The Method of Machining Process Parameter Generation Based on MBD

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Abstract. The steering engine room is one of the key structural components of the carrier rocket. It has many types of parts features and a large number of process parameters. Moreover, it needs a long processing cycle. The processing parameters are generally set manually by the technicians based on experience, and the design information obtained from the parts cannot directly provide a reference for the generation of subsequent process parameters. In order to correlate the non-geometric information extracted from the MBD (Model Based Definition) model with the process parameters generation process and make the MBD model run through the entire process parameter generation process, a method of process parameter generation based on MBD is proposed in this paper. The feature information of MBD model can be identified with feature recognition algorithm. The non-geometric information of MBD model can be extracted by information extraction algorithm. In addition, processing parameters can be generated automatically by using BP neural network according to the acquired information. This method can shorten the generation time of the entire process parameters, reduce the production cycle and increase the production efficiency.

1. Introduction
Carrier rockets are of great significance for the security. In order to meet the demands of increasing launch requirements, higher requirements are placed on the production cycle and production efficiency of launch vehicles. The steering engine room of carrier rocket is one of the key structures, which has irregular surface shapes, staggered features, and complex feature structures. Nowadays, identification and extraction of parts information by means of manual methods takes a long time. According to part machining information, manual selection of processing parameters will increase production time and reduce processing efficiency. These processing methods relying on experience and knowledge not only seriously affect the efficiency of the design and the quality of machining, but also cannot meet the requirements for integrated manufacturing of different types of products. Therefore, it is necessary to combine the actual manufacturing process with digital technology and propose a method that can automatically extract part information and automatically generate process parameters from the design to the manufacturing process to change the current status of low digitization and intelligence in the development and production process.

Domestic and foreign experts have conducted in-depth research on the extraction and processing parameters of non-geometric information till this moment. Qiao et al. proposed an approach to region-based feature recognition for structural parts [1]. Zubair et al. proposed the volume decomposition method to recognize feature automatically of regular features for symmetrical and non-symmetrical cylinder part [2]. Sui proposed the method to parts information extraction and storage of 3D-CAPP
system [3]. Fang et al. proposed the method to coordinate measuring information extraction of parts based on MBD dataset [4]. These research mainly from the MBD model to identify the part features or to extract the part information. The digitized information obtained is not directly used as a basis for generating the process parameters. Vafadar et al. proposed a simulation model using genetic algorithms to find the optimal process parameters [5]. Torres-Treviño et al. proposed a hybrid system that sets processing parameters from experimental data [6]. Roy et al. proposed a method to optimization of process parameters in CNC lathe by using taguchi coupled genetic algorithm [7]. Kant uses artificial neural network and genetic algorithm to predict and optimize the surface roughness [8].

The above studies mainly use genetic algorithms or neural networks to realize the generation and optimization of process parameters. These methods input the existing processing information into the trained model to generate the process parameters, but do not fully consider the source of processing and manufacturing information. It makes the extracted non-geometric information and process parameter generation process not directly related. In summary, the entire manufacturing process from part information extraction to process parameter generation is not closely related and there is no suitable method to solve this problem.

In order to associate the non-geometric information extracted from the part with the process of the process parameters generation and make the MBD model of the part run through the entire process parameter generation process, this paper proposes a method for generating process parameters based on MBD. This method can identify feature and extract information of parts based on the MBD model to obtain the design information of parts. Also, it can use BP neural network to generate process parameters directly with the acquired non-geometric information. The workload of the process personnel can be reduced, the time for generating the process parameters can be reduced, and the processing efficiency can be improved through this method.

2. The framework of process parameter generation

![Figure 1. The framework of automatic generation of process parameters.](image)

The automatic generation system of process parameters in this paper mainly includes three parts, i.e. feature identification, information extraction and automatic process parameter generation. The designer designs the model in the three-dimensional software, and then uses the feature recognition algorithm to identify the typical features in the model, such as hole features, groove features, and cavity features. After identifying the feature of the part, the non-geometric information of the part is extracted through the information extraction algorithm, including the geometric dimensions, dimensional tolerances, shape and position tolerances, and surface roughness of the part. After the feature recognition and information extraction are completed, the two types of different information data need to be unified and stored. Then, the craftsman formulates the process and determines the working step according to the obtained geometric information and non-geometric information. The
processing features, such as drilling or milling planes, are determined by human-computer interaction and the non-geometric information, which is extracted before, are used as inputs for the module of process parameter generation.

The module of process parameter generation uses the BP neural network to train the existing process parameter samples, and then obtains the corresponding network structure model. Finally, the obtained data are input into the BP neural network to generate processing parameters directly for machining. The framework of the system is shown in Figure 1.

3. Specific generation process of process parameter

3.1. The method of feature recognition based on MBD

During the automatic generation of the entire process parameters, feature recognition and information extraction are the most basic parts. The design information of the parts mainly comes from manual identification in the current production process. However, the work of converting design information into manufacturing information is heavy. The method based on artificial identification has the disadvantages of low efficiency and great manpower. It also increases preparation time and extends manufacturing cycle. Feature recognition and information extraction are the key technologies of integrated CAD, CAM and CAPP [9], which can replace manual information extraction and automatically transform design information into manufacturing information, so as to reach the goal of reducing preparation time and improve process efficiency.

This paper divides these features into concave and convex features to identify feature information in the MBD model. In order to make the software automatically identify the concave and convex manufacturing features in the part model, the following feature recognition method is proposed, as shown in Figure 2.

First, the feature recognition module needs to create a part feature library. The feature of the part can be divided into hole features, closed cavity features, slot features, open cavity features and boss features. After completing the typical feature classification, we can use adjacency relationship model of the three-level attribute including top layer, geometric layer and newly added outer adjacency layer [10] to record the required information for manufacturing feature recognition in matrix form and store this information in the part feature library. Different from the recognition mode of sub-graph segmentation-Feature database matching method, we use the descriptive information of the feature model in the Part feature library to establish the necessary conditions for searching. The search algorithm is used to select and record the feature surface satisfying the conditions based on the search condition. Finally, all the features can be identified and confirmed. The result of identifying a groove feature in the steering engine room is shown in Figure 3.

![Figure 2. The process of the feature recognition.](image-url)
Figure 3. The result of identifying a groove feature.

3.2. The theory of information extraction based on MBD

After using the feature recognition algorithm to obtain the feature information in the part MBD model, the non-geometric information can be acquired by extraction algorithm [11]. MBD model contains a lot of non-geometric information. The information play important role in the entire process, which affect the processing parameters in the manufacturing process, such as tool parameters and cutting parameters. Therefore, this algorithm can extract non-geometric information during the manufacturing process and show the information in a 3D solid model in order to guide the production process. The running process of entire algorithm is shown in Figure 4.

First, all the annotation information is obtained from the part MBD model, and then the attached elements of all the acquired annotation information are converted into unified geometric element information. Next, the geometric element information is matched with the geometric information in the feature to obtain the feature information associated with the annotation. Then, the category of three-dimensional annotation is divided according to the associated feature information. For example, the dimension is classified into the position size and the shape size and the tolerance annotation information is classified into the correlation tolerance and the independent tolerance. Finally, the rules for defining the shape and size of information are made and the annotation information is output in more detail based on the features. After the annotation information is extracted and classified, it is stored in the corresponding feature data structure. The non-geometric information extracted from a groove feature of the steering engine cabin is shown in Figure 5.
3.3. Automatic generation of process parameters

The characteristics of the parts can be obtained through the research of the front feature recognition part. Information extraction module can obtain non-geometric information such as feature size information, tolerance information and surface roughness. The acquisition of feature information and design information provides the basis for the generation of process parameters.

The machining processing parameters play an important role in the mechanical manufacturing process. It affects directly the machining quality and efficiency of the parts. If traditional manual methods are used to determine the process parameters, there will be low efficiency and errors maybe occur. Therefore, automatic generation of process parameters based by using BP neural network is proposed in the process parameter generation section. The process of automatic generation of process parameters is shown in Figure 6.

![Figure 6. The process of automatic generation of process parameters.](image)

First, the data of feature recognition and information extraction need be unified and these data information need be stored. Next, the craftsman formulates the process planning according to the acquired information and selects the working step in the form of human-computer interaction. The BP neural network model trains the existing process parameter files continuously and generates a network model finally. During the training process, the process parameter database including cutting parameter database and tool database is generated at the same time. The data of parameter database will become more and more accurate as the number of training becomes more and more. Finally, the operator input the step name and non-geometric information to the established network model and then the machining parameters will be output automatically.
3.3.1. Uniformity of datasets. The features identified in the feature recognition module, such as closed cavities, slots, open cavities and bosses, are geometric solid features, while the information of information extraction module including geometry dimension, dimensional tolerance, geometric tolerance, datum and surface roughness is non-geometric information. They belong to two different types of data information. If different types of data are to be input to a neural network, the two types of data must be uniformly expressed.

3.3.2. Process parameter generation with BP neural network. The unified expression of feature information and non-geometric features is to use the data they contain as the input of BP. It will facilitate the generation of the following process parameters. Before the data is input into the BP neural network, the system established a human-machine interface. The craftsman formulates the process route and selects the work step based on the feature information and the non-geometric information, which is input to the interactive interface. The information of current machining step and design information is expressed in a unified manner and input to a well-established neural network model, and then the required process parameters will be generated. Here is a set of step information and corresponding design information. This set of data is used as the input parameter of the BP neural network, as shown in Table 1.

**Table 1.** The input parameters of BP neural network.

| No. | feature | Step name | Length (mm) | Width (mm) | Depth (mm) | Tolerance type | Tolerance size (mm) | Surface roughness (um) |
|-----|---------|-----------|-------------|------------|------------|-----------------|---------------------|------------------------|
| 1   | groove | Milling plane | 560         | 500        | 100        | Flatness        | 0.05                | 1.6                    |

BP neural network [12] is a kind of multi-layer feedback network which is trained according to error back-propagation algorithm. It is one of the most widely used neural network models. BP neural network can learn and store a large number of the mapping relationship of input and output without revealing the mathematical equations describing the mapping relationship beforehand. Its learning rule is to use the steepest descent method to adjust the weights and thresholds of the network continuously by back propagation, which can make the sum of the squared error of the network minimally. As shown in Figure 7, it mainly includes input layer, hidden layer and output layer. The input layer mainly includes the step name, geometric size, dimensional tolerance, shape tolerance, surface roughness and other information of the part. The obtained output layer has the processing parameters such as cutting speed, feed rate, tool diameter and other parameters.

![Figure 7. BP neural network model structure.](image-url)
Before the prediction of the neural network data, there must be a network model established. Therefore, the data of the files in the existing library must be trained to establish a suitable model. The training process is as follows:

1. Initialize the neural network model and set the threshold and weight of the process parameter training model.
2. Set the corresponding output expectations and select 30000 input samples randomly in the existing technology library for input to the model for training.
3. Calculate the input and output of each layer neuron, and then constantly modify the weights and thresholds of each neuron according to the input and output of each node.
4. Calculate the error of the output parameters such as cutting parameters, feed amount and tool diameter.
5. Determine whether the network error meets the requirements. The algorithm ends when the error reaches the requirement of the precision. Otherwise, it needs to select the next learning sample, return to the third step and enter the next round of learning.

Through the above steps, appropriate thresholds and weights can be obtained, and then a suitable neural network model can be established. Inputting the data of Table 1 into the established BP neural network model can generate cutting parameters and tool parameters, and the output process parameters are listed in Table 2. The output parameters can be provided for next manufacturing.

**Table 2.** The output parameters of BP neural network.

| No. | $v$ (m/min) | $f_z$ (mm/z) | $a_p$ (mm) | $a_z$ (mm) | $d$ (mm) | $Z$ |
|-----|-------------|-------------|------------|------------|---------|-----|
| 1   | 250         | 0.03        | 2          | 2          | 10      | 4   |

**4. Calibration and correction of process parameters**

These generated machining parameters, such as cutting parameters and tool parameters, have a great influence on the machining time and machining quality of the parts of steering engine room. The machining time and machining quality of parts need to meet certain requirements, otherwise the process parameters should be corrected. The effect of process parameters on machining time and machining quality is shown in Figure 8.

![Figure 8. The effect of process parameters on machining time and machining quality.](image-url)

The entire machining time of the part includes the information acquisition time of the part, the generation time of the process parameters, the cutting processing time and other auxiliary time, as shown in formula (1). In order to reduce the processing production cycle, it is necessary to reduce the
consumption time of each phase. The design information of the parts is extracted using the corresponding algorithm, and the process parameters are generated through the BP neural network. These processes are realized automatically, which can shorten the preparation time of the early stage. The cutting time is related to the value of the process parameters, such as formula (2). We can generate appropriate machining process parameters through the neural network to reduce the cutting time. If the calculated machining time is more than the time determined by the manually selected process parameters, the process parameters must be regenerated. However, only pursuing the reduction of cutting time may increase the value of cutting force, which leads to the deformation of parts and affects the machining quality of parts. Therefore, we must make the cutting force of the part lower than the maximum allowable cutting force before reducing the cutting time, as in formula (3).

$$t = t_a + t_g + t_m + t_p$$  \hspace{1cm} (1)

Among them, $t_a$ is the time of the feature recognition and information extraction, $t_g$ is the time of the process parameter generation, $t_m$ is machining time of the working step, and $t_p$ is the auxiliary time.

$$t_m = \frac{\pi \times d \times L \times H}{1000 \times v \times f_z \times a_p \times Z}$$ \hspace{1cm} (2)

Among them, $d$ is the tool diameter, $L$ is the milling length of the workpiece, $H$ is the milling depth, $v$ is the milling speed, $f_z$ is the feed per tooth, $a_p$ is the axial depth of cut, and $Z$ is the number of cutter teeth.

$$F = C_F v^k a_p^{k_2} f_z^{k_3} a_e^{k_4} \leq F_{\text{max}}$$ \hspace{1cm} (3)

Among them, $C_F$ is the coefficient that depends on the processing material and the cutting condition. $v$ is the cutting speed. $a_p$ is the axial cutting depth, $f$ is the feed. $a_e$ is the radial cutting depth. $k_1$, $k_2$, $k_3$, and $k_4$ are undetermined parameters. $F_{\text{max}}$ is the maximum allowable cutting force.

We used the identified groove characteristics as an example to compare the machining time consumed in two different ways. The machine type is DMC 70V hi-dyn. The tool parameters and cutting parameters are shown in Table 2. The tool material is cemented carbide. The machining size of the groove is $560 \times 500 \times 100$. Under the constraint condition of cutting force, we calculated the processing time of two different process parameters according to formula (2). The results are shown in Table 3.

| ways            | Cutting parameters | Tool parameters | $t_m$ (s) |
|-----------------|--------------------|----------------|-----------|
| Manual setting  | $v$ (m/min) $f_z$ (mm/z) $a_p$ (mm) | $a_e$ (mm) $d$ (mm) $Z$ | 29.32     |
| BP—NN           | 254 0.0247 2.515   | 1.88 10 4      | 27.87     |

From Table 3, it can be seen that the time of cutting process is 29.32 second by manually selecting process parameters, while that is 27.87 second by BP neural network to generate process parameters. Therefore, the latter consumes less time. Meanwhile, the use of feature recognition and information extraction methods can reduce the processing time of machining preparation. Consequently, for mass production of the parts of steering engine room, it can reduce the time of the entire machining and improve the machining efficiency by using the method of process parameter generation proposed in this paper.
5. Conclusion
In this paper, a method of process parameter generation based on MBD is proposed. It is analysed from three parts of feature recognition, information extraction and process parameter generation, which makes the MBD model run through the process of process parameter generation. The characteristic information of the MBD model is quickly identified by the feature recognition algorithm and the MBD information of the model is obtained by using the algorithm of information extraction. Moreover, the process parameters are generated quickly and accurately by using BP neural network according to the characteristic of recognition and the extracted non-geometry information. The results show that this method can reduce the preparation time of processing and generate the process parameters quickly. It can reduce the whole processing time and improve the production efficiency. The next work is to apply this method to the different parts and improve the result of its parameter generation continuously.

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