An Intelligent Decision-making System for Complex Products Assembly Process Planning

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An intelligent decision-making system for complex products assembly process planning

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Abstract:

Current assembly process planning of complex products depends largely on the experience of technical personnel, which results in low design efficiency, low intelligence, and difficult to extract the assembly knowledge. To address these problems, this paper proposes an intelligent decision-making system for complex products assembly process planning through a comprehensively improved BP neural network with considering the assembly unit variability. Firstly, the characteristics, variations and similarities of assembly process for complex products are analyzed. A hierarchical model of product assembly process is established, which decomposes assembly process decision-making for overall structure into several units. A training set of each assembly unit is built considering the effect of assembly unit variability, based on which, an assembly process structure tree can be constructed quickly by connecting the nodes in the assembly process hierarchy model and the assembly process decision results. Secondly, to improve the efficiency and accuracy of decision-making, an ant lion optimizer (ALO)-BP neural network is proposed for complex products assembly process planning, which can optimize the selection of initial weights, thresholds, learning rate and feedback process of BP neural network automatically. Finally, with the case study of assembly process of the marine diesel engines, the proposed approach is compared with other algorithm models. The comparison results demonstrated that the proposed intelligent decision-making system is more precise than the other models.

Key words: Assembly process planning; Intelligent decision-making; Assembly unit variability; Hierarchy model; ALO-BP neural network

1 Introduction

Assembly stage is one of the most important stage in product life cycle, which consumes a lot of resources and time [1, 2]. Among them, the assembly process of complex products needs to occupy about 33 % of human resources, more than 40 % of production costs and 40 ~ 60 % of total production hours in the whole production process. If the problems occur in the assembly process, which will add extra costs and assembly time. These directly affects the overall production cycle and product quality. As the information source and guiding principle of assembly process, assembly process planning has a profound impact on the length of assembly cycle and the quality of product assembly, which is more obvious in the assembly process of complex products.

Due to the characteristics of large volume, complex structure and numerous assembly modules of complex products such as Marine diesel engines, aircraft and so on, the assembly and use of complex products are related to mechanical, electrical, hydraulic, gas and other aspects, which brings great challenges to the assembly process design and actual assembly process. Therefore, the assembly process planning of complex products is generally decomposed into assembly process route design, part assembly sequence planning, assembly process resource assignment, and assembly path planning, assembly process simulation optimization. Among them, the assembly process route design is a macro assembly process design based on the assembly process hierarchical model divided by the structural characteristics of complex products and assembly relations. It is generally shown in the form of top-down assembly process structure tree, which is an important basis for subsequent design.

Currently, with the “Industry 4.0”, “Advanced Manufacturing Partner Program”, “Made in China 2025” and other manufacturing development strategies are proposed, the manufacturing industry has been changing towards intelligence. Machine learning algorithms are techniques for automatically building models of complex systems to discover patterns, and making predictions about future events.

In which, neural network [3-5] is one of the important research contents in the field of machine learning. It is the most mature and representative machine learning method that has been widely used to solve various problems in the field of machinery.

According to above analysis, this paper aims to provide an intelligent assembly process design method based on intelligent algorithm with consideration of variations of assembly units, and the output of which is variable with the change of assembly units' composition. The research on the intelligent design method of assembly process based on neural network, the construction of assembly process structure tree, and the formation of intelligent decision-making scheme of assembly process are of great significance to promote the intelligent design of complex product assembly process and the intelligent manufacturing industry.

The rest of this paper is organized as follows: Section 2 reviews the related previous researches. Section 3 describes the process of selection and optimization of related algorithms, and the establishment process of intelligent decision-making model of assembly process. Section 4 shows a real assembly process of the marine diesel engines to demonstrate the presented intelligent decision-making system. Conclusion and future work are given in Section 5.

2 Related previous work

Many researchers have studied on the assembly process design of complex products. Bikas et al. [2] proposed an assembly processing planning system which reduces the human intervention and the computational effort. Zhang et al. [6] developed the assembly process design system of marine diesel engine, and established the digital assembly simulation scene. In addition, the process model is applied as the same data source of process simulation, which improves the reliability of marine diesel engine manufacturing. Saivaew and Butdee [7] proposed AHP and Fuzzy Logic for making a decision of assembly process and selecting optimal plans for each stage of assembly. Yang et al. [8] proposed a digital twin reference model for intelligent assembly process design, and proposed an application framework for DT-based smart assembly with three layers. Tsutsumi et al. [9] proposed an optimization approach, integrating product design, process planning, and production planning with considering jointly solving tolerance allocation, assembly resource configuration, regarding process and production planning. Krist et al. [10] obtained technical expertise and knowledge from non-experts from assembly operations during the assembly workshop, and integrated them into the implementation process of assembly planning. Chen et al. [11] processed a novel approach to discover assembly process case for assembly process reuse using multimedia information source. Lu et al. [12] proposed an assembly sequence planning approach considering the effect of assembly resources, and a discrete fireworks algorithm was used to obtain assembly sequence planning. Zhang et al. [13] constructed a fuzzy-rough set mapping model of parallel disassembly with considering five disassembly factors which was adopted to generate the optimum parallel disassembly sequence. Zhuang et al. [14] proposed a framework of digital twin-based smart production management and control approach for complex product assembly shop-floors.

Although more studies focused on promoting the planning of assembly process, there are still following limitations in the assembly process design of complex products: (1) Complex products involve a large amount of professional knowledge, and the difficulty of acquiring and integrating expert knowledge increases with the increase of the complexity of products themselves; (2) The design process mainly relies on the engineer's experience, retrieval of templates and cases, which leads to the inconsistent quality and low efficiency of the assembly process, as well as the low degree of intelligence of the whole process; (3) A considerable number of complex product manufacturing industries have imperfect management of assembly process documents, which in turn leads to the documents are dispersed in different electronic documents. These will result in

confusion of process data, long design cycle and unclear expression of process information, which cannot meet the needs of complex product manufacturing industry to improve production capacity.

To address above problem, many studies have carried out on the intelligent decision technology. Hou et al. [15] proposed an intelligent decision support system based on neural network and expert system, which ensures that the assembly sequence planning process can not only make full use of the experience of technical personnel, but also avoid duplication of effort. Ahmad et al. [16] presented a knowledge-based intelligent decision system that takes information from a vision sensor within the manufacturing process and generates automatic planning/path-planning decisions in for collision avoidance in virtual CAM production. Simeone et al. [17] developed an intelligent decision-making support tool based on a manufacturing service recommendation system, and a neural network procedure for data regression was employed to process historical data on user manufacturing solution preferences. Burggräf et al. [18] proposed a model to assess artificial intelligence (AI) performance in contrast to human decision-making. Teixeira et al. [19] presented a situation-aware model to support multi-objective decision making for objectives with equal importance. Mahmoodzadeh et al. [20] used Gaussian Process Regression (GPR) and Support Vector Regression (SVR) to forecast geology, construction time and construction costs of a road tunnel project. Zhao et al. [21] developed a wind energy decision system according to swarm intelligence optimization and data preprocessing. Bettinelli et al. [22] proposed a new theoretical decision support system framework through multiagent systems which make it able to design new products from post-used components.

It can be concluded from the above analysis that intelligent decision-making technology can accurately predict similar new cases based on past experience, and which can be widely used in various fields. However, there are still some limitations in the application of complex product assembly process: (1) When making decisions on process templates through similar cases, we need to establish different expert systems, and the implementation process is very complex; (2) The traditional template decision-making method cannot well adapt to the differences of each model.

3 Modeling of intelligent decision-making for assembly process

3.1 Building assembly process hierarchy model

The characteristics of complex products (such as various parts, various functional modules, and complex structure) lead to a long assembly process design cycle and difficulty. The structured process design pattern is oriented to the whole process design process of the product, which can effectively manage the data and information generated in the process design and production process, and provide strong support for the evaluation and data exchange of various processes in the production process.

Therefore, for the assembly design process of complex products, it is necessary to analyze the assembly structure characteristics of complex products and the composition of each assembly module in details. Then, the top-down product structure and assembly level are hierarchically processed, and the hierarchical structure model of assembly process is constructed.

According to the assembly process of products from parts to the whole and the relationship between each functional module in the product, the assembly process hierarchy model is constructed by analyzing the assembly process documents and production experience. The establishment process of assembly process hierarchy model is illustrated in Fig.1. As shown in Fig.1, the assembly products are divided into several parts: Product, level 1 assembly, level 2 assembly, level n assembly and bottom parts. Among them, the product node is also the root node of the assembly process structure tree. Assemblies at all levels are part groups to achieve product functions, which are composed of lower-level assembly and

related parts. The bottom parts are directly constituting the lowest assembly in the product.

The assembly hierarchy model construction steps can be concluded as the following steps:

Step 1: Get product design BOM.

Step 2: Read the code of each component defined by the engineer during the product structure design phase.

Step 3: Complete automatic product level division according to the code.

As shown in Fig. 1, the coding of each component is automatically obtained by the program, and the hierarchical structure of the assembly product is constructed. Through above process, the automatic division of the assembly product hierarchy can be completed.

The design of assembly process based on assembly level that enables all process nodes to be interrelated in a reasonable way, which can significantly improve the parallelism of assembly process design and efficiently design and manage all assembly sub-process objectives. When making decisions for the assembly process, the decisions between different levels are relatively independent and interrelated, which simplifies the decision model of the overall structure and ensures the accuracy of the decision results, so as to quickly build the assembly process structure tree.

3.2 Modeling of assembly process training set considering assembly unit variability

This study proposes the hierarchical model of assembly process structure, which takes each component or sub-assembly in each assembly level as a unit to make assembly process decision. Since each assembly level is independent of each other and has a certain assembly relationship at the same time, it is necessary to construct the assembly process training set according to the characteristics of each component in each level when making decisions on the assembly process.

The method of building training set is given as follows:

(1) Build the information database of each assembly level. Read all the same types or series of product structure and assembly process files in the past production, and build the hierarchical model of assembly process structure. Obtain the information of assemblies, parts and assembly processes at all levels, and then establish the corresponding information database of the whole machine-components-subassemblies-parts-assembly process. The database contains the structure and process information of each model in the current product, which can be used as the comparison set when building the training set. For instance, the information database of diesel engine cylinder cap components is a collection of subassemblies information, parts information and corresponding assembly process information contained in all diesel engine models.

(2) Code and build the training set. According to the information database of each assembly level of the product, the corresponding transformation of the assembly units' information in the assembly process files of each model is carried out to establish the corresponding training set.

Considering the variability of assembly unit of different models, which lead to the variability of assembly process. When building the training set, the structure and process information in the current assembly unit comparison set is used as the nodes in neural network. The information of the assembly unit of different models is integrated into row vectors as several training samples. In the training samples, the variability of the structure and assembly process of each assembly unit is reflected in the difference of the information of each node when compared with the comparison set, which is presented in the training set by the coding form of 1 and -1.

(3) According to the comparison of the assembly units, the assembly process training set in the form of matrix $APTS$ can be expressed as follows:

$$APTS = \begin{bmatrix} A1 & \cdots & An & O1 & \cdots & On \\ 1 & \cdots & -1 & 1 & \cdots & 1 \\ \vdots & \ddots & \cdots & \vdots & \ddots & \cdots \\ 1 & \cdots & 1 & 1 & \cdots & -1 \end{bmatrix} \quad (1)$$

In Eq. (1), $APTS$ represents the assembly training set matrix of the current object. The column

vectors (A_1~ A_n) represent the information of parts and subassembly contained in the unit of all sample models, and the column vectors represent whether the current part or subassembly exists in sample models. If there is, it is denoted as 1, otherwise, it is denoted as -1. The column vectors (O_1~ O_m) represent the assembly process information contained in the unit of all sample models, and the column vectors represent whether the current assembly process exists in the assembly process of sample models. If it exists, it is denoted as 1, otherwise, it is denoted as -1. Therefore, the training set matrix realizes the full coverage of parts information and assembly process information of the same assembly unit in different models.

3.3 Modeling of intelligent decision-making of single assembly unit

BP neural network [23, 24] is the most mature and representative in the neural network algorithm, which has been widely used to solve various problems in the field of machinery. However, the traditional neural network is easy to fall into local extremum. Especially when solving small sample and high dimension problems, the convergence speed becomes slow and the network performance becomes poor. In addition, when the initial weights and thresholds of the neural network are not properly selected, it is often impossible to obtain good prediction results. To address above problems, the traditional BP neural network algorithm needs to be optimized.

3.3.1 Ant lion optimizer algorithm

Ant lion optimizer (ALO) algorithm is a heuristic swarm intelligence optimization algorithm proposed by Mirjalili [25] in 2015. ALO introduces random walk, roulette wheel strategy and elite strategy, which is an algorithm with diverse population, few adjustment parameters, easy realization and strong optimization performance. It is one of the important algorithms in the field of evolutionary computation in recent years, which has been successfully applied to the optimization of many problems such as UAV route planning, reactive power optimization scheduling of power system and leverage structure optimization. The specific steps of ant lion optimizer algorithm are already described in Ref. [25].

Therefore, to realize the optimization of BP neural network, the global search ability of ALO algorithm with combination of the local optimization ability of BP neural network is applied in this study.

3.3.2 Improved BP neural network based on ALO algorithm

In order to solve the problem of BP neural network as mentioned above, the ALO-BP neural network is proposed as shown in Fig. 2. The optimization of BP neural network can be expressed as follows:

(1) The initial weights and thresholds of BP neural network are optimized by using ALO algorithm. According to the actual model of BP neural network, the population is encoded and the initial population is generated. The mean square error loss function of BP neural network is used as the objective function of ALO algorithm. The mean square error loss function is as follows:

$$MSE\left(O,O^{'}\right)=\frac{\sum_{i=1}^{n}\left(O_i-O_i^{'}\right)^2}{n} \tag{2}$$

In Eq. (2), $MSE(O,O')$ is the mean square error loss function, O' is the standard value, O is the output result of the neural network, and n is the number of nodes in the output layer.

According to the function, the fitness of ALO algorithm is calculated. When the ALO algorithm reaches the maximum iteration or meets the requirements of termination iterations, the optimal individual is recorded and extracted. After decoding, the optimal initial weights and thresholds are generated.

(2) Adopt adaptive learning rate to improve the convergence rate of the network and reduce the training time:

$$\eta(t+1)=\begin{cases}(1+\beta)\eta, & err(t)\le err(t-1)\\(1-\beta)\eta, & err(t)>err(t-1)\end{cases} \tag{3}$$

In Eq. (3), η is the learning rate, t is the

current training number, β is a decimal, and usually 0.01 ~ 0.03. $err(t)$ is the loss function value after the tth training, which represents the error between the actual output and the standard value. From Eq. (3), it can be concluded that when the error becomes small, the learning rate should be increased, and when the error becomes large, the learning rate should be reduced, so as to achieve the goal of reducing the effective learning time.

(3) Adopt the additional momentum method to avoid the weights and thresholds converge to local optimum:

$$\Delta w(t) = \alpha \Delta w(t-1) - \eta \frac{\partial err(t-1)}{\partial w(t-1)} \quad (4)$$

$$\Delta b(t) = \alpha \Delta b(t-1) - \eta \frac{\partial err(t-1)}{\partial b(t-1)} \quad (5)$$

In Eqs. (4) ~ (5), α is a momentum factor, the general value is 0.95.

The additional momentum method makes the network not only consider the effect of the error on the gradient, but also consider the influence of the change trend on the error surface. In the absence of additional momentum, the network may fall into shallow local minima, and it may slip over these minima by using the additional momentum.

Based on the back propagation method, a new weight (or threshold) change is generated by adding a value proportional to the previous weight (or threshold) change to each weight (or threshold) change.

3.3.3 Intelligent decision-making model through ALO-BP neural network

In order to solve the problem of assembly process planning for a single assembly unit, this study combines the ALO-BP neural network with assembly process hierarchy model and training set model, which can be used to make decisions rapidly and generate assembly process structure tree. The assembly process of complex products is often divided into components such as assembly, pre-assembly and final assembly according to the division of each functional structure in the product. The variability of assembly process is also mainly caused by the variability of assembly units. Therefore, in the construction of neural network decision model, the column vectors (A_1~ A_n) are used as the nodes of the input layer, the column vectors (O_1~ O_m) are used as the nodes of the output layer, and the number of elements in the column vector is the number of machines involved, which fully reflects the influence of component composition on the assembly process composition. Taking a component neural network decision model as an example, the neural network model is shown in Fig.3.

In the ALO algorithm, the individual position vector of ant and ant lion population directly reflects the weight and threshold quality of each layer. Therefore, in order to facilitate the algorithm, the weight and threshold matrix w_1, b_1 from the input layer to the hidden layer and the weight and threshold matrix w_2, b_2 from the hidden layer to the output layer are merged, and stretched into a row vector as the individual position vector of ant and ant lion.

Therefore, the number of elements Dim of each individual position vector in the ant and ant lion population should be determined by w_1, b_1 and w_2,b_2 :

$$Dim = N_{w_1} + N_{b_1} + N_{w_2} + N_{b_2} \quad (6)$$

In Eq. (6), $N_{w_1}, N_{b_1}, N_{w_2}, N_{b_2}$ are the number of elements in w_1,b_1,w_2,b_2, respectively. The number of elements in w_1, b_1, w_2, b_2 is determined by the nodes of the input layer, hidden layer and output layer of the neural network.

$$N_{w_1} = N_{in} \times N_{hd} \quad (7)$$

$$N_{b_1} = N_{hd} \quad (8)$$

$$N_{w_2} = N_{hd} \times N_{out} \quad (9)$$

$$N_{b_2} = N_{out} \quad (10)$$

In Eqs. (7) ~ (10), N_{in}, N_{hd}, N_{out} are the number of nodes in input layer, hidden layer and output layer, respectively.

Generate initial population according to Dim:

$$Ant = [\alpha_1, \alpha_2, \alpha_3, \mathrm{L}, \alpha_{Dim}] \quad (11)$$

After iterative optimization, the best individual

$Best\_pos$ is obtained. The $Best\_pos$ is sliced according to the number of columns and rows of w_1,b_1,w_2,b_2, and split into several row vectors, and these row vectors are reorganized to obtain optimized w_1,b_1,w_2,b_2 matrices, and specific steps as follows:

Step 1: The row vector $Best\_pos$ is divided into four row vectors $w'_{1,}$ $b'_{1,}$ $w'_{2,}$ b'_2 according to N_{w_1}, N_{b_1}, N_{w_2}, N_{b_2};

Step 2: Divide $w'_{1,}$ $b'_{1,}$ $w'_{2,}$ b'_2 into several row vectors according to the number of rows respectively, take w'_1 as an example, divide it into N_{hd} rows, and each row has the number of elements as N_{in};

Step 3: Rearrange the row vectors to generate optimized $w'_{1,}$ $b'_{1,}$ $w'_{2,}$ b'_2 matrices.

The population initialization formula of the ALO algorithm is as follows:

$$Ant_{n,d} = Lb + rand(Ub - Lb) \quad (12)$$

In Eq.(12), $Ant_{n,d}$ is the initial position of the ant, $n = 1,2,\cdots N, d = 1,2,\cdots Dim$, the number of ants and ant lions are both N, Ub and Lb are the upper and lower search space bounds respectively.

Since each node element of the input layer and output layer of the neural network is composed of 1, -1, in order to ensure that the actual output result of the neural network remains near 1, -1, after many experiments, the initial search bounds of the ALO algorithm are set as: $Ub = 0.5$, $Lb = -0.5$.

During the wandering process, the ants enter the "trap" of the ant lions, which reduces the wandering boundary, so the search space satisfies the following adaptive strategy:

$$c^t = \frac{c^t}{I}, \ d^t = \frac{d^t}{I} \quad (13)$$

In Eq. (13), c^t、d^t are the lower and upper bounds of all variables in the t iteration of the ALO algorithm, I is the trap reduction factor, if the number of iterations increases, I increases linearly in pieces:

$$I = 10^{w\frac{t}{T}} \quad (14)$$

t is the current number of iterations, T is the maximum number of iterations, w depends on the current algebra:

$$w = \begin{cases} 2, & t > 0.1T \\ 3, & t > 0.5T \\ 4, & t > 0.75T \\ 5, & t > 0.9T \\ 6, & t > 0.95T \end{cases} \quad (15)$$

In the BP neural network, the input layer, hidden layer, and output layer have the following mathematical relationships:

$$BP_{hd} = f_1(w_1 BP_{in} + b_1) \quad (16)$$

$$BP_{out} = f_2(w_2 BP_{hd} + b_2) \quad (17)$$

In Eqs. (16)~(17), BP_{in} is the input of the neural network, f_1, f_2 are the activation functions, w_1, b_1 are the weight and threshold matrices from the input layer to the hidden layer, respectively. After calculation, the result, BP_{hd}, is output to the hidden layer, w_2, b_2 are the weight and threshold matrices from the hidden layer to the output layer, and the neural network output BP_{out} is obtained after calculation.

The mean square error of the standard value and the actual output is selected as the loss function. In order to find the individual that minimizes the network training error, the mean square error of the output layer needs to be calculated. The mean square error formula is:

$$MSE(BP_{out}, BP'_{out}) = \frac{\sum_{i=1}^{n}\left(BP_{out_i} - BP'_{out_i}\right)^2}{n} \quad (18)$$

In Eq. (18), $MSE(BP_{out}, BP'_{out})$ is the mean square error loss function, BP'_{out} is the standard value, and BP_{out} is the output of the neural network. n is the number of nodes in the output layer. The smaller the loss function value, the greater the performance of the network model.

Through the above steps, the model is trained to generate the better decision-making parameters. Then, the obtained decision-making parameters can be used to quickly make decisions on the new complex products assembly process.

3.4 The method of assembly process intelligent decision-making for overall structure

When assembles the complex products, the overall order can be operated from bottom to top

according to the single assembly unit model. Firstly, the lower-level assembly units are assembled, and then assemble them into higher level components as a whole. During the process of complex products assembly planning and the construction of assembly process structure tree, which needs to be built from the product node to the bottom parts nodes. Therefore, the essence of assembly process intelligent decision-making for the overall structure is the cycle of assembly process intelligent decision-making events of a single assembly unit in each assembly level and assembly body.

Through the connection and expansion of each node, a complete assembly process structure tree can be finally constructed. The intelligent decision-making system for the overall structure assembly process is shown in Fig. 4. Firstly, the hierarchical model of assembly process is constructed according to the product structure in the training samples, and the product node is established as the root node of the assembly process structure tree of multi models. Then, the structure and process information of each assembly unit in level 1 of the product node are obtained. Expand the assembly process structure tree of multi models and construct the corresponding information database. After that, the training set of the product node is constructed, and the ALO-BP neural network algorithm is used for training and the test samples are used for testing. When the training error and test results meet the requirements, the current level decision-making parameters are output and linked under the product node. Finally, the assembly process decision parameters of each assembly unit are obtained.

Secondly, in the decision-making stage, the designed overall structure is obtained, the hierarchical model of assembly process is constructed, and the product nodes of the current assembly process structure tree are generated. By traversing the information of each assembly unit in the first level, the input set of the decision-making of the product nodes are determined according to the above training set construction method. Read the saved decision-making parameters, calculate and output the related process through Eqs. (16) ~ (17), and expand the assembly process structure tree. The repeated process can be implemented in each level and each assembly unit, then a complete assembly process structure tree is obtained finally.

4 Case study

In order to verify the proposed intelligent decision-making system for complex products assembly process planning, different cylinder cap models in marine diesel engine are used as case product that includes the historical assembly process file data in a marine diesel engine manufacturer's database.

4.1 Intelligence decision-making for cylinder cap assembly process

Currently, the marine diesel engine is divided according to the levels of products, assemblies, small assemblies, and components and parts. Fig. 5 shows the model of the cylinder cap assembly of a marine diesel engine. According to the characteristics of the assembly process of the marine diesel engine cylinder cap, the automatic division of the assembly process level and the construction of the model are completed, and partial selection of result is illustrated in Fig. 6. The assembly process data of the cylinder cap is processed according to the above-divided assembly levels to form the assembly process training set. The features corresponding to the input in the training set are used as the input of the network training corresponding to the number of nodes in the input layer, and the features corresponding to the output in the training set are used as the output of the network training, corresponding to the number of nodes in the output layer.

The comparison results between the proposed intelligent decision-making algorithm and other neural network algorithms are shown in Fig. 7. It can be found that the value of the loss function gets smaller gradually as the number of training times increases. Finally, the training is completed using the proposed ALO-BP neural network when the

termination condition is reached at about 2000 training times, which speeds up each iteration. The output results using the trained neural network parameters to make intelligent decision-making on the cylinder cap assembly process for several marine diesel engine models are shown in Table 1. The standard value is shown in Table 2. The value of the predicted output result of each process is the degree of support for whether the process exists in the current component assembly process. It is standardized according to the "rounding" principle, and the result is compared with the standard value "1, -1". Take model 2 as an example: the output result of fuel injector installation is 0.9787, and the standard value is 1, indicating that fuel injector installation is included the cylinder cap assembly process of model 2; The output result of indicator valve installation is -0.9651, and the standard value is -1, indicating that fuel injector installation exists in the cylinder cap assembly process of model 1.

4.2 Comparison with other neural networks and experimental data

In order to verify the superiority of the proposed intelligent decision-making algorithm, other neural networks (traditional BP neural network, GA-BP neural network, PSO-BP neural network, GWO-BP neural network and ABC-BP neural network) are conducted to train and predict the assembly process of cylinder caps. The loss function of each algorithm is shown in Fig. 7, and the output results are listed in Tables 3-7. It can be seen from Fig. 7 that the training times of other algorithms are relatively large, which fully proves that the ALO-BP algorithm proposed in this paper has good convergence speed.

In addition, the prediction output results of each neural network algorithm are compared with the standard value of the four models, as shown in Fig. 8. It can be seen from Fig. 8 that the output results of ALO-BP neural network are basically consistent with the standard value, while the output results of the other neural network algorithms are quite different from the standard value. Therefore, it can be concluded that the ALO-BP neural network has the advantage of high correct rate in intelligent decision making of assembly process.

The errors between the predicted results and the standard values of each algorithm are shown in Figs. 9 -12. It can be seen clearly from Figs. 9-12 that the percentage error of ALO-BP neural network is smaller than that of other algorithms, which indicates the intelligent decision-making model based on ALO-BP neural network is more accurate and suitable for the assembly process planning.

Considering that with the progress of technology and the increase of demand, manufacturing enterprises will continuously develop new products. Furthermore, there are more and more products models owned by enterprises, and the database will continue to expanded and changed. When the intelligent decision-making of assembly process for new models, it is often necessary to expand the training set and re-train the neural network parameters. Therefore, it is very important for enterprises to maintain the accuracy and stability of neural network in multiple training. In order to study the stability of neural networks in multiple training, the above neural networks are used to train four diesel engine models, and the stability is characterized by the standard deviation of the five training results. Fig. 13 illustrates the comparison results between the proposed intelligent decision-making algorithm and other neural networks. It can be seen from Fig. 13 that the standard deviation of the ALO-BP neural network has always maintained at a low value in multiple tests, which is more advantageous than other algorithms. The comparison results indicate that the ALO-BP neural network has stronger adaptability to the intelligent decision-making of complex products assembly process.

4.3 Construction of assembly process structure tree based on intelligent decision results

According to the mentioned parameters training and testing process of decision system for the assembly process of marine diesel engine cylinder

caps. Applying the same logical idea to sort out information, build training sets, and make intelligent decisions on each assembly level and assembly of marine diesel engines. Then, mapping the prediction results to the Teamcenter platform. Finally, the assembly process of marine diesel engine can be shown to the designer through the assembly process structure tree. An example of the structure tree of marine diesel engine assembly process is shown in Fig. 14. In this platform, the modification function of human-computer interaction is retained. Thus, the designer can supplement and improve it according to their own experience and rules, which finally forms a highly reliable assembly process for the entire marine diesel engine.

5 Conclusion and future work

Aiming at the problems that the assembly process design of complex product depends largely on worker experience, low efficiency, low intelligence, and lack of structural expression in the assembly process, this study proposes an intelligent decision-making system for complex products assembly process planning through a comprehensively improved BP neural network with considering the assembly unit variability. The main research results are as follows:

(1) The ALO algorithm is used to optimize the initial weights and thresholds of the BP neural network, and the adaptive learning rate method and the additional momentum method are used to optimize the learning efficiency and feedback process of the BP neural network, which improves the convergence speed and accuracy of the neural network.

(2) The division and construction of the assembly process level model of complex products is completed, the assembly process design disassembled into process design issues of each assembly level from top to bottom, and the efficiency of the assembly process design of the overall structure is improved.

(3) With consideration of variations of assembly units, the training set model of parts and assembly process was constructed, which realized the full coverage of the same component parts information and assembly process information of different models. Based on the training set model, an intelligent decision-making model was established and the assembly process decision-making process of the complete machine is given.

(4) Other neural networks and case study are applied to verify the effectiveness of the proposed system. The comparison results proves that the proposed approach has stronger adaptability to the intelligent decision-making of complex products assembly process.

(5) The proposed intelligent decision-making system for complex products assembly process, which is helpful to quickly build a complex product assembly process structure tree and improve the efficiency and quality of assembly process design.

However, this study only considers the influence of component composition on the assembly process, and builds the assembly process structure tree from top to bottom. The influence of the specific shape of the part on the assembly process was not considered. In addition, there is still a lack of researches on assembly sequence planning and assembly path planning from bottom to top for each part. In the future, we will continue to study the intelligent design method of assembly process and optimize the existing research, and further study the assembly sequence, path planning and other issues.

Declarations

Funding

No funding was received for conducting this study.

Conflicts of interest/Competing interests

The authors declare they have no financial interests

Availability of data and material

The datasets used or analyzed during the current study are partial available from the corresponding author on reasonable request.

Code availability

The code is partial available from the corresponding author on reasonable request.

Authors' contributions

All authors contributed to the study conception and design.

Sheng-Wen Zhang: Supervision, Method design, Review.

Zhan Wang: Method design, Programming, Data collection and analysis, Writing-original draft.

De-Jun Cheng: Supervision, Method design, Review, Editing.

Xi-Feng Fang: Method design, Review.

Ethics approval:

Not applicable.

Consent to participate:

Not applicable.

Consent for publication:

Written informed consent for publication was obtained from all participants.

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Figures

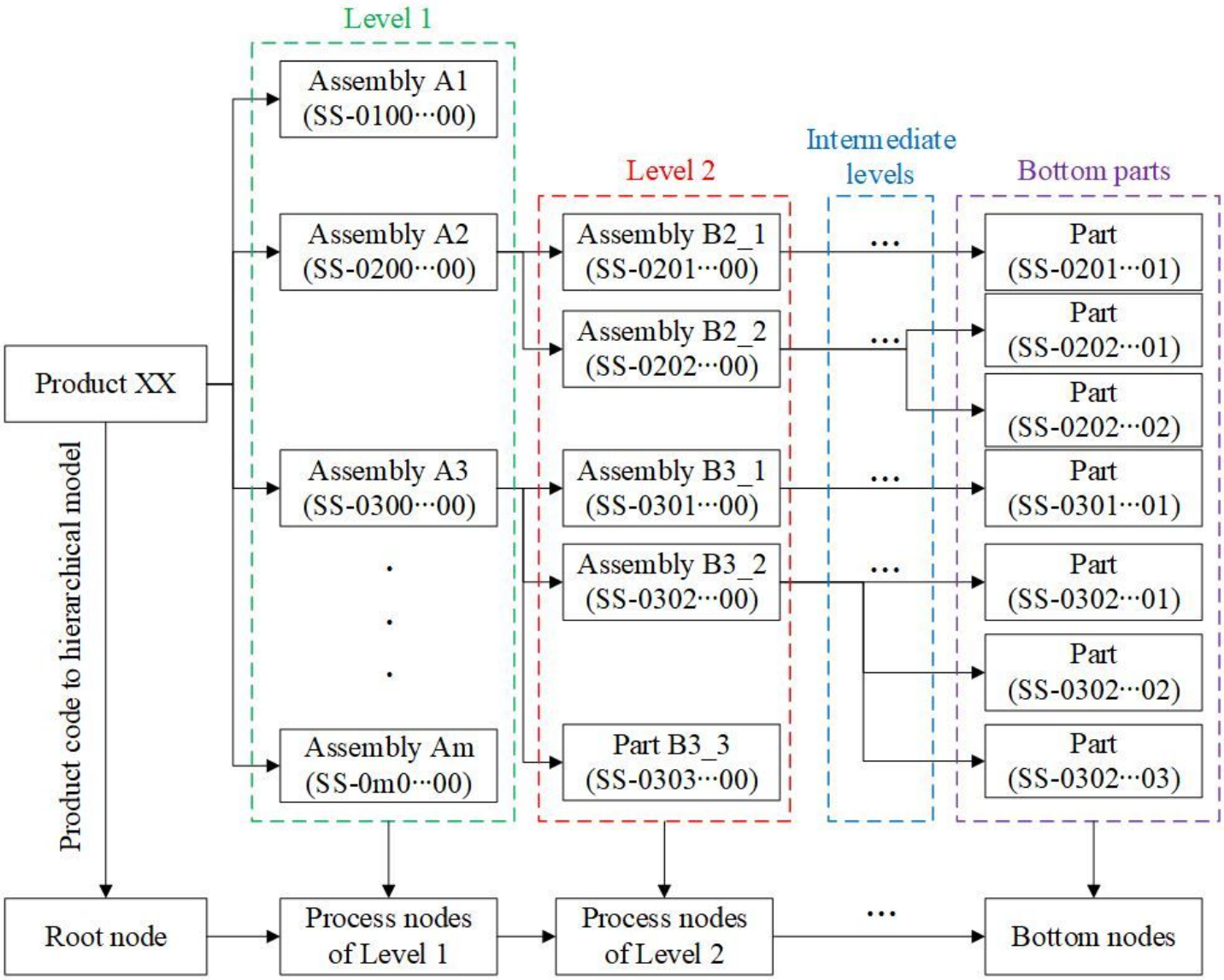

Figure 1

Example of product structure code definition

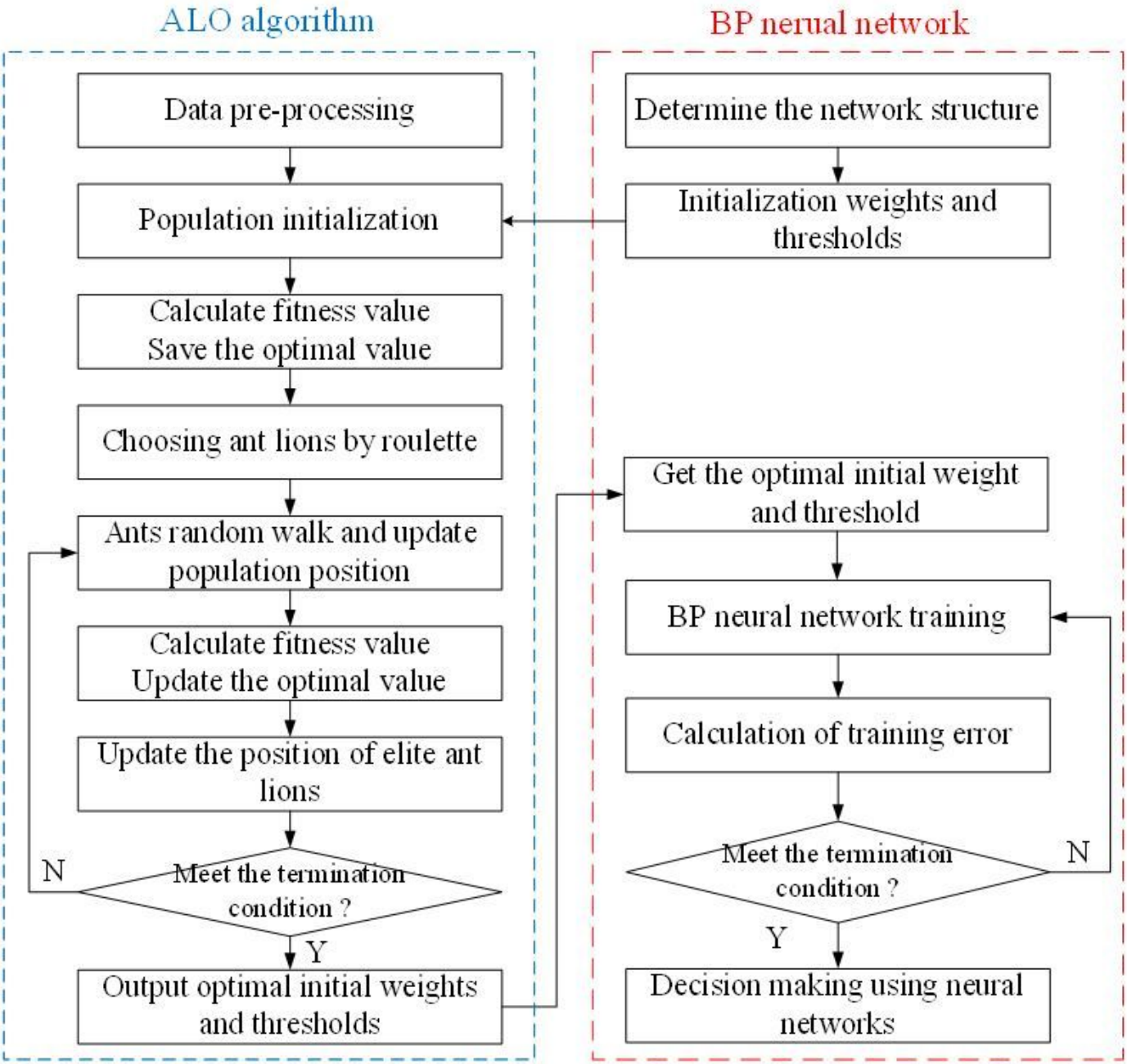

Figure 2

Flow chart of ALO-BP neural network

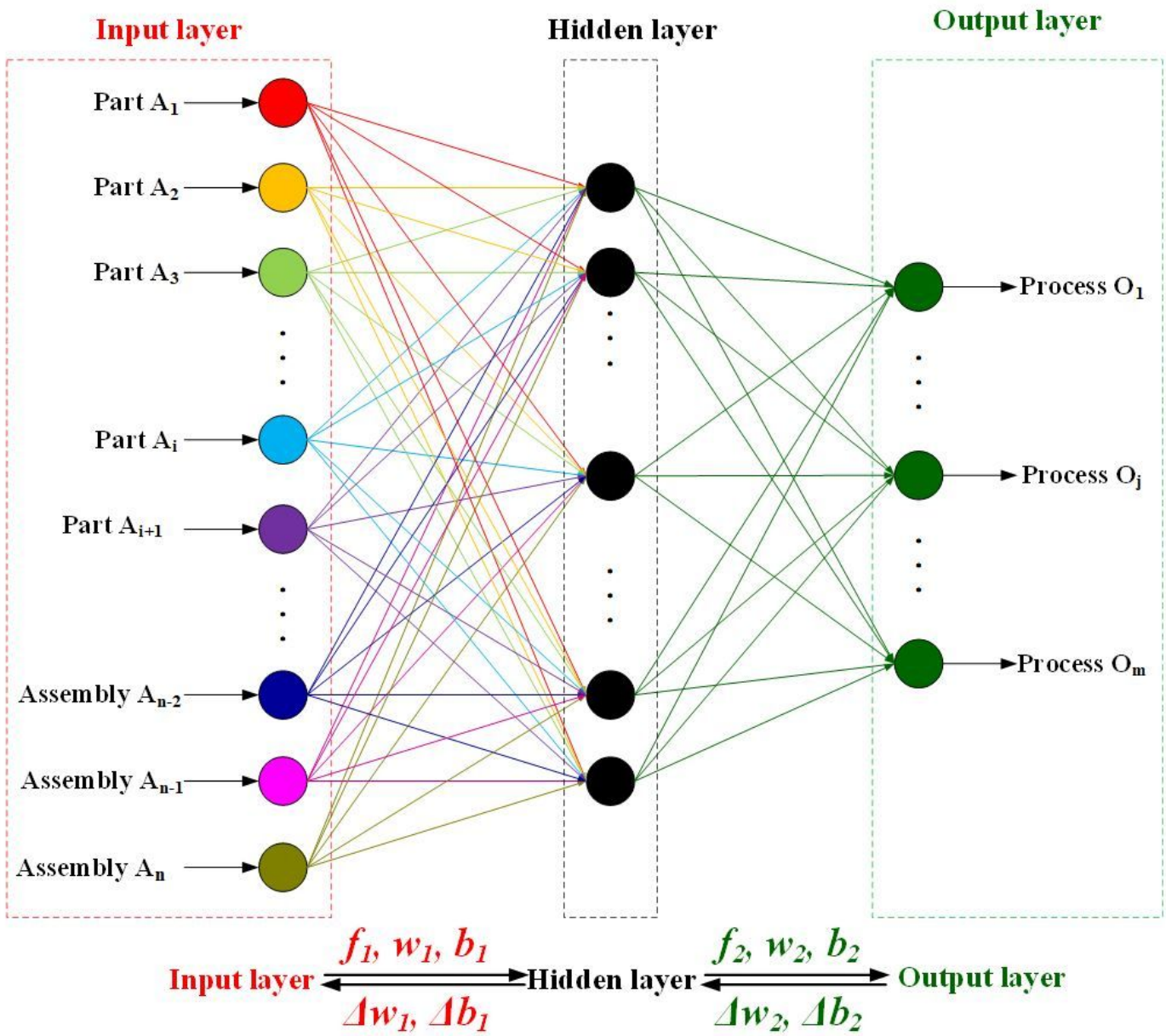

Figure 3

Example of neural network decision model

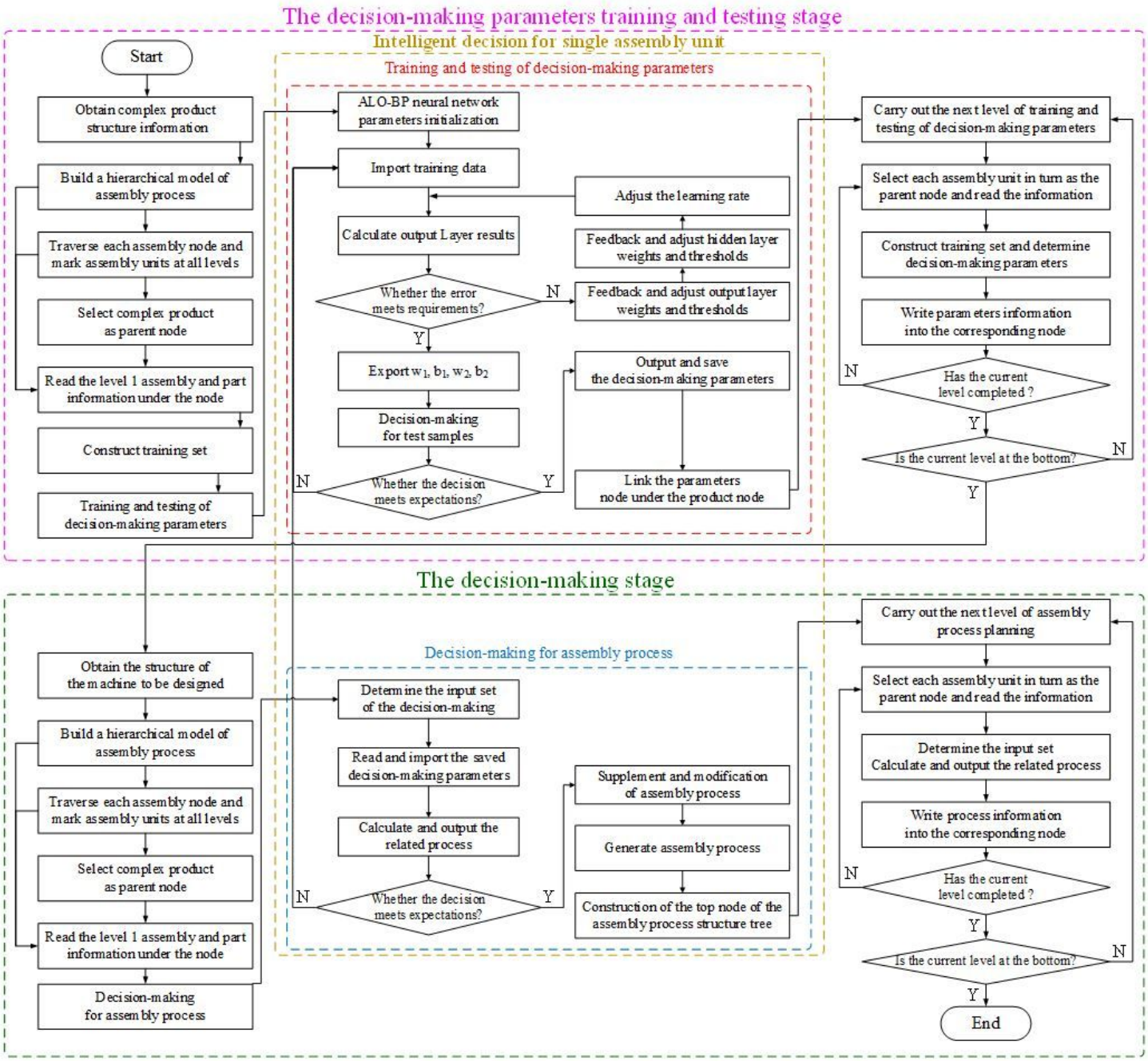

Figure 4

The whole machine assembly process intelligent decision-making process

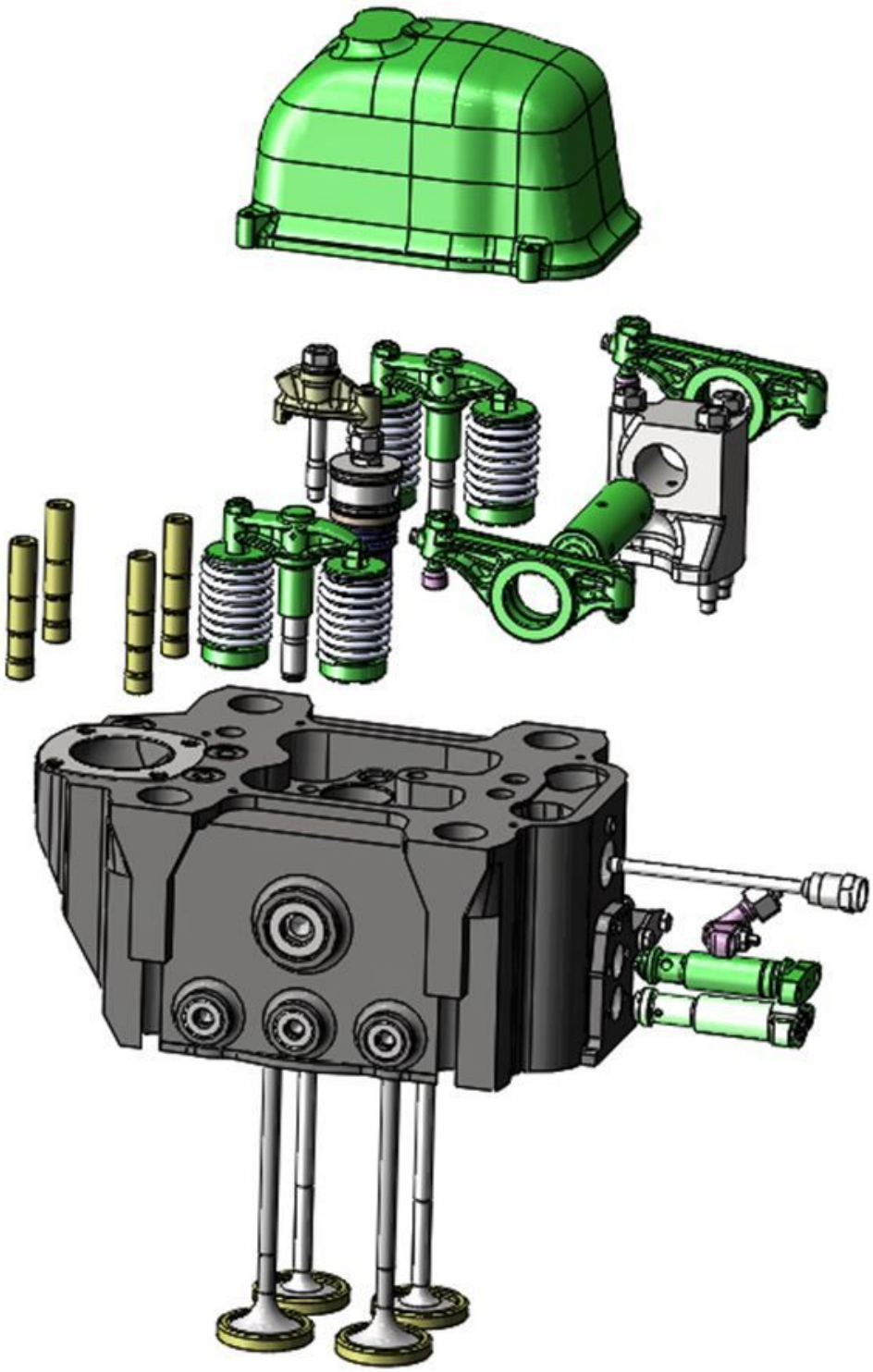

Figure 5

Example of an exploded view of a cylinder cap assembly

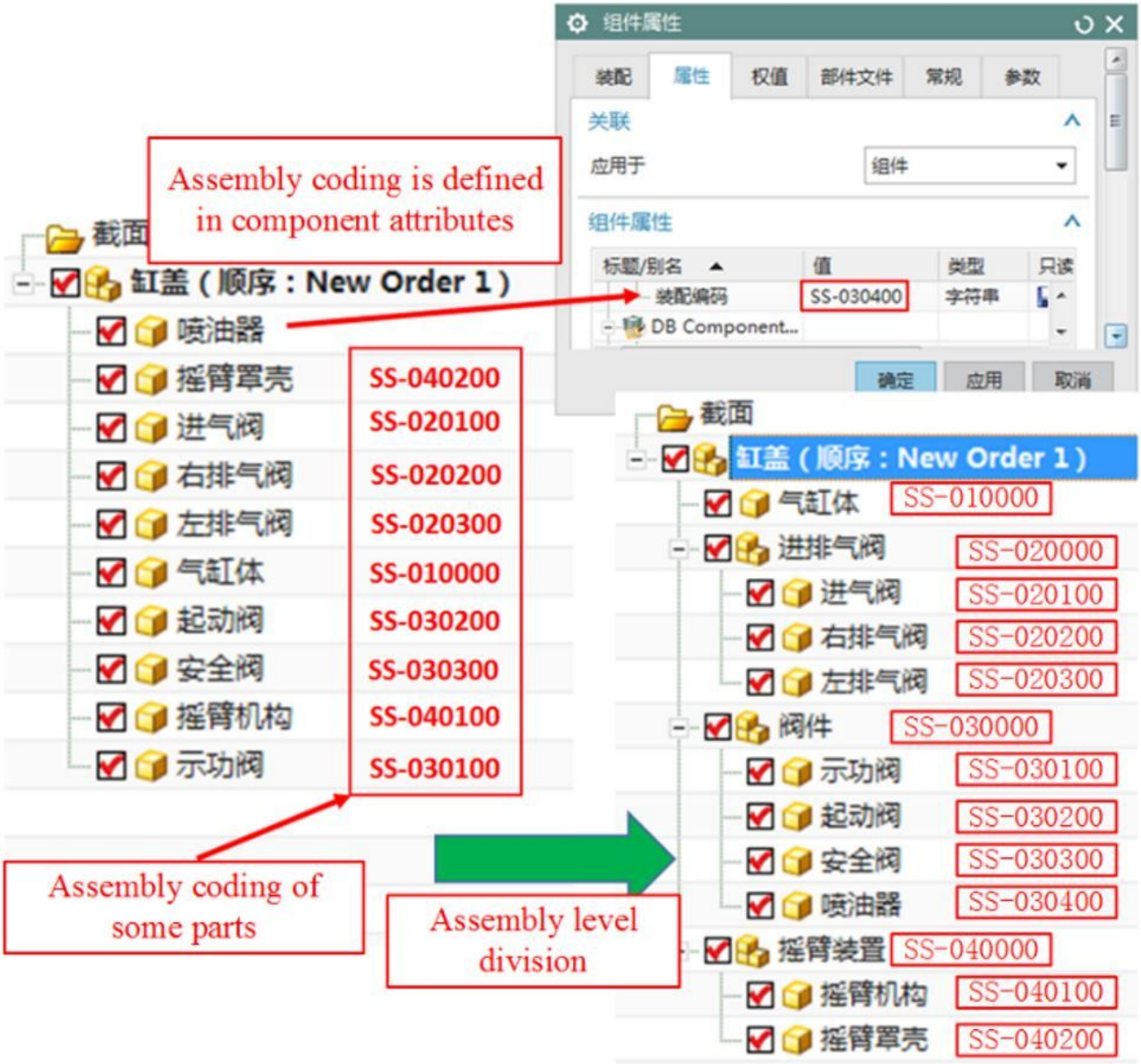

Figure 6

Example of cylinder cap assembly hierarchy division

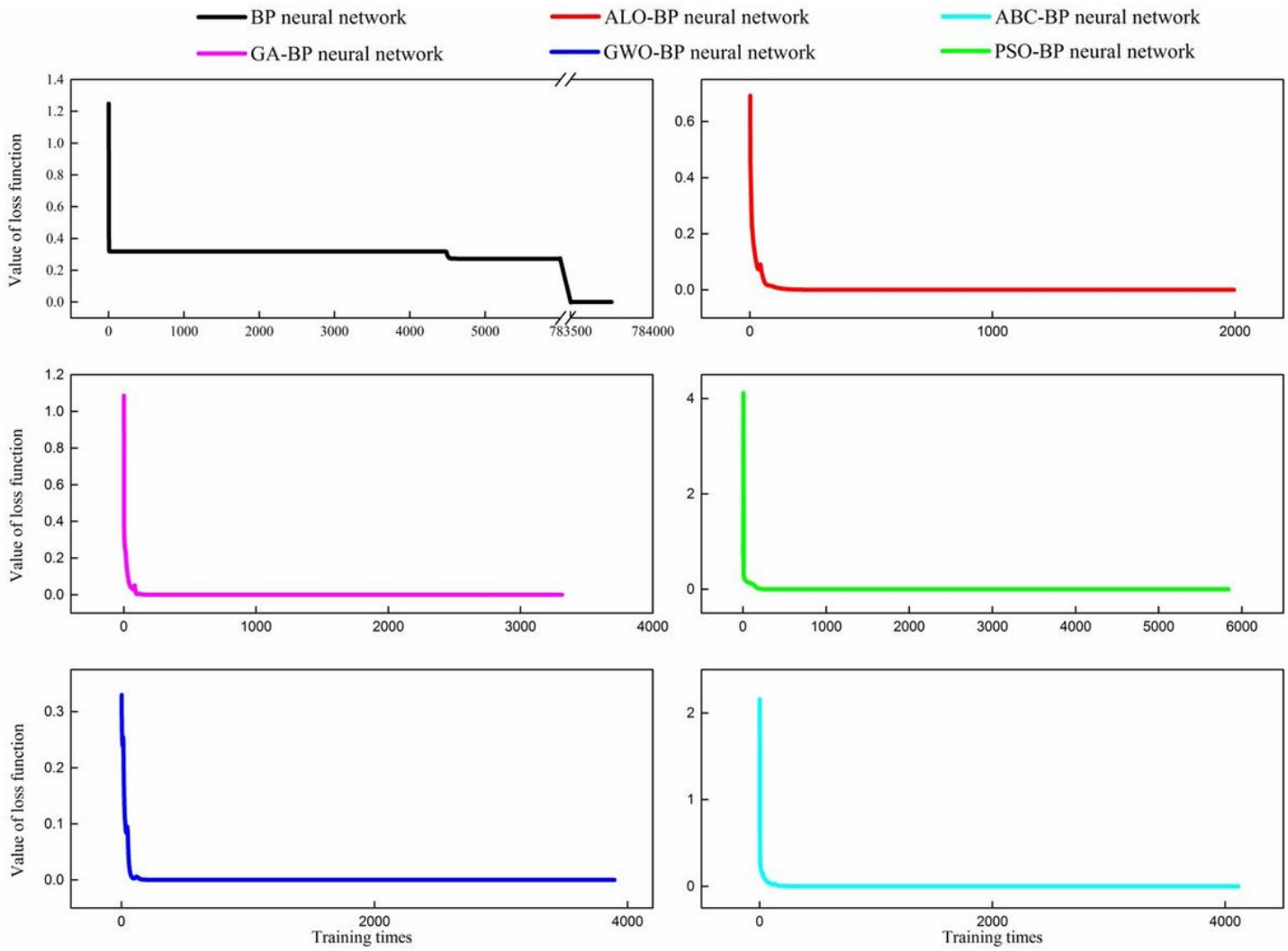

Figure 7

Loss function image of each algorithm

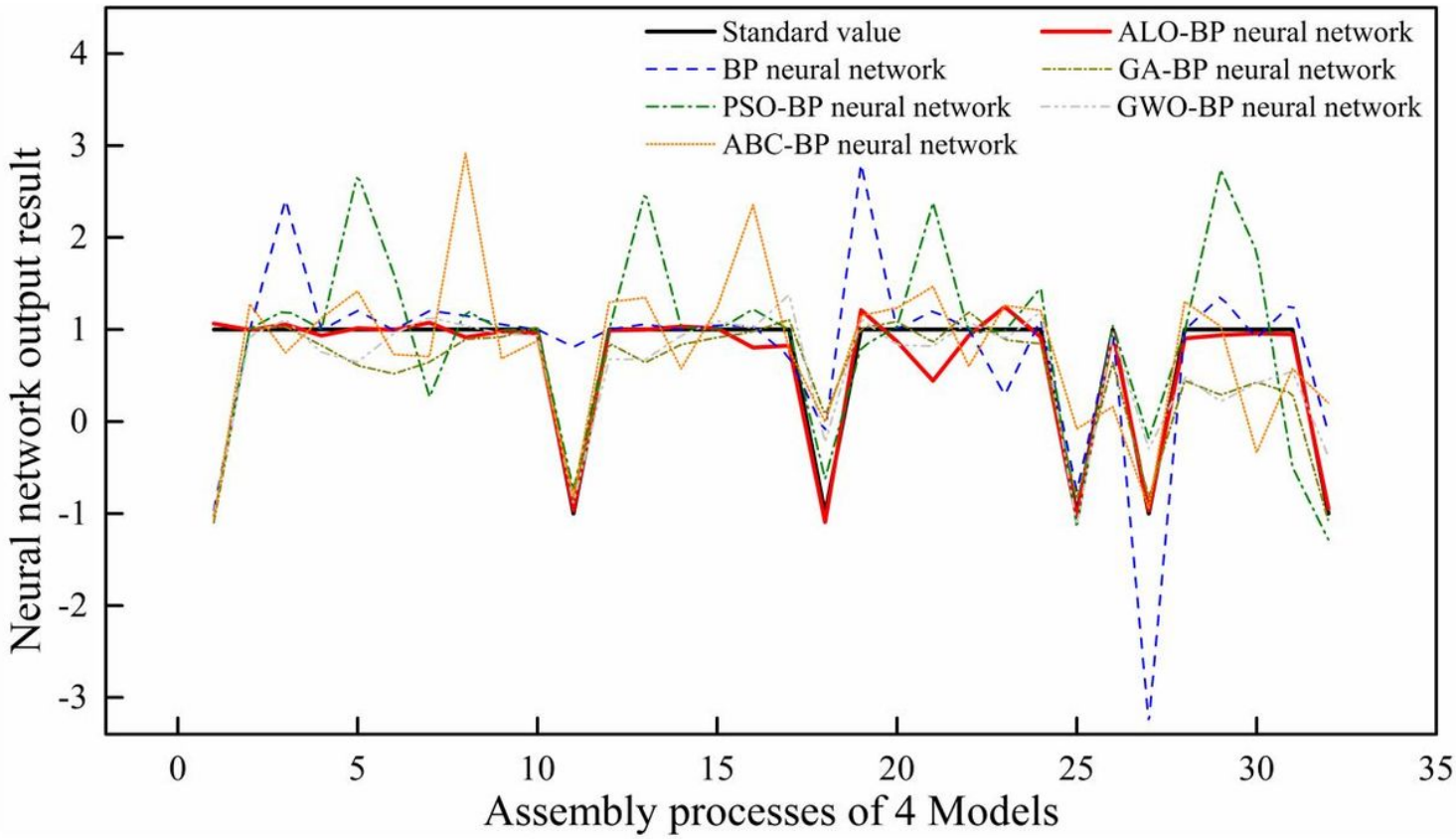

Figure 8

Comparison of the output results of each algorithm

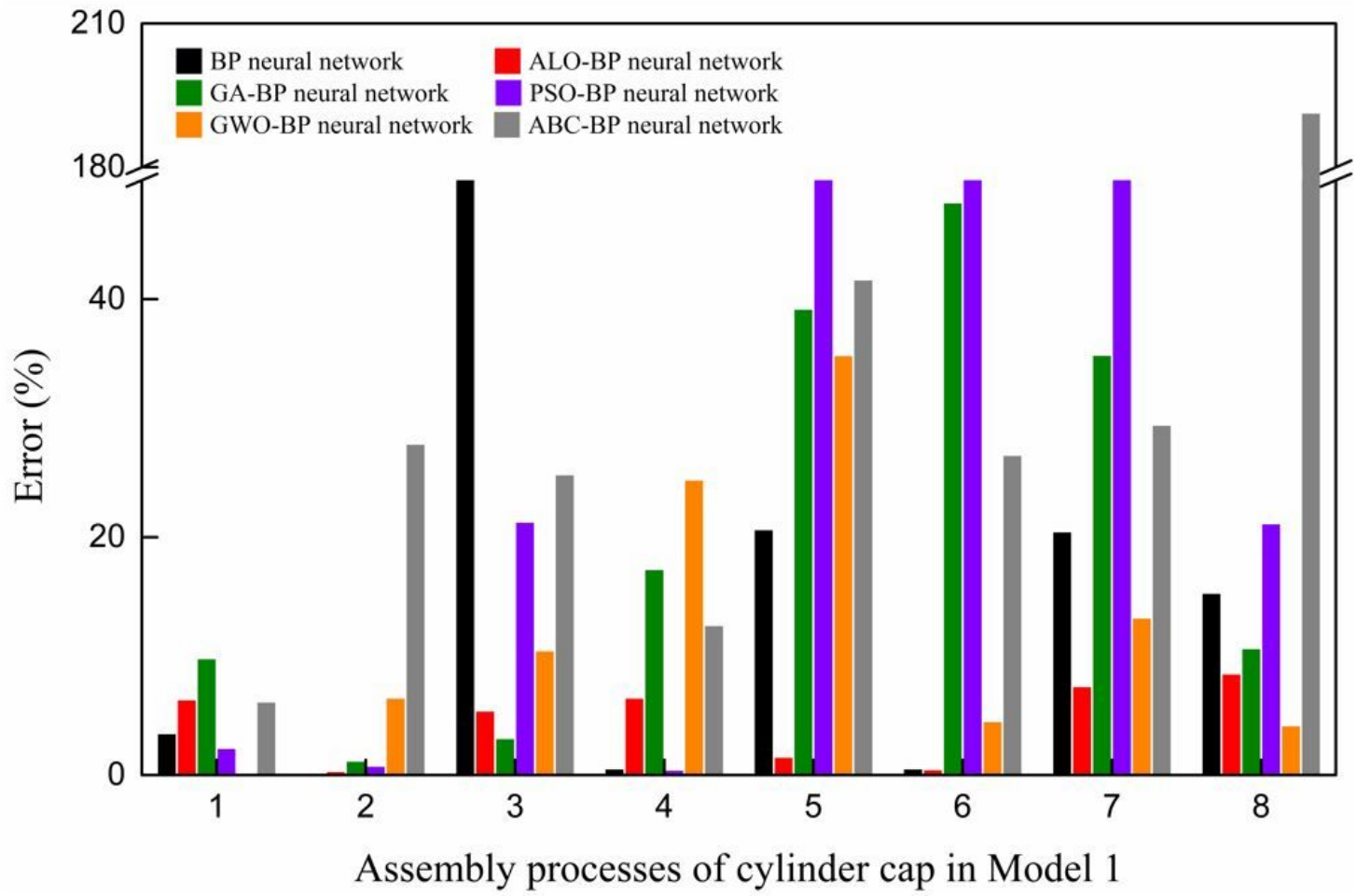

Figure 9

Percentage error comparison of neural network output results of model 1

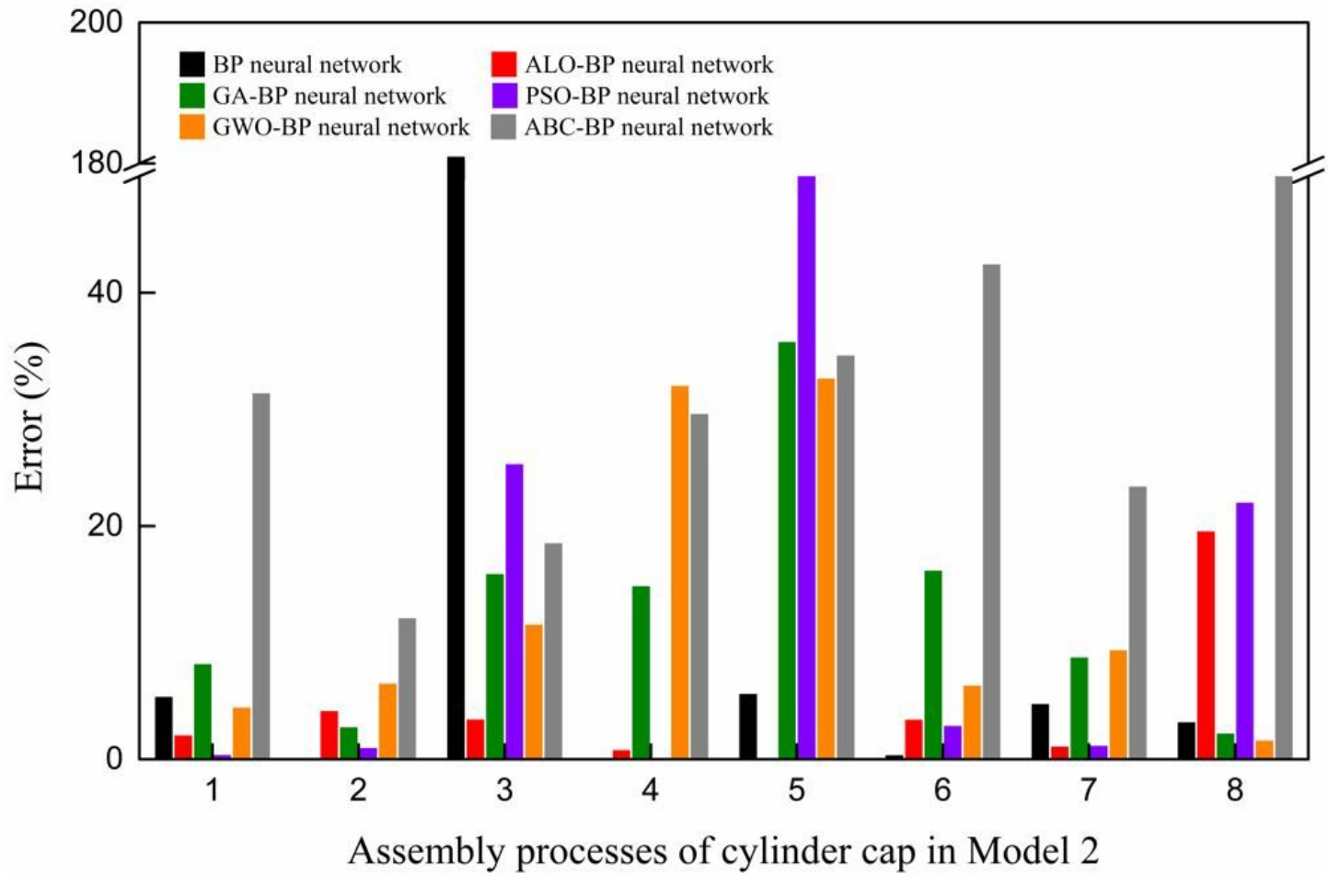

Figure 10

Percentage error comparison of neural network output results of model 2

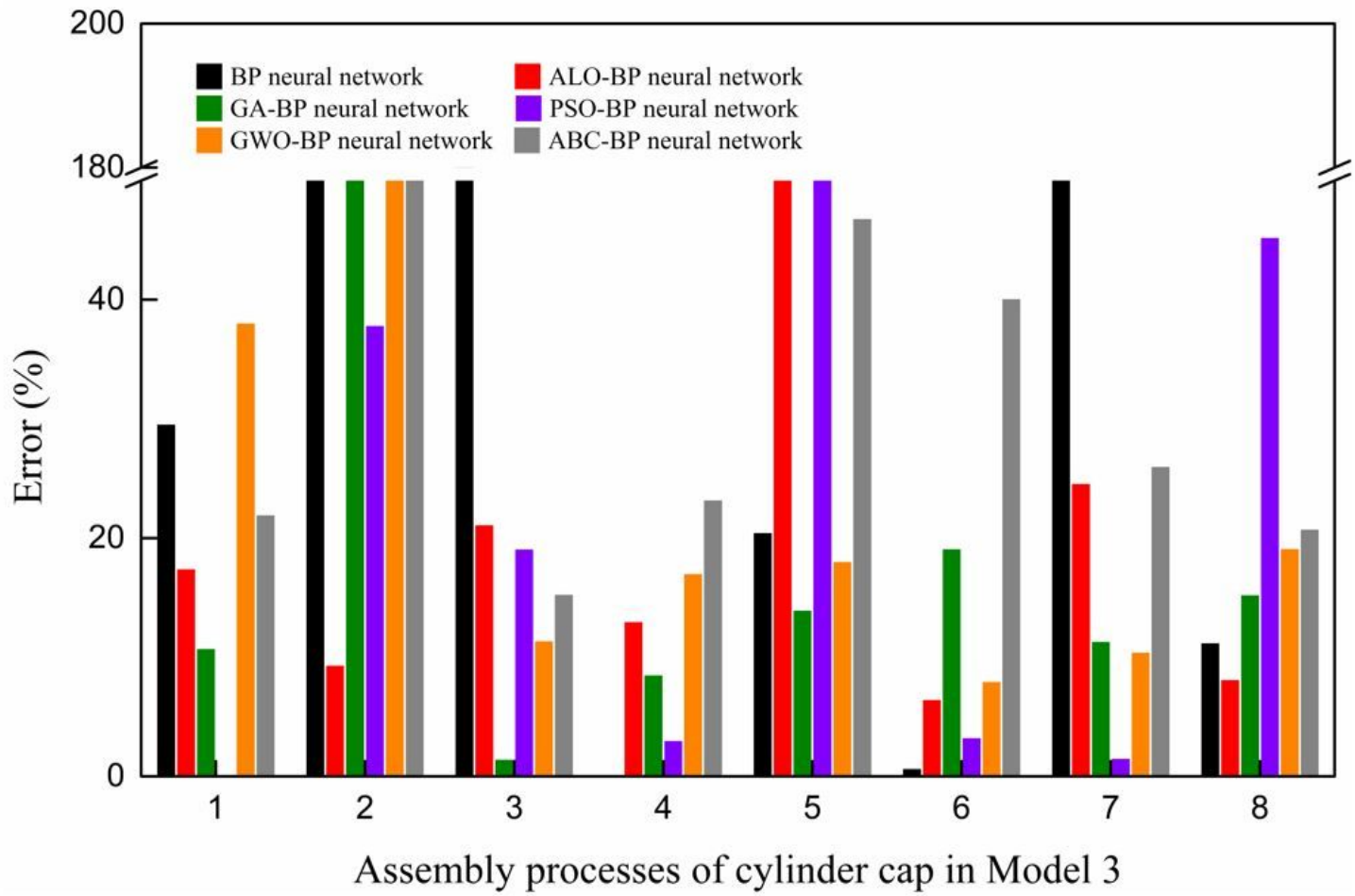

Figure 11

Percentage error comparison of neural network output results of model 3

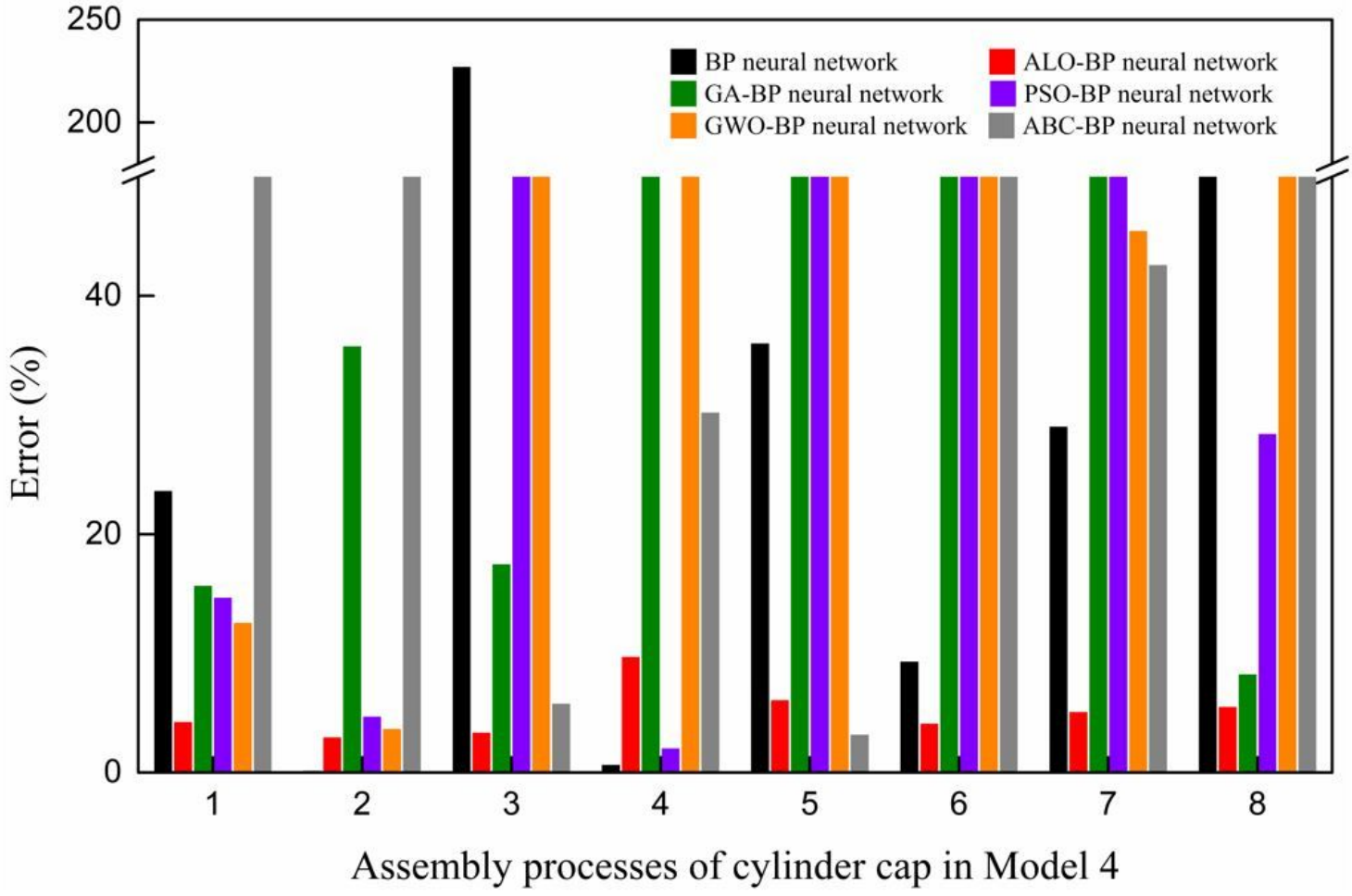

Figure 12

Percentage error comparison of neural network output results of model 4

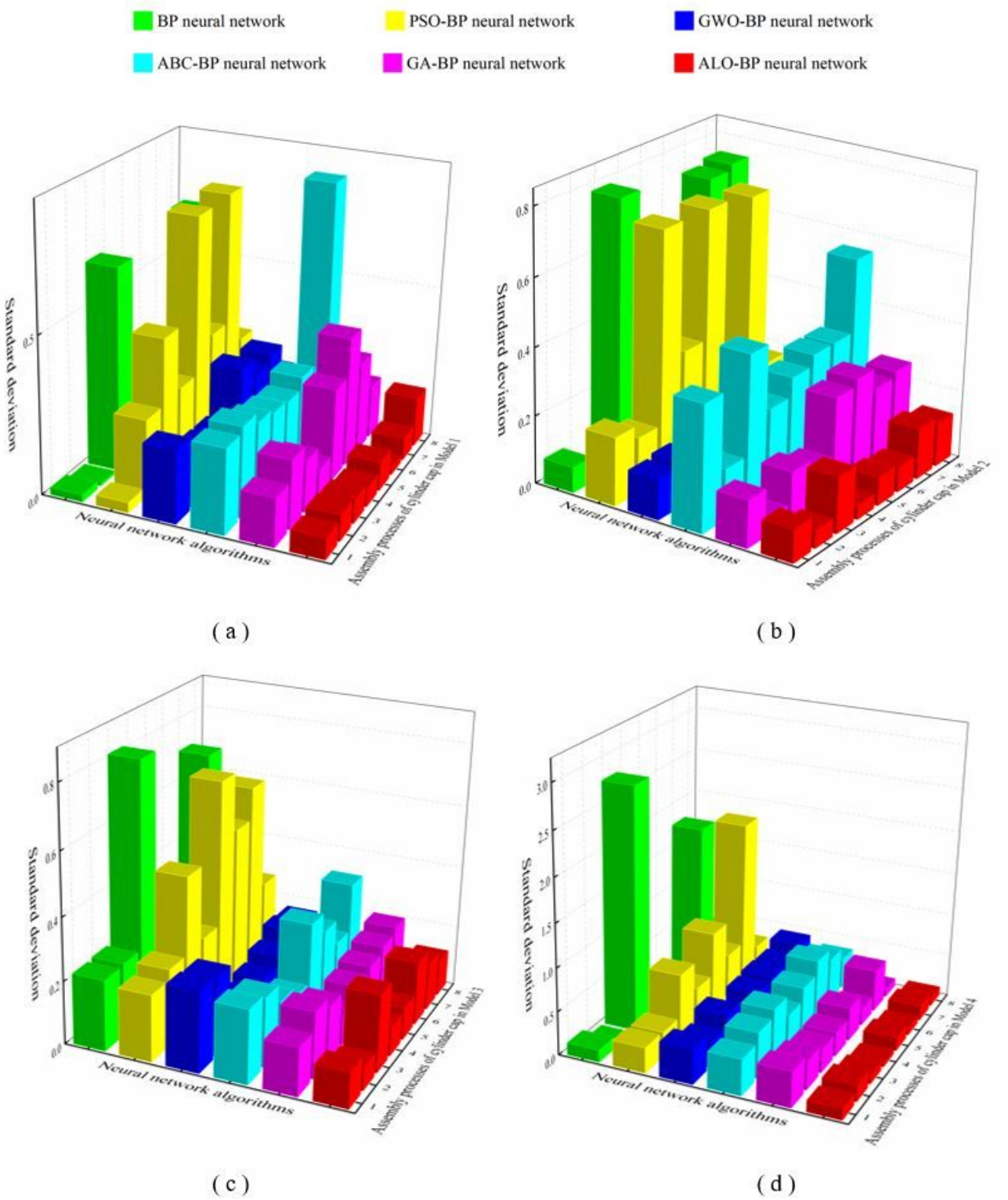

Figure 13

Standard deviation comparison of neural network output results of 4 Models

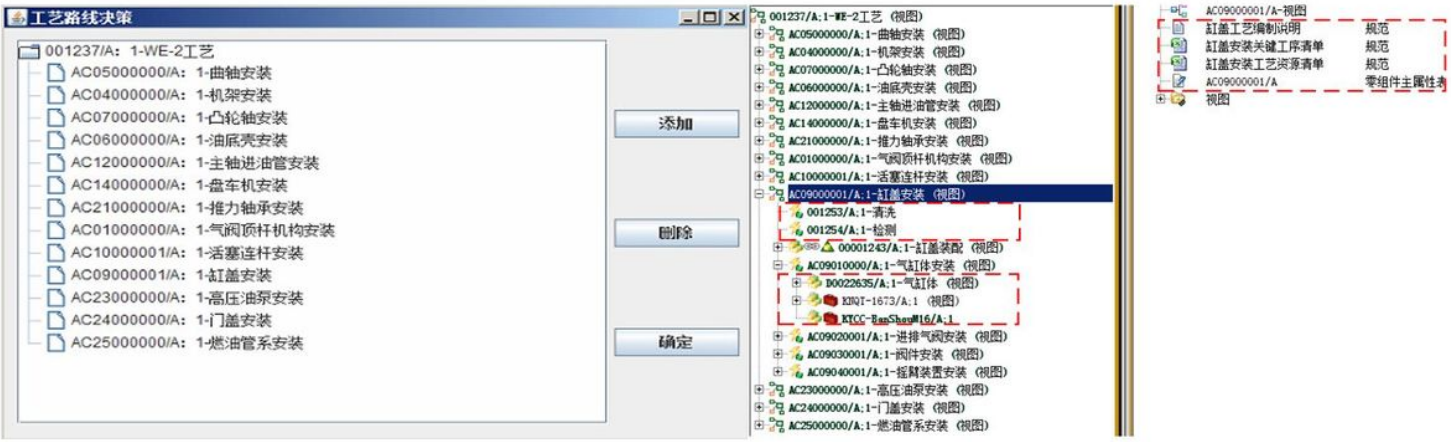

Figure 14

An example of the structure tree of marine diesel engine assembly process