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FATA-ResNet Network for CAD/CAM Integration in Cloud Manufacturing

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Abstract

This paper focuses on the application of mechanical engineering CAD/CAM integration technology under the cloud manufacturing framework, aiming at solving the current technical integration problems in manufacturing informatization. The study analyzes the demand and current situation of 3D CAD/CAM integration in a cloud manufacturing environment, combines the mirage optimization algorithm (FATA) and residual neural network (ResNet), and proposes a CAD/CAM integration application analysis model based on the FATA-ResNet network. Firstly, the functional requirements of CAD/CAM technology integration in a cloud manufacturing platform are clarified, including 3D model uploading and downloading, process file generation, and cross-platform data sharing. Then, the hyperparameters of the ResNet network are optimized by the FATA algorithm to improve the accuracy and efficiency of the model in integration application analysis. The experimental results show that the FATA-ResNet model outperforms the traditional model in terms of accuracy, recall, and F1 score while possessing faster convergence speed and higher computational efficiency. In addition, the operation modules in the cloud platform, including the task management interface and 3D process editing function, were designed and validated, further demonstrating the practicality of the method. Future research will focus on the validation of multi-scene data, model resource optimization, and real-time collaborative operation to promote the in-depth application of CAD/CAM technology in intelligent manufacturing and provide support for the digital and intelligent development of manufacturing.

Keywords: Cloud Manufacturing; Mirage Optimisation Algorithm; Residual Neural Networks; CAD/CAM Integration Techniques.

1. Introduction

In recent years, the manufacturing industry has undergone significant transformation with the advent of Industry 4.0 and initiatives like "Made in China 2025" [1]. These advancements have shifted the focus from mere product manufacturing to delivering high-value-added products and services [2]. As a core sector within manufacturing, mechanical engineering relies heavily on information technologies such as 3D CAD/CAM to shorten product design cycles and enhance market responsiveness.

Cloud manufacturing, which leverages cloud computing to virtualize manufacturing resources and capabilities, has emerged as a promising paradigm [3]. It combines technologies like IoT, big data, and AI to improve efficiency, reduce costs, and increase flexibility [4]. The integration of CAD/CAM technologies within this framework is crucial for achieving collaborative and integrated manufacturing processes.

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Numerous studies have explored CAD/CAM integration [5-7]. For instance, researchers have proposed various methods such as data exchange interface-based integration, collaborative design-oriented integration, PDM-based integration, and manufacturing feature-based integration [8, 9]. However, despite these efforts, several limitations persist. First, the integration of soft manufacturing resources often fails to fully utilize the functionalities of various software modules. Second, there is inadequate research on the integration and evaluation of 3D CAD/CAM technologies specifically within the cloud manufacturing context [10].

To address these gaps, this study proposes a novel approach. A CAD/CAM integration analysis model is developed by combining the Mirage Optimization Algorithm (FATA) with the Residual Neural Network (ResNet). The Mirage Optimization Algorithm (FATA) is employed to optimize the hyperparameters of the ResNet architecture. In this study, no modifications are made to the core structure of the standard ResNet. Specifically, ResNet50 is utilized in its original form, including its standard layers and connections. The FATA algorithm was only used to optimize ResNet's hyperparameters, with no changes to ResNet's internal architecture. The FATA algorithm uses specific parameters and symbols to represent different aspects of the optimization process. This model not only enhances the accuracy and efficiency of integration analysis but also offers faster convergence and improved computational performance [11]. By designing and validating operation modules within a cloud platform, we demonstrate the practical applicability of our method [12]. This research aims to advance the application of CAD/CAM technologies in intelligent manufacturing and provide robust support for the digital and intelligent transformation of the manufacturing industry.

This paper constructs a comprehensive system based on the IASB framework and enhanced with a PO-BP model. Section 2 focuses on the theoretical foundation and construction of the data asset accounting system, including recognition, measurement, recording, and reporting. Section 3 presents the integration of the Political Optimizer (PO) algorithm with the BP neural network to develop a data asset valuation model. Section 4 offers a comparative analysis using open-source datasets to validate the model's performance against traditional algorithms. Finally, Section 5 concludes with a summary of findings, acknowledges the limitations, and proposes directions for future research. This structured approach ensures a thorough exploration of both conceptual foundations and practical implementations, offering valuable insights into data asset accounting in the digital economy.

2. CAD/CAM Integration Technology in Cloud Manufacturing Framework

2.1. Status of Research

In recent years, the concept of cloud manufacturing has attracted international academic attention, and many countries have researched cloud manufacturing [13]. Cloud manufacturing is a new manufacturing model based on cloud computing technology, which virtualizes and services manufacturing resources and manufacturing capabilities and provides them to users through the Internet [14], as presented in Figure 1. It combines cloud computing, the Internet of Things, big data, artificial intelligence, and other technologies, aiming to improve manufacturing efficiency, reduce costs, and enhance the flexibility and responsiveness of manufacturing systems.

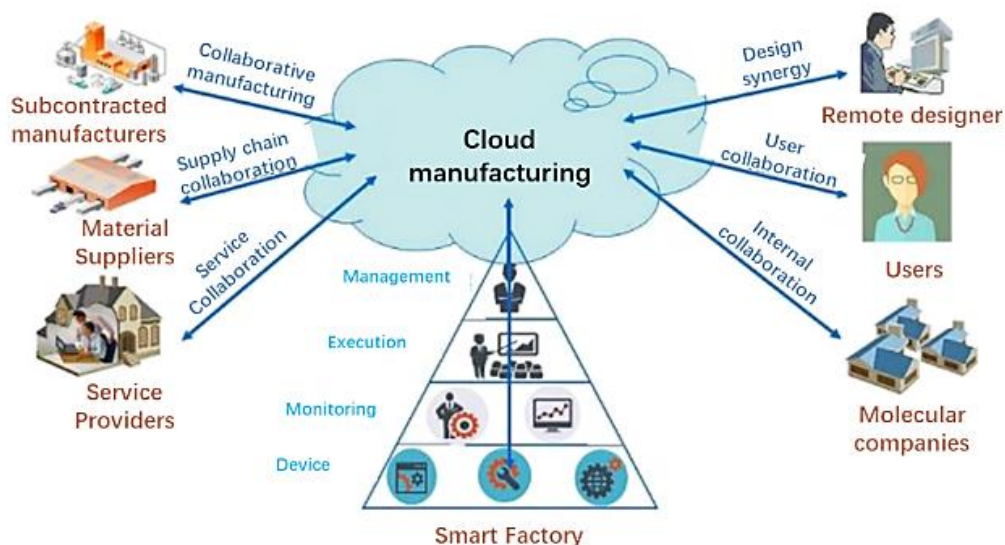


Figure 1. Cloud manufacturing

The main features of cloud manufacturing include 1) resource virtualization; 2) servitization; 3) on-demand customisation; 4) flexibility and scalability; 5) data-driven; and 6) remote monitoring and maintenance, as shown in Figure 2.

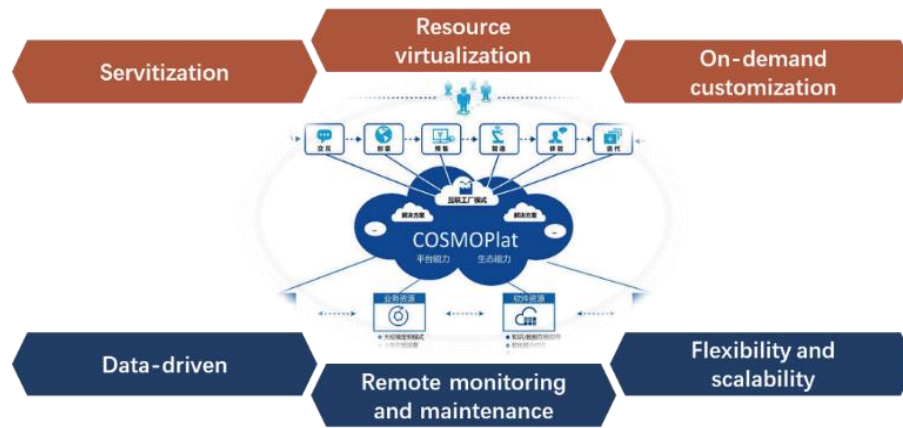


Figure 2. Cloud Manufacturing Characteristics

For cloud manufacturing, all domestic and foreign studies have achieved remarkable results. The concept, background, architecture, and technical features of cloud manufacturing have been described. Its application in the aerospace R&D process has been proposed to reduce informatization costs and enhance efficiency. Platforms integrating various CAD/CAM/CNC interfaces have been developed to resolve CAX compatibility issues. A cloud manufacturing model based on the STEP standard for process collaboration and data integration has also been investigated [17-20].

CAD/CAM integration research and development (Figure 3), is the core link of manufacturing information technology, but also to achieve an important part of cloud manufacturing, many developed countries have always attached great importance to the integration of CAD/CAM. CAD/CAM integration methods are mainly the following four, as shown in Figure 4, specifically including: 1) data exchange interface-based integration technology [21]; 2) collaborative design-oriented integration technology [22]; 3) PDM-based integration technology [23]; 4) manufacturing feature-based integration technology [24].

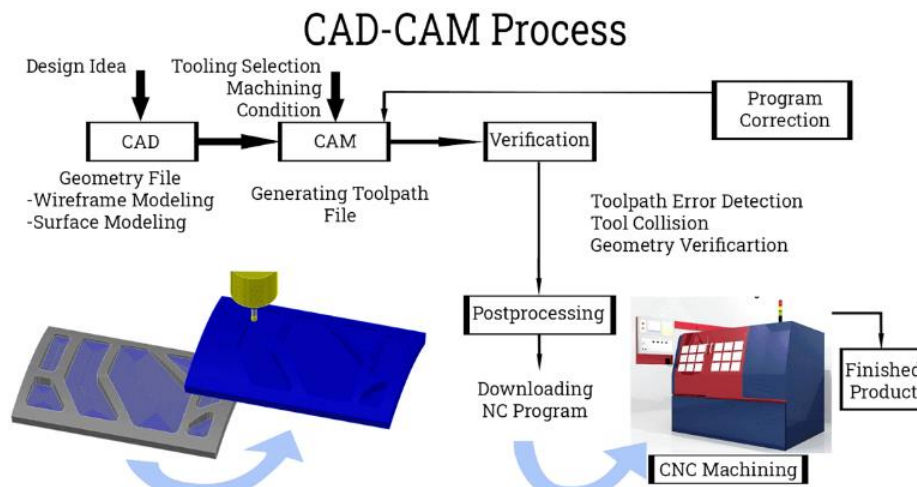


Figure 3. CAD/CAM integration technology concept

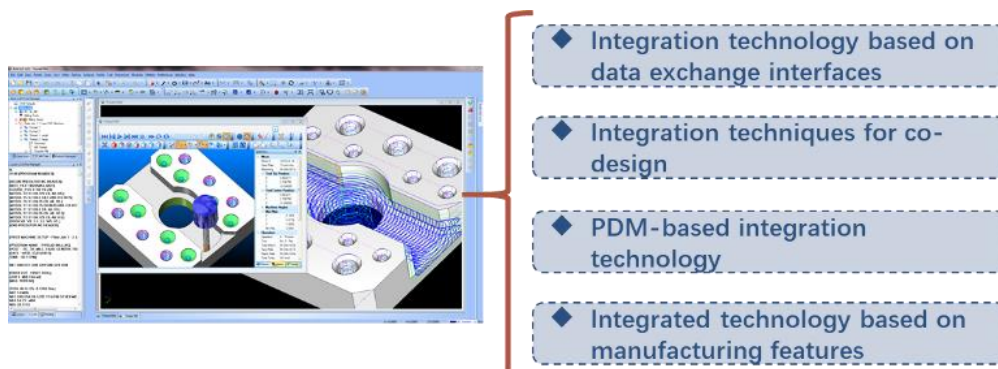


Figure 4. CAD/CAM integration method

2.2. Needs analysis

The cloud manufacturing platform provides users with CAD/CAM and other soft manufacturing resources data and information calls are an important part of the cloud manufacturing platform information technology services [25]. Achieving the integration service of 3D CAD/CAM and PDM is an important part of product co-design and process co-design, and the specific integration module requirements are shown in Figure 5, which include the following: 1) CAD parts information extraction; 2) uploading and downloading of 3D CAD models, and intelligent loading and generation of 3D process files; 3) 3D CAM process information extraction; 4) 3D CAM and CAPP integration; 5) manufacturing information browsing on mobile devices [25].

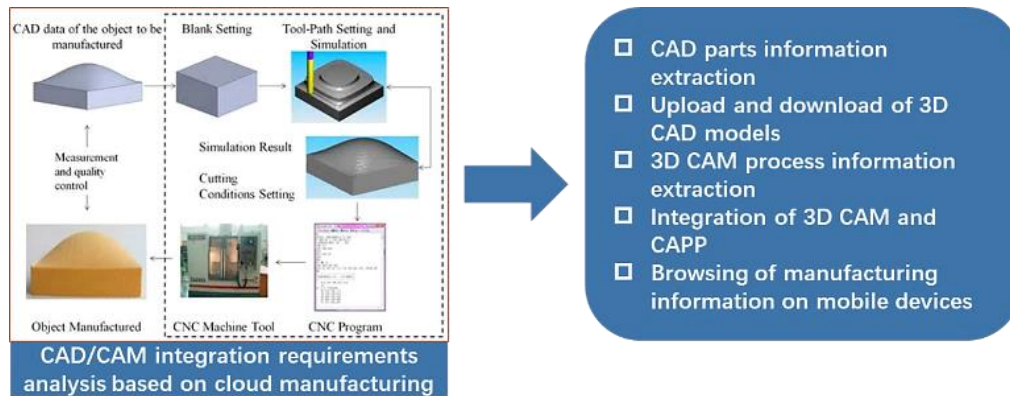


Figure 5. Requirement analysis of CAD/CAM integration based on cloud manufacturing

2.3. Architecture Analysis and Design

The cloud manufacturing platform system is composed of a resource layer, an intermediate layer, a core functional layer, a platform portal layer, and a service application layer, as shown in Figure 6.

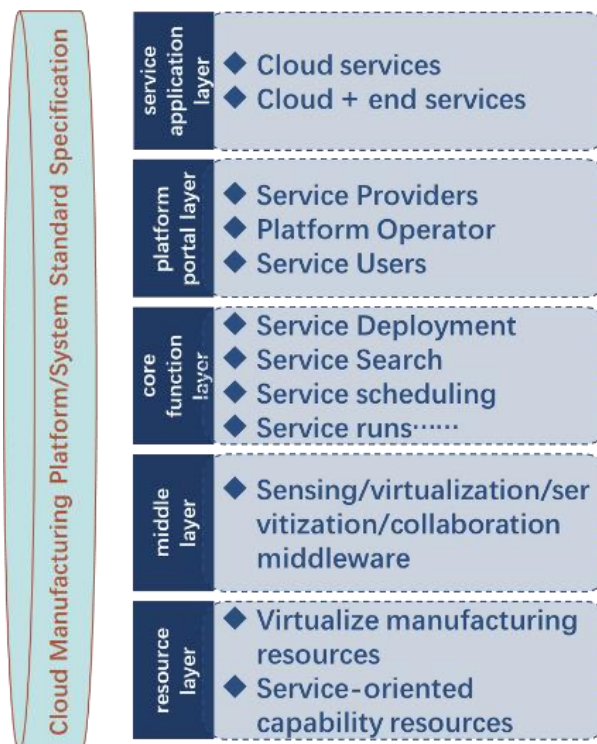


Figure 6. Cloud manufacturing application architecture

The mechanical engineering CAD/CAM integration and integration framework for cloud manufacturing is shown in Figure 7. From Figure 7, in the cloud manufacturing platform, digital design software such as CAD/CAM and PDM are integrated to provide technical support for the management and transfer of data and models in the process of collaborative production, and by uploading the data generated by CAD/CAM and so on to the cloud database through PDM, it can provide data support for the product's full life cycle design.

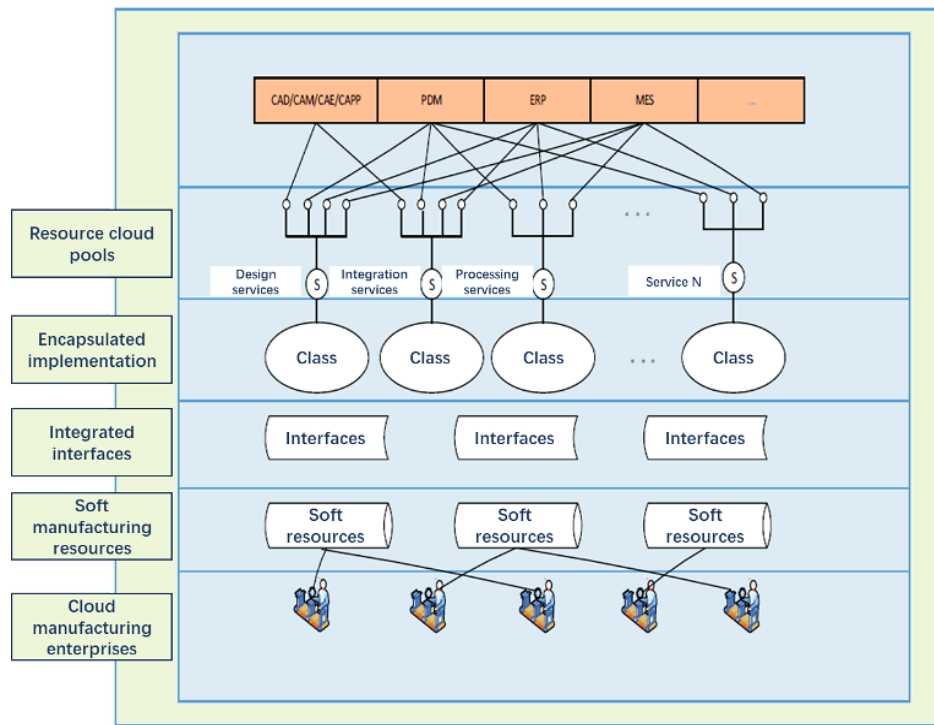


Figure 7. CAD/CAM integration framework

2.4. CAD/CAM Technology Integration Application Analysis

According to the CAD/CAM integration and integration design ideas, this paper takes the design function value as input and the integration and integration test value as output to construct the CAD/CAM technology integration application analysis model, as shown in Figure 8. To improve the integration technology application analysis efficiency, this paper adopts a machine learning algorithm, through learning training, to construct a CAD/CAM technology integration application analysis model, and then uses an intelligent optimization algorithm to optimize the model to improve.

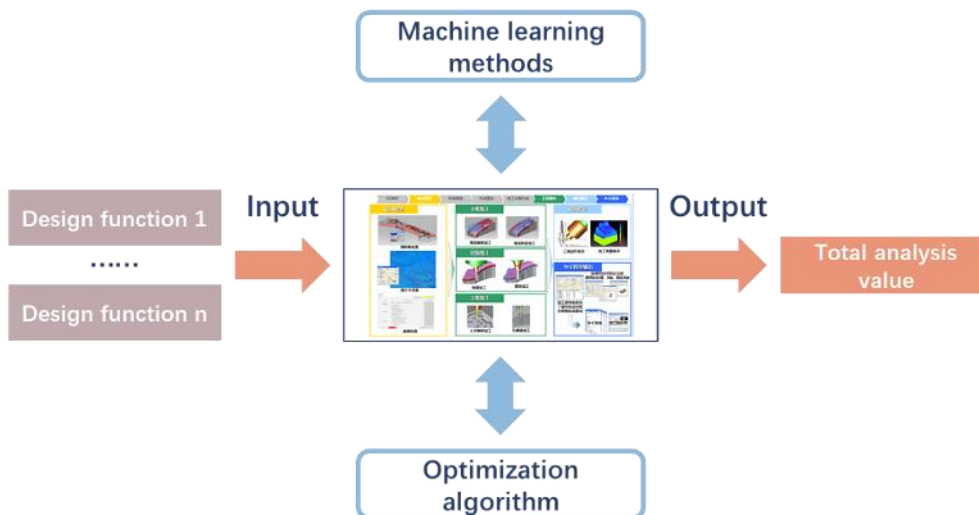


Figure 8. CAD/CAM Integration Application Analysis Model Input and Output

3. Mirage Optimization Algorithm

The Mirage Algorithm (Fata Morgana Algorithm, FATA) [9] is a novel population intelligence optimization algorithm proposed in 2024, which is inspired by the mirage formation process in natural phenomena as shown in Figure 9. The FATA algorithm proposes two core strategies by mimicking the propagation of light in an inhomogeneous medium --Mirage Light Filtering Principle (MLF) and Light Propagation Strategy (LPS) to optimize the search process and enhance the algorithm's global search capability and local exploitation.

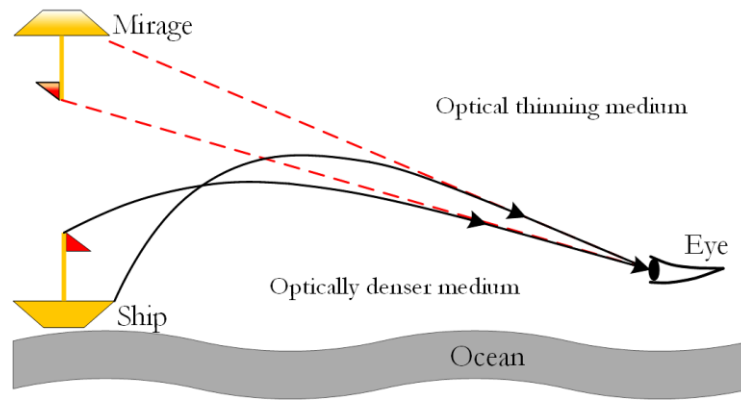


Figure 9. Principle of the FATA algorithm

3.1. Initialization

As with the other algorithms, random initialization is used:

$$x_i = rand \cdot (U_b - L_b) + L_b \quad (1)$$

where U_b denotes the upper bound of the optimization problem, L_b denotes the lower bound of the optimization problem and r and denotes the random number.

3.2. Mirage Filtering Strategy

In the physical process of mirage formation, objects emit two types of light. Most light rays belong to the first type (other rays), which do not propagate and form mirages. The other type of light undergoes a physical change to form a mirage and is called mirage light (Figure 10). The specific mathematical model is calculated as follows:

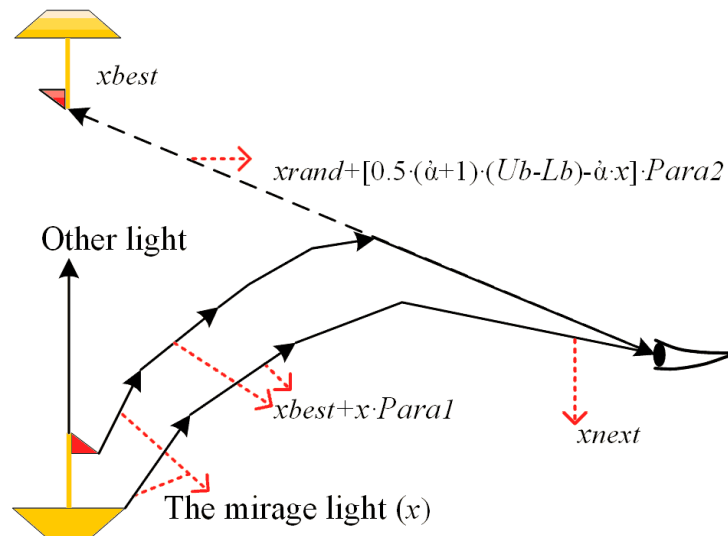


Figure 10. FATA algorithm mirage filtering strategy

$$x_i^{next} = \begin{cases} L_b + (U_b - L_b) \cdot rand & rand > P \\ x_{best} + x_i \cdot Para_1 & rand \leq P \& rand < q \\ x_{rand} + [0.5 \cdot (\alpha + 1)(U_b - L_b) - \alpha x_i] \cdot Para_2 & rand \leq P \& rand \geq q \end{cases} \quad (2)$$

$$P = \frac{S - S_{worst}}{S_{best} - S_{worst}} \quad (3)$$

$$q = \frac{fit_i - fit_{worst}}{fit_{best} - fit_{worst}} \quad (4)$$

where x_i denotes a ray individual, x_i^{next} denotes a new ray individual, P denotes a ray population quality factor, q denotes an individual quality, S denotes a population quality, S_{worst} denotes the worst population quality, S_{best} denotes the best population quality, fit_i denotes the i th ray fitness value, fit_{best} denotes the optimal individual ray fitness value,

fit_{worst} denotes the worst individual ray fitness value. The parameter $Para_1$ represents the first stage refractive index, which is initially set to 0. The parameter $Para_2$ represents the second stage refractive index, also initially set to 0. The symbol α (alpha) is used to denote the refractive step, which is a key factor in the light propagation strategy. Other parameters include FEs, which stands for the number of function evaluations, and MaxFEs, representing the maximum number of function evaluations allowed for the optimization process. The algorithm also utilizes a population of individuals, where each individual represents a potential solution in the search space. The quality of these individuals is assessed using a fitness value, with the best and worst fitness values denoted as fit_{best} and fit_{worst} , respectively. The algorithm iteratively updates these parameters to enhance the search efficiency and convergence speed.

3.3. Principle of Light Propagation

The light propagation principle in FATA is executed after the mirage light filtering principle, which acts as an individual search strategy for the algorithm and is responsible for local exploitation in the search space to find local minima, as shown in Figure 11.

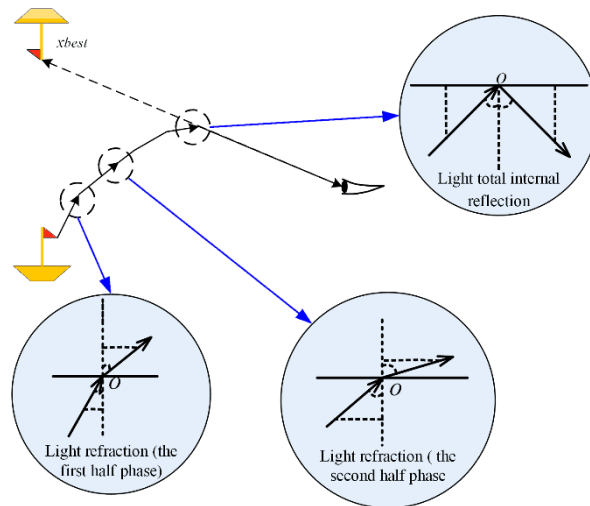


Figure 11. FATA algorithm light propagation strategy

The specific formula for light refraction (first stage) is as follows:

$$x^{next} = x_{best} + x_z \quad (5)$$

$$x_z = x \cdot Para_1 \quad (6)$$

$$Para_1 = \frac{\sin(i_1)}{c \cdot \cos(i_2)} = \tan(\theta) \quad (7)$$

where, x_{best} denotes the optimal individual, x_z denotes the refractive step, $Para_1$ denotes the first stage refractive index, i_1 denotes the angle of incidence, i_2 denotes the angle of refraction, and θ denotes the angular change of the FATA algorithm, which is shown schematically in Figure 12.

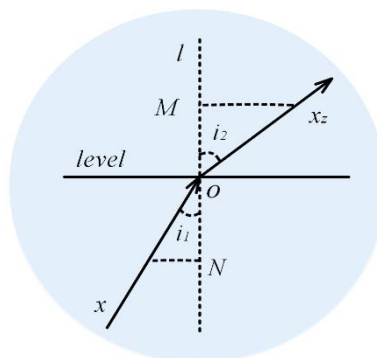


Figure 12. The first stage of the refraction process

The variation curve of the parameter $Para_1$ with the number of iterations is shown in Figure 13.

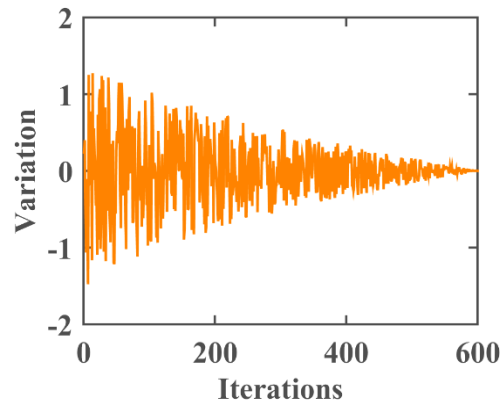


Figure 13. Para1 trends

The specific formula for light refraction (second stage) is as follows:

$$x^{next} = x_{best} + x_s \quad (8)$$

$$x_s = x_f \cdot Para_2 \quad (9)$$

$$Para_2 = \frac{\cos(i_3)}{c \cdot \sin(i_4)} = \frac{1}{\tan(\theta)} \quad (10)$$

where, x_s represents the second stage refraction step, $Para_2$ represents the first stage refractive index, x_f represents the light individual and the refraction process is shown in Figure 14.

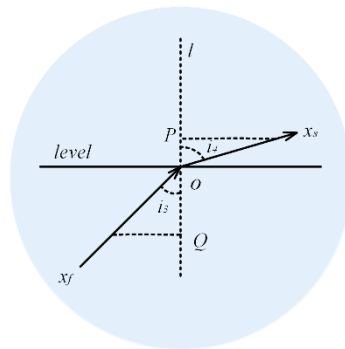


Figure 14. The second stage of the refraction process

The variation curve of the parameter $Para_2$ with the number of iterations is shown in Figure 15.

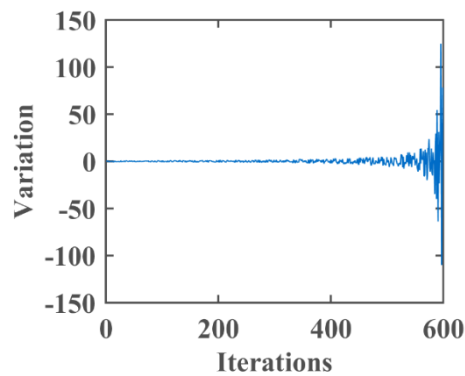


Figure 15. Para2 trends

The total reflection model is calculated as follows:

$$x^{next} = x_f = 0.5 \cdot (\alpha + 1)(U_b + L_b) - \alpha x \quad (11)$$

$$\alpha = \frac{F}{E} \quad (12)$$

$$x_0 - x_f = \frac{F \cdot (x - x_0)}{E} \quad (13)$$

$$x_0 = \frac{U_b - L_b}{2} + L_b = \frac{U_b + L_b}{2} \quad (14)$$

where x_f is the total reflection model emitting individual and α is the reflectivity, the total reflection strategy is shown in Figure 16.

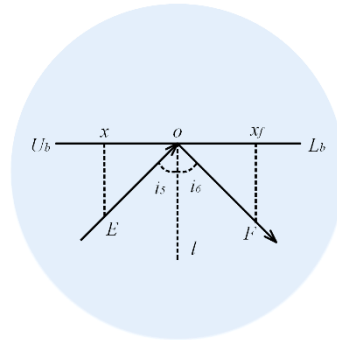


Figure 16. Total-reflective strategy

The pseudo-code of the FATA algorithm is shown in Table 1, and the specific flowchart is shown in Figure 17.

Table 1. Pseudo0cond of the fata algorithm

Algorithm 1: FATA algorithm pseudo-code	
Inputs: the FATA parameters n , d , MaxFES ;	
Output: optimal individuals for the FATA algorithm;	
1	Initialise the FATA algorithms Para1 , Para2 , α ;
2	Initialize the FATA algorithm population;
3	Calculate the FATA algorithm light adaptation value;
4	$\text{FES}=0$;
5	While $\text{FES} < \text{MaxFES}$
6	Update the optimal solution and optimal value;
7	Calculate the weights P ; calculate the parameters Para1 and Para2 ;
8	If $\text{rand} > P$
9	Random initialization of light populations;
10	Else
11	If $\text{rand} < p$
12	Update the population according to the Phase 1 refraction strategy;
13	Else
14	Update the population according to the second phase of the refraction strategy;
15	Using all-reflective renewal populations;
16	End if
17	End if
18	$t=t+1$;
19	End while

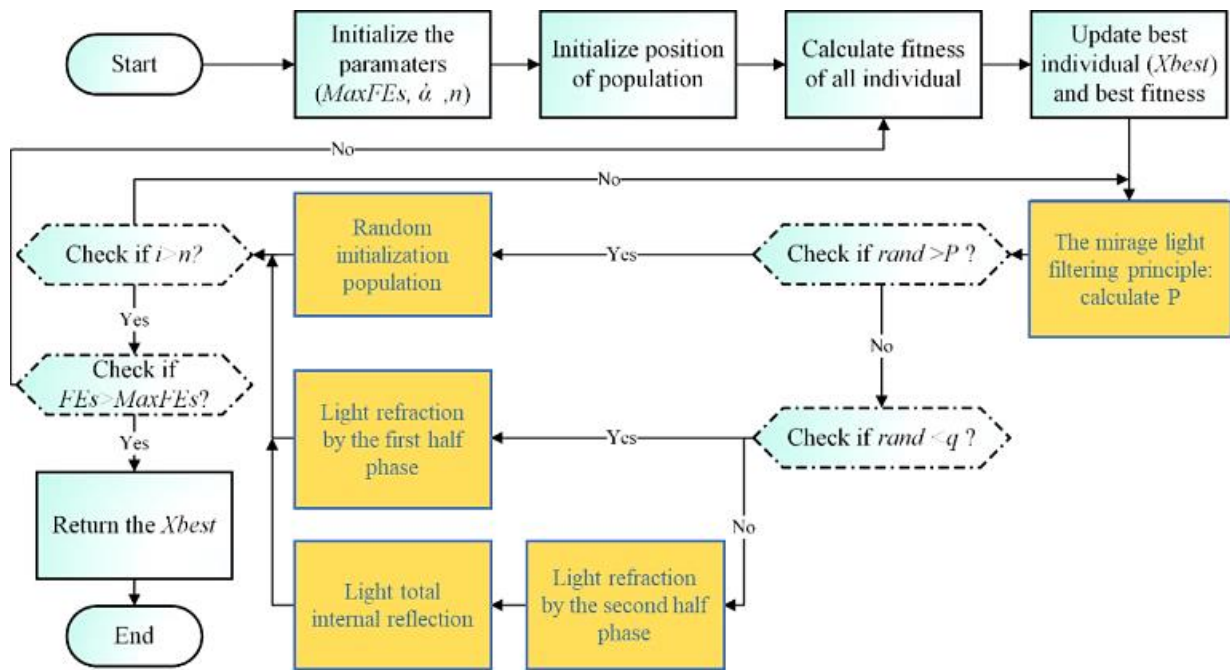


Figure 17. Flowchart of FATA algorithm

4. FATA-ResNet network and CAD/CAM application

4.1. ResNet Neural Network

ResNet (Residual Neural Network) [26] is a deep learning model proposed by researchers at Microsoft Research in 2015, which makes it possible to train very deep networks by introducing residual learning and solving the gradient vanishing problem, as illustrated in Figure 18. The core innovation of ResNet is its Residual Block design, which allows the network to learn the residuals between inputs and outputs through Skip Connection rather than directly learning complex nonlinear mappings [27]. The core innovation of ResNet is its Residual Block design, which allows the network to learn the residuals between inputs and outputs through Skip Connection instead of learning complex nonlinear mappings directly [27].

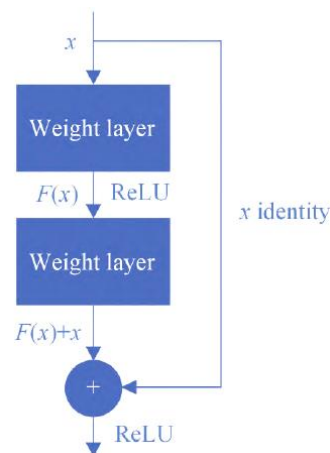


Figure 18. ResNet neural network structure

The basic unit of ResNet is the residual block, which consists of two or more convolutional layers that are usually followed by Batch Normalisation and ReLU activation functions. The output of the residual block consists not only of the results of these convolutional layers but also of the input itself, which is realized by element-level summation [28]. This structure helps the gradient to flow more easily during backpropagation, thus alleviating the gradient vanishing problem [29].

To enhance the CAD/CAM integration technology to improve the analysis accuracy, this paper adopts ResNet50 [30]. ResNet50 contains 49 convolutional layers and 1 fully connected layer. The overall structure of ResNet50 is shown in Figure 19. The overall structure consists of the Conv convolutional layer, the Batch Norm normalization layer, the ReLU activation function, and other basic structures.

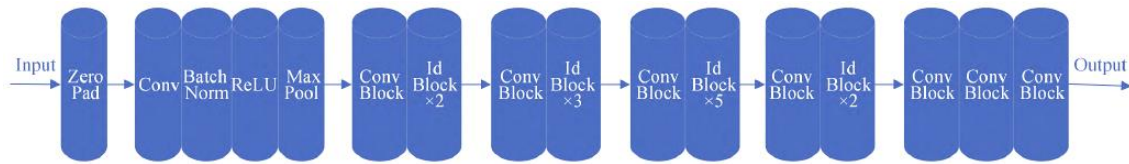


Figure 19. Structure of ResNet50

4.2. FATA-ResNet Network

To further improve the analysis accuracy of CAD/CAM integration technology applications under the cloud manufacturing framework, this paper proposes the FATA-ResNet network model. The FATA algorithm enhances convergence and accuracy through its unique search strategies. The Mirage Light Filtering Principle (MLF) evaluates and filters the population based on the definite integration principle, improving exploration capability. The Light Propagation Strategy (LPS), leveraging trigonometric principles, accelerates convergence and boosts exploitation efficiency. Combined, these strategies optimize both population and individual search abilities. Comparative experiments with other optimization algorithms on 23 benchmark functions and IEEE CEC 2014 show FATA's superior optimization capability. Furthermore, when applied to three practical engineering optimization problems, FATA outperformed its counterparts, proving its effectiveness in real-world scenarios. The model is to construct the FATA-ResNet network model by taking the ResNet network parameters as the optimization object and the loss function as the adaptation value, and the specific model structure is shown in Figure 20.

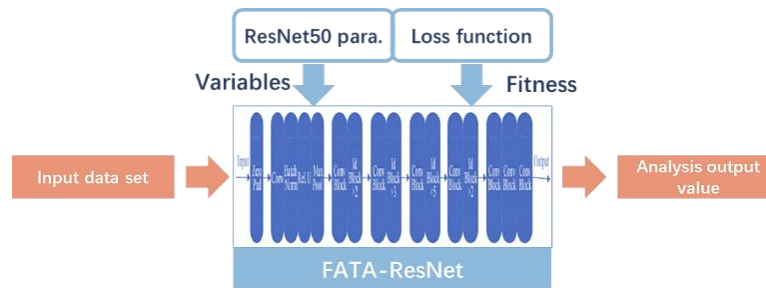


Figure 20. Structure of FATA-ResNet

4.3. CAD/CAM Integration Application Method Based on FATA-ResNet Network

Based on cloud manufacturing, the CAD/CAM integration architecture is designed based on the demand analysis of CAD/CAM integration technology. The CAD/CAM integration technology under the cloud manufacturing framework includes two key technologies, i.e., CAD/CAM integration method and CAD/CAM integration application analysis. For the CAD/CAM integration application analysis problem, this paper proposes a CAD/CAM integration application analysis method based on the FATA-ResNet network, and its specific flow chart is shown in Figure 21.

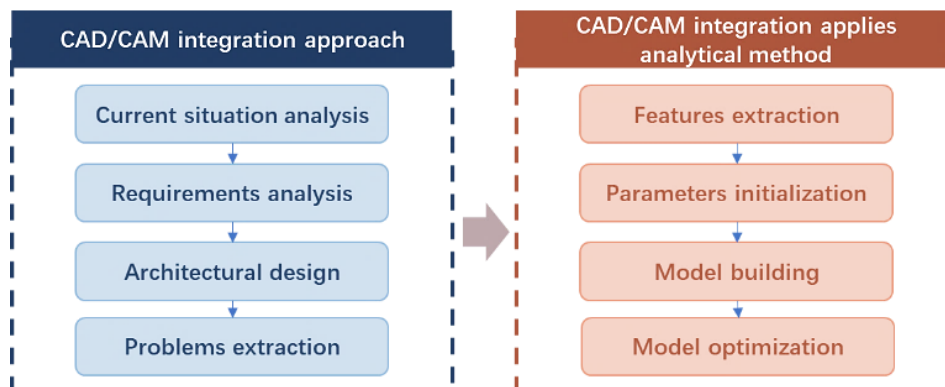


Figure 21. Flow of CAD/CAM integration application

5. Results and Discussion

5.1. Experimental Set-up

Experiments were conducted on a computer with the following configurations: 1) Windows 10 operating system, 16 GB RAM, AMD Ryzen7 7735H-3.20 GHz processor for the CPU, and RTX4060 for the GPU; 2) using the programming

language Python 3.10 and the deep learning framework Pytorch 1.7.1, the experiments were set up with a training number of times is 40 epochs, and the AdamW optimizer is used in the training process. In the experimental setup, the dataset used for training and testing the FATA-ResNet model comprised 5000 samples collected from actual industrial CAD/CAM integration scenarios. The data were formatted as 200 - dimensional feature vectors in CSV files, with each vector representing a specific CAD/CAM integration case. These cases included information on 3D model complexity, process file parameters, and integration outcomes. The dataset was divided into a training set (70%, 3500 samples) and a testing set (30%, 1500 samples). Before use, data underwent normalization to a [0, 1] scale to enhance model training stability and efficiency. This dataset provided a realistic basis for evaluating the model's performance in practical applications.

Data collection from CAD/CAM systems involved extracting operational data and integration outcomes via automated scripts. This data, stored in CSV files, included 200 - dimensional feature vectors representing 3D model attributes and process parameters. Preprocessing steps included data cleaning to remove incomplete or inconsistent entries, followed by normalization using Min - Max scaling to adjust all feature values to a [0, 1] range. This ensured consistent input for the FATA-ResNet model, enhancing training stability and accuracy. The model was trained and deployed using a computer with a Windows 10 OS, 16 GB RAM, an AMD Ryzen7 7735H CPU (3.20 GHz), and an RTX4060 GPU. Given its moderate computational demands, the model could potentially run in factories with limited resources. However, deployment in such environments would require optimization to reduce memory and processing requirements.

Training is performed on CAD/CAM integrated design case datasets to validate the effectiveness and stability of the integrated application analysis models in this study. The algorithms compared include SCA-ResNet, AOA-ResNet, ACOR-ResNet, DE-ResNet, and ResNet, where the parameter settings of SCA-ResNet, AOA-ResNet, ACOR-ResNet, DE-ResNet, and FATA-ResNet optimization algorithms are shown in Table 2.

Table 2. Parameter settings for different optimization algorithms

Modelling	Parameterization
SCA-ResNet	$A=2$
AOA-ResNet	$\alpha = 5; \mu = 0.5$
ACOR-ResNet	$k = 10; \xi = 1; q = 0.5$
DE-ResNet	Crossing probability = 0.5; scaling factor = 0.5
FATA-ResNet	Para1=0; Para2=0

5.2. Analysis of Design Effects

The CAD/CAM integration technology designed in this paper mainly includes obtaining tasks, uploading tasks, logging into the cloud platform, and operating models, and the specific design effects are shown in Figures 22 to 24. Figure 22 gives the manufacturing cloud platform login interface. Figure 23 gives the manufacturing cloud platform login task management interface. Figure 24 gives the browsing and editing interface of the 3D process. As can be seen from Figures 22 to 24, the CAD/CAM integration method designed in this paper can meet the design requirements and solve the CAD/CAM integration problem.

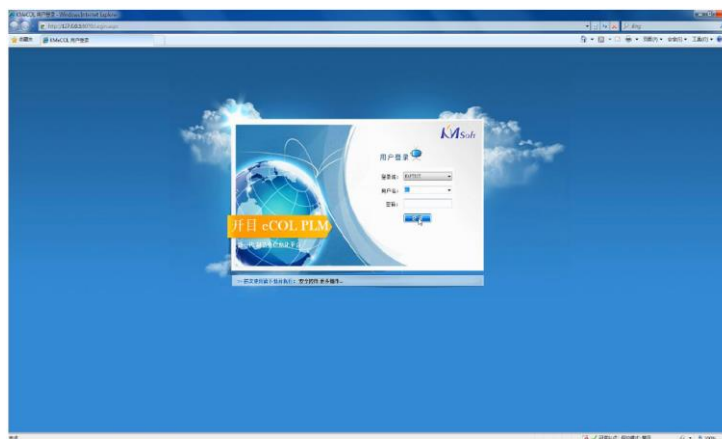


Figure 22. Manufacturing Cloud Platform Login Interface

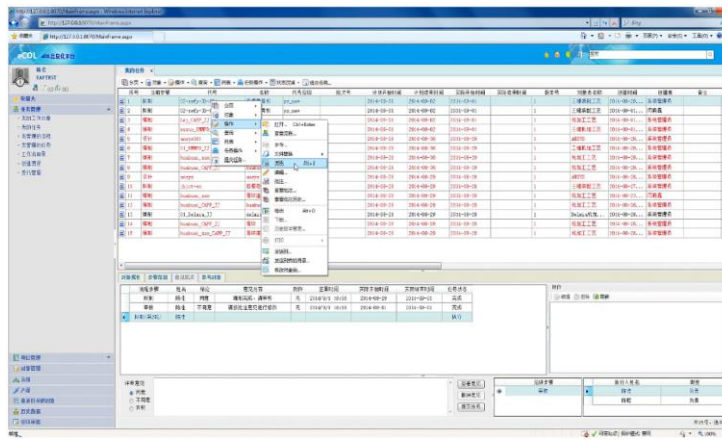


Figure 23. Task Management Interface

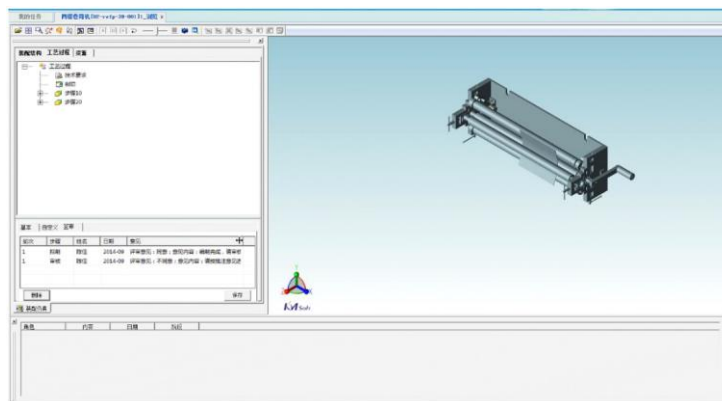


Figure 24. Browsing and editing interface of CAD/CAM 3D process

Figure 22 shows the design of the login interface of the cloud manufacturing platform, which serves as the entrance for users to interact with the system and reflects the security and convenience of the cloud platform. The design incorporates a user authentication and permission management mechanism to ensure that different users (e.g., designers, engineers, and administrators) can access the corresponding modules and data resources according to their roles. This hierarchical design of permissions can effectively protect the platform's core data security and avoid potential information leakage due to confusing operation permissions. In addition, the interface layout is simple and intuitive, and the operation guidelines are clear, which helps users quickly familiarise themselves with the system functions and efficiently complete the task entry operations. The login interface also supports real-time connection with the cloud database, which allows users to enter the task management or model editing module directly after logging in, without additional loading, optimizing the smoothness of operation and time cost. This interface design not only improves the user experience but also provides a basic guarantee for the efficient operation of subsequent functional modules, reflecting the balance between functionality and user-friendliness in the design of the cloud manufacturing platform.

Figure 23 shows the design of the task management interface of the cloud manufacturing platform, which is one of the core functions of achieving collaborative manufacturing and task optimization management. The interface layout is intuitive and clear, providing several key functions such as task creation, assignment, tracking, and status monitoring. Users can view the priority, current progress, and completion of tasks through this interface, and make dynamic adjustments based on real-time updated information, such as reallocating resources or modifying task parameters. The task management interface adopts a modular design with a clear division of labor between different functional blocks, allowing users to access key information efficiently.

In addition, the interface supports cross-platform sharing and manipulation of task data, allowing users to seamlessly collaborate between different devices via the cloud platform, which is particularly important in a cloud manufacturing environment. Task status updates are displayed with visual progress bars and identifiers, further enhancing the efficiency and accuracy of information acquisition. Meanwhile, the task history function provides a reference basis for subsequent data analysis and optimization decisions.

From the perspective of system functions, the task management interface not only improves the transparency and flexibility of the manufacturing process but also provides efficient support for inter-team collaboration. Its design reflects the adaptability of the cloud manufacturing platform for complex task decomposition and dynamic management, laying a technical foundation for the efficient operation of intelligent manufacturing.

Figure 24 shows the design of the 3D process browsing and editing interface in the cloud manufacturing platform, which is designed to support the user's real-time viewing and dynamic editing functions of the CAD/CAM model. The interface provides a comprehensive visual presentation of the 3D model, including model rotation, scaling, and detail zoom operations, enabling users to analyze and optimize design details from multiple perspectives and in a holistic manner. In addition, the interface integrates intelligent process editing tools that support online modification of model parameters, adjustment of process paths, and generation of new process files, which greatly enhances operational flexibility and efficiency.

The 3D process interface also features real-time updates and multi-user collaboration, with user changes instantly synchronized to the relevant task modules via the cloud platform, allowing team members to follow up based on the latest design. This collaboration mechanism is especially important for geographically distributed manufacturing teams. At the same time, the interface design focuses on interactivity and ease of use, with a clear layout and intuitive operation guidelines to reduce user learning costs and improve the operability of the system.

From the technical realization level, the 3D process interface relies on the efficient data transfer and storage capabilities of cloud manufacturing to ensure smooth loading and editing of complex models.

5.3. Analysis of Calculation

To solve the problem of analyzing the application of CAD/CAM integration technology based on cloud manufacturing, this paper adopts the CAD/CAM integration software based on cloud manufacturing to collect data to analyze and compare ResNet, SCA-ResNet, AOA-ResNet, ACOR-ResNet, DE-ResNet, and FATA-ResNet, and the specific results are shown in Figure 25 and Table 3.

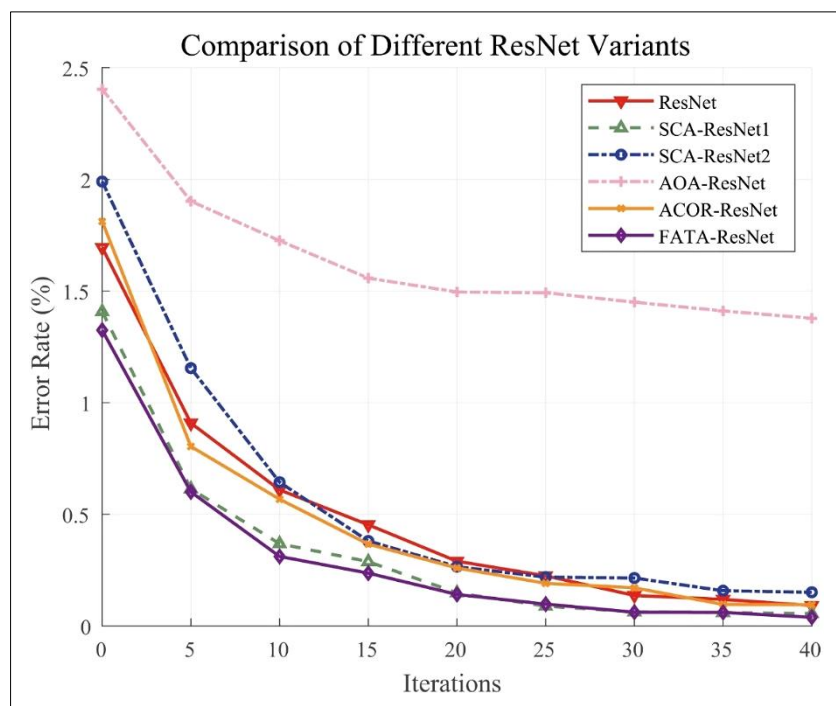


Figure 25. Optimization iteration curves for different models

Table 3. Performance comparison results of different models

Analytical model	Accuracy/%	Recall rate/%	F1 score
ResNet	87.1	83.2	0.801
SCA-ResNet	85.3	80.8	0.765
AOA-ResNet	86.3	82.6	0.812
ACOR-ResNet	88.0	85.7	0.853
DE-ResNet	92.4	90.2	0.890
FATA-ResNet	97.6	95.3	0.945

The training loss values for different models are given in Figure 25. From Figure 25, it can be seen that the training of different models converges to near 0 as the number of iterations increases. The learning and training convergence speed of the optimized ResNet model based on the FATA algorithm is better than the other models and the convergence accuracy is better than the other models. Figure 25 shows the optimized iteration curves of different models during training for comparing the convergence speed and accuracy performance of the FATA-ResNet model with the other compared models such as ResNet, SCA-ResNet, AOA-ResNet, ACOR-ResNet, and DE-ResNet. From the figure, it can be observed that the training loss values of all the models gradually decrease with the increase in the number of iterations, indicating that all the models can fit the data effectively during the training process. However, there are significant differences in the convergence speed and final loss values of different models.

The FATA-ResNet model has the fastest decreasing training loss values, rapidly approaching the convergence state at the initial stage, and has the lowest final loss values. This suggests that the FATA algorithm significantly improves the global search capability and local exploitation of the model by optimizing the parameters of the ResNet network, thus speeding up the optimization process and improving the accuracy of the results. In contrast, ResNet and other comparison models (e.g., SCA-ResNet, AOA-ResNet, etc.) exhibit slower convergence speeds and higher final loss values than FATA-ResNet, indicating that these models may suffer from local optimal point traps or insufficient parameter tuning during the optimization process.

The comprehensive analysis shows that FATA-ResNet outperforms other models in terms of training efficiency and accuracy performance, and is suitable for application in CAD/CAM integration technology analysis tasks that require high optimization accuracy and efficiency. This further validates the effectiveness of the FATA algorithm in optimizing complex neural networks.

The accuracy, recall, and F1 scores of different models are given in Table 3. Table 3 demonstrates the performance comparison of different models in the analysis of CAD/CAM integration technology applications, including three key metrics, namely accuracy, recall, and F1 score, which are used to evaluate the classification accuracy, coverage ability of positive examples, and comprehensive performance of the models, respectively. The experiments compare ResNet, SCA-ResNet, AOA-ResNet, ACOR-ResNet, DE-ResNet, and FATA-ResNet models. As can be seen from the table, the FATA-ResNet model outperforms the other compared models in all metrics, with an accuracy of 97.6%, a recall of 95.3%, and an F1 score of 0.945, which reflects its excellent performance in data-driven analysis. This indicates that the FATA optimization algorithm successfully improves the parameter tuning capability of the ResNet network, enabling the model to more accurately capture complex features in CAD/CAM integration data.

In comparison, the performance of the traditional ResNet model is low, with accuracy and recall of 87.1% and 83.2%, respectively, and an F1 score of only 0.801, reflecting the inadequacy of the unoptimized model in coping with complex data. Other optimized models (e.g., SCA-ResNet, AOA-ResNet, ACOR-ResNet, DE-ResNet), despite improving the performance to a certain extent, are not up to the level of FATA-ResNet, and the gap is especially obvious in the F1 score of the comprehensive performance index.

The experimental results demonstrate the FATA-ResNet model's superiority in analyzing CAD/CAM integration technology. Its high accuracy, recall, and F1 score indicate excellent classification performance. The faster convergence speed and higher computational efficiency mean it can handle complex data more effectively than other models. These advantages make it highly applicable in the cloud manufacturing environment, providing a robust tool for analyzing CAD/CAM integration. The study thus offers a significant advancement in the field of intelligent manufacturing. Overall, the superiority of the FATA-ResNet model lies in the efficiency and adaptability of its optimization algorithm, which not only improves the model's ability to learn complex data features but also ensures the comprehensiveness and reliability of the classification results, which provides effective technical support for CAD/CAM integration technology in the cloud manufacturing environment.

Compared to prior studies, our results show significant improvement. Previous models like ResNet and SCA-ResNet exhibited lower accuracy and slower convergence rates. For example, traditional ResNet only achieved an accuracy of 87.1%, while our FATA-ResNet model reached 97.6%. This indicates that the integration of the FATA algorithm with ResNet substantially enhances performance. The difference lies in our optimized parameter tuning and the efficient global search capability of FATA. This advancement addresses the limitations of previous research and offers a more effective solution for CAD/CAM integration analysis in cloud manufacturing.

To validate the effectiveness of the FATA optimization, ablation studies were conducted. We compared the FATA-ResNet model with the original ResNet model under identical experimental conditions. Results showed that FATA-ResNet achieved an accuracy of 97.6% and a rapid convergence speed, while the original ResNet only reached 87.1% accuracy with slower convergence. This confirms FATA's significant enhancement to ResNet's integration analysis capability. The FATA algorithm enhances convergence and accuracy through its unique search strategies. The Mirage Light Filtering Principle (MLF) evaluates and filters the population based on the definite integration principle, improving exploration capability. The Light Propagation Strategy (LPS), leveraging trigonometric principles, accelerates convergence and boosts exploitation efficiency. Combined, these strategies optimize both population and individual search abilities. Comparative experiments with other optimization algorithms on 23 benchmark functions and IEEE CEC 2014 show FATA's superior optimization capability. Furthermore, when applied to three practical engineering optimization problems, FATA outperformed its counterparts, proving its effectiveness in real-world scenarios.

6. Conclusion

Aiming at the problem of CAD/CAM technology integration application under the cloud manufacturing framework, this paper designs a CAD/CAM technology integration scheme for mechanical engineering under the cloud manufacturing framework and proposes a CAD/CAM technology integration application analysis method based on the FATA-ResNet model. By analyzing the demand for CAD/CAM technology integration under the cloud manufacturing framework, a CAD/CAM technology integration application analysis model based on FATA-ResNet is proposed, and data analysis is performed by using CAD/CAM technology integration design software to collect data to verify the FATA-ResNet model performance. ResNet model performance. The results show that the FATA-ResNet model accuracy, recall, and F1 score are better than other models, and the convergence speed is faster than other optimization algorithms. A variety of mechanical engineering CAD/CAM designs will be carried out in the future to further validate the performance of the FATA-ResNet model.

Although this paper proposes a CAD/CAM integration application analysis method based on the FATA-ResNet network and verifies its superior performance under the cloud manufacturing framework, there are still some shortcomings and room for improvement. On the one hand, the dataset of the current study is mainly derived from a single experimental environment, which does not fully consider the diverse needs in actual complex manufacturing scenarios, such as cross-platform data compatibility, dynamic task allocation, etc., which may affect the wide applicability of the model. On the other hand, although model optimization has achieved significant results in terms of accuracy and efficiency, its high dependence on computational resources may limit its ability to be deployed in resource-limited enterprises. Future research can be carried out in the following aspects: first, introducing heterogeneous data from multiple sources to verify the applicability of the method in complex industrial scenarios; second, optimizing the model structure to reduce the computational complexity and improve the efficiency of resource utilization; third, exploring the real-time cloud collaboration capability to support multi-user, multi-task parallel operation, providing a more efficient and flexible technological solution in the field of smart manufacturing. Meanwhile, the research can be extended to more engineering application fields to further promote the digital and intelligent development of manufacturing.

7. Declarations

7.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.2. Funding

The author received no financial support for the research, authorship, and/or publication of this article.

7.3. Institutional Review Board Statement

Not applicable.

7.4. Informed Consent Statement

Not applicable.

7.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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