Cost Estimation of Plastic Injection Products through Back-Propagation Network

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Abstract: With science and technology development, the world plastics production and consumption have been increasing continuously in the recent twenty years. The plastic injection molding has become the most widely applied mass-production technology, as it can shorten the finished product manufacturing cycle to raise productivity with products of low plastics waste, high size precision and high quality stability in addition to fully automated production. Hence, the main purpose of this study is to design the cost estimation model for plastic injection products in the design and development initial stage by the advantages of back-propagation network(BPN), which belongs to monitoring style learning network of the neural networks with advantages such as excellent diagnosis, prediction, simple theory, fast response and high learning precision through the integration of 3D mode features data, price quotations and purchase costs.

Key-Words: Plastic injection products, Cost estimation, Back-propagation network, 3D mode features.

1 Introduction

The competition between enterprises brings in the meager profits as well as the increasing labor cost. On the other hand, customers always place higher standard on the product quality and wish to purchase the product at the lower price. Therefore to realize the low-cost operation, actualize profits, respect product differentiation, and formulate the strategies for high efficiency, innovation, quality and swift customer response, the manager shall exercise good control over the product cost, fully understanding the product cost of each product. Only in this way can the company enjoy continued operation, share profits and make customers satisfied. With the advent of the low margin age (Kim and Mauborgne, 2005), effectively reducing product cost and gaining market share have constitute two golden ways to promote competitiveness.

As regards the whole process of the concept development, Bode (2000) argued that the cost was in relation to sales price, sales volume and profit. It explains why the final cost is usually considered an important quantifiable reference parameter for appraising the product. In product mix, plastic injection products have been widely applied to all kinds of daily necessities and hi-tech commodities. However, facing the increasingly fierce competition, the enterprises which engage in manufacturing plastic injection products have to commit themselves to shortening the time for developing new product in order to gain their competitiveness in the market. The traditional cost estimation grows incapable of handling the current situation that the plastic injection molds are found widely applied to the products. The traditional method goes this way: the total cost of the final product is figured out on the basis of cost on the molded components estimated by mold shop and plastic molding plant after the research and development units have completed designing the component of product. Furthermore, the engineering staffs in plastic injection molding plants usually estimate the product cost by means of rule of thumb. Its timeliness and accuracy are left in dispute. Additionally, it is less accurate in calculating the costs of direct and indirect raw materials.

2 Literature Review

Currently plastic products can be found everywhere in our daily life, to name only a few, electronic appliances, means of transportation, interior decoration, switch, toy, tableware and external device of computer. All of these items, without any exception, contain plastic molded products. In Fig. 1 Takahiro (2005) pointed out that global plastic consumption approximated 65 million tons in 1980 but the figure rose to 185 million tons in 2000. It is expected that the consumption will amount to 295 million tons in 2008.

In exploring the pre-estimation of the automobile parts, Cavalieria et al. (2004) pointed in a study that during the last stage of the life cycle of the product, a large portion of product cost continues to happen, which is determined in the stage of product concept design. Yang et al. (1997), Rehman et al. (1998) and Gayretli et al. (1999) proposed that 70%-80% of the total product cost has been determined during the initial stage of product design. Therefore it is of paramount importance to pre-estimate production cost. Fig. 2 shows the potential of the reduction of product cost during each stage of product design. For instance, although design and planning stage only accounts for 7% of production cost, it has the potential of reducing 65% of the cost.

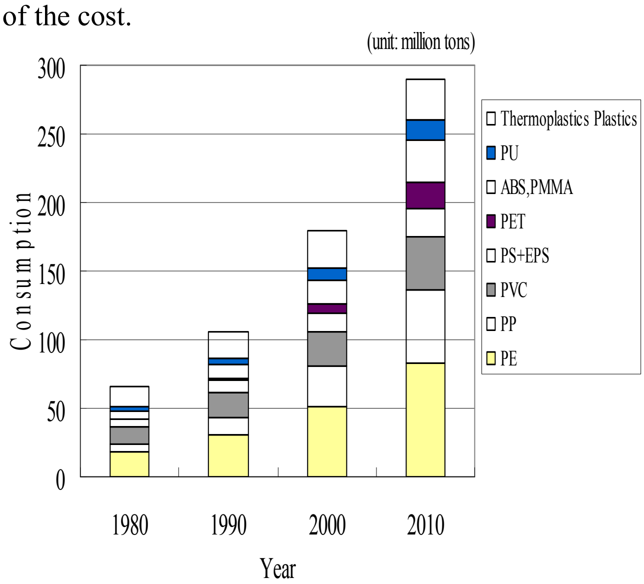

Fig. 1 Global plastic consumption

Due to the fact that a lot of parameter feature drawing software such as Pro/Engineer or SolidWorks has been applied in R&D units, the feature geometry of the plastic injection molded products can be designed by this software at the design stage. Then the diagrams can be delivered to molding plant for price estimation according to its mold size, material of the product, molding time and the injection equipment tonnage. The parameter—based estimation on the cost is detailed as follows (Yen, 1996):

(1) The step for analyzing single molding price

Prior to the production of each molded product, an R&D unit shall discuss the diagram to evaluate the manufacturability (Design for Manufacture, DFM). After the mold is designed at molding shop, the appropriate number of molding cavities will be determined. Then injection molding plant will figure out the net weight of the molded product and the weight of runner to facilitate the calculation of materials cost. Next, the appropriate molding machine will be selected in accordance with the molded product and mold before calculating the molding processing fee, cooperage, secondary processing and manufacturing cost. Finally the ideal price is determined. The steps for analyzing the prices of plastic injection products are shown in Fig. 3.

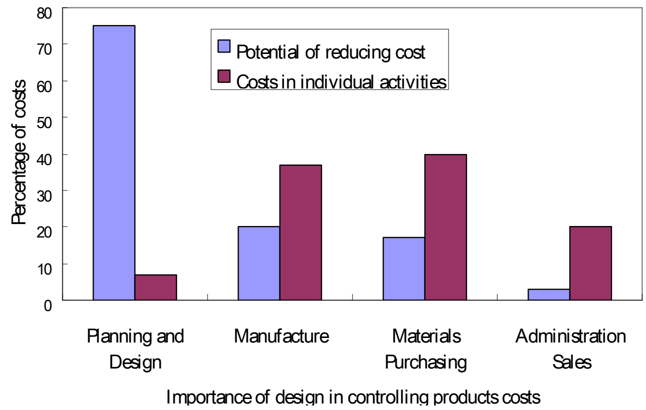

Fig. 2 Influence of each stage of life cycle on cost

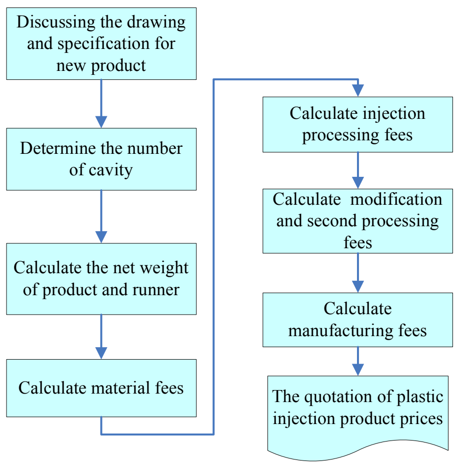

Fig. 3 Cost evaluation procedure for traditional plastic injection industry

Table 1 ANN network model name

ANN model code	Input quantity	Input parameters	Removal parameter	Removal parameter
ANN1	9	Material, volume, surface area, cavity quantity, length, width, height, thickness, projection area	--	--
ANN2	6	Material, volume, surface area, length, width, projection area	thickness, height, cavity quantity	By driver analysis, in accordance with 80/20 rule to remove drivers less than 0.6 in terms of their corresponding

				similarities as shown in Fig. 8.

(2) Cost Factors Influencing the Molded Products

The net weight of the molded product and runner, as well as the selection of injection machine, shall take into account the injection weight, injection area, the size, dimension and height of the molded products, the price of raw material, mold replacement, the loss weight of the no good materials, the weight of waste materials, costs of other materials such as insert, mold decoration, the labor cost for processing molded product, remolding and the secondary processing fee, other expenses, including packing costs, materials management, profits and taxes.

(3) Mold cost

Mold cost includes 10% of the fee for mold design, 15% of the cost on materials for mold, 40% of the fee for processing mold and 30%-40% of operating costs and profit.

The present study attempts to explore the possibility of R&D unit's pre-estimating the cost according to the characteristics of the product at the initial stage of designing plastic injection products. The traditional parameter-based cost estimation shall estimate the unit price of the product after considering the following parameters including mold cost, net weight of runner, molding time, machine cost, operating cost of injection plant, secondary processing cost and product management expenses, in addition to feature data. For most R&D units, it is difficult to obtain these parameters, which increases the difficulty in estimating the plastic products.

On the basis of the sufficient information about the previous product feature and unit price, R&D units develops the cost estimation model (as is shown in Fig. 4) through neutral network, in the hope of conducting cost estimation in accordance with the parameters easily available to R&D units at the initial stage of product development.

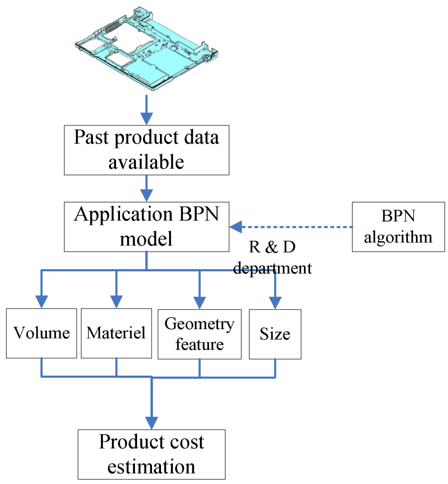

Fig. 4 Technique of estimating plastic injection cost through BPN

3 BPN Model Construction & Case Analysis

The cost estimation of the plastic injection products in the present study can be based on the major factors that influence the cost in the design specification for plastic injection products. Its advantages such as conciseness in theory, fast response speed, high learning accuracy can be taken to establish a cost estimation method (as is shown in Fig. 5 modeled on the back-propagation neutral network. The establishment of the input and output variable as required by the network, together with the training and adjustment to neutral network can help achieve the objective of swiftly estimating the quotation for the plastic injection products.

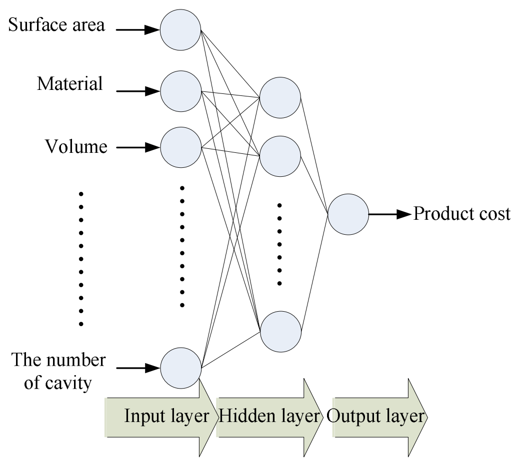

Fig. 5 BPN structure for estimating the cost of plastic injection molded products

The quotation for the plastic injection molded products is firstly gathered to prepare sample for network learning and test in order to confirm the practicability of estimating quotation through back-propagation network. With the practicability confirmed, the network weight value obtained from the training will be output to the system program developed by the system in order to estimate the quotations corresponding to the designed 3D model features. The detailed model process is shown in Fig. 6. to include your paper in the Proceedings. When citing references in the text of the abstract, type the corresponding number in square brackets as shown at the end of this sentence [1].

After considering the major factors that influence the cost of producing injection molding, the present study draws out the important items of the design specification in product feature model through parameter-based drawing software (also referred to as feature-base 3D software, such as Pro/Engineer or Solidworks), and refers to the parameter for pre-estimating the cost of plastic injection molding pieces explored by Wang & Che et al. (2005). The major factors that influence plastic injection molding pieces are described as follows:

(1) Volume: the space occupied by plastic injection molding pieces. It can be viewed through drawing software.
(2) Material quality: Different material qualities have different unit prices and densities.
(3) Surface area: the total area of all components.
(4) Cavity number: the quantity of the molded products after opening mold each time in the injection molding program.
(5) Project area: the area (cm2) of the part of the product that is on parting line. Its parameter will influence the selection over the injection machine.

(6) Maximize dimension: the minimally required length, width and height of the box that house the product, as is shown in Fig. 7.

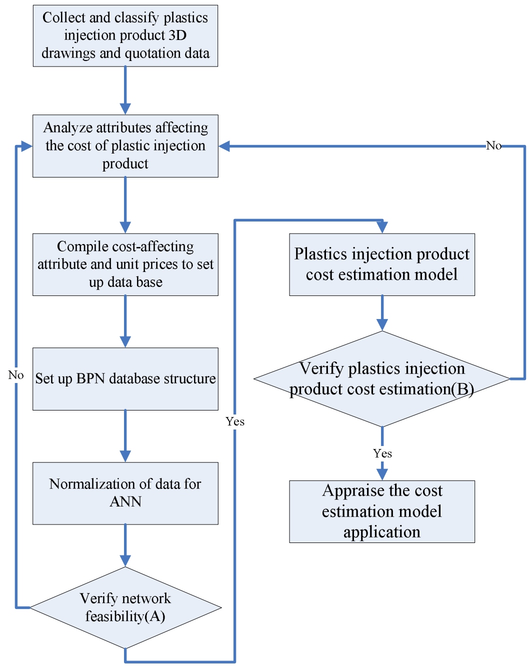

Fig. 6 Flow chart for cost pre-estimation study

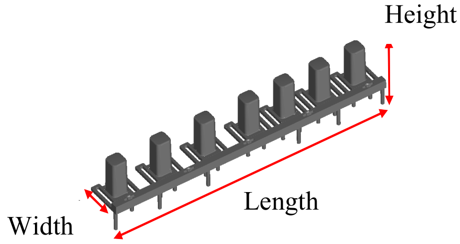

Fig. 7 Maximal dimension of the product

Due to the properties of learning and fault tolerance of the neutral network, in accordance with Looney (1996), the data will be divided into several sets---training set, cross-validation set and verification testing set in the process of constructing network model. There are 1070 pieces of data gathered for current study. After random distinguishing, we got 955 training sets and 95 verification testing sets for the network to conduct training and verification (as in shown in (A) of Fig. 6). Under different back-propagation neutral network structure, MAE (mean absolute error) is compared to foresee and confirm the optimized parameter of the neutral network structure of the plastic injection molding cost. Finally cost percentage error (CPE) is taken to verify 20 testing sets to predict the accuracy range (As is shown in (B) of Fig. 6).

There is no absolute standard for selecting neutral network structure and setting the related parameters. The current study explores the influence over the network accuracy with two groups of different input parameters, as is shown in Table 1. Trial and error method is adopted at two stages to adjust and set network parameter. At the first stage, the optimal learning rate and momentum of each network model are found; at the second stage, the optimal parameters for each network model are taken to conduct the test on the learning times. Network structure is shown in Fig. 9.

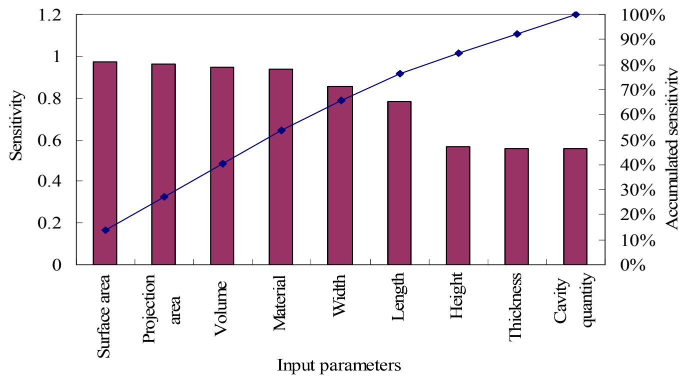

Fig. 8 The analysis of cost drivers

The subitems of the preset parameter design are described as follows:

(1) The number of the hidden layer

When the number of the hidden layer is usually 1 to 2, there will be the best convergence property. Meanwhile, it is fully capable of reflecting the interaction between input units. By rule of thumb, general questions mostly take a hidden layer. As for the complex questions, they take 2 hidden layers. The present study estimates the unit prices of the components that correspond with feature parameters. They are general questions. Therefore we take 1 hidden layer.

(2) Hidden layer unit

In accordance with the calculation formula as provided by 2 sets of NeuroShell software, the input layer, output layer and data ratio are respectively calculated to get the number of hidden layer.

(3) Activation function

The activation function used in the present study is Sigmoid Function, namely

$$f(net) = \frac{1}{1+e^{-anet}}$$ (Chiang et al, 2006)

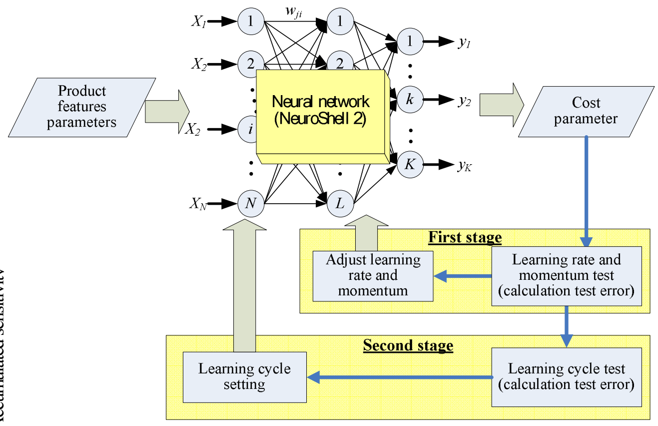

Fig. 9 ANN testing network structure

(4) Learning rate

0 < Learning rate < 1, Learning rate= 0.1, 0.3, 0.5, 0.7, 0.9.

(5) Momentum

0< Momentum < 1, Momentum= 0.1, 0.3, 0.5, 0.7, 0.9.

(6) Learning cycle

The first stage network takes 10,000 learning cycles as the basis for comparison. After optimal parameters are set for each network model, the second stage learning follows the rule of thumb and the learning cycle is set to be 100 times that of the training sample. The training sample for the present study takes 955 pieces of data. The learning cycle will be adjusted gradually until 95,000 times.

(7) Weighing & evaluating indices

In this study the commonly used is mean absolute error (MEA) to indicate the performance of the network training and testing, and gain an understanding of the convergence rate.

$$MAE = \frac{\sum_{i=1}^{n}|T_i - E_i|}{n} \quad (1)$$

T represents the actual value and E predicted value. MAE can help us understand the divergence of the predicted value and actual value. The smaller the value is, the smaller the divergence is and the better the result is.

(8) Network model test

The optimal parameters above will be taken as the indices for evaluating the ANN1 and ANN2---two groups of the combination of learning rate and momentum in network model. After the tabulation and analysis, the adopted optimal parameters for each model are shown in Table 2.

The test results are shown in learning curve of the network model (Fig. 10) which displays the convergence efficacy. For network models ANN1 and ANN2, the full convergence is obtained when the learning cycle reaches 50,000 and 30,000 times. Of two models, ANN1 consumes less time than ANN2 in terms of learning cycle, but its evaluation index MAE is the smallest in time of convergence, as shown in Table 2 and Fig. 11.

Table 2 Optimal parameters of network model

ANN model	Number of hidden neurons	Learning rate	Momentum	Learning cycle
ANN1	36	0.9	0.9	50,000
ANN2	34	0.9	0.9	30,000

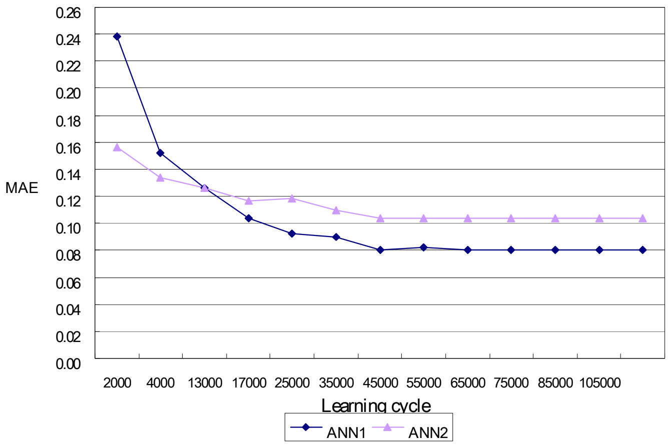

Fig. 10 ANN network learning curve

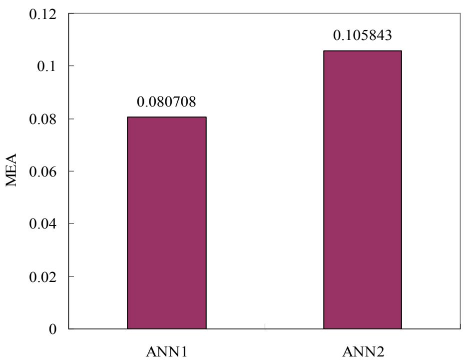

Fig. 11 Comparison in evaluation index of network model

4 Analysis of the accuracy of Forecast Model

To confirm the forecast accuracy of cost pre-estimation model constructed in the current study, cost percentage error (CPE) formula (2) (Zhang and Fuh, 1998) was taken to measure the range of forecast accuracy.

$$CPE = \frac{E(i) - T(i)}{T(i)} \times 100\% \qquad (2)$$

$E(i)$= the estimated cost of sample i

$T(i)$= the actual cost of sample i

A total of 20 pieces of verification testing data were selected again to evaluate forecast accuracy of the model. Fig. 12 reveals that the cost percentage error of the forecast model constructed in the current study is within ±8%, and the cost percentage error of only 3 verification sample goes beyond the range of ±4%. In the view with the engineers at the injection plant on the verification, we know that all think the cost percentage error is acceptable.

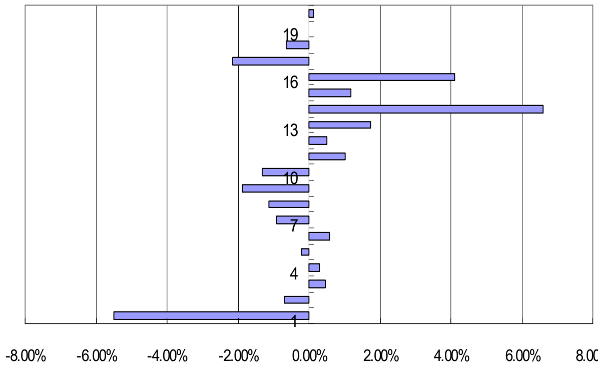

Fig. 12 Cost percentage error of verification data of ANN2

5 Conclusion

The ability to develop and create products has turned into the core ability to initiate competitive advantage of the enterprise. As for R&D units, their role has changed from the previous decision support force to the tool for enterprise strategy and plan. Therefore, the current study puts forward the cost estimation model based on the neutral network. The model can help R&D units quickly estimate product at the initial period of design stage, without depending heavily on the costs estimated by mold shop and injection plant. The estimated cost can be used as the strategic reference for the enterprise to make the comparison in the market price and decide how much profit can ensure the price competitiveness. If the profit falls short of our expectation, the product design shall be immediately criticized and even the product development be terminated so as to avoid the meaningless investment in the product development and greater losses possibly incurred in the future. On the other hand, if the cost is overestimated, it will make customers distrust the product and the enterprise may lose business opportunities.

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