# 行政院國家科學委員會專題研究計畫 成果報告

## 智慧型組裝順序規劃 KBE 系統
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行政院國家科學委員會補助專題研究計畫 ■ 成果報告
□期中進度報告

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# A systematic optimization approach for assembly sequence planning using Taguchi method, DOE, and BPNN

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**Abstract**

Research in assembly planning can be categorised into three types of approach: graph-based, knowledge-based and artificial intelligence approaches. The main drawbacks of the above approaches are as follows: the first is time-consuming; in the second approach it is difficult to find the optimal solution; and the third approach requires a high computing efficiency. To tackle these problems, this study develops a novel approach integrated with some graph-based heuristic working rules, robust back-propagation neural network (BPNN) engines via Taguchi method and design of experiment (DOE), and a knowledge-based engineering (KBE) system to assist the assembly engineers in promptly predicting a near-optimal assembly sequence. Three real-world examples are dedicated to evaluating the feasibility of the proposed model in terms of the differences in assembly sequences. The results show that the proposed model can efficiently generate BPNN engines, facilitate assembly sequence optimisation and allow the designers to recognise the contact relationships, assembly difficulties and assembly constraints of three-dimensional (3D) components in a virtual environment type.

**Keywords**: assembly sequence planning; assembly precedence diagrams; neural networks; design of experiment; Taguchi method

## 1. Introduction

In general, assembly involves the integration of components and parts to create a product or system through computer-aided design and manufacturing (CAD/CAM) systems. Assembly planning is a crucial design step for generating a feasible assembly sequence. Traditional assembly planning is manual and based on the experience and knowledge of industrial engineers; however, manual analysis does not allow the feasibility of assembly sequences to be easily verified. In the electronics industry, the approximate 40%- 60% of total wages was paid to assembly labors (Kalpakjian, 1992). The implementation of design for assembly (DFA) and design for manufacturing (DFM) resulted in enormous benefits, including the simplification of products, reduction of assembly product costs, improvement of quality, and shrinkage of time to market (Kuo et al., 2001). Good assembly sequence planning (ASP) has been recognised as a practical way of reducing operational difficulties, the number of tools and the working time (Lai and Huang, 2004).

De Fazio and Whitney (1987) adopted the concept of Bourjault (1984) to generate a complete set of assembly sequences. They generated sequences in two stages – creating the precedence relations between liaisons or logical combinations of liaisons in a product and verifying the liaison sequence. Homen de Mello and Sanderson (1991a) made a representation of the directed AND/OR graphs to create feasible assembly sequences. In addition, Kroll (1994) used graph-based procedures with conventional representations to reduce the number of sorting operations required. He then extended his previous approach from uniaxial assemblies to triaxial assemblies and presented a set of rules for resolving conflicts between multiple parents and multiple offspring. However, in practice most assembly companies use semi-automatic systems to generate an assembly plan and employ 2D cross-sectional views to represent their heuristic models (Lin and Chang, 1993).

Assembly planning is also regarded as "assembly by disassembling," i.e., an assembly sequence results from systematically disassembling the final product and reversing the disassembling sequence (Lee, 1989). This approach usually employs the contact-based feature to represent the precedence relationships of the product. A designer can successively assign the assembly relations to form the assembly plan based on the precedence diagram. However, the contact-based precedence diagram cannot effectively express the complexity of the assigned assembly relations. An effective assembly plan must include other graphs, such as the explosion graph, the relational model graph, the incidence matrix, the assembly precedence diagram (APD), etc. In reality, few experts or engineers know exactly how to derive a correct explosion graph, draw a complete relational model graph or incidence matrix among the components, or determine a complete APD to generate an optimal assembly sequence (Chen et al., 2004b; Chen et al., 2008).

The other approach to Knowledge-based engineering (KBE) is a technology that allows an engineer to create a product model based on rules and the powerful CAD/CAM applications that used to design, configure and assemble products, examples of which include the so-called expert systems, web-based knowledge bases involving the engineering knowledge (i.e., Knowledge Fusion) and becoming an critical part of business strategy (Homen de Mello and Sanderson, 1991b). In addition, numerous researchers have employed an artificial intelligence (AI) tree search or graph search methodology to generate an assembly sequence (Homen de Mello and Sanderson, 1991b; Chen et al., 2004a). Unfortunately, the search space increases explosively when the number of components in a design grows. To relieve this combinational complexity, heuristic rules and genetic algorithms (GAs) have been used in the searching process (Marian et al., 2003; Chen et al., 2004a). Other studies have used the Hopfield and BPNN as the means to generate optimum or sub-optimum assembly sequences(Chen, 1990; Hong and Cho, 1993; Sinanogˇlu, 2006).

This study proposes a three-stage integrated approach with some heuristic working rules to assist the planner to obtain an optimal assembly plan. In the first stage, the Above Graphs with spatial constraints are used to create a correct explosion graph of the assembly model; these two graphs can be used to represent the correct geometric constraints among the assembly parts. In the second stage, a three-level relational model is developed to generate a complete relational model graph (RMG) and the incidence matrix. The relational model graph can be advanced and transformed into an assembly precedence diagram (APD), which is used to describe the assembly precedence relations of the parts. Based on these graphs, the designer can easily find feasible sequences and evaluate the difficulty of assembly. In the third stage, the CAD-based Knowledge Fusion (KF) programming language and BPNN engines via Taguchi method and design of experiment (DOE) are employed to validate the available assembly sequences. The three kinds of real-world toy products are utilised to evaluate the feasibility of the proposed model in terms of the differences in underlying assembly characteristics and predict a near-optimal assembly sequence according to the defined performance criteria.

## 2. The working concepts and procedures

The working concepts and procedures of the proposed approach are shown in Fig. 1. Initially, detailed data is input from a 2D engineering drawing and related assembly information into a CAD assembly package. Then, the correct explosion graph is developed using the transforming rules. Finally, the relational models are generalized to represent the assembly precedence relations, and an evaluating mechanism is then employed to find a global feasible solution. The planning process is recursive until the defined criteria was satisfied. The main outputs of the integrated graph and BPNN-based assembly planning are the complete RMG, APD, and BPNN engines. In addition, Fig. 2 represents the knowledge-based engineering (KBE) system rendering a UG-based operational interface to access the potential graph and BPNN-related details via different types of database, and a robust BPNN engine dedicated to promptly generating a near-optimal assembly sequence.

## 3. Back-propagation neural network

In much of the literature, back-propagation neural networks (BPNNs) have been adopted because they have the advantages of a fast response and high learning accuracy (Maier and Dandy, 1998; Liu *et al*., 2001; Lee *et al*., 2001; Yao *et al*., 2005; Chen and Hsu, 2007). The superiority of a network's functional approach depends on the network architecture and parameters, as well as the problem complexity. If inappropriate network architecture or parameters are selected, undesirable results may be obtained. Conversely, the results will be much more significant if good network architecture and parameters are selected. The BPNN consists of an input layer, hidden layer, and output layer. The parameters for the BPNN include the number of hidden layers, number of hidden neurons, learning rate, momentum, etc. All of these parameters can significantly impact the performance of the neural network. Fogel (1991) proposed a final information statistical (FIS) process based on Akaike's information criterion (AIC) to determine the number of hidden layers and neurons. One hidden layer is sufficient to compute arbitrary decision boundaries and quite adequate to model nonlinearity in most cases of the BPNN (Khaw *et al*., 1995; Anjum *et al*., 1997). The limitation of Fogel's research is that the process can only perform simple binary classifications. Murata and Yoshizawa (1994) and Onoda

(1995) respectively proposed methods to improve AIC. These methods, called the network information criterion (NIC) and neural network information criterion (NNIC), use statistical probabilities together with an error energy function to determine the number of hidden neurons.

In this research, the steepest-descent method was used to find the weight change and to minimize the error energy function. The activation function is a hyperbolic sigmoid function. According to past studies (Hush and Horne, 1993; Cheng and Tseng, 1995), there are a few conditions for network learning termination: (1) when the root mean square error (RMSE) between the expected value and network output value is reduced to a preset value; (2) when the preset number of learning cycles has been reached; and (3) when cross-validation takes place between the training samples and test data. The first two methods are related to the preset values. This research adopts the first and second approaches by gradually increasing the network training time to gradually decrease the RMSE until it is stable and acceptable. The RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(d_i - y_i\right)^2} \; ; \qquad (1)$$

where $N$, $d_i$, and $y_i$ are the number of training samples, the actual value for training sample $i$, and the predicted value of the neural network for training sample $i$, respectively.

In network learning, input information and output results are used to adjust the weighting values of the network. The more detailed the input training classification and the greater the amount of learning information which are provided, the better the output will conform to the expected result. Since the learning and verification data for the BPNN are limited by the functional values, the data must be normalized by the following equation:

$$PN = \frac{P - P_{\min}}{P_{\max} - P_{\min}} \times \left(D_{\max} - D_{\min}\right) + D_{\min} \quad ; \qquad (2)$$

where PN is the normalized data, P is the original data, $P_{max}$ is the maximum value of the original data, $P_{min}$ is the minimum value of the original data, $D_{max}$ is the expected maximum value of the normalized data, and $D_{min}$ is the expected minimum value of the normalized data.

When applying the neural network to the system, the input and output values of the neural network fall in the range of [0.1, 0.9].

## 4. Taguchi method

Taguchi's parameter design method normally selects an appropriate formulation of the S/N ratio and calculates the S/N ratio for each treatment. There are three types of S/N ratios: nominal the best, the larger the better, and the smaller the better. Most engineers choose the highest S/N ratio treatment as the preliminary optimal initial process parameter setting. Taguchi method has also been used to design the parameters for neural networks in previous research (Khaw *et al.*, 1995; Santos and Ludermir, 1999). Khaw *et al.* (1995) applied Taguchi method to design the parameters and verified that the method could rapidly and robustly design the optimal parameters.

Santos and Ludermir (1999) applied a factorial design to assist the design and implementation of a neural network. The formulae of the three types of S/N ratios are given as follows:

nominal the best: $$S/N = 10 \times \log\left(\frac{\bar{y}^2}{\bar{S}^2}\right), \tag{3}$$

the larger the better: $$S/N = -10 \times \log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right), \text{ and} \tag{4}$$

the smaller the better: $$S/N = -10 \times \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) = -10 \times \log[\bar{y}^2 + \bar{S}^2]\ ; \tag{5}$$

where $y_i$ is the response value of a specific treatment under $i$ replications, $n$ is the number of replications, $\bar{y}$ is the average of all $y_i$ values, and $\bar{S}$ is the standard deviation of all $y_i$ values.

## 5. Optimization of the neural network parameters using RSM & Taguchi method

In this research, we applied the Taguchi method and DOE to obtaining the optimal parameter settings of the BPNN. Since the number of hidden layers did not have a significant effect on convergence, the number of hidden layer was set to 1. The controlling factors of Taguchi method are transfer function ($F_t$), the number of hidden neurons ($N_h$), learning rate ($R_l$), momentum ($M_t$), and Epochs ($E_p$). The numbers of neurons in the hidden layer under different levels were obtained by the method proposed by Khaw *et al*. (1995) and Haykin (1999). Information on the factors' assumptive settings at different levels is listed in Table 1. Apart from transfer function ($F_t$), the number of hidden neurons ($N_h$), learning rate ($R_l$), momentum ($M_t$) and the numbers of calculation generations i.e. epochs ($E_p$) are determined by first finding the range in which these factors have better converging results, and second by determining the equal-distance value for the three levels.

Under the condition of five factors, one for two levels and four for three level, and no correlation among the five factors, the total degrees of freedom were 17 (i.e., 1× (2-1) +4 × (5 – 1)). An $L_{18}$ ($2^1 \times 3^4$) orthogonal array is selected for arranging the factors and carrying out the experiment. In this experiment, there are two replications, and the predicted performance (Mean square error, MSE) of Y is the evaluation value for different combinations of factor levels. $\bar{Y}$ is the average of two Y's in each replication. The optimal combination of factor levels is the experiment with the largest S/N ratio. From the experimental results of Taguchi method, the main effects plots of BPNN's factors through Taguchi method can be seen in Fig. 3. The optimal combination of factor levels is represented by the following: BPNN architecture of 5-13-1, the transfer function is Hyperbolic Tangent, the number of calculation generations of 35,000, a learning rate of 0.9, and a momentum of 0.9.

Subsequently, the result of the DOE with response surface methodology (RSM) on the factors' assumptive settings at two levels listed in Table 2 is revealed: the number of neurons of 15, a learning rate of 0.9, a momentum of 0.9, and the number of calculation generations of 50,000. The response optimization of BPNN's parameters via DOE is represented in Fig. 4.

## 6. Illustrative examples

In this section, the examples of a toy car, a toy motorbike and a toy boat are used to demonstrate the generation procedures of assembly planning.

### *6.1 Creating the exploded view, RMG and APD*

The exploded view can be directly created from the Above Graph, which possesses the contact relationships of a spatial structure. Fig. 5 shows the parts list, assembly codes and the exploded view. The validity of each exploded view can be confirmed by the contact relationships of the spatial structure and Above Graphs. Applying a correct exploded view allows us to derive the exact assembly plans. For brevity, the detailed planning steps are omitted. Fig. 6 shows the complete relational model graph (RMG) and APD for the proposed case study.

### *6.2 Assembly sequence generation using the back-propagation neural network*

In this study, a toy car is used as a training sample, whereas a toy motorbike and a boat are employed as verifying samples. Fig. 7-10 show the parts list, assembly codes, the exploded view, and the complete relational model graph (RMG) and APD of the above latter samples. The characteristics of each assembly part include the number of the assembly incidence (AI), total penalty value (TPV), feature number (FN), weight and volume. These characteristics are commonly regarded as the larger the better for the assembly sequence priority. The optimal sequence results with information on five characteristics of a toy car, a toy boat and a motorbike are shown in Tables 3, 4 and 5, respectively.

### 6.3 *Experimental results and discussion*

The toy car, the toy motorbike and the toy boat can be decomposed into 28, 17 and 15 parts, respectively. Each part of the afore-mentioned experimental articles has five characteristics parameters: the value of assembly incidence (AI), total penalty value (TPV), feature number (FN), weight and volume, which are used as network input parameters, and one expected network output adopts the ranking number of the optimal assembly sequence.

Table 6 shows the performance of BPNN engine 2 via DOE is superior to that of BPNN engine 1 via Taguchi method as implements testing BPNN data. Fig. 11 and Fig. 12 demostrates an assembly sequence prediction for testing toy motorbike (17 data) using BPNN engine 1 and 2, respectively. In addition, the trend is normally the larger the potential samples of KBE database get, the more precise is the assembly sequence predition via a robust BPNN engine.

## 7. Conclusions

Theoretically, an assembly plan can be optimised based on the factors of shortest assembly time and assembly sequence optimisation. However, these are uncertain factors prior to the determination of the optimised assembly scheme and the completion of the jig and fixture. The proposed model adopts a three-stage integrated assembly planning approach to express the complexity of the assembly relations and to evaluate the feasibility of the respective assembly sequences in the design phase. The experimental results for the case study verify the feasibility of the proposed approach, which facilitates the DFA in potential applications of 3D component models to assist manual or automatic assembly in a virtual environment, and allows the designer to recognise the relative position, geometric constraints and relationships of the 3D components using the following graph-oriented methods: the Above Graph, APD and relational model graph. The planner can further generate a correct explosion graph and construct an incidence matrix for validating the assembly relations through applying the Above Graph and relation models. In addition, this three-stage integrated approach can effectively promote the quality of the generated assembly plan and facilitate assembly sequence optimization via knowledge-based engineering (KBE) system and a robust BPNN engine.

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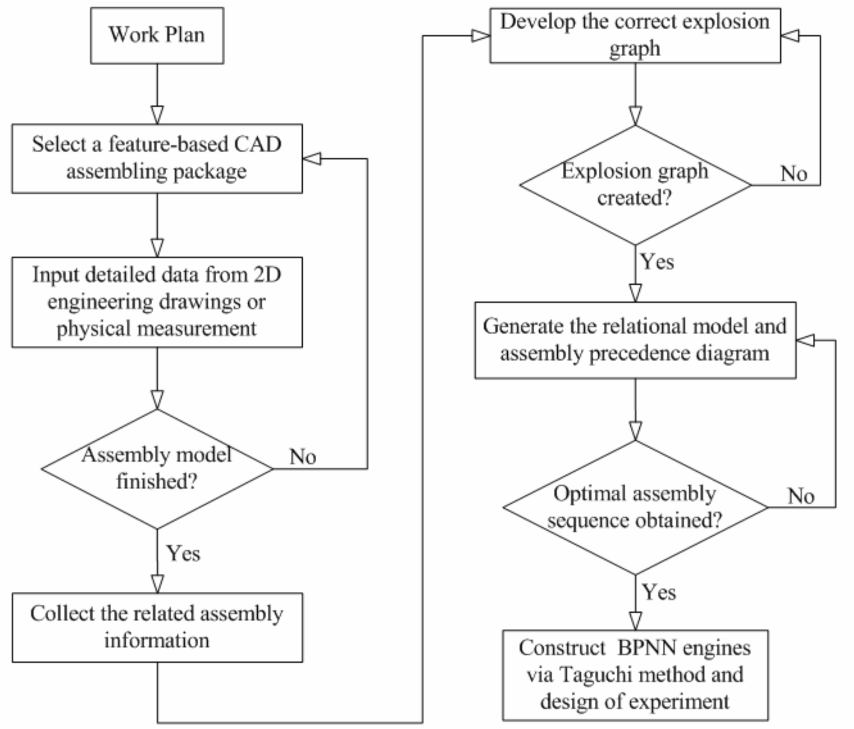



Fig. 1. Working concepts and procedures.

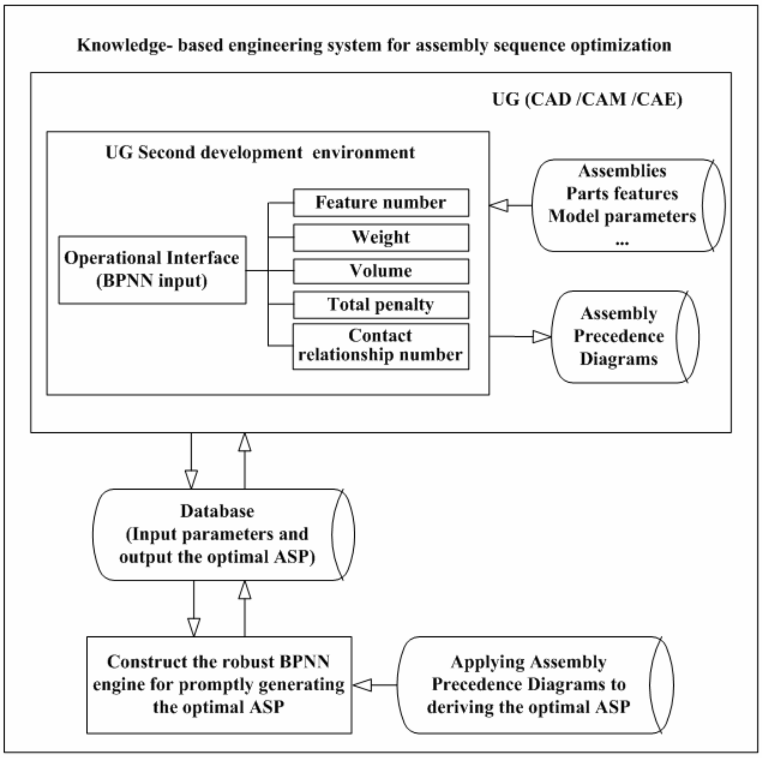



Fig. 2. KBE model for assembly sequence optimisation.

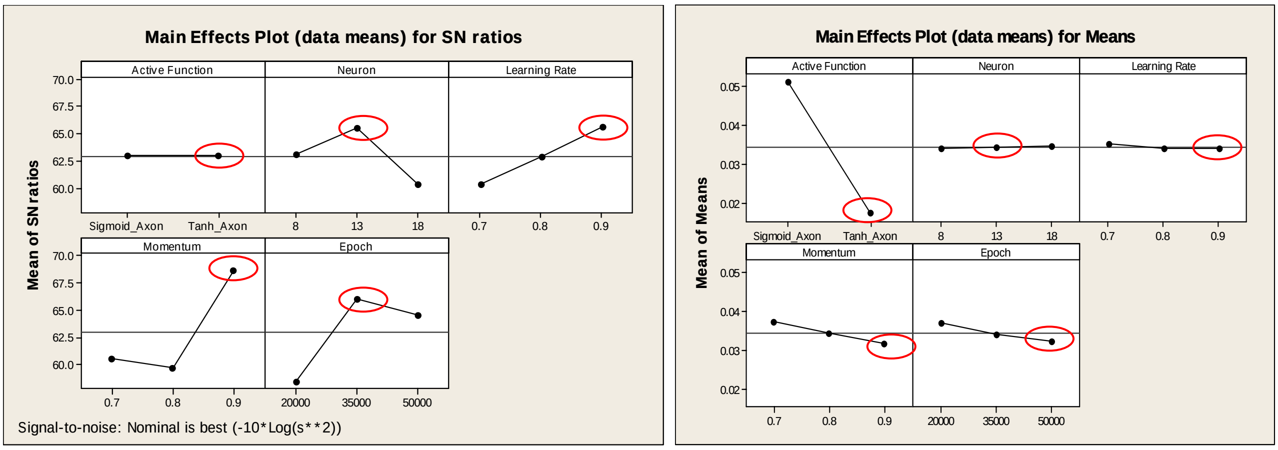



Fig. 3. Main effects plots of BPNN's factors.

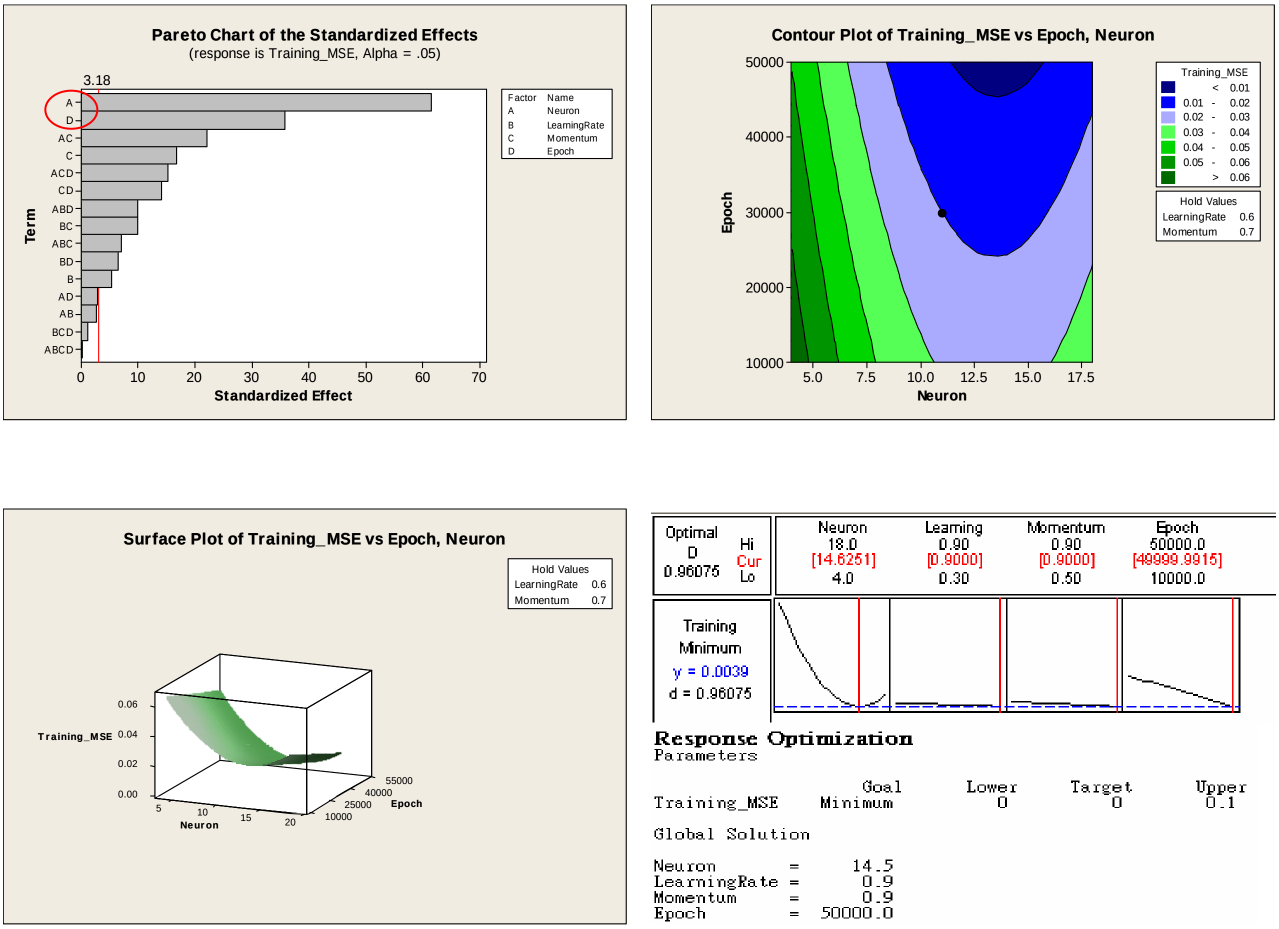
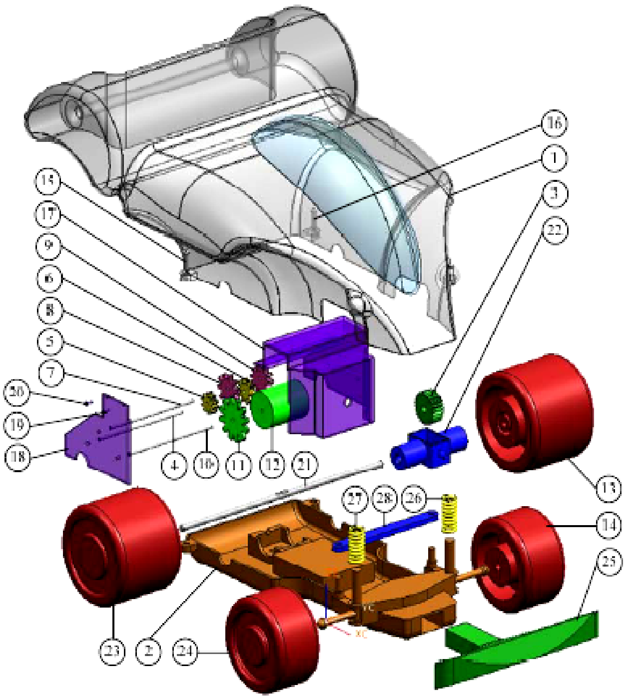



Fig. 4. The RSM response optimization of BPNN's parameters.




| No | Parts' name |
|---|---|
| 1 | MB(MainBody) |
| 2 | CP(ChassisPan) |
| 3 | DG(DriveGear) |
| 4 | GS1_1(GearSet1_1) |
| 5 | GS1_2(GearSet1_2) |
| 6 | GS1_3(GearSet1_3) |
| 7 | GS2_1(GearSet2_1) |
| 8 | GS2_2(GearSet2_2) |
| 9 | GS2_3(GearSet2_3) |
| 10 | GS3_1(GearSet3_1) |
| 11 | GS3_2(GearSet3_2) |
| 12 | PO(Power) |
| 13 | LBW(LeftBackWheel) |
| 14 | LFW(LeftFrontWheel) |
| 15 | BS1(BaseScrew1) |
| 16 | BS2(BaseScrew2) |
| 17 | PP1(PowerPack1) |
| 18 | PP2(PowerPack2) |
| 19 | PPS1(PowerPackScrew1) |
| 20 | PPS2(PowerPackScrew2) |
| 21 | RA(RearAxis) |
| 22 | RD(RearDiff) |
| 23 | RBW(RightBackWheel) |
| 24 | RFW(RightFrontWheel) |
| 25 | SL(Spoiler) |
| 26 | SP1(Spring1) |
| 27 | SP2(Spring2) |
| 28 | SR(SteeringRack) |

Fig. 5. The parts list and exploded view of a toy car.

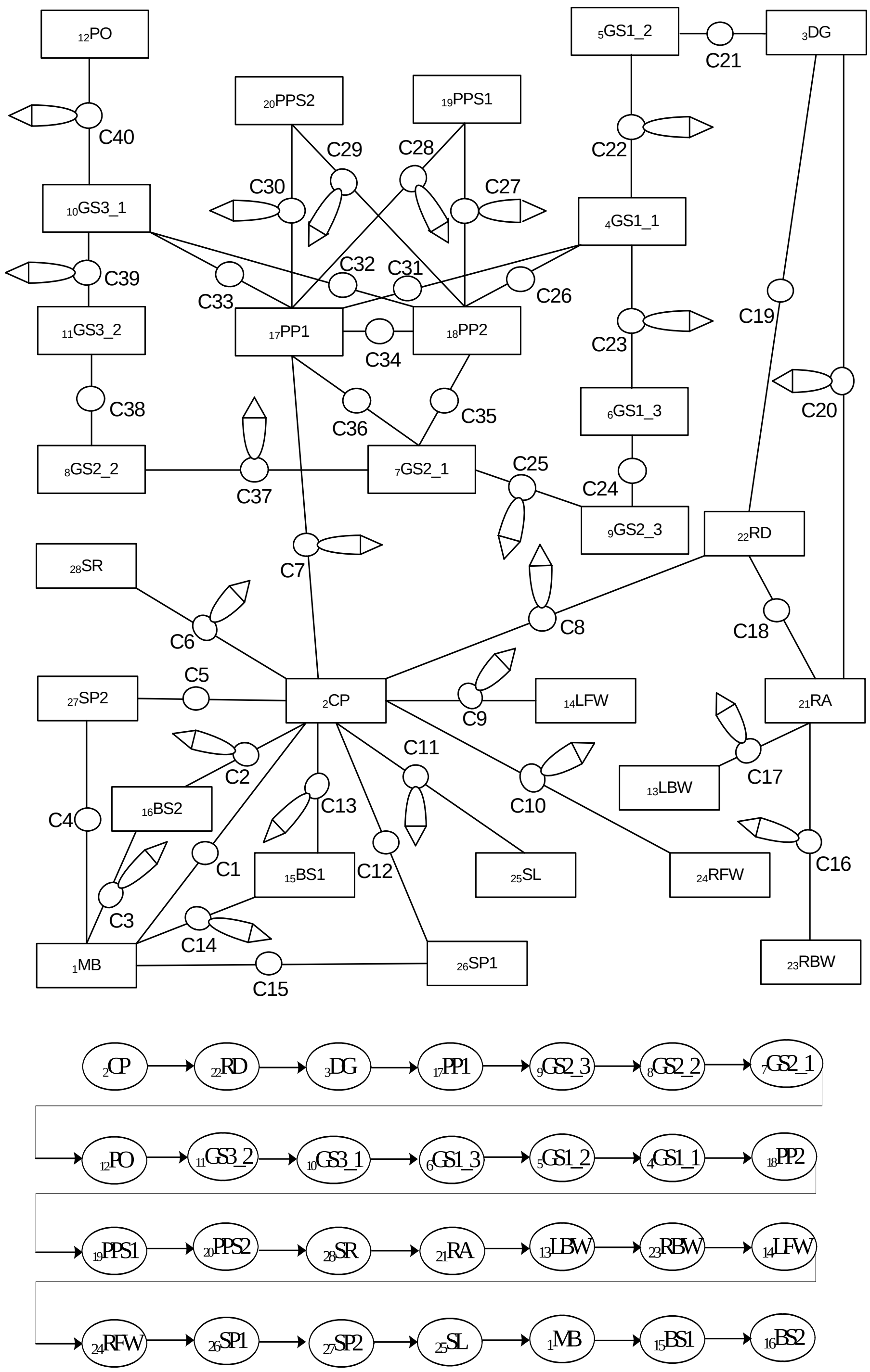
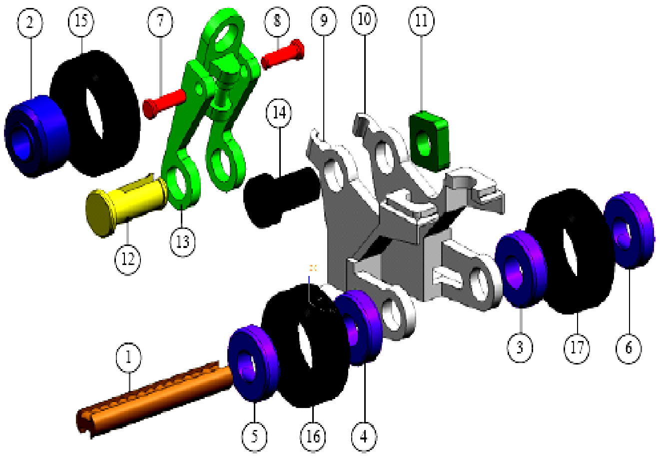



Fig. 6. The complete RMG and APD of a toy car.



| No | Part name |
|---|---|
| 1 | MA(MotorbikeAxle) |
| 2 | MB1(MotorbikeBearing1) |
| 3 | MB2_1(MotorbikeBearing2_1) |
| 4 | MB2_2(MotorbikeBearing2_2) |
| 5 | MB3_1(MotorbikeBearing3_1) |
| 6 | MB3_2(MotorbikeBearing3_2) |
| 7 | MH1(MotorbikeHandlE1) |
| 8 | MH2(MotorbikeHandlE2) |
| 9 | MMB1(MotorbikeMainBody1) |
| 10 | MMB2(MotorbikeMainBody2) |
| 11 | MN(MotorbikeNut) |
| 12 | MPN(MotorbikePin) |
| 13 | MPE(MotorbikePlate) |
| 14 | MS(MotorbikeScrew) |
| 15 | MW1(MotorbikeWheel1) |
| 16 | MW2(MotorbikeWheel2) |
| 17 | MW3(MotorbikeWheel3) |

Fig. 7. The parts list and exploded view of a motorbike.

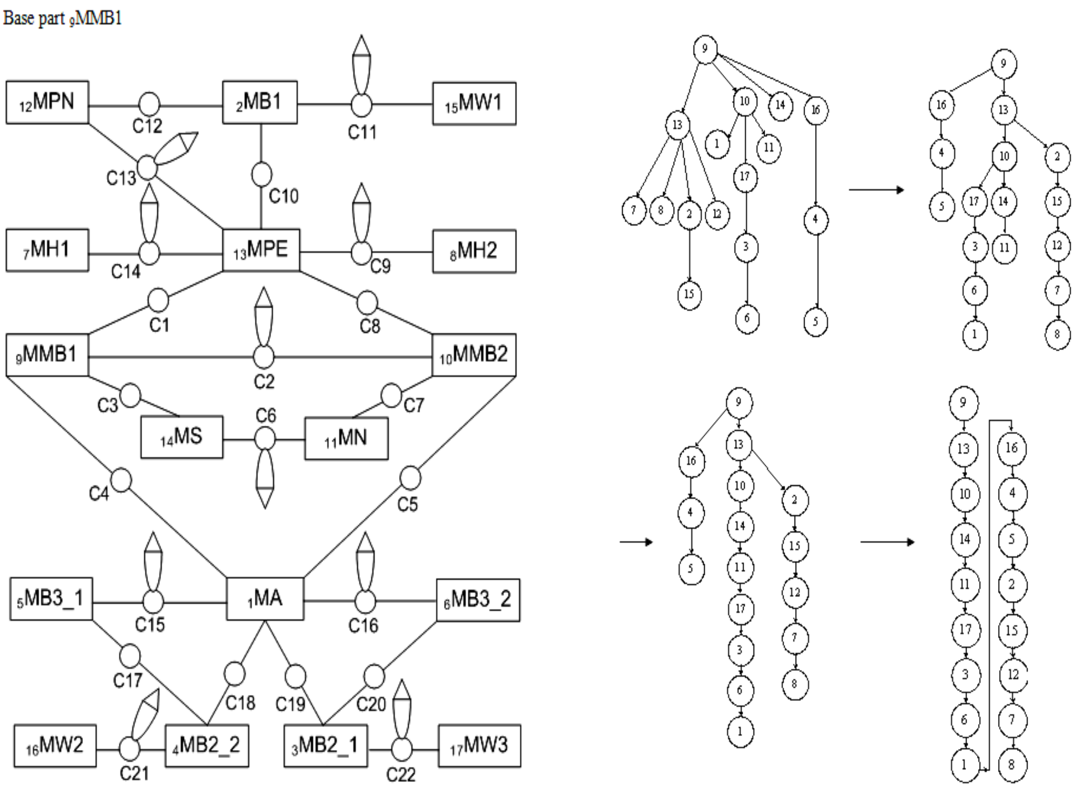
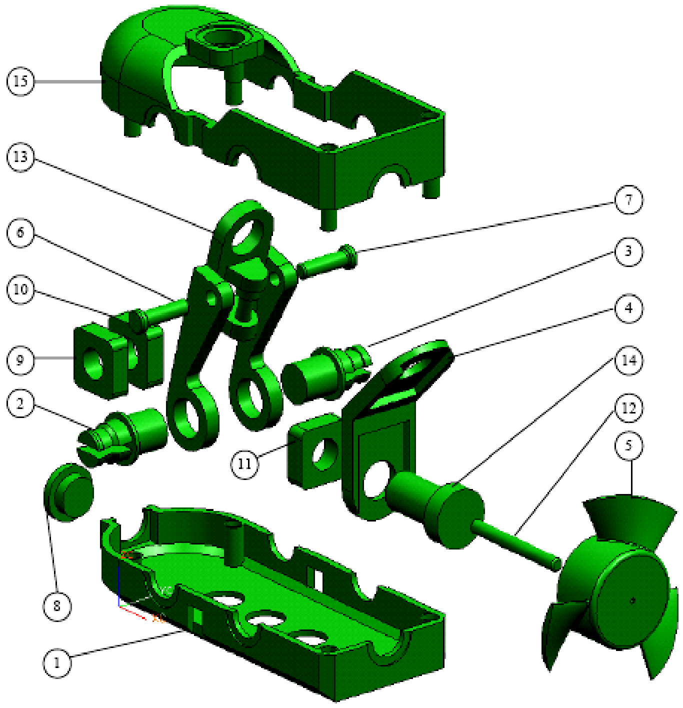



Fig. 8. The complete RMG and APD of a motorbike.



| No | Part name |
| --- | --- |
| 1 | BM (BaseboatMainbody) |
| 2 | BB1 (BoatBolt1) |
| 3 | BB2 (BoatBolt2) |
| 4 | BC (BoatChair) |
| 5 | BF (BoatFan) |
| 6 | BH1 (BoatHandle1) |
| 7 | BH2 (BoatHandle2) |
| 8 | BL (BoatLight) |
| 9 | BN1 (BoatNut1) |
| 10 | BN2 (BoatNut2) |
| 11 | BN3 (BoatNut3) |
| 12 | BPR (BoatPillar) |
| 13 | BP (BoatPlate) |
| 14 | BS (BoatScrew) |
| 15 | TM (TopBoatMainBody) |

Fig. 9. The parts list and exploded view of a toy boat.

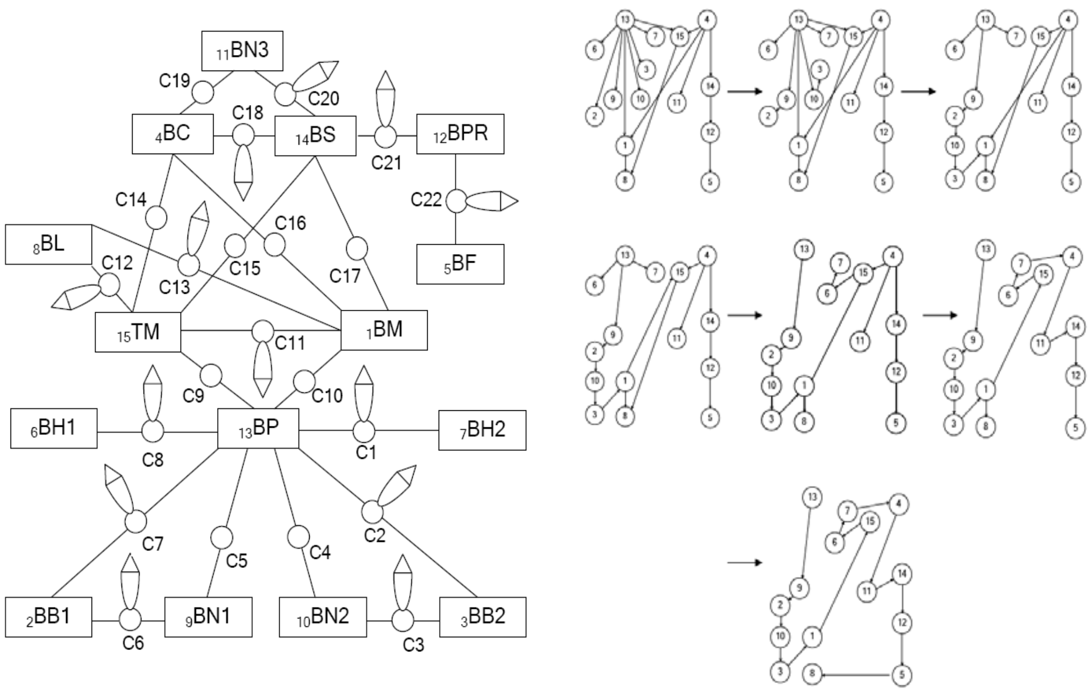



Fig. 10. The complete RMG and APD of a boat.

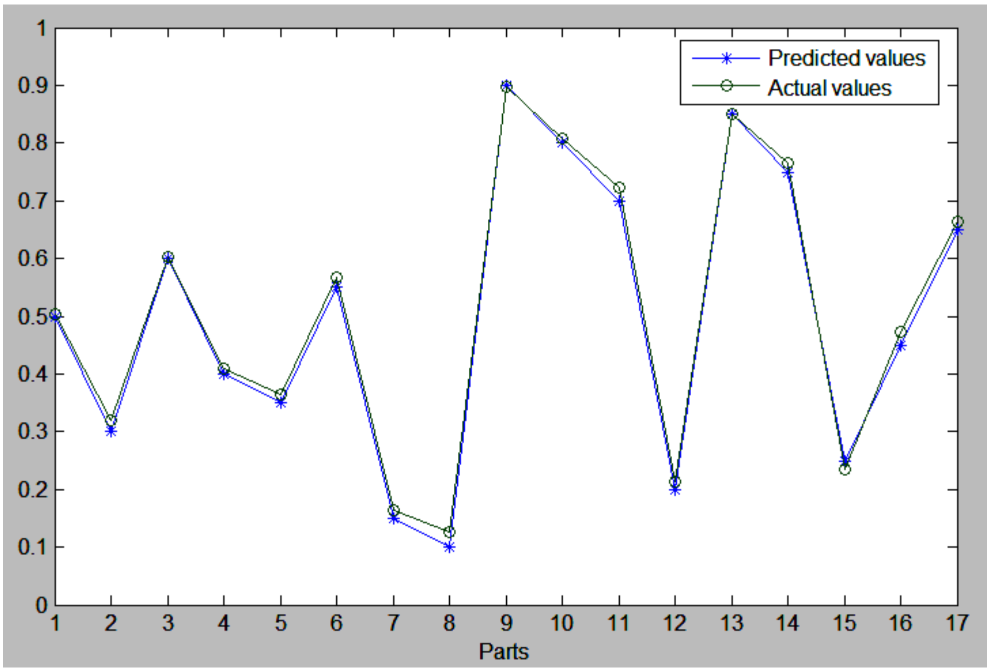



Fig. 11. An assembly sequence prediction via BPNN engine 1.

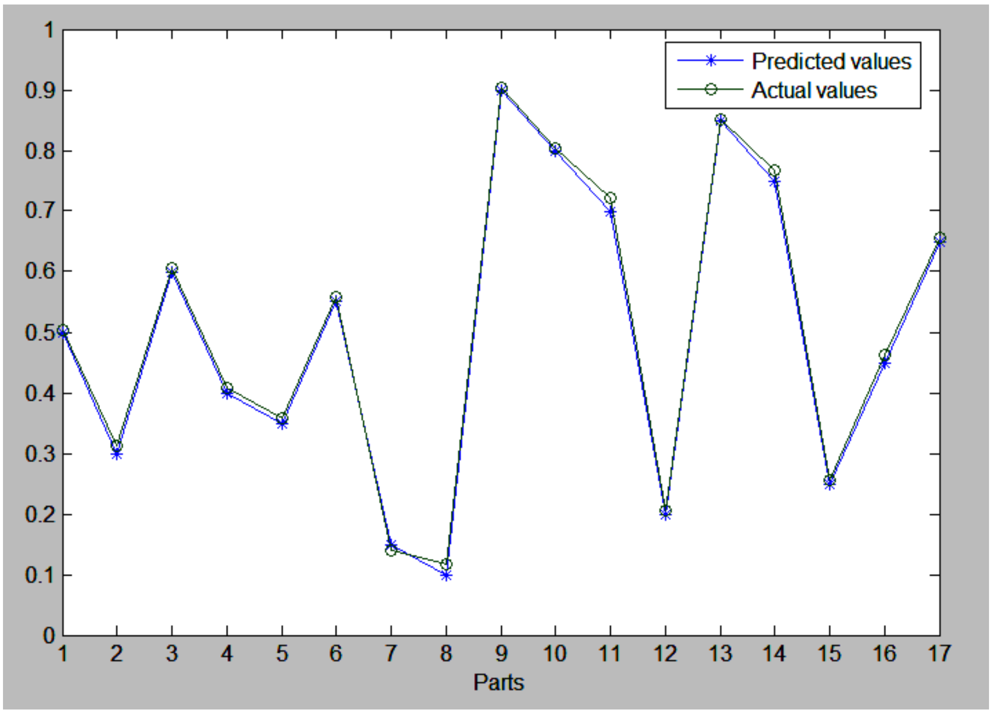



Fig. 12. An assembly sequence prediction via BPNN engine 2.

Table 1 Information on the factors' assumed settings at different levels via Taguchi Method.

| Item | Control factor | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|
| $F_t$ | Transfer function | Hyperbolic Tangent | Sigmoid | |
| $N_h$ | Number of neurons in the hidden layer | 8 | 13 | 18 |
| $R_l$ | Learning rate | 0.7 | 0.8 | 0.9 |
| $M_t$ | Momentum | 0.7 | 0.8 | 0.9 |
| $E_p$ | Epochs | 20,000 | 35,000 | 50,000 |

Table 2 Information on the factors' assumed settings at different levels.

| Item | Control factor | Level 1 | Level 2 |
|---|---|---|---|
| A | Number of neurons in the hidden layer | 4 | 18 |
| B | Learning rate | 0.3 | 0.9 |
| C | Momentum | 0.5 | 0.9 |
| D | Number of epochs | 10,000 | 50,000 |

Table 3 The optimal assembly sequence of a toy car.

| Optimal Assembly Sequence | Parts | AI | TPV | FN | Weight | Volume |
|---|---|---|---|---|---|---|
| 1 | $_{2}$CP | 19 | 47 | 9 | 981.88 | 125415.99 |
| 2 | $_{22}$RD | 4 | 8 | 10 | 31.42 | 11246.39 |
| 3 | $_{3}$DG | 5 | 8 | 27 | 4.83 | 3452.57 |
| 4 | $_{17}$PP | 10 | 29 | 11 | 83.64 | 29935.98 |
| 5 | $_{9}$GS2_3 | 3 | 5 | 22 | 1.96 | 1397.92 |
| 6 | $_{8}$GS2_2 | 3 | 5 | 22 | 1.12 | 802.85 |
| 7 | $_{7}$GS2_1 | 6 | 16 | 1 | 3.07 | 392.7 |
| 8 | $_{12}$PO | 2 | 3 | 2 | 56.34 | 20165.61 |
| 9 | $_{11}$GS3_2 | 3 | 5 | 26 | 2.28 | 1628.77 |
| 10 | $_{10}$GS3_1 | 6 | 16 | 1 | 3.07 | 392.7 |
| 11 | $_{6}$GS1_3 | 3 | 5 | 22 | 1.08 | 771.23 |
| 12 | $_{5}$GS1_2 | 3 | 5 | 22 | 0.87 | 623.61 |
| 13 | $_{4}$GS1_1 | 6 | 16 | 1 | 3.07 | 392.7 |
| 14 | $_{18}$PP2 | 8 | 22 | 11 | 17.66 | 6321.76 |
| 15 | $_{19}$PPS1 | 4 | 6 | 3 | 0.13 | 14.99 |
| 16 | $_{20}$PPS2 | 4 | 5 | 3 | 0.11 | 14.86 |
| 17 | $_{28}$SR | 7 | 4 | 4 | 27.58 | 3522.26 |
| 18 | $_{21}$RA | 7 | 13 | 3 | 29.79 | 3804.98 |
| 19 | $_{13}$LBW | 2 | 5 | 7 | 308.9 | 219936.4 |
| 20 | $_{23}$RBW | 2 | 3 | 7 | 307.67 | 219928.32 |
| 21 | $_{14}$LFW | 2 | 3 | 9 | 176.9 | 119227.68 |
| 22 | $_{24}$RFW | 2 | 3 | 9 | 164.33 | 119214.45 |
| 23 | $_{26}$SP1 | 2 | 6 | 3 | 9.99 | 1288.59 |
| 24 | $_{27}$SP2 | 2 | 6 | 3 | 9.85 | 1276.48 |
| 25 | $_{25}$SL | 2 | 3 | 2 | 234.01 | 83756.14 |
| 26 | $_{1}$MB | 7 | 17 | 28 | 932.5 | 333750.12 |
| 27 | $_{15}$BS1 | 4 | 10 | 3 | 2.38 | 303.99 |
| 28 | $_{16}$BS2 | 4 | 10 | 3 | 2.36 | 302.45 |

Table 4 The optimal assembly sequence of a toy motorbike.

| Optimal Assembly Sequence | Parts | AI | TPV | FN | Weight | Volume |
|---|---|---|---|---|---|---|
| 1 | $_{9}$MMB1 | 5 | 13 | 20 | 7.35 | 7697.04 |
| 2 | $_{13}$MPE | 9 | 19 | 4 | 5.19 | 5176.46 |
| 3 | $_{10}$MMB2 | 5 | 17 | 20 | 6.78 | 7696.73 |
| 4 | $_{14}$MS | 3 | 8 | 2 | 1.53 | 2297.29 |
| 5 | $_{11}$MN | 3 | 10 | 3 | 0.78 | 856.50 |
| 6 | $_{17}$MW3 | 1 | 9 | 4 | 8.13 | 7296.14 |
| 7 | $_{3}$MB2_1 | 4 | 23 | 3 | 1.2 | 1931.29 |
| 8 | $_{6}$MB3_2 | 3 | 16 | 5 | 1.41 | 1892.18 |
| 9 | $_{1}$MA | 8 | 52 | 2 | 3.32 | 2907.56 |
| 10 | $_{16}$MW2 | 2 | 9 | 4 | 8 | 7295.23 |
| 11 | $_{4}$MB2_2 | 4 | 18 | 3 | 1.18 | 1930.96 |
| 12 | $_{5}$MB3_1 | 3 | 5 | 5 | 1.4 | 1891.72 |
| 13 | $_{2}$MB1 | 4 | 11 | 4 | 2.49 | 3841.38 |
| 14 | $_{15}$MW1 | 2 | 4 | 4 | 7.99 | 7294.86 |
| 15 | $_{12}$MPN | 3 | 12 | 5 | 1.28 | 1619.55 |
| 16 | $_{7}$MH1 | 2 | 4 | 3 | 0.17 | 231.61 |
| 17 | $_{8}$MH2 | 2 | 3 | 3 | 0.15 | 230.56 |

Table 5 The optimal assembly sequence of a toy boat.

| Optimal Assembly Sequence | Parts | AI | TPV | FN | Weight | Volume |
|---|---|---|---|---|---|---|
| 1 | $_{13}$BP | 12 | 28 | 4 | 40.53 | 5176.46 |
| 2 | $_{9}$BN1 | 3 | 7 | 3 | 6.81 | 857.5 |
| 3 | $_{2}$BB1 | 4 | 10 | 4 | 10.95 | 1393.43 |
| 4 | $_{10}$BN2 | 3 | 8 | 3 | 6.71 | 857.1 |
| 5 | $_{3}$BB2 | 4 | 11 | 4 | 10.9 | 1392.87 |
| 6 | $_{1}$BM | 7 | 34 | 12 | 86.96 | 11105.48 |
| 7 | $_{15}$TM | 7 | 30 | 12 | 75.11 | 9591.47 |
| 8 | $_{6}$BH1 | 2 | 3 | 3 | 1.82 | 231.61 |
| 9 | $_{7}$BH2 | 2 | 3 | 3 | 1.81 | 230.92 |
| 10 | $_{4}$BC | 5 | 20 | 8 | 19.98 | 2551.01 |
| 11 | $_{11}$BN3 | 3 | 7 | 3 | 6.61 | 856.2 |
| 12 | $_{14}$BS | 8 | 26 | 2 | 17.99 | 2297.29 |
| 13 | $_{12}$BPR | 4 | 6 | 2 | 2.4 | 306.77 |
| 14 | $_{5}$BF | 2 | 3 | 11 | 26.63 | 3401.12 |
| 15 | $_{8}$BL | 4 | 8 | 3 | 5.69 | 726.57 |

Table 6  Comparisons of BPNN performance between Taguchi method and DOE approach.

| Item | Training RMSE | Testing RMSE | Approach |
|---|---|---|---|
| BPNN engine 1 | 0.055357604 | 0.015026421 | Taguchi method (13-0.9-0.9-35000) |
| BPNN engine 2 | 0.048829895 | 0.010480437 | DOE (15-0.9-0.9-50000) |

附件二

# 可供推廣之研發成果資料表

□ 可申請專利　■ 可技術移轉　日期：98 年 10 月 05 日

| | |
|---|---|
| **國科會補助計畫** | 計畫名稱：智慧型組裝順序規劃 KBE 系統<br>計畫主持人：　徐永源<br>計畫編號：NSC 97-2221-E-216 -026<br>學門領域：：電腦繪圖及應用 |
| **技術/創作名稱** | 智慧型組裝順序規劃 KBE 系統 |
| **發明人/創作人** | 徐永源 |
| **技術說明** | 中文：<br>本研究計劃主要成果是建立「智慧型組裝順序規劃 KBE 系統」。多年來，工業界企盼如何能將知識工程(KBE)與 CAD 系統有效結合，以整合性 CAX(CAD/CAM/CAE)系統及 KBE 工具為平台，實現智慧型設計、組裝、製造及維護等。另外，目前組裝順序規劃均由產品設計工程師依個人經驗判斷決定，其產品爆炸圖在空間之相對位置及組裝關係限制並無理論根據。因此，此研究將以建構產品的最佳組裝順序為目標，應用以產品重量、體積、幾何特徵值、組件間接觸值、總懲罰值為輸入參數及上位圖(Above graph)、關係模型圖(Rational model graph)、組裝優先順序圖(Assembly precedence graph)、空間限制關係的分析等，建構穩健的組裝順序最佳化類神經網路(ANN)引擎及知識庫。最後，應用 UG/KF 二次開發系統將此知識引擎有效整合於 UG/CAD 系統中，呈現完整的「智慧型組裝順序規劃 KBE 系統」。<br><br>關鍵詞:知識工程,組裝順序,最佳化,類神經網路,知識庫 |

| | |
|---|---|
| | 英文：<br>In recent years, the efficient integration among CAX (CAD/CAM/CAE) systems through knowledge-based engineering (KBE) and Computer aided design (CAD) systems is employed to achieve intellectual design, assembly, manufacturing, and maintenance in most industries. Assembly sequence planning (ASP) is normally based on engineers' personal experience and intuition, and lack of theoretical support in determining spatial relative positions and assembly relationship constraints of product components. Thus, the aim of this project is to develop the KBE assembly sequence planning system and further generate an optimal assembly sequence applying weight, volume, geometric features, contact relationships and total penalty values as input parameters of neural networks (NN), and an output variable (optimal assembly sequence) derived by Above graphs, Relational model graphs, assembly precedence graphs (APD) and analysis of spatial constraint relationships to construct a robust NN-based ASP engine and Knowledge database. Finally, the CAD second development tool, Unigraphics/Knowledge Fusion (UG/KF), is herein implemented to complete the KBE assembly sequence planning system through the integration of NN engine and UG/CAD system.<br><br>**Keywords:** knowledge-based engineering, assembly sequence planning, assembly sequence optimization, neural networks, Knowledge Fusion. |
| **可利用之產業<br>及<br>可開發之產品** | CAD 軟體 |
| **技術特點** | 應用 UG/KF 二次開發系統將此知識引擎有效整合於 UG/CAD 系統中，呈現完整的「智慧型組裝順序規劃 KBE 系統」。 |
| **推廣及運用的價值** | 可將此一模組應用於 CAD 軟體的組裝模組中。 |

※ 1. 每項研發成果請填寫一式二份，一份隨成果報告送繳本會，一份送 貴單位研發成果推廣單位（如技術移轉中心）。

※ **2. 本項研發成果若尚未申請專利，請勿揭露可申請專利之主要內容。**

※ 3. 本表若不敷使用，請自行影印使用。