FAMILY CARS' LIFE CYCLE COST (LCC) ESTIMATION MODEL BASED ON THE NEURAL NETWORK ENSEMBLE

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Abstract: Design for cost (DFC) is a method that reduces life cycle cost (LCC) at design stage. From the angle of DFC, the design features of family cars were obtained, such as all dimensions, engine power and displacement. At conceptual design stage, cars' LCC were estimated using back propagation (BP) artificial neural networks (ANN) method based on the features. An example was given. Levenberg-Marquardt (LM) and Genetic algorithm (GA) were used to train BP ANN' s weights. The results obtained through the adoptions of neural network ensemble is better than simply use GA or LM algorithm.

Key words: life cycle cost (LCC); artificial neural networks (ANN) ensemble; family cars

1. INTRODUCTION

Now family cars have become popular among some areas in China as a symbol of growing rich from a well-off standard. The demand of family cars has increased strongly, but market competition is also aggravated increasingly. As the continuous reduction of the sales prices, the profits of cars' production enterprises were also depressed. As a result, to increase benefits, the key is to reduce cars' cost. Generally, about 60%-70% of production cost is decided implicitly during the design stage[1]. So the cost estimation in the design stage is crucial.

With the crisis of petroleum, customers consider not only the purchase price of the car but also the expense in use. Therefore in this paper, through a

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review of the car's design, the artificial neural networks (ANN) method of back-propagation model based on feature is selected to establish a model to estimate life cycle cost (LCC) and some performances of cars at the conceptual design stage from the viewpoint of design for cost (DFC). The estimation results can help designers enhance the accuracy of the LCC estimation.

2. BRIEF DISCUSSION OF DFC

Design for Cost (DFC) is a design method which analyzed and evaluated the 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[2]. DFC need confirming parameters of manufacturing, usage, maintenance phases, for example, assembly cost percent unit, usage cost percent unit. Designer should balance performance, schedule, reliability, LCC and so on. In DFC, LCC serve as a critical parameter for design and provide 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)[3].

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[4,5]. 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%, so the research for LCC must be conducted then. But the technique developed by DoD aim at purchase instead of design. LCC include 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%[5].

3. ANALYSIS OF LCC FEATURES

3.1 Selection of LCC Estimation Methods

In order to reduce the LCC of a product, the key is to adopt a proper method to estimate it. In the conceptual design stage, design information is not integrated and is uncertain highly. For example, material information is not decided basically; machining process is considered roughly and is not include detail information. In this case it is difficult for us to translate highly uncertain design feature into detail cost feature. Therefore in this paper the ANN method based on feature is selected according to the character of conceptual design.

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.

The advantages of this method are as follows:

1. No need of detailed machining time.
2. No need of cost function in practice, due to the self-study ability to real cost statistics of ANN.
3. The cost estimation among different designs at the conceptual stage can help to improve design.
4. From the viewpoint of DFC, in order to conduct cost estimation in the design stage, the design feature of family cars need to be transformed into cost features, namely, feature mapping[6]. Using neural network method, mapping can be realized automatically and then decrease the work of people consequently.

3.2 The presentation and application of neural network ensemble

Hansen and Salamon first presented the trailblazing method of neural network ensemble in 1990.They proved that the generalization ability can be prominently improved simply by training several neural networks and combining their results in some way. Sollich and Krogh defined neural network ensemble as a collection of a (finite) number of neural networks or other type of predictors that are trained for the same task[7]. Now, this definition has been widely acknowledged.

Perrone and Cooper proved in 1993 that, compared with the mean value of each network's generalization error, ensemble generalization error decrease by N times when merge regression estimation with neural network ensemble, if simply mean is adopted and error of each network is independent random variable and their likelihoods are zero. Here, N refers to the number of network included[8].

It's an easy trap for some common-used neural networks to fall into local minimum during its study, which is considered to be one of the biggest weaknesses for neural networks. But Perrone and Cooper argue that this characteristic play an important role for neural network in the promotion of its generalization ability. Since these neural networks are uncorrelated to each other, they will easily be trapped by local minimum. Thus the variance of neural network ensemble should be pretty big and then reduce generalization error. In other words, the negative effect of each local minimum counteracts in the end. All the networks included in the neural network ensemble give the same or approximate outputs to the same input. At this moment the diversity factor of the ensemble is close to zero while its generalization error is close to the weighted average of each network's generalization error. On the contrary, if the network included in the ensemble is independent, then the diversity factor of the ensemble will be pretty big, and its generalization error will be far smaller than the weighted average of each network's generalization error. Consequently, to enhance the generalization ability of neural network, the errors in the ensemble should be as uncorrelated to each other as possible.

3.3 Obtain the design features of family cars

Vehicle design process included conceptual design, technology design, trial-manufacture and sales stage[9]. 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 and so on. 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 characters. But in consideration of the difficulty in data-collecting and the characteristics to the conceptual design stage, we select these parameters: length, width, high, wheelbase, maximum power, maximum twisting moment/ torque and exhaust quantity.

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 adding sale price to usage expense. The data of this paper are obtained through Internet, which may not be fully accurate, but that's definitely enough to illustrate the feasibility of our method.

4. A CASE ABOUT FAMILY CAR'S LCC ESTIMATION BASED ON NEURAL NETWORK ENSEMBLE

4.1 Structure of Back Propagation 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 with 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 units number are 7, hidden units number are 8. The training error is 0.001. To facilitate programming, the neural network tool box of MATLAB 6.5 is chosen to carry out some relevant calculations.

4.2 Collection and choice of samples

We collected 19 groups' data of economic family cars on Internet. In this paper we adopt 12 groups of data as train sample of ANN, 7 groups as inspection sample of ANN. The output value of train samples are:

T=[11.132 15.514 16.122 15.488 18.572 20.076 24.124 24.198 37.29 35.788 21.133 40.074] Unit: 10thou. Yuan

ANN value of inspection samples are :

TT=[35.388 10.112 14.618 17.096 19.887 20.29 24.514] Unit: 10thou. Yuan

4.3 The training and LCC estimation of neural network

The train 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 train 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 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 train was performed toward the network with different initials. The final calculations were given in Table 1. Through actual application, we discovered that LM and GA methods can get comparatively better results than traditional train algorithm of ANN.

GA algorithm has a characteristic to convergence at the global optimum, so to optimize the weight of ANN with it might acquire global optimum result.

Table 1. results on LCC estimation with different train methods

NO.	LCC computational value	Appended momentum technique		Momentum technique combined with self-adapting learning rate		LM method		ANN's weight selection method based on GA	
		Train step:21150 Train error: 1.653		Train step 11881 Train error:0.01		Train step: 30 Train error:0.001		Evolution generation number:25 Mean train error:13.0%	
		predictive value	relative error(%)	predictive value	relative error(%)	predictive value	relative error(%)	predictive value	relative error(%)
1	35.3880	39.236	10.8740	42.1587	19.1326	39.3300	11.1395	27.8739	-21.2335
2	10.1120	8.0722	-20.1721	11.1669	10.4321	11.2599	11.3516	10.8568	7.3652
3	14.6180	17.951	22.8014	15.2406	4.2590	14.1796	-2.9992	16.2908	-11.4435
4	17.0960	18.192	6.4102	15.0595	-11.9121	14.5095	-15.1295	16.1443	-5.5670
5	19.8866	22.732	14.3060	26.9708	35.6228	25.3349	27.3966	21.5937	8.5842
6	20.2900	21.135	4.1639	24.1018	18.7867	23.6370	16.4956	19.8623	-2.1079
7	24.5140	36.541	49.0629	21.7315	-11.3506	24.2586	-1.0417	21.1299	-13.8047
mean relative error(%)		18.256		15.928		12.222		10.0151	

We get the LCC estimation result through the application of LM train method and GA train method in Table 1 to apply Neural Network Ensemble. The estimation result is showed in Table 2; we can find mean relative error is obviously smaller than simply use LM method or GA method.

Table 2. Results on LCC estimation of neural network ensemble based on LM train method and GA train method

NO.	LCC computational value	Estimation results of neural network ensemble	
		predictive value	relative error(%)
1	35.3880	33.60195	-5.04705
2	10.1120	11.05835	9.358683
3	14.6180	15.2352	4.222192
4	17.0960	15.3269	-10.348
5	19.8866	23.4643	17.99051
6	20.2900	21.74965	7.193938
7	24.5140	22.69425	-7.42331

NO.	LCC computational value	Estimation results of neural network ensemble	
		predictive value	relative error(%)
mean relative error(%)		8.797673	

The content discussed before treat LCC as a whole to estimate, so in the rest part we will estimate usage expense (oil consumption cost) and purchase expense respectively, and then add the latter to the former to obtain the estimation result. Because the effect of LM train method and GA train method is pretty good, the following estimation use them respectively. From the comparison of Table 3, Table 4 and Table 1, we can find some errors of estimation value increase while some others decrease without regularity, but all the overall mean errors decrease. The final calculations are given in Table 5. It can be observed that its mean relative error is the smallest and actually that's the result of neural network ensemble, namely, estimate LCC by neural network: estimates every part of LCC respectively, and then add all of them to obtain LCC which is feasible. Though this method add to the computation quantity, but the information obtained are more abundant than simply estimate the total quantity of LCC.

Table 3. purchase expense and usage expense obtained through LM train method

NO.	LCC computational value	Purchase expense train step: 40 train error: 0.001			Usage expense train step: 24 train error: 0.001			LCC estimation	
		actual value	predictive value	relative error(%)	actual value	predictive value	relative error(%)	predictive value	relative error(%)
1	35.3880	24.000	31.558	31.490	11.388	12.581	10.4775	44.138	24.727
2	10.1120	3.9800	5.0449	26.756	6.1320	5.9085	-3.6446	10.953	8.3208
3	14.6180	6.8800	7.1125	3.3797	7.7380	7.0825	-8.4709	14.195	-2.8937
4	17.0960	10.380	6.5844	-36.567	6.7160	8.8224	31.3644	15.407	-9.8806
5	19.8866	10.820	12.004	10.940	9.0666	8.3671	-7.7149	19.719	-0.8448
6	20.2900	10.800	11.977	10.898	9.4900	9.0846	-4.2721	21.062	3.8023
7	24.5140	12.980	11.977	-7.6677	11.534	11.566	0.2759	23.543	-3.9622
mean relative error(%)		18.2426			9.4601			7.7758	

Table 4. purchase expense and usage expense obtained through GA train method

NO.	LCC computational value	Purchase expense Evolution generation number:25 train error: 28.7%			Usage expense Evolution generation number:25 train error: 14.6%			LCC estimation	
		actual value	predictive value	relative error(%)	actual value	predictive value	relative error(%)	predictive value	relative error(%)
1	35.3880	24.000	23.1705	-3.4561	11.3880	12.5943	10.5931	35.7648	1.06477

NO.	LCC computational value	Purchase expense Evolution generation number:25 train error: 28.7%			Usage expense Evolution generation number:25 train error: 14.6%			LCC estimation	
		actual value	predictive value	relative error(%)	actual value	predictive value	relative error(%)	predictive value	·elative error(%)
2	10.1120	3.9800	3.5479	-10.8571	6.1320	5.4205	-11.6034	8.9684	-11.3093
3	14.6180	6.8800	10.9628	59.3432	7.7380	7.1751	-7.2747	18.1379	24.0792
4	17.0960	10.380	9.5297	-8.1917	6.7160	7.7368	15.2002	17.2665	0.99731
5	19.8866	10.820	13.2279	22.2542	9.0666	0.8987	20.2067	24.1266	21.3209
6	20.2900	10.800	11.1698	3.4244	9.4900	9.5213	0.3302	20.6911	1.97684
7	24.5140	12.980	13.0058	0.1986	11.5340	11.1505	-3.3251	24.1563	-1.45917
mean relative error(%)		15.3893			9.7905			8.8868	

Table 5. Results on LCC estimation of neural network ensemble based on purchase expense and usage expense

NO.	LCC computational value	LCC value estimated through LM method		LCC value estimated through GA method		LCC value estimated through neural network ensemble	
		Predictive value	relative error(%)	Predictive value	relative error(%)	Predictive value	relative error(%)
1	35.3880	44.1382	24.7265	35.7648	1.06477	39.9515	12.89561
2	10.1120	10.9534	8.3208	8.9684	-11.30934	9.9609	-1.49426
3	14.6180	14.1950	-2.8937	18.1379	24.0792	16.16645	10.59276
4	17.0960	15.4068	-9.8806	17.2665	0.99731	16.33665	-4.44168
5	19.8866	19.7186	-0.8448	24.1266	21.3209	21.9226	10.23805
6	20.2900	21.0615	3.8023	20.6911	1.97684	20.8763	2.889601
7	24.5140	23.5427	-3.9622	24.1563	-1.459166	23.8495	-2.7107
mean relative error(%)		7.7758		8.8868		6.466096	

Reference 10 hold the view that in the data acquisition process, requirement change in the various phases and product information keep enriched. Because information are unavailable and incomplete during conceptual design stage, the accuracy of cost estimation range from -30% to +50%; When design information are 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 -5% to +13%.

5. CONCLUSIONS

This paper adopt self-adapting learning rate, LM algorithm and genetic algorithm respectively to train Back Propagation neural networks, LCC estimation was made for economically family cars through the application of neural network ensemble method. The results obtained through the adoptions of neural network ensemble is better than simply use genetic algorithm or LM algorithm, and we can easily find that its computational results are pretty stable, with mean error between 7% to 9% while other methods such as LM is not quite stable.

In order to better estimation LCC and function index to conformed them to the real practice, Something more can be research in the fields of enterprise size, repair and maintenance etc. We are fully convinced that the application of these methods must lead to the reduction of family car's LCC and actively enhance the level of design.

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