Neural Computing and Applications (2021) 33:4111–4117
https://doi.org/10.1007/s00521-020-05604-0

S.I. : SPIOT 2020

Product modeling design based on genetic algorithm and BP neural network

Jia-Xuan Han[1] · Min-Yuan Ma[1] · Kun Wang[1,2]

Received: 29 August 2020 / Accepted: 11 December 2020 / Published online: 21 March 2021

Abstract
At present, the rapid development of industrial products still lacks reliable theoretical support in terms of styling design. In order to provide a set of effective reference basis for designing a better product appearance plan, this paper takes the shape design of drones as an example. The optimization feature of genetic algorithm optimizes the BP neural network to construct a hybrid GA–BP model, so as to efficiently evaluate and screen out scientific design schemes. By adding 13 of the 16 selected product design schemes to the hybrid GA–BP evaluation system, we perform training to obtain simulated and actual values, and finally, the remaining three design schemes are used for verification. Our results show that the relative errors of the two sets of data verification are 3.4%, 1.9% and 3.1%, respectively. In theory, such accuracy is very high, which basically reflects that the evaluation system of hybrid GA–BP product modeling design enables the design plan to be evaluated quickly, conveniently, effectively and scientifically.

Keywords Genetic algorithm · BP neural network · Product modeling design · Design evaluation system · Product design

1 Introduction

In the process of product design, the function is the first issue we must consider [1], but we should also consider good modeling style including appearance shape, color matching, material texture, space size, etc. [2, 3]. To better reflect the function of the product, it is also conducive to conveying usage information and shaping the brand image. Many manufacturers regard optimized styling design as an important strategy to eliminate homogeneous competition and implement differentiated brand competition according to the designers' styling.

There are still many obstacles to the design method. The main obstacles are as follows: (1) too much reliance on empirical parameter adjustment, which is difficult to master [4]; (2) the current method of modeling optimization using algorithms for optimization design usually requires a lot of finite element calculations [5], which will take a lot of time, but the results are usually not satisfactory; and (3) it is impossible to ensure that the obtained shape is the optimal solution.

In response to the above problems, neural network methods can be introduced as an exploration direction in the field of product modeling optimization [6–8]. Neural network has been studied by many related scholars in the field of industrial manufacturing. On the basis of these existing explorations, Parichatprecha and Nimityongskul [9] and others established and evaluated a three-layer network model and used product genetic design to achieve optimization with the help of genetic algorithms; Zeng and Kuiper [10] studied suppression of cavitation. The initial multi-objective new profile design technology is also based on genetic algorithm. Aguir et al. [11] combined neural networks with partial least squares, which is a system for new materials and new solutions. The design analysis and evaluation of Taplak et al. [12] are also based on the establishment of neural network to study bearing design; Ramasamy and Rajasekaran [13] used this method to train and verify the results and found that the method of artificial

✉ Kun Wang
P38043027@ncku.edu.tw

1 Department of Industrial Design, National Cheng Kung University, Tainan, Taiwan, ROC

2 Institute of Fine Arts and Design, Quanzhou Normal University, Quanzhou, China

neural network model allows designers to more accurately evaluate our product design. Many design researchers realize that the single genetic algorithm proposed in the 1970s has not been able to better solve the problems of large-scale calculations and structural optimization, mainly because using this method to carry out a large number of evolutionary evaluations means repeated conduction of multiple structural analyses.

The rapid mapping and convergence ability of BP neural network overcomes the problem of over-calculation of genetic algorithm. Combining the two and complementing each other can produce more productive styling methods. Taking this into consideration, this study establishes a hybrid GA–BP neural network model by combining genetic algorithm and BP neural network and uses this model to evaluate product modeling design, thereby shortening the development cycle, improving efficiency, design efficiency, as well as scientific product styling.

2 Methodology

2.1 Genetic algorithm

The first proposer of the genetic algorithm was John Holland in the USA in 1975. The genetic algorithm is basically a computer model [14] and at the same time simulates the genetic selection process based on evolutionary theory [15]. Finally, we will find the best solution with inherent implicit parallelism and greater global optimization ability. The chromosome represents the solution of the GA problem, and then, the chromosome is placed in the environment of the problem, and they are screened, depending on the degree of physical shape. Choosing environment-friendly chromosomes for replication or reproduction, these two types of gene manipulations are mainly carried out through mating and mutation, creating a new generation that is more adaptable to the environment. Then, they cross-propagate and mutate with each other, and converge to the most suitable individuals according to some convergence criteria, which becomes the best solution to the problem [16].

2.2 BP artificial neural network

Artificial neural network [17] is the most commonly used and most popular neural network that imitates the human brain to create and analyze the learning state of things in the process of recognizing things [18]. BP artificial neural network is composed of three levels: input, output and hiding. Each level consists of a certain number of neurons. Each of these neurons has a threshold, and each level is connected by weight. The relationship between the two levels of input and output can be regarded as a mapping relationship, that is, each set of input corresponds to a set of output, and the relationship is represented by the weight (or threshold), and then, the problem is processed. Neural networks with relatively good fault tolerance can be studied using the nonlinear fitting ability of the nonlinear relationship between variables and targets. First, one needs to get sample data as a sample for neural network training; secondly, we train the neural network; and thirdly, we describe the feature parameter of the corresponding problem as the numerical input of the neural network. The last step is to get the final result of the corresponding problem through the neural network algorithm. It should be noted that this algorithm has the disadvantages of slow convergence and insufficient local extremum, but it can still be improved by various methods to overcome the local extremum phenomenon. The algorithm is simple, easy to operate and does not require excessive calculations. It also possesses the characteristics of strong parallelism, so it can be used as the network's preferred algorithm.

2.3 GA-optimized BP neural network algorithm

Genetic algorithm-optimized BP neural network is divided into three parts: BP neural network structure, genetic algorithm optimization and BP neural network prediction. To solve the problem of nonlinear mapping, GA and BP neural networks are generally used [19], because both have extremely strong functions. As such, this study is based on the MATLAB R2011b platform to achieve the establishment of GA–BP hybrid algorithm [20]. Among them, the GA–BP method can obtain the algorithm result after the most important structural optimization design steps. If the result is wrong but meets the requirements of the training target, the calculation is to be ended; otherwise, if the error is not met, the test is added to the training. Next, we focus on the sample and repeat steps 3–5 until the error meets the requirements. This method combines the two together. On the one hand, we overcome the hindrance of optimization. On the other hand, the issue of the BP falling into local convergence can be effectively improved, thereby greatly improving the generalization performance of the network. Figure 1 shows the overall design flow of the hybrid algorithm.

2.4 Model evaluation index system

In this study, an industrial product that has been rapidly developed with the fermentation of the Internet of things concept and the integration of information, communication and network technology is taken as a specific case to study the product shape design [21, 22]. We optimize the BP neural network to build a hybrid GA–BP model. First of

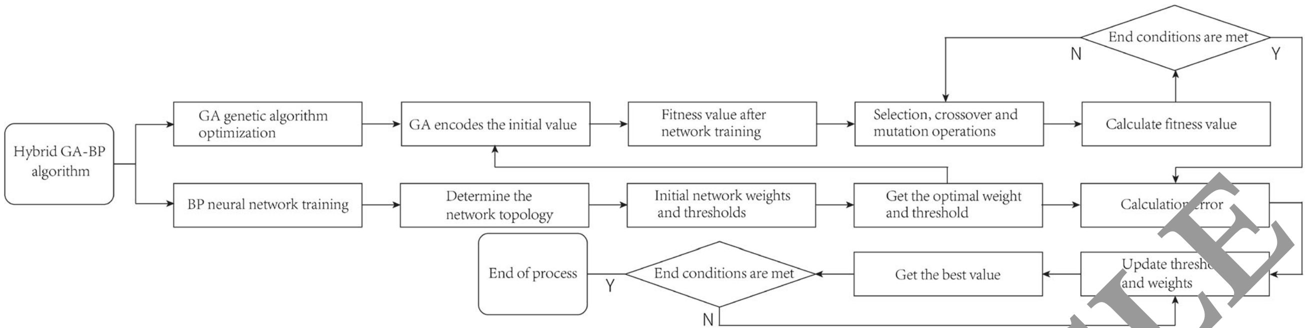

Fig. 1 GA-optimized BP neural network algorithm flow

all, it is necessary to establish a rating index. This article uses the three first-level indicators of overall appearance, detail craftsmanship and individual components as the evaluation index system of product styling [23] is more scientific and standardized. Table 1 shows the detailed evaluation index. The appearance design of the product is based on the overall appearance, individual parts, and details of the three first-level indicators: style, appearance, body size, material texture, color matching, emotional cognition, flight controller, blade modeling, camera, 13 evaluation indexes; for example, motor, surface technology, location of heat dissipation port, and portability are used as specific evaluation indexes.

3 Establishment of hybrid GA–BP model

3.1 Sample design of the network

This article selects 75 different types of aircraft from more than 20 popular brands in the drone market, according to the second-level index evaluation system, and invites eight members who have received professional KJ method training and have contacted drones (including one designer, one engineer, two PhD students and four master students) formed an expert group. The KJ method is a quality management tool proposed by Jiro Kawakita [24]. This method is a way to sort out ideas, grasp the essence of ideas, and find new ways to solve problems from intricate phenomena. Using the KJ method to analyze the overall appearance, single form and details of 51 drones, combined with the selection of consumer satisfaction rankings, the drones with a greater degree of similarity were integrated, and 16 drones were finally obtained. The design plan, as the network training sample is the evaluation data of 13 model design plans randomly taken from the 16 model design plans of the drone, and the remaining three models are used for the network effect verification sample.

A survey questionnaire was conducted for people in the 18–45 age group. The target group included college students, young and middle-aged teachers, businessmen, white collar workers, and other members of the broad society of 18–45 years. There were 285 copies, and a total of 270 valid questionnaires were obtained after screening. The pass rate of the questionnaire was 90%. Then, use the fifth-order Likert scale method to score the indicators of the 16 UAV modeling design schemes. The scale is composed of a set of statements. The subject is selected to test the 13 evaluation indicators, and the subject is asked to point out each evaluation indicator is favorable or unfavorable and is selected in the following directional strength descriptors, generally using the so-called five-point scale: a, strongly agree, b, agree, c, neutral, d, disagree, and e, strongly disagree and then score each answer; for example, the preferred items from strong agreement to strong opposition are 5, 4, 3, 2 and 1, respectively; on the contrary, the project score is 1, 2, 3, 4 and 5.

This scale method is used to calculate the algebraic sum based on the score of each item in the object, so as to obtain the total score of personal attitudes characterized by the arithmetic mean, and is characterized according to the arithmetic mean (Table 2), which A score can basically

Table 1 Evaluation index system of notebook computer design

Target level	First-level indicators	Secondary indicators
Drone modeling evaluation system	Overall appearance	X1 modeling style, X2 appearance shape, X3 body size, X4 material texture, X5 color matching, X6 affective cognition
	Single part	X7 flight controller, X8 blade shape, X9 camera, X10 motor
	Detail craft	X11 surface technology, X12 heat dissipation position, X13 portability

indicate his strong or weak attitude or his different status on this scale.

3.2 Specific analysis methods

The part of the BP algorithm adopts a three-layer network structure as the analysis method in this study when using the hybrid GA–BP model to evaluate the design of products. The three-layer network structure is divided into three layers: input, hidden, and output. The training process includes two forms of forward and backward propagation, and then, using $W_{i,j}$ and $W_{k,\ j}$ these two sets of data, respectively, represent the weight of neurons input to the hidden layer and hidden to the output layer, as shown in Fig. 2 which shows the structure of the neural network. The genetic algorithm finds the optimal solution through global optimization and then optimizes the weight and threshold of the BP neural network.

3.3 Encoding and normalization

As sample data, 16 modeling designs of drones are used as sample indicators. To establish a database of mixed GA–BP evaluation models, the 13 evaluation indicators of X1 to X13 are used as the input layer data of the model, and the output layer data are the scores of the evaluation results obtained through the survey of the respondents. Because the training function needs to output parameters in the interval [0, 1], and the value obtained by the interviewee's perceptual evaluation results is not completely within this interval, at the same time, the evaluation indicators should be given due attention. The data in are subjected to normalization preprocessing. The research results show that when the output layer activation function uses a logarithmic function (S function), it is better to normalize the input and output variables to [0.1, 0.9] interval [28]. This study uses a simpler and faster normalization algorithm, and the equation is:

$$X_i = 0.1 + 0.8\frac{X_i - X_{\min}}{X_i - X_{\min}} \tag{1}$$

Among them, $X_{\min}$ is the minimum value of X, and the maximum value is $X_{\max}$. From Table 3, it can be shown that after analyzing the UAV modeling design, and then combining the UAV modeling with a relatively similar degree among the 13 evaluation indicators, the optimal scheme score data of the 16 models obtained are 0.90, and the points of the lowest value of scheme F data are 0.10.

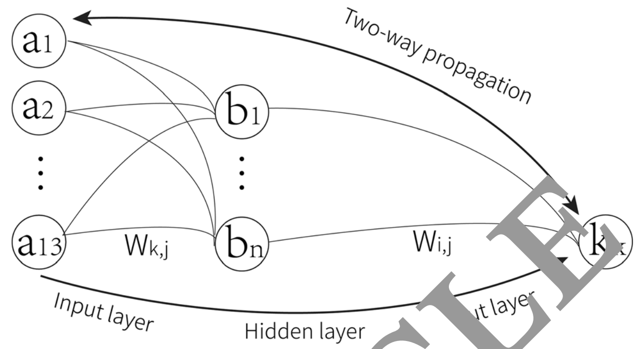

Fig. 2 Three-layer BP neural network structure

3.4 Network training

Thirteen models of drones were selected in a random way, and these models were trained with network models [25]. In training, 0.01 is set as the learning rate, the expected error is set to 0.001, and 3000 times is set as the maximum number of learning times. Continuously transforming the number of genetic algorithm population and genetic algorithm's genetic algebra, we can conclude that the number of population is 40, the genetic algebra is 100, and the number of hidden layers is 10 which is the best choice. The data show that when the number of iterations reaches the 1840th time, the mean square error is $0.00099 < 0.001$. At this time, the training achieves the goal and stops continuing the iteration. At this point, the BP neural network model of the product model can be initially obtained. Then, one can use the acquired network to simulate 13 sample simulation programs to obtain the simulated value score of the training sample score.

Figure 3 shows the comparison curve between the actual and simulated values. The data values show 13 sample schemes, in which the simulated and actual values tend to be the same during training. Only small changes around the actual values indicate that the accuracy of the sample scheme reached a higher accuracy during training.

Table 2 Arithmetic average of 16 design scheme evaluation indexes

Number	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
X1	3.8	3.1	3.4	3.8	3.7	4.2	4.1	3.5	2.8	2.9	3.2	4.1	3.2	3.1	2.6	3.6
X2	2.8	4.3	3.1	4.4	3.0	2.3	2.8	3.9	2.6	4.1	2.9	3.5	3.1	2.7	4.4	2.9
X3	4.1	3.2	3.4	3.3	2.5	2.5	3.2	3.1	4.0	2.7	4.5	3.6	4.7	2.3	4.3	3.8
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
X13	3.1	3.3	3.7	4.1	4.2	3.2	3.6	3.3	3.2	4.1	3.9	3.8	3.9	3.1	4.0	3.7

Table 3 Evaluation results and normalization of intention scale method

Number	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Total score	51.5	52.3	45.2	54.6	40.8	37.5	39.1	45.5	54.3	60.1	45.8	53.9	57.7	46.2	50.5	43.1
P	0.37	0.70	0.30	0.42	0.69	0.11	0.17	0.39	0.61	0.91	0.36	0.64	0.81	0.46	0.55	0.27

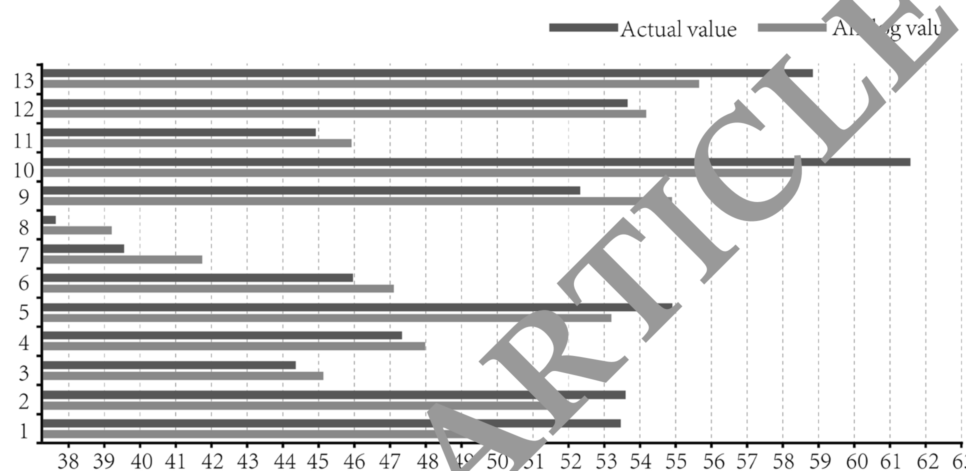

Fig. 3 The comparison curve between the simulated value and the actual value of the 15 programs during the training period

After network training, we need to evaluate the performance of the BP neural network model used for UAV modeling. The principle of evaluation detection is to use test samples for testing. The sequence is: first, encode and process the test samples, and then use them as parameters of the input layer to obtain the output layer value of the UAV modeling network. At the same time, the test samples are evaluated in the target audience and the sensory evaluation values are standardized. Finally, the MSE function is used to detect the data obtained by the two methods. The expression of the function is:

$$\mathrm{MSE} = \frac{1}{p}\sum_{k=1}^{p}\left(y_k - y_k^*\right)^2 \tag{2}$$

If the MSE value is less than 0.01, it can prove that the modeling BP neural network model of the UAV is scientific. In this study, the user's evaluation result and the value of the output layer of the BP neural network model of the drone model are measured. Using the MSE function, the measured result can be calculated to be less than 0.01, which is feasible.

3.5 Verification and results of the backup scheme to the network

In order to further verify the overall performance of the evaluation system in this study, the remaining three schemes X, Y, and Z are used to verify the hybrid GA–BP evaluation system after training. If the verification fails, the network needs to be retrained until the verification accuracy meets the requirements. The relative error is used to evaluate the error of the verification scheme. The verification results are shown in Table 4.

Table 4 shows that the simulated values of the mixed GA–BP evaluation models for the three verification schemes X, Y, and Z are 49.2, 50.4, and 51.1, respectively. Compared with the actual values of the scheme scores, the relative error can be estimated. The model verification results show that they are 3.4%, − 1.9% and 3.1%, respectively, with high accuracy. This evaluation model can be judged as the optimal combination plan, and this model can be used as the winning model, guiding the direction of product shape design scientifically.

3.6 Scheme modeling verification

Finally, in order to further understand the practical application of the research to the modeling design, the GA–BP will be mixed and the remaining three schemes X, Y, and Z will be subjected to modeling simulation, as shown in Fig. 4. Then, use the three-dimensional software Rhino and the rendering software KeyShot to make the Z plan to make a 3D drone model for the actual model verification of the plan, as shown in Fig. 5. Follow-up can be used as a product proposal.

4 Discussion

As the sample data, the evaluation indicators of this study will be 16 modeling designs of the product and construct a mixed GA–BP evaluation model index system. Then,

Table 4 Verification results of mixed GA–BP evaluation model

Verification scheme	Actual score value	GA–BP simulation value	Relative error Re/%
Scheme X	46.8	49.4	3.4
Scheme Y	50.9	51.2	− 1.9
Scheme Z	48.8	50.3	3.1

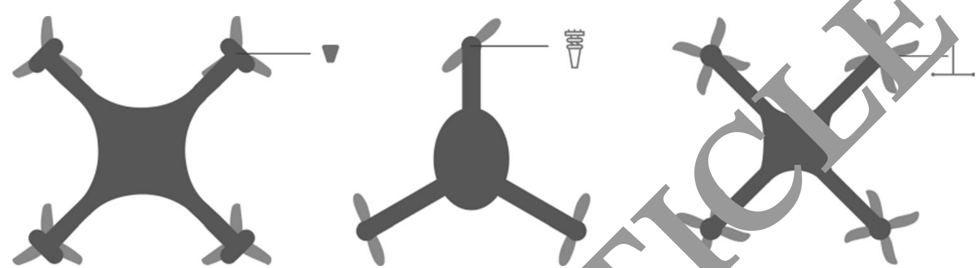

Fig. 4 Modeling simulation of three schemes X, Y, and Z with different fuselages and blades

Fig. 5 Actual rendering model effect of Z scheme (modeling design by Jia-xuan Han and Bo-Hsiang Peng)

select 13 models of the products in a random manner, and conduct model training through the network to verify the generalization performance of the evaluation system, and then, use the three programs that have not been used to train the hybrid GA–BP evaluation system. Perform verification to determine whether the accuracy of verification can meet the requirements. The final product was put on the questionnaire again for preference test, and the difference between satisfaction and computer-aided results was 0.26. Although the results obtained in this study using the hybrid GA–BP model to evaluate the design of UAV products are not absolutely perfect, there are still some relative errors that exceed this range, but most of the relative errors are within 10%. From this, we can draw: first, the mixed GA–BP model can be implemented to evaluate the design of UAV products; second, the network input and output parameters should be selected more reasonably, and attention should be paid to the selection of network input parameters. The input data parameters have more obvious characteristics, and try to avoid the overlap between the data parameters, especially need to pay attention to: in this study, the data screened by correlation analysis still cannot exclude all contradictory parameters or data, because the evaluation of appearance and shape, especially the two of X5 color matching and X6 emotional cognition, can be said to be a degree of artificial emotion evaluation of visual comfort, which is largely affected by individual factors. The influence of many factors, such as environmental factors and human test status, may lead to slightly different predictions. Some of the data in Table 5 show the individual contradictory parameters in these two evaluation indicators. In response to the above problems, we can continue to expand the scope of research, increase the sample size, and increase or decrease the neural network input indicators accordingly, so that the input parameters of the network training samples have better representation.

5 Conclusion

In this study, combining genetic algorithm and BP neural network, a hybrid GA–BP product modeling design evaluation system was established, and a total of 16 selected drone product modeling example programs were evaluated for design evaluation. By constructing a two-level index system for evaluation of UAV model design, and then quantifying the questionnaire, 13 models were selected as training samples, and the hybrid GA–BP model was trained. The remaining three model schemes are used to verify the training results, the final evaluation data value can indicate that the relative errors of the two are 3.4%, − 1.9% and 3.1%, respectively. In addition, using the MSE function to detect the data obtained by the two methods, the MSE value is less than 0.01, which also shows a higher accuracy. Secondly, we use Rhino and KeyShot to make the 3D UAV modeling and verify the actual model of the Z scheme, which can also be used as the product proposal in the future. Therefore, this evaluation system has a great role in reducing the risks and uncertainties in UAV modeling design. It can help designers design a drone product form that is closer to consumer needs,

Table 5 Two indicators that are greatly affected by differences in individual factors

Number	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
X1	3.8	3.1	3.4	3.8	3.7	4.2	4.1	3.5	2.8	2.9	3.2	4.1	3.2	3.1	2.6	3.6
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
X5	3.0	4.9	1.7	4.8	2.9	3.9	4.6	3.9	3.7	4.1	2.2	3.5	4.2	4.9	3.9	2.0
X6	4.7	2.2	4.1	2.9	2.0	4.8	3.0	3.8	4.0	2.9	2.5	3.9	45	3.1	4.3	3.4
…	…	…	…	…	…	…	…	…	…	…	…	…	…	[illegible]	[illegible]	…
X13	3.1	3.3	3.7	4.1	4.2	3.2	3.6	3.3	3.2	4.1	3.9	3.8	3.9	3.1	4.0	3.7

thereby making the product more competitive in the market, and at the same time improve the practicality and higher mathematical evaluation of drone product styling in the optimal choice of appearance design solutions. Universal applicability. It is believed that with the rapid development of science, the application range of the hybrid GA–BP product styling design evaluation system will also be more extensive, and more outstanding results will also be achieved in auxiliary product design.

Compliance with ethical standards

Conflict of interest The authors declared that they have no conflicts of interest to this work.

References

1. Green PE, Krieger AM, Zelnio RN (1989) A componential segmentation model with optimal product design features. Decis Sci 20(2):221–238
2. Laverk E, George S, Thomas S (2016) Virtual reality for stroke rehabilitation. Phys Ther 2(9):60–[illegible]
3. Davis A (2015) Virtual reality simulation, an innovative teaching tool for dietetics experiential education. Appl Spectrosc 60(4):373–374
4. Ge L (2012) The search of modularized digital modeling and structural parameter design based on 3-D product model. Adv Mater Res 9(11):4[illegible]–467
5. Hua E, Cao W, Chen Y (2012) Evaluation-driven product evolutionary design based on criteria-structure-gene model. Comput Eng Des 33(8):3184–3188
6. Giannakoglou KC, Papadimitriou DI, Kampolis IC (2006) Aerodynamic shape design using evolutionary algorithms and new gradient-assisted metamodels. Comput Methods Appl Mech Eng 195(44):6312–6329
7. Nouri NM, Zeinali M, Jahangardy Y (2016) AUV hull shape design based on desired pressure distribution. J Mar Sci Technol 21:203–215
8. Meen TH, Prior SD, Artde KTL (2014) Green technology automotive shape design based on neural networks and support vector regression. Eng Comput 31(8):1732–1745
9. Parichatprecha R, Nimityongskul P (2009) An integrated approach for optimum design of HPC mix proportion using genetic algorithm and artificial neural networks. Comput Concr 6(3):253–268
10. Zeng K (2013) Product form de-sign using customer perception evaluation by a combined per ellipse fitting and ANN approach. Adv Eng Inform 85(273):386–394
11. Aguir H, Belhadjsalah H, Hambli R (2011) Parameter identification of an elasto-plastic behaviour using artificial neural networks-genetic algorithm method. Mater Des 32(1):48–53
12. Taplak H, Uzmay I, Yildirim S (2006) An artificial neural network application to fault detection of a rotor bearing system. Ind Lubr Tribol 58(1):[illegible]2–44
13. Ramasamy JV, Rajasekaran S (1996) Artificial neural network and genetic algorithm for the design optimizaton of industrial roofs—a comparison. Comput Struct 58(4):747–755
14. Yang J, Honavar V (2010) Feature subset selection using a genetic algorithm. Intell Syst 13(2):386–394
15. Smith D, Lapedes A (2004) Mapping the antigenic and genetic evolution of influenza virus. Science 305(5682):371–376
16. Saha S, Bandyopadhyay S (2009) A new multiobjective simulated annealing based clustering technique using symmetry. Pattern Recogn Lett 30(15):1392–1403
17. Saeed MS (2019) Electric load forecasting using an artificial neural network. Middle East J Sci Res 6(2):442–449
18. Hsu KL, Gupta HV, Sorooshian S (1995) Artificial neural network modeling of the rainfall-runoff process. Water Resour Res 31(10):2517–2530
19. Su L, Qi H, Zhou M (2009) Reversing design on combined parameters of liquid-solid extrusion process based on the predictive model using hybrid GA-BP algorithm. Suxing Gongcheng Xuebao J Plast Eng 16(5):29–36
20. Lin L, Zhang Z, Zhang R (2015) Product modeling design evaluation based on genetic algorithm optimization neural network. Comput Eng Des 36(3):180–187
21. Guyton AA (2006) Developing sustainable product semantics for consumer products: a sustainable designer's guide. Georgia Institute of Technology 2006(1): 8–31
22. Li PH (2013) Research on the evaluation index of product design based on consumer, designer and manufacturer. Adv Mater Res 7(10):481–483
23. Price M, Raghunathan S, Curran R (2006) An integrated systems engineering approach to aircraft design. Prog Aerosp Sci 42(4):331–376
24. Munemori J, Nagasawa Y (1991) Development and trial of groupware for organizational design and management, distributed and cooperative KJ method support system. Inf Softw Technol 33(4):259–264
25. Zhang PG (2003) Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing 6(2):128–346

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.