) algorithm and the tool surrogate model; and

10 designing the tool according to the target geometric feature parameter.

2. The tool design method according to claim 1, wherein the step of using a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of the service life parameters to get the tool surrogate model comprises:

15 constructing a training dataset based on the plurality of sets of the geometric feature parameters and the service life parameter; and

using neural network algorithm to get the tool surrogate model based on the training dataset, by using the geometric feature parameters as input data of the tool surrogate model and using the service life parameter as output data of the tool surrogate model

20 3. The tool design method according to claim 2, wherein the step of optimizing the target geometric feature parameter with the optimal service life parameter by integrating the PSO algorithm based on the model to get the tool surrogate model comprises:

outputting the optimal service life parameter by adjusting the input data of the tool surrogate model through the PSO algorithm; and

determining the target geometric feature parameter according to the optimal service life

parameter.

4. The tool design method according to claim 3, wherein the step of outputting the optimal service life parameter through the tool surrogate model by adjusting the input data of the tool surrogate model through the PSO algorithm comprises:

5 initializing a group of parameters of the PSO algorithm, wherein the group of parameters comprises learning factors C_1 and C_2 , an inertia weight ω , and a number of iterations t ;

initializing a position and a velocity of all particles in a particle swarm;

10 updating the initialized position and the initialized velocity of all particles in the particle swarm according to a preset formula, calculating a fitness value of each particle using the tool surrogate model and a preset optimal service life parameter, and updating the position and the velocity of all particles based on the fitness value until a preset condition is satisfied, and determining the target position of the corresponding particle; and

obtaining the optimal service life parameter by verifying the preset optimal service life parameter based on the target position.

15 5. The tool design method according to claim 4, wherein the preset formula is represented as follows:

$$V_i^{t+1} = wV_i^t + C_1 \text{random}(0,1)(P_i^b - X_i^t) + C_2 \text{random}(0,1)(P_g^b - X_i^t),$$

$$X_i^{t+1} = X_i^t + V_i^{t+1},$$

20 Wherein P_i^b is an optimal position of a i -th particle at a b -th iteration, P_g^b is a global optimal position of all particles at the b -th iteration, w is the inertia weight, C_1 and C_2 are the learning factors, $\text{random}(0,1)$ is a random number between (0,1), X_i^{t+1} is current position of the i -th particle at the $(t+1)$ -th iteration, and t is the number of iterations.

6. The tool design method according to claim 4, wherein the preset condition comprises a condition that the fitness value is less than or equal to a fitness threshold, or a condition that the

number of iterations reaches a maximum number.

7. The tool design method according to claim 5, wherein the geometric feature parameters comprise a radial rake angle and a radial relief angle of an end mill of the tool, the service life parameter comprises a contact stress of the tool.

5 8. A tool design apparatus comprising:

 a processing module, configured to obtain a group of simulation service life parameters by simulating a plurality of sets of geometric feature parameters of a tool on a simulation software;

 a training module, configured to use a neural network algorithm with the plurality of sets of the geometric feature parameters and the group of simulation service life parameters to get a

10 tool surrogate model;

 the processing module, further configured to optimize a target geometric feature parameter with an optimal service life parameter by integrating a Particle Swarm Optimization (PSO) algorithm and the tool surrogate model model; and

 the processing module, further configured to design the tool according to the target
15 geometric feature parameter.

9. A computer device comprises a storage device, at least one processor, and the storage device storing one or more programs that, when executed by the at least one processor, cause the at least one processor to execute a tool design method according to any one of claims 1 to 7.

10. A non-transitory storage medium having instructions stored thereon, when the
20 instructions are executed by a processor of a computer device, the processor is caused to perform a tool design method according to any one of claims 1 to 7.