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A Family Cars' Life Cycle Cost (LCC)-Oriented Hybrid Modelling Approach Combining ANN and CBR

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***Abstract*—**Design for cost (DFC) is a method that reduces life cycle cost (LCC) from the angle of designers. Multiple domain features mapping (MDFM) methodology was given in DFC. Using MDFM, we can use design features to estimate the LCC. From the angle of DFC, the design features of family cars were obtained, such as all dimensions, engine power and emission volume. At the conceptual design stage, cars' LCC were estimated using back propagation (BP) artificial neural networks (ANN) method and case-based reasoning (CBR). Hamming space was used to measure the similarity among cases in CBR method. Levenberg-Marquardt (LM) algorithm and genetic algorithm (GA) were used in ANN. The differences of LCC estimation model between CBR and artificial neural networks (ANN) were provided. ANN and CBR separately each method has its shortcomings. By combining ANN and CBR improved results accuracy was obtained. Firstly, using ANN selected some design features that affect LCC. Then using LCC estimation results of ANN could raise the accuracy of LCC estimation in CBR method. Thirdly, using ANN estimate LCC errors and correct errors in CBR's estimation results if the accuracy is not enough accurate. Finally, economically family cars and sport utility vehicle (SUV) was given as LCC estimation cases using this hybrid approach combining ANN and CBR.

***Keywords*—**case-based reasoning, life cycle cost (LCC), artificial neural networks (ANN), family cars

I. Introduction

FAMILY cars have been popular in developed countries. In China however, cars are just growing in popularity. The total amount of family cars goes up increasingly. With the crisis of energy supply, the price of gasoline goes up increasingly. Consequentially, users pay more attention to gas consumption of the car, and that in turn, demand manufacturers to take life cycle cost (LCC) of family cars into consideration. The concept of LCC is first presented by Department of Defense (DoD) from the angle of purchase. However, LCC can be cut down more effectively if it is considered in the early design stage. Among different methods, the artificial neural network (ANN) of artificial intelligence and case-based reasoning (CBR) are both techniques that have been discussed a lot before. This paper builds on previous work to improve the LCC estimation accuracy [1][2]. Reference [1] has provided an ANN ensemble method, but didn't include CBR method. Reference [2] provided CBR's methods, but didn't use ANN methods. In this paper, the hybridization of ANN and CBR methods are applied to conduct LCC estimation and improve the accuracy.This paper is organized as follows. Section 1 presents the research situation of CBR and ANN on LCC estimation. Section 2 discusses the mapping of design features and cost features. Section 3 presents a hybrid model of combining CBR and ANN. Section 4 presents the procedure and functionality of the proposed approach with a case study. Finally, Section 5 presents research conclusions and avenues for further research**.**

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A. Brief Discussion of DFC

Dean and Unal described designing for cost as "a state of mind supported by tools and the tools discussed include rules derived from parametric cost analysis and the robust design process of Taguchi in 1991"[3]. Design for Cost (DFC) is a design method that analyzes and evaluates a product's life cycle cost (include manufacturing cost, sale cost, use cost, maintenance cost, recycle cost, etc.), then modified the design to reduce the life cycle cost [4]. DFC needs confirming parameters of manufacturing, usage, maintenance phases, (for example, assembly cost percent unit, usage cost percent unit). A designer should balance performance, schedule, reliability, LCC and so on. In DFC, LCC serves as a critical parameter for design and provides support tools for designers to analyze and evaluate cost. For more details about DFC, please refer to Methodology and technology of design for cost (DFC) [5].The cost in DFC refers to LCC, which consists of the total expense of research, design, development, production, usage, maintenance and disuse used in a large range from plan, argumentation, research, design, development, production, usage, maintenance to the final disuse phases[6][7]. The concept of LCC is first presented and then used by DoD (Department of Defense). In a typical weapon system, the cost of usage and maintenance occupy about 75% of the overall cost, so the research for LCC must be conducted. Nevertheless, the technique developed by DoD was aimed at purchase instead of design. LCC includes plan cost, manufacturing cost, sale cost, maintenance cost, use cost, recycle and disuse cost, while design cost occupies about 10%-15%, manufacturing cost 30%-35%, use and maintenance cost 50%-60%, others less than 5% [6].There are many costing methods available. Generally, ANN cost method can be used at the conceptual design stage; ANN and parameter cost method can be selected at the earlier overall (general) design stage; then parameter cost method can be used at the general design stage; finally, engineering cost method can be selected at the detailed design stage. For more information, see Reference [8]. Cheung *et al.* presents a review of research in the area of life cycle costing and offers a critique of current commercial cost estimation systems.

B. CBR Method and LCC Estimation

Case based reasoning, CBR, is a set of new theory and research method developed by the domain of artificial intelligence in 1977 by Schank and Abelson[9]. It is a problem-solving approach that makes use of previous, similar situations and reuses information and knowledge about such situations [10]. CBR is useful for a wide variety of problem solving tasks, including planning, diagnosis, and design [11].Basically, CBR technology is a reasoning procedure or framework instead of a specific algorithm. Hence, as long as the practical measure proposed meets the requirements of case-based reasoning, it is a CBR solution. According to Aamodt and Plaza [12], the CBR cycle has the following four major procedures:

1. Retrieve: the system searches and retrieves the case(s) most similar to the problem case, according to a predefined similarity measure.
2. Reuse: the user evaluates this case in order to decide if the solution retrieved is applicable to the problem.
3. Revise: if it cannot be reused, the solution is revised (adapted) manually (by the user) or automatically (by the CBR system).
4. Retain: the confirmed solution is retained with the problem, for future reuse, as a new case in the database.

The difference between a database search and CBR retrieval is that the latter employs searching mechanisms that are based on classification and decision tree algorithms, or on assessment of the similarity of cases using predefined similarity measures [13]. Therefore, the key issues in the CBR process are retrieving similar cases in the case base, measuring case similarity to match the best case, and adapting a similar solution to fit the new problem [14].In the early stage of design, information is uncertain or even self-contradictory. The information often has a qualitative, subjective or sometimes unclear argumentation. Depending on experiences accumulated individually, individuals will take different measures in their reasoning principles. Consequently, a sound and comprehensive decision is hard to be made at this point but it does need to be. In order to overcome such a shortcoming, CBR is an alternative for use. CBR systems deal with case specific knowledge and do not require that the domain must be modeled with strict rules [13]. CBR is thus suitable for domains lacking a computational model (mathematical or rule based).Xu *et al.* adopted case-based reasoning as a methodology in a product lifecycle costing system for supporting decision making, especially the decision making at very early stages of a product lifecycle to help new product development [15]. Mendes *et al.* described the application of case-based reasoning for estimating Web hypermedia development effort using measures collected at different stages in the development cycle and compared the prediction accuracy of those measures as well[16].Sumaira and Marin described a method for modeling costs throughout the design phase of a product's life-cycle, from the concept to the detail design. The cost modeling incorporates the use of both knowledge-based and case-based approaches. “This approach to design evaluation has the advantages of allowing management to make more accurate bid estimates, encouraging designers to design to cost and reducing the amount of design rework, hence reducing the product's time to market and controlling product cost” [17].

C. ANN and LCC Estimation

During the early design stage, over 70% of the total life cycle cost (LCC) of a product is committed and there may be competing concepts with dramatic differences. Additionally, both the lack of detailed information and the overhead in developing parametric LCC models for a range of concepts make the application of traditional LCC models impractical. Kwang-Kyu *et al.* described the development of predictive models for the product LCC during conceptual design [18]. The results show that the ANN model outperforms the traditional regression model used for predicting the product LCC.By using artificial neutral networks (ANN) and grey system theory, LCC can be estimated from design parameters. For more details about how to provide nonlinear relations between design parameters and life cycle cost (LCC) value in design for cost (DFC), refer to Xiao-chuan and Ming-lun [19]. The application of artificial neural networks (ANN) to engine diagnostic activities has generated research interest especially when the capabilities of a network are put into focus. Ogaji S.O.T., Singh R. reviewed some common gas turbine faults, presented some contemporary diagnostic techniques, highlighted features of ANN that are required for effective diagnostic applications and finally discussed the benefits derived from the application of ANNs with a developed case study[20].During the early design stages there may be competing requirements. In addition, detailed information is scarce and decisions must be made quickly. Thus, both the overhead in developing parametric life cycle cost (LCC) models for a wide range of concepts or requirement and the lack of detailed information make the application of traditional LCC models impractical. A different approach is required because a traditional LCC method should be incorporated into the very early design stages. Seo *et al.* explored an approximate method for providing the preliminary life cycle cost [21]. Learning algorithms are trained to allow the life cycle cost of new products to be approximated quickly without the overhead of defining new LCC models. Artificial neural networks are trained to generalize product attributes and life cycle cost data from preexisting LCC studies. Then, the product designers query the trained artificial model with new high-level product attribute data to quickly obtain an LCC for a new product concept.

II. Analysis of LCC Features and Design Features

A. The Concept of Cost Features and Design Features

Research on feature identified technology and feature-based product modeling has many fruits, but mostly research results are on the special applications and it is difficult for definitions of features to be applied to other areas. In 1985, Pratt and Wilson gave a widely conceptual definition of feature: A feature is a local interested configuration on the surface of a manufactured part [22]. Namely, a feature is part information that is useful for research or operation in different application areas. For example, design domains are concerned with geometric modeling information for parts: point, line, face, loop, body and other low geometry and topology information; manufacturing process domain concern about feature semanteme and function information, process parameters and materials information, but not the geometric information. It is interested in size tolerance and semantic information that is translated from geometric information. The manufacturing domain needs the design domain to provide geometric information and machining information in the manufacturing process, and then the CNC program will be automatically finished. Based on the above discussions, we proposed the conceptual definition of feature as following:The feature is a model that has been made beforehand for an application and it can describe a part’s geometric configuration and engineering significance.This definition gave a general description for feature, then we can conveniently classify feature in terms of the definition. It is an important definition for multiple domain features mapping (MDFM) methodology. Reference [23] gives more information on MDFM. Product design is a process of feature mapping among feature spaces. We can divide feature domain into two domains (design feature domain and cost feature domain) in DFC. According to different design stages, we divided design feature domain (DFD) into four domains: concept design domain, initial general design domain, general design domain and detail design domain. According to product life cycle and feature extraction, we divided cost feature domain (CFD) into six domains: manufacturing cost domain, assembly cost domain, sale cost domain, repair cost domain, usage cost domain, recycle and disposal cost domain [23] (see Fig.1).

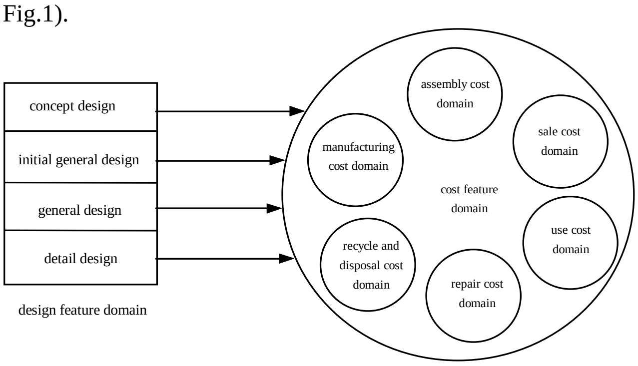

Fig. 1 Design feature domain and cost feature domain

The above feature domains can be continuatively divided into some son feature domains. For example, manufacturing cost domain can be divided into heat machining cost domain, cold machining cost domain, and heat treatment cost domain and so on; assembly cost domain also can be divided into handwork assembly cost domain, automatic assembly cost domain; the other divisions were omitted in this paper. Some son feature domains can be continuatively divided.

B. *Feature Mapping and LCC Estimation in Conceptual Design*

In the conceptual design stage, design information is not integrated and is highly uncertain. For example, material information is not decided; machining process is considered roughly and does not include detailed information. In this case it is difficult for us to translate highly uncertain design feature into detail cost feature. In this paper, we consider design feature parameter as cost feature and estimate LCC using Back Propagation (BP) ANN. Then we can know which design is better than the other about LCC. Using BP ANN we provide some reasons as follows:

1) Traditionally, we described a two-dimension figure with product type and cost value, we got a variety on cost. This method is a regression method, estimating a product cost. In practice, BP ANN is better than regression method.

2) BP ANN has good non-line mapping ability and self-study ability.

3) At the conceptual design stage, because design information has high uncertainty, most common methods are not easily used.

In a machine system function design includes: power system design, implement system design, transmission system design and control system design [24]. The four design systems parameters for a car was classified as follows [25]:

1) Power train system: mainly gas motor or electromotor power.
2) Chassis system: refinement and reduced emissions; drive and steer systems; suspension, *etc*.
3) Body structure/systems: body shell, doors, windows and panels, *etc*.
4) Other parts: control systems, electrical and electronic systems.

Those design features are quantity as the input of BP ANN directly. The general factors that were not included in four systems’ factors are selected. When BP ANN has been trained, they can provide LCC estimation result. The detailed information was given in section IV.

III. LCC Estimation Model Combining ANN and CBR Method

In this section, the process of using BP ANN is presented at first in LCC estimation. Then the process of using CBR method was provided in LCC estimation. Thirdly, the analysis of BP ANN and CBR method on LCC estimation was given. Finally, the hybrid modeling approach was given.

A. *Process of BP ANN’s LCC Estimation Method*

In the conceptual design stage, design information is not integrated and is highly uncertain. Therefore, in this paper the Back Propagation (BP) ANN method based on feature is selected according to the character of conceptual design. The mainly steps of LCC estimation using BP ANN proposed are as follows:

1. Identify cost-related features, such as material, process, product structure, tolerance, *etc*.

2. Classify and quantify the identified features. As the value of feature input into the neural network is usually between 0-1, a method called quantification must be conducted to deal with the value in practice.
3. Construct and train neural network.
4. Train and adjust the weight of neural network continuously in practice.

BP ANN is a kind of unsupervised neural networks. It adjusts the weights depending on the training data.

B. Process of CBR's LCC Estimation Method

CBR's main spirit lies in how to systematically save and process previous problem-solving knowledge and experience to solve new or repetitive problems encountered to reduce mega volume of information and avoid repetitive process loads. Meanwhile, CBR enables accumulated experiences. The new experience is saved with each problem that is solved.

Nearest neighbor technique is perhaps the most widely used technology in CBR. Nearest neighbor algorithms all work in a similar fashion. The similarity of the problem (target) case to case in the case-library for each case attribute is determined. This measure might be multiplied by a weighting factor. Then the sum of the similarity of all attributes is calculated to provide a measure of the similarity of that case in the library to the target case. This can be represented by the equation:

$$\text{Similarity}(T,S) = \sum_{i=1}^{n} w_i \times \left| T_i - S_i \right| \qquad (1)$$

Where T is the target case; S the source case; n the number of attributes in each case; i an individual attribute from 1 to n; and w the importance weighting of attribute i.

In this paper, we will generalize some LCC-related features in a case-library and compare different feature similarities by calculating their Hamming distance. Thereafter, we can take the LCC of the nearest case as a final estimation result. We do not apply a minimum threshold for similarity because LCC estimation results are enough accuracy in this case.

C. Hybrid Modelling Approach Combining ANN and CBR Method

By comparing the method of CBR with BP ANN, we can find out the following differences:

1) CBR model's estimation scope of LCC gets the restriction of sample value, it cannot be push outside the value; but its feature parameter quantities and sample quantities are unconcerned. Namely, the quantity of feature attributes can increase quite a lot. We do not need to judge the quantity of feature coefficients by taking account of the quantity of samples. However, in ANN method, as we need to train neural network, if the quantity of feature coefficients are more, then more training samples are needed.

2) CBR calculation method is simple and can obtain fine estimation result; ANN need longer time to be trained and its calculation is quite complicated while the selection of its structure is still blindfold without too much scientific support; ANN method has some outside push ability and self study ability, but it is unstable, maybe convergent. The sample feature parameter quantities and sample quantities are related to each other. Two methods are complement; it is meaningful for raising estimation accuracy to combine two methods to carry out LCC estimation.

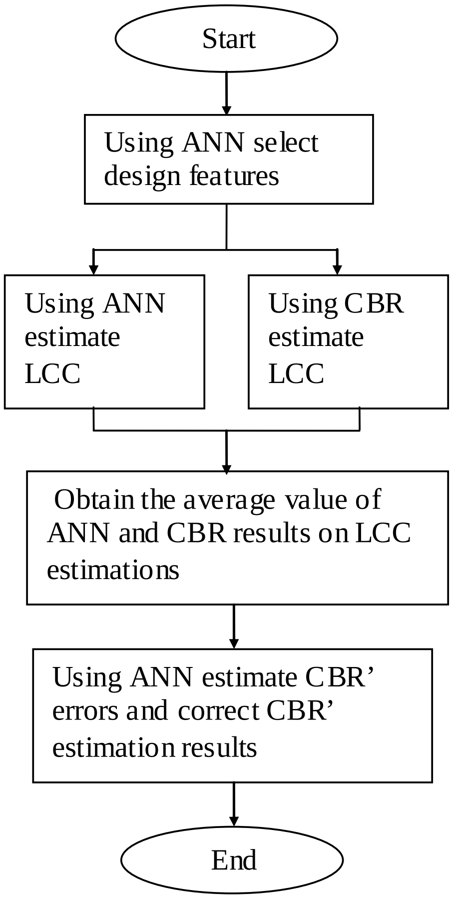

Fig. 2 Hybrid modeling approach

Because the above reasons, we combine ANN and CBR method that shows in Figure 2. At first, using ANN we select design features. Then we separately use ANN and CBR method to estimate LCC. Finally, using ANN's estimation results, we can improve CBR's estimation results. Here we select a simple method that the results are added and averaged. In order to compare the estimation results, we select the same samples in CBR and ANN methods. The following is a case study that shows how the accuracy of LCC estimation is improved.If the following method has not provided enough accuracy, we can use the CBR's estimation errors and ANN methods to establish another hybrid model. Namely, the design parameters are inputted and the errors data are outputted in an ANN. When the ANN is trained, this ANN estimate CBR estimation errors and we can correct CBR estimation errors.

IV. A Case Study

In this section, the detailed method was given to show how to use ANN select design features at first. Then we used the data that collected from the Internet to estimate family cars' LCC by ANN and CBR separately. Finally, the results were obtained through the adoption of combining ANN and CBR. In order to prove the model's effectiveness, in the appendix, we give another type of car's case — sport utility vehicle (SUV).

A. Obtain the Design Features of Family Cars

As an illustrative example, we will discuss the early stage design of family cars and the selection of their features in general terms. In this paper, we research the earlier stage of conceptual design. At this stage, the following features can be confirmed in a car: general dimension/size, wheelbase, engine, etc [26].

Based on the feature mapping theory, we present the extraction method of cost features and design features with ANN method. Pilot calculation was conducted first to compare the parameter selected. 3-layer structure was applied as the structure of Back Propagation (BP) ANN. The number of input units was the same as that of input features, and the number of hidden units was 1 more than that of input features while there was only 1 output number: LCC. The training error is 0.001. The result of pilot calculation is shown in Table I. It can be found out that the mean relative errors of group 2 and group 3 are better than group 6 while group 6 is best in terms of convergence. Considering enough parameters to be applied in practice, we chose seven parameters of group 6 as input units. To facilitate programming, the neural network toolbox of MATLAB 7.0 was chosen to carry out some relevant calculations.

TABLE I
THE PILOT CALCULATION RESULT WITH DIFFERENT INPUT FEATURES

Group number	Input feature parameter	The structure of ANN	Minimum mean relative error (%)	The times of non-convergence occurred among 50 times of pilot calculation
1	Length, width, height and emission volume	5 hidden nodes	9.3821	25
2	Length, width, height, wheelbase and emission volume	6 hidden nodes	8.7855	10
3	Length, width, height, maximum power and maximum torque	6 hidden nodes	6.6093	6
4	Wheelbase, maximum power, maximum torque and emission volume	5 hidden nodes	13.1484	25
5	Wheelbase and emission volume	4 hidden nodes	12.3558	49
6	Length, width, height, wheelbase, maximum power, maximum torque and emission volume	8 hidden nodes	7.9631	1

Considering DFC theory and some facts, we pick volume (length, width, and height), engine's parameter, car's weight, feature of electronic equipment and actuating feature as design characteristics. However, consideration of the difficulty in data collection and the characteristics to the conceptual design stage, we select these parameters: length, width, height, wheelbase, maximum power, maximum twisting moment/ torque and emissions.

Because it is difficult to collect LCC data, we compute use cost by oil/100KM , 100KM/day and 10 years in this paper. Then we get LCC by adding sale price to usage expense. The data of this paper are obtained from the Internet, which may not be fully accurate, but that is definitely enough to illustrate the feasibility of our method.

B. Data Collection

As mentioned earlier, it is difficult to collect LCC data. We collected 19 groups of data of economic family cars from the Internet. The process included the following principles.

1) Select some important websites on family cars;
2) Select cars data of famous brand or popular;
3) Compare the price data and select the lowest one on the same type of car;
4) Select the same parameters on cars.

In this paper, we adopt 12 groups of data as case sample, 7 groups as inspection sample. The LCC values of case samples are:

The values of case attribute are as follows:

p = [
0.3550 0.1508 0.1491 0.2340 0.0380 0.0700 0.1100;
0.4071 0.1702 0.1425 0.2540 0.0550 0.1350 0.1400;
0.4115 0.1620 0.1410 0.2400 0.0765 0.1422 0.1600;
0.4185 0.1660 0.1510 0.2370 0.0680 0.1240 0.1600;
0.4300 0.1690 0.1495 0.2450 0.0790 0.1430 0.1496;
0.4285 0.1690 0.1440 0.2500 0.0680 0.1240 0.1498;
0.4687 0.1700 0.1450 0.2656 0.0740 0.1550 0.1781;
0.4376 0.1735 0.1446 0.2513 0.1100 0.2100 0.1781;
0.4780 0.1740 0.1470 0.2803 0.1100 0.2100 0.1781;
0.4548 0.1772 0.1428 0.2650 0.1200 0.2250 0.1781;
0.4416 0.1668 0.1438 0.2471 0.0640 0.1350 0.1600;
0.4984 0.1845 0.1438 0.2769 0.1260 0.2500 0.4400;
]

LCC values of inspection samples are:

TT=[35.388 10.112 14.618 17.096 19.887 20.29 24.514]

Unit: 10thou. Yuan

The values of case attribute of inspection samples are as follows:

x = [
0.4810 0.1800 0.1450 0.2754 0.1270 0.2250 0.2500;
0.3550 0.1508 0.1491 0.2350 0.0380 0.0700 0.0812;
0.4026 0.1608 0.1402 0.2443 0.0650 0.1280 0.1598;
0.4187 0.1650 0.1465 0.2460 0.0550 0.1260 0.1400;
0.4525 0.1725 0.1425 0.2610 0.1120 0.1430 0.1599;
0.4515 0.1725 0.1445 0.2600 0.0780 0.1420 0.1598;
0.4469 0.1746 0.1536 0.2612 0.1060 0.1420 0.1600;
]

In order to give an example in errors compensator, we collected more data as following. The data are split two groups. One is a checking data group and the other is a verification data group.

Group one x1=[
0.4183 0.1710 0.1430 0.2540 0.0630 0.1100 0.1342;

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0.4735 0.1775 0.1450 0.2850 0.1450 0.2420 0.2497;
0.4785 0.1818 0.1445 0.2711 0.0960 0.1680 0.1997;
0.4855 0.1780 0.1480 0.2850 0.1450 0.2420 0.2497;
]
Group two x2=[
0.4664 0.1695 0.1408 0.2620 0.1066 0.1780 0.1998;
0.4152 0.1680 0.1440 0.2434 0.0787 0.1370 0.1587;
0.4705 0.1705 0.1430 0.2540 0.0630 0.1100 0.1342;
0.4735 0.1775 0.1450 0.2850 0.1700 0.3000 0.2995;
]

C. Structure of ANN

Pilot calculation has been conducted first so as to compare the parameter selected. 3-layer structure is applied as the structure of Back Propagation (BP) ANN. The number of input units is the same as that of input features, and the number of hidden units is 1 more than that of input features while there is only 1 output number: LCC. Namely, input unit's number is 7, hidden unit's number is 8. The structure of BP ANN is shown in Figure 3. The training error is 0.001.

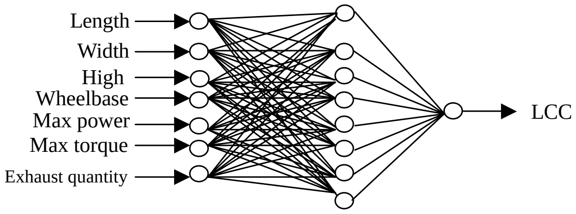

Fig. 3 Structure of BP ANN

D. LCC Estimation Based on ANN

The training algorithm of traditional BP ANN adopts Gradient Descent. Its rapidity of convergence is slow and it is easy to fall into local minimum value. We have applied improved training algorithm, namely, Levenberg-Marquardt (LM) algorithm and genetic algorithm (GA). The advantage of LM is its swift convergence ability when the quantity of network weights is not too much. It has combined the advantage of Gradient Descent and Newton method. We need to point out that there exists local minimum value in this algorithm. Due to the problem of local minimum for all the algorithms applied in this article, repeated training was performed towards the network with different initials. The final calculations were given in Table II [1]. Through actual application, we discovered that LM and GA methods could get comparatively better results than traditional training algorithm of ANN. Using ANN ensemble base on LM and GA, the result is that it is better to use only one ANN method. The deep analysis is described in Reference [1].

TABLE II
RESULTS ON LCC ESTIMATION WITH DIFFERENT TRAIN METHODS

No	LCC computational value	LM method		ANN's weight selection method based on GA		Estimation results of neural network ensemble based on LM training method and GA training method	
		Train error:0.001		Mean train error: 13.0%			
		Predicted value	Relative error(%)	Predicted value	Relative error(%)	Predicted value	Relative error(%)
1	35.3880	39.3300	11.1395	27.8739	-21.2335	33.6020	-5.0471
2	10.1120	11.2599	11.3516	10.8568	7.3652	11.0584	9.3587
3	14.6180	14.1796	-2.9992	16.2908	11.4435	15.2352	4.2222
4	17.0960	14.5095	-15.1295	16.1443	-5.5670	15.3269	-10.3480
5	19.8866	25.3349	27.3966	21.5937	8.5842	23.4643	17.9905
6	20.2900	23.6370	16.4956	19.8623	-2.1079	21.7497	7.19394
7	24.5140	24.2586	-1.0417	21.1299	-13.8047	22.6943	-7.4233
Mean relative error(%)		12.222		10.0151		8.797673	

E. LCC Estimation Based on CBR Method

We assign the weighted value in similarity calculation by 1 (wi=1), namely ignore the difference of the important extent of the 7 factors in this case and assume that the influence on LCC is the same. The similarity was resulted from the Hamming distance formula (1) among different calculation cases. The result is shown in Table III (wi=1) [2]. The deep analysis described in Reference [2].

TABLE III
THE ESTIMATION RESULT OF CBR ACCORDING TO HAMMING DISTANCE

No.	*LCC computational value*	*Hamming distance*	*Predicted value*	*Relative error(%)*
1	35.3880	0.01711	37.2900	5.3747
2	10.1120	0.004257	11.1320	10.0870
3	14.6180	0.005871	16.1220	10.2887
4	17.0960	0.005400	15.5140	-9.2536
5	19.8870	0.01256	21.1330	6.2675
6	20.2900	0.007200	21.1330	4.1548
7	24.5140	0.01160	18.5720	-24.2392
Mean relative error (%)				9.9522

F. CBR LCC Estimation of Combining ANN Method

According to the above LCC estimation results, we use the estimation results of neural network ensemble to improve CBR's estimation results. The results were shown in Table IV.

TABLE IV
RESULTS ON CBR LCC ESTIMATION OF COMBINING ANN METHOD

No.	*LCC computational value*	*Estimation results of CBR and ANN (LM and GA)*	
		Predicted value	*Relative error(%)*
1	35.3880	34.1777	-3.4100
2	10.1120	11.0405	9.1825
3	14.6180	15.3916	5.29211
4	17.0960	15.5726	-8.9109
5	19.8866	21.4217	7.7171
6	20.2900	20.7303	2.1699
7	24.5140	20.1284	-17.89
Mean relative error(%)		7.7975	

When we finished the above research, we get an estimation model. Then the new data' CBR estimation results are shown in Table V. The estimation errors are bigger than the above results. We can use ANN to establish an error compensation model in order to decrease the errors. Firstly, using the above research errors train the ANN. The train results are shown in Table VI. Secondly, using group 1 of the new data select the suitable parameters and structure of ANN. Finally, using the trained ANN estimates the errors of group 2 and corrects errors for them. The errors compensator method results are shown in Table VII

TABLE V
RESULTS ON CBR LCC ESTIMATION OF NEW DATA

No.	*LCC computational value*	*Hamming distance*	*Predicted value*	*Relative error(%)*
	Group 1 (Checking data)			
1	13.76	0.0042571	15.514	12.7471
2	35.25	0.0058714	37.29	5.7872
3	19.49	0.005400	24.124	23.7763
4	40.02	0.012557	37.29	-6.8216
Mean relative error (%)				12.28305
	Group 2 (Verification data)			
1	25.324	0.012557	24.124	-4.7386
2	15.87	0.0035429	16.122	1.5879
3	14.06	0.011871	20.076	42.7881
4	44.992	0.039386	40.074	-10.9308
Mean relative error (%)				15.0113

TABLE VI
RESULTS ON ERRORS CBR LCC ESTIMATION OF USING ANN METHOD

No.	*LCC errors value of checking data*	*Estimation results of compensating errors (LM method, Train error:0.001)*	
		predicted value	*Relative error(%)*
1	13.76	13.569	1.3881
2	35.25	37.856	7.3929
3	19.49	19.763	1.4007
4	40.02	40.213	0.4823
Mean relative error(%)		2.6660	

TABLE VII
RESULTS ON CBR LCC ESTIMATION OF COMBINING ANN METHOD COMPENSATING ERRORS

No.	*LCC errors value of verification data*	*Estimation results of compensating errors (LM method, Train error:0.001)*	
		Predicted value	*Relative error(%)*
1	25.324	21.41	-15.4557
2	15.87	15.904	0.21424
3	14.06	16.926	20.3841
4	44.992	40.456	-10.0818
Mean relative error(%)		11.5339	

We get the LCC estimation results through the application of combining CBR method and ANN methods. The mean relative error is between 7% and 12%. We observe that mean relative error is obviously smaller in the case of combining CBR and ANN methods as only to use CBR method or ANN method separately.

Reference [27] held the view that in the data acquisition process, requirement change in the various phases and product information could be kept enriched. Because information is unavailable and incomplete during conceptual design stage, the accuracy of cost estimation range is from -30% to +50%. When design information is further enriched and the historical data resembling to current design are available, the accuracy of estimation can achieve -15% ~ +30%. According to the results of LCC estimation in this paper, error is well controlled between -19% to +11%.

V. CONCLUSION

A lot of research works have been done on LCC estimation of CBR or ANN separately. However, the hybrid modeling approach is a new attempt of LCC estimation. In this paper, using ANN selected design features in DFC and LCC estimation was made for economical family cars and SUV cars through the application of combining CBR and ANN methods. The results obtained through the adoption of combining ANN and CBR is better than simply using CBR or ANN method, and we expand the generalization ability of ANN by using CBR method, and obtain more stable and precise estimation results.

In order to obtain better estimation, LCC and function index must confirm them to the real practice, something more can be researched in the fields of enterprise size, repair and maintenance, etc. We have presented the method and explained it by means of experimental results obtained. The more theoretical research is needed in the future.

APPENDIX

In order to compare the method, we use the same parameters and similar process to estimate SUVs' LCC. We adopt 12 groups of data as case sample, 6 groups as inspection sample. However, the errors compensation research cannot be done because we are absent of new SUV data.The values of case attribute are as follows:

p = [0.4860 0.1725 0.1780 0.2615 0.075 0.190 0.2237;
0.4285 0.1765 0.1705 0.2510 0.080 0.144 0.1597;
0.4765 0.1750 0.1860 0.2725 0.076 0.193 0.2230;
0.4010 0.1680 0.1700 0.2450 0.089 0.168 0.1999;
0.4800 0.1800 0.1750 0.2760 0.084 0.163 0.2000;
0.4550 0.1840 0.1880 0.2650 0.110 0.208 0.2388;
0.4325 0.1795 0.1680 0.2630 0.104 0.188 0.1975;
0.4710 0.1860 0.1790 0.2750 0.0147 0.302 0.3497;
0.4325 0.1795 0.1680 0.2630 0.128 0.246 0.2656;
0.4550 0.1840 0.1880 0.2650 0.125 0.265 0.3275;
0.4754 0.1928 0.1726 0.2855 0.162 0.305 0.3189;
0.4798 0.1784 0.1898 0.2858 0.200 0.380 0.2922;]

LCC values of inspection samples are:

TT=[21.8200 20.6000 24.6380 32.4920 47.3200 75.0220] Unit: 10thou. Yuan

The values of case attribute of inspection samples are as follows:

x = [
0.5010 0.1780 0.1900 0.3025 0.090 0.200 0.2350;
0.4285 0.1765 0.1705 0.2510 0.092 0.167 0.1997;
0.4010 0.1680 0.1700 0.2450 0.089 0.168 0.1999;
0.4545 0.1750 0.1675 0.2652 0.118 0.235 0.2378;
0.4830 0.1885 0.1855 0.2780 0.117 0.244 0.2972;
0.4565 0.1853 0.1674 0.2795 0.141 0.245 0.2494;]

TABLE VIII
THE PILOT CALCULATION RESULT WITH DIFFERENT INPUT FEATURES OF SUV

Group number	*Input feature parameter*	*The structure of ANN*	*Minimum mean relative error*	*The times of non-convergence occurred among 50 times of pilot calculation*
1	Length, width, height and emission volume	5 hidden nodes	17.2042%	39
2	Length, width, height, wheelbase and emission volume	6 hidden nodes	17.1651%	30
3	Length, width, height, maximum power and maximum torque	6 hidden nodes	7.8275%	30
4	Wheelbase, maximum power, maximum torque and emission volume	5 hidden nodes	13.1050%	29
5	Wheelbase and emission volume	4 hidden nodes	16.9468%	49
6	Length, width, height, wheelbase, maximum power, maximum torque and emission volume	8 hidden nodes	10.5633%	7

TABLE IX
THE ESTIMATION RESULT OF ANN AND CBR

No	*LCC computational value*	*ANN method (training by LM)*		*CBR method according to Hamming space*		*CBR LCC estimation of combining ANN method*	
		Predicted value	*Relative error(%)*	*Predicted value*	*Relative error(%)*	*Predicted value*	*Relative error(%)*
1	21.82	22.2242	1.852429	20.66	-5.31622	21.4421	-1.7319
2	20.6	18.0813	-12.2267	22.93	11.31068	20.50565	-0.4580
3	24.638	22.93	-6.932381	22.93	-6.93238	22.93	-6.9324
4	32.4920	35.8907	10.460113	27.368	-15.77	31.62935	-2.6550
5	47.32	62.381	31.82798	44.58	-5.79036	53.4805	13.0188
6	75.022	74.9621	-0.079843	42.58	-43.2433	58.77105	-21.6616
Mean relative error(%)		10.5633		14.7272		7.74294	

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