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A Hybrid Artificial Neural Network and Genetic Algorithm based Cost Estimation Approach for Feature-based Plastic Injection Products

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특징기반 플라스틱 사출제품을 위한 하이브리드 인공신경망과 유전자 알고리즘 기반의 비용 평가 방법

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Abstract Plastic injection products have been widely used in various electronic appliances and high-tech commodities. However, plastic injection product manufacturers have to spare no efforts to shorten new product development period to introduce new products into the market ahead of other competitors, gaining competitiveness and satisfying customers. The manufacturers cannot only get big target market share rapidly but also the advantage of leading the product price in order to survive in highly competitive market. This paper proposes the cost estimation approach of feature-based plastic injection products by using hybrid artificial neural network and genetic algorithm. The proposed method is to dramatically simplify and shorten the complex conventional cost estimation procedures and the requested computation parameters of plastic injection products. The case study demonstrates the efficiency and effectiveness of the proposed model in solving the cost estimation problem of plastic injection products at the development stage.

요 약 플라스틱 사출 제품은 다양한 가전제품과 하이테크 제품에 널리 사용되고 있다. 그러나 플라스틱 사출 제품 제조업자들은 고객을 만족시키면서 경쟁력을 얻기 위하여 다른 경쟁자들보다 먼저 새로운 제품을 시장에 출시하고 신제품의 개발기간을 줄이기 위한 노력을 할 여유가 부족하다. 따라서 무한 경쟁의 시장에서 살아남기 위해서는 제조업자들은 시장 마켓 점유를 빠르게 올리는 것과 동시에 제품의 가격 경쟁력을 가져야 한다. 본 연구에서는 하이브리드 인공신경망과 유전자 알고리즘을 이용한 특징기반 플라스틱 사출제품의 비용 평가 모델을 제안한다. 제안하는 방법은 기존의 플라스틱 사출제품의 비용평가절차와 계산을 위해 필요로 하는 변수들을 극적으로 간단하게 하고 줄일 수 있다. 사례연구는 제안하는 모델이 플라스틱 사출 제품의 개발단계에서의 비용평가문제를 해결하는데 효율성과 효과성이 있음을 입증한다.

Key Words : Cost Estimation, Feature-based Model, Plastic Injection Product, Artificial Neural Network(ANN), Genetic Algorithm(GA), Hybrid Approach.

1. 서론

The cost estimation plays an important role in design and production stages as well as a fairly important role in the company business decision-making. Accurate cost estimation can satisfy the optimization demand at design as well as the customers' satisfaction requirements for minimum cost, highest quality and timely delivery when selecting suppliers as proposed by Wang and Che [1].

Hundal pointed out the controllable potentials to reduce

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the cost at different stages of product design [2]. If all the production problems can be solved as early as possible at the initial design stage, the huge cost resulting from modification at post-production stages can be greatly reduced.

Niazi et al. pointed out that back-propagation network (BPN) could be applied for training to deduce unprecedented problems by accumulated knowledge and information [3]. McKim proposed the discussion on applying BPN in cost estimation projects and obtained the fast response cost estimation at initial product development stage [4].

Although Artificial Neural Network(ANN) is an effective algorithm, there are only few approaches to design the network and most of them rely on iterative procedures. ANN architecture is still designed through a time consuming iterative trial and error procedure. In order to make ANN-based cost estimation approach more efficient, there is a need to improve the convergence speed and reduce the computational complexity of ANN.

The main purpose of this study is to develope the cost estimation model for plastic injection products in the initial stage by the advantages of hybrid ANN and GA approach. In addition, the hybrid approach is proposed to reduce the computational complexity and time required to design the ANN for the cost estimation model.

2. Overview of the Hybrid Approach for Plastic Injection Cost Estim ati on Model

In this study, we adopts BP algorithm for ANN training. Sometimes, it may perform poorly on some problems and some shortcomings exist related to employed search process. There is a need to conduct a large number of experiments with different combination of inputs designing the network for each new combination evaluating the performance to find the best network model. It is a time consuming trials and error approach; in addition, it is hard to understand the network model topology.

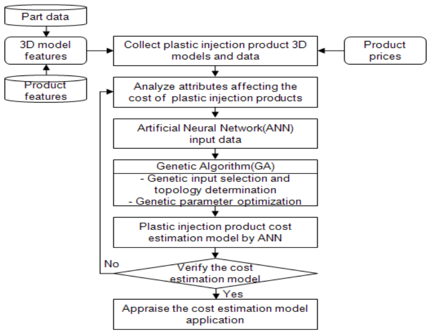
GA is a search algorithm based on the mechanics of natural selection and natural genetics and has capability to search a large number of combinations, which there may be interdependencies and redundancies between variables [5]. GA is a very effective and robust approach in solving problems from a wide range of applications, which is difficult to solve with traditional techniques. The purpose of this paper is to present an alternative network design approach for ANN applications using GA for input selection, topology determination and parameter op timization..

In this study, GA is used to find the best combination of effective input features, topology and learning parameters of ANNs to provide a solution with less computational process. This is an important point especially in case of reasonably sized ANN problems, since cases for combinatorial problems of this type.

3. Plastic Injection Cost Estimation Model with a Hybrid ANN and GA Approach

This study is to establish a hybrid approach for its advantages such as simple theory, fast response, high accurate learning based on the factors for the plastic injection product cost estimation model. By input/output variants requested for network construction and the training as well as the neural network adjustment, we could quickly estimate the plastic injection product quotations.

The plastic injection product quotations data previously collected are used to set up samples for network learning and testing to verify the feasibility of applying BP algorithm in quotation estimation. After verification, then input the network weights trained into the system program established in this study to estimate the corresponding quotations of the features of the 3D model designed. The detailed research procedure is as shown in Fig. 1.



[Fig. 1] Procedures of Plastic Injection Product Cost Estimation

3.1 Features Data Collection

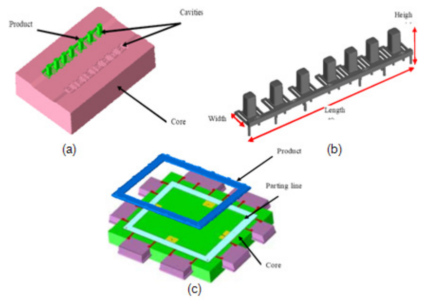
This study only discusses the cost estimation model on the basis of notebook computer industry with one supplier's data collected. The model in this study is mainly to collect the features data with the product design and development team as the main factor considered. We obtained the price quotations of manufacturers quoted or the purchase prices from the buyers according to material numbers. Moreover, we obtained the cost-affecting items from the drawings, and adjusted according to the plastic injection product manufacturing types. The collected reference factors for plastic injection cost estimation are as shown in Table 1.

[Table 1] Cost Factors

Cost factors	Cost factors adapted in this study
Raw material cost	Product volume, Surface area, cavity quantity, product net weight
Manufacturing cost	projection area, minimum length, width, height and thickness of the product, cavity quantity
Quality control fee	Spare parts quotations or purchase unit price
Selling cost	supplier's cost
Profit	profit rate is about 20%

With the development of CAD/CAM technologies, plastic injection products tend to be streamlined and complex in appearance. However, veteran technologists in the in jection product plants will often appraise on the key items of product benchmarks and specific product design specification items. Hence, this study lists the following parameter drawing software (or feature-based 3D software such as Pro/Engineer or SolidWorks) after considering cost-affecting factors data to get the most important item of the product feature model design specifications in addition to referring to the discussion of Wang and Che et al. [6] on the plastic injection product cost estimation parameters. The factors having comparatively bigger effects on cost are found out from plastic injection product collects as follows and some examples are also shown in Fig. 2:

- Volume: the space the product occupies
- Material: different materials have different unit prices and mass densities
- Product net weight: volume (cm^3) * material density (g/cm^3)
- Surface area: the sum of spare parts surfaces
- Number of Cavity: number of products for each molding in injection molding process
- Projection area: the area of the product in the parting line (cm^2), affecting the injection machine selection
- Maximum measurements: the minimum length, width and height of the box to contain the product



[Fig. 2] Feature of Plastic Injection Pr oduct:
(a) Number of cavities
(b) Maximum measurement of finished product
(c) Projection areas of finished product

In accordance with the cost estimation model parameters in Table 1, we collect the relevant data after distinguishing each spare part' features into material features, form features, and molding conditions and parts of the sample data after collection are as shown in Table 2. Table 3 shows the partial list of part feature data of a notebook.

[Table 2] Part Features Structure

Product	Feature	Attribute
Product  (notebook)	Material features	Material Volume Weight Surface area
	Form features	Length Width Height Thickness
	Molding conditions	Cavity quantity Projection area

[Table 3] Partial List of Part Feature Data of a Notebook

P/N	Attributes	Value		
P0001	Material	ABS	PP	PE
	Volume	2488.5	2488.5	2488.5
	Weight	2.9	2.8	2.2
	Surface area	4325.5	4325.5	4325.5
	Length	90.4	90.4	90.4
	Width	41.5	41.5	41.5
	Height	8.5	8.5	8.5
	Thickness	1.5	1.5	1.5
	Cavity quantity	10	10	10
	Projection area	1655.8	1655.8	1655.8
	Price	1.1	1.1	0.9

3.2 Learning Process of the Hybrid ANN and GA Model

In this case, the binary string masks consist of three parts such as input features, topology and learning parameters which are used to determine which input features, the number of hidden layers and the processing element of its layer and learning parameters such as learning rate and momentum are most useful to construct the ANN architecture. The bits in the first part of string indicate whether to accept or reject each possible input feature. For the present problem, the string is represented by collection of ten elements corresponding to attributes to describe a part. A "0" indicates that a input feature should not be used and a "1" indicated that it should be used. The bits in the second part of string present the number of hidden layers and its elements. We designed that the maximum number of hidden layer is 2 and the maximum number of neurons of hidden layer is 40. The bits in the third part of string present the learning rate and momentum which are greater than 0 and less than 1.

GA creates a population such as strings which are bred together to form a new population. Over a period of generation, successfully better strings are produced. Eventually, the best number of the final generation is selected as a solution. After computational experiments with GA for input, topology and learning parameters selection, the best results are obtained with ANN architecture, which has 8 input features, single hidden layer and the number of neuron in this layer is 24 and the learning rate is 0.5 and momentum is 0.9. Computational experiments are carried out to test the alternative solutions in terms of network learning accuracy and computational complexity.

3.3 Experimental Results

This study will refer to three test appraisal benchmark data as follows:

(1) MAE (mean absolute error).

$$MAE=\sum_{i=1}^{n}|T_i-E_i|/n$$

T is real value.

E is the estimated value.

i cross-validation data index, $i=1, 2, ..., n$.

n total number of cross-validation data.

We can learn the diversion rate between the real value and the estimated value by MAE value. The smaller the value is, the smaller the diversion rate is leading to better results.

(2) RMSE (root mean squared error)

$$RMSE=\sqrt{\sum_{i=1}^{n}|T_i-E_i|/n}$$

The smaller the value is, the smaller diversion rate is, yielding better results.

(3) r^2(coefficient of determination)

r^2 = SSR/SST = (SST-SSE)/SST = 1-SSE/SST,

$$0 \le r^2 \le 1$$

SST: total sum of squares.

SSR: sum of squares due to regression.

SSE: sum of squares due to error.

We can understand the matching degree between the estimated values and the real values by r2. The closer to 1 the value is, the better the result is.

After the aforesaid learning process, the last step is to validate the network. Take a new injection product design specifications as the test example to learn the difference between the estimated results and the real quotations for further feasibility appraisal of this network. If the difference is acceptable to veteran business staff and designing staffs, then the hybrid model can work as the cost estimation model for the plastic injection product.

In this study, we compare the conventional ANN and the proposed hybrid model. The network structure and parameters of the conventional ANN experiment are as follows:

- Input: 10 features
- Number of hidden layers: 1
- Number of hidden neurons: 10, 15, 20, 25, 30, 35, 40
- Learning rate: 0.1, 0.3, 0.5, 0.7, 0.9
- Momentum: 0.1, 0.3, 0.5, 0.7, 0.9

When the number of hidden neurons is 35 and the learning rate and momentum are 0.9, the best results of the conventional ANN are obtained.

The comparative results between the conventional ANN and the proposed hybrid model are summarized in Table 4 and the proposed hybrid model outperforms the conventional ANN.

[Table 4] Comparisons Results

		The conventional ANN	The hybrid model
Input		10	9
Hidden layer		1	1
Nodes of Hidden layer		35	24
Learning rate		0.9	0.5
Momentum		0.9	0.9
Appraisal indictor	MAE	0.10585	0.08021
	RMSE	0.01453	0.01025
	r2	0.99872	0.99953

The McNemar tests [7] are used to examine whether the proposed hybrid model shows better performance than the conventional ANN. The test results show that the proposed hybrid model outperforms the conventional ANN at a 1% statistical significance level.

4. Conclusion

This study proposes the hybrid ANN and GA approach-based cost estimation model. At the initial stage of product structure design, the R&D departments can quickly estimate the product cost without depending on the molding and injection plants quotations. Moreover, even an inexperienced designer can easily accomplish the product spare part cost estimation to serve as the strategy reference in comparison with market prices. Further, we can estimate how many percentages of the profits can be sacrificed for price competition. If the profit is less than the expected, we can immediately review the product design or even terminate the product development projects to avoid research and development investment waste and the possible bigger losses in the future. Otherwise, too high estimated cost may lead to loss of customer trust and business opportunities.

The cost estimation model based on the proposed hybrid approach was used to estimate plastic product quotations and makes it possible for inexperienced engineers to reduce professional judgments of product model design. That is to say, the newly designed injection product specifications were inputted into network to estimate the corresponding quotations with mean absolute error rate reaching less than 1%. This study discussed the input variants considered, which affect the cost in the plastic injection product design specifications. However, as products of injection molding, extrusion molding, die casting and pressing molding all have feature drawings with similar cost structures, it is a topic for us to discuss in depth how to make cost estimation by a hybrid model with parameters input in addition to collecting features and cost data in future.

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<Research Interests>
Production & Operation Management, Data-mining & CRM, Information System, Artificial Intelligence