Application of a hybrid genetic algorithm and neural network approach in activity-based costing

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Abstract

Activity-based costing (ABC) has received extensive attention since it achieves improved accuracy in estimating costs, by using multiple cost drivers to trace the cost of activities to the products associated with the resources consumed by those activities. However, it has some problems. The first problem is that ABC does not have general criteria to select relevant cost drivers. Second, ABC assumes linearity between the uses of activities and the assigned quantities of indirect cost. When cost behavior shows a nonlinear pattern, conventional ABC may distort product costs. This paper proposes hybrid artificial intelligence techniques to resolve these two problems. Genetic algorithms are used to identify optimal or near-optimal cost drivers. In addition, artificial neural networks are employed to allocate indirect costs with nonlinear behavior to the products. Empirical results show that the proposed model outperforms the conventional model.

Keywords: Activity-based costing; Genetic algorithms; Artificial neural networks; Cost-driver optimization; Cost estimating relationships

1. Introduction

Cost allocation is a very important task involved in many engineering and business decisions. In this sense, activity-based costing (ABC) has received extensive attention during the past decade because it was developed for overcoming the problems of the traditional costing system through more a reasonable cost allocation process. Conventional ABC, however, has some problems to be resolved. The first problem is that ABC does not have general criteria to select relevant cost drivers. This problem is related to the cost-drivers optimization (CDO) problem and associated with the efficiency of costing systems. Second, conventional ABC generally assumes a linear cost function. The linear cost function is a function where the graph of total costs versus a single cost driver forms a straight line within the relevant range. Horngren, Foster, and Datar (1997) pointed out that a cost function, in practice, is not always linear, but sometimes shows nonlinear behavior. They described a nonlinear function as a cost function where the graph of total costs versus a single cost driver does not form a straight line within the relevant range. In this aspect, conventional ABC may distort product costs when a cost behavior shows a nonlinear behavior. Thus, the second problem is associated with cost estimating relationships (CERs), and it is also related to the effectiveness of costing systems.

Prior researchers have endeavored to overcome these problems of conventional ABC. Some of these studies showed that the estimating performance of artificial neural network (ANN) outperforms that of linear regression for optimal cost allocation in ABC (Bode, 1998a,b; Creese & Li, 1995; Garza & Rouhana, 1995; Lee, 1993; Lee & Ahn, 1993; Smith & Mason, 1997). Other studies proved the efficiency of heuristic search techniques to select optimal cost drivers (Babad & Balachandran, 1993; Levitan & Gupta, 1996). However, they did not consider these two problems simultaneously.

This study proposes a hybrid model composed of genetic algorithms (GAs) and ANN to resolve the above two problems of conventional ABC simultaneously. First, GA portion of the model is proposed as an optimization method of relevant cost drivers. Second, ANN portion of the model is used to reflect a nonlinear cost function for the cost allocation process. In the hybrid model, the GA globally searches and seeks an optimal or near-optimal ANN topology.

The paper is organized as follows: Section 2 reviews...
related prior studies. Section 3 presents a description of our hybrid model of GA and ANN. In addition, Sections 4 and 5 describe the process of experiments and experimental results. Finally, Section 6 discusses the conclusions and the limitations of the study and future research issues.

2. Prior research

In general, traditional costing systems, volume-based costing systems usually with a single cost driver, distort the cost allocation process because they allocate costs by only one criterion such as direct labor-hour, machine-hour, or unit of production. Indirect costs, however, do not always behave in proportion to the single cost driver in practice. In addition, if cost drivers are not selected appropriately, traditional approach does not accurately allocate indirect costs to the products. This may cause distorted decision-making.

ABC is the costing method that assigns costs to activities using multiple cost drivers, then allocates costs to products based on each product’s use of these activities (Maher & Deakin, 1994). ABC differs from traditional costing systems in two ways (Cooper, 1989). Cost pools are defined as activities rather than as production cost centers. In addition, the cost drivers are used to assign activity costs to products, which differs from traditional costing systems. ABC reduces the risk of distortion because it uses multiple activities as cost drivers based on CER.

There are two practical issues related to the proper allocation of indirect cost for ABC systems. The first issue is how to select proper cost drivers for cost allocation. It focuses on the efficiency of ABC because optimal cost drivers save the information-gathering cost without sacrificing major accuracy in cost estimation. It is a task currently handled by application of human judgment for the purpose of selecting appropriate cost drivers from the larger set of available candidate drivers (Schniederjans & Garvin, 1997). The second issue is how to determine the cost relationship. It focuses on the accurate estimation of a cost function. It is related to the effectiveness of ABC systems because effectiveness can be achieved by the proper cost function for cost allocation. Incorrect estimation of the cost function will have repercussions in the areas of cost management and control (Horngren et al., 1997).

Prior research has tried to resolve these two problems. For the CDO problem, Maher and Deakin (1994) suggested the following three criteria to select relevant cost drivers: causal relation, benefits received, and reasonableness. However, their criteria were abstract and subjective. Babad and Balachandran (1993) attempted to optimize cost drivers in ABC using greedy algorithms. They also identified a priority order, according to which low-priority and relatively insignificant activities with their associated drivers would be combined to save costs without sacrificing much accuracy in cost estimation. In addition, Levitan and Gupta (1996) tried to optimize the selection of relevant cost drivers using the GA in ABC systems. In their study, the GA and the greedy algorithm are used to solve two cases from the published literature. They concluded that a GA approach achieved superior results to the greedy algorithm for both cases. They found that the GA not only reduces information-gathering costs through fewer drivers, but also produces more accurate costs even with fewer drivers.

A more recent study of Schniederjans and Garvin (1997) proposed the combined analytic hierarchy process (AHP) and zero–one goal programming to select relevant cost drivers in ABC. They showed how the AHP approach could bring consistency to the cost driver selection process. They also illustrated how the AHP weighting can be combined in the zero–one goal programming model to include resource limitations in the cost driver selection process.

For the CERs, many researchers have made advances in the cost allocation process. Several studies reported that ANN outperforms linear regression for cost estimation (Creese & Li, 1995; Garza & Rouhana, 1995; Lee, 1993; Lee & Ahn, 1993). Smith and Mason (1997) suggested that ANN has advantages when dealing with data for which there is little a priori knowledge of the appropriate CER to select for regression modeling. Bode (1998a) reported that ANN after grouping of data outperforms linear and nonlinear regression for cost estimation. He suggested that ANN produces better cost predictions than conventional costing methods when the following conditions are satisfied: a sufficient case-base, known cost-driving attributes, few cost drivers, and no explicit knowledge about cost effects. In addition, Bode (1998b) suggested that ANN could be used for R&D management. He carried out the estimation of final cost of a new product under development, a typical R&D management application, using ANN.

In this section, we describe prior studies which tried to resolve the CDO and the CER problems in ABC systems. However, they did not consider these problems simultaneously. There has been much research interest since these two problems are interrelated for the estimation of product costs. This study proposes the hybrid GA and ANN model to resolve the CDO and the CER problems simultaneously. Section 3 presents our research model.

3. The hybrid model of GA and ANN

The GA is a search algorithm based on survival of the fittest among string structures (Goldberg, 1989). Recently, the GA has been investigated and shown to be effective in exploring a complex space in an adaptive way, guided by the biological evolution mechanisms of reproduction, crossover, and mutation (Adeli & Hung, 1995).

The first step of the GA is problem representation. The problem must be represented in a suitable form to be handled by the GA. Thus, the problem is described in terms of genetic code, like DNA chromosomes. The GA often
works with a form of binary coding. If the problems are coded as chromosomes, the populations are initialized. Each chromosome within the population gradually evolves through biological operations. There are no general rules for determining the population size. But, population sizes of 100–200 are commonly used in GA research. Once the population size is chosen, the initial population is randomly generated (Bauer, 1994). After the initialization step, each chromosome is evaluated by a fitness function. According to the value of the fitness function, the chromosome associated with fittest individuals will be reproduced more often than those associated with unfit individuals (Davis, 1994).

The GA works with three operators that are iteratively used. The selection operator determines which individuals may survive (Hertz & Kobler, 2000). The crossover operator allows the search to fan out in diverse directions looking for attractive solutions and permits chromosomal material from different parents to be combined in a single child. In addition, the mutation operator arbitrarily alters one or more components of a selected chromosome. Mutation randomly changes a gene on a chromosome. It provides the means for introducing new information into the population. Finally, the GA tends to converge on a near-optimal solution through these operators (Wong & Tan, 2000).

The GA is usually employed to improve the performance of artificial intelligence (AI) techniques. For ANN, the GA is popularly used to select neural network topology including optimizing relevant feature subsets, and determining the optimal number of hidden layers and processing elements. The feature subsets, the number of hidden layers, and the number of processing elements in hidden layers are the architectural factors of ANN to be determined in and the number of processing elements in hidden layers are initialized. The feature subsets, the number of hidden layers, and the number of processing elements in hidden layers are the architectural factors of ANN to be determined in advance for the modeling process of ANN (Kim & Han, 2000). However, determining these factors is still part of the art. These factors were usually determined by the trial and error approach and the subjectivity of designer. This may lead a locally optimized solution because it cannot guarantee a global optimum.

In this paper, we propose the hybrid GA and ANN model to resolve two problems of conventional ABC systems. In this study, the GA is used for the step of selecting relevant cost drivers and optimizing the network topology of ANN. The GA globally searches an optimal or near-optimal ANN topology in the hybrid model. The estimating process of the hybrid model consists of the following three stages:

In the first stage, the GA searches (near-)optimal cost drivers and the number of hidden nodes. The populations, cost drivers and the number of hidden nodes, are initialized into random values before the search process. The parameters for searching must be encoded on chromosomes. The encoded chromosomes are searched to optimize a fitness function. The fitness function is specific to applications. In this study, the fitness function is the average deviation between expected and predicted values of product costs. The parameters to be searched use only the information about the training data. In this stage, the GA operates the process of crossover and mutation on initial chromosomes and iterates until the stopping conditions are satisfied.

The second stage is the process of feed-forward computation in ANN. In this stage, a sigmoid function is used as an activation function. This function is a popular activation function for the backpropagation neural network because it can easily be differentiated. A linear function is used as a combination function for the feed-forward computation with selected cost drivers and ANN topology.

In the third stage, selected cost drivers and ANN topology are applied to the holdout data. This stage is indispensable to validate the generalizability because ANN has the eminent ability of learning the known data. If this stage is not carried out, the model may fall into the problem of overfitting with the training data.

4. Research data and experiments

This study selects a revised case excerpted from Cooper and Kaplan (1991) and Lee (1993). This is the case of Destin Brass Products Co., which produces valves, pumps, and flow controllers. The initial cost drivers (activities) are ‘Setup labor’, ‘Receiving’, ‘Materials handling’, ‘Engineering’, ‘Packing and shipping’, ‘Maintenance’, and ‘Machine usage’. The description of the research data is as follows:

The possible production range of valves is 3500–10,500 products at intervals of 2000 products, that of pumps is 7500–17,500 at intervals of 1500 products, and that of flow controllers is 2400–5600 at intervals of 800 products. A standard production unit for valves, pumps, and flow controllers are 7500 products, 12,500 products, and 4000 products. If the number of valves is over 10,000 products, then we put two units to the number of runs, otherwise put one unit. In case of pumps, the number of runs increases by one unit as the number of pumps increases by 2500 products from the standard production. For flow controllers, standard production runs are 10 units for 4000 products, and the number of runs increases by two units as the number of products increases by 800 products from the standard production. The application rate is summarized in Table 1.

The following rules are applied for simulation of activity values. For example, the value of the activity Setup labor is calculated as $8 \times (\text{the number of runs of valves}) + 8 \times (\text{the number of runs of pumps}) + 12 \times (\text{the number of runs of flow controllers})$. The application rate is presented in Table 2.

Backpropagation algorithm and a sigmoid function are used in ANN. The learning rate and momentum is 0.1, and initial connection weight is 0.3 in ANN. Among the data, 60% of the data is training, 20% is testing, and 20% is holdout data in order to avoid overfitting. The training and testing data is used to search the optimal or near-optimal
The holdout data is used to test the results with the data that is not utilized to develop the model. Using 125 data items, we train and validate the hybrid model of GA and ANN and the conventional ANN model. In addition, 50,000 and 100,000 training patterns are presented to ANN since minimum average error of the test data is recorded. For the controlling parameters of the GA search, the crossover and mutation rates vary to prevent ANN from falling into a local minimum. The crossover probabilities and probability of mutation are 0.7 and 0.1.

5. Experimental results

For validating the proposed model, 25 holdout data items are used. After experiments, the GA selects four cost drivers including Receiving, Materials handling, Maintenance, and Machine usage from all seven drivers. In addition, the GA recommends three hidden nodes in ANN. Table 3 presents mean-absolute-percent-error (MAPE) by different experimental conditions.

The results show that the proposed hybrid model consistently outperforms conventional ANN, regardless of changes in the number of hidden nodes and the number of learning patterns. Although the hybrid model uses fewer cost drivers than conventional ANN, it produces higher accuracy in allocating indirect costs.

6. Concluding remarks

This study has proposed the hybrid AI model to resolve the problems of designing ABC systems. In this study, the GA was used for the step of selecting relevant cost drivers and optimizing the network topology of ANN. The GA globally searched an optimal or near-optimal ANN topology in the hybrid model. The proposed model outperformed the conventional model. From the experimental results, we concluded that the proposed model has advantages when the model analyzes the data with complex and nonlinear CER.
The major advantage of the proposed model was simultaneous consideration of efficiency and effectiveness issues for designing ABC systems.

However, this study had some limitations. In this study, a simulated data based on a real-world case was used for testing the proposed model. This study cautiously managed the simulation process, but the results on simulated data might not guarantee consistency in the real world. Thus, it is necessary to test the proposed model with the real-world data. In addition, while ANN performed well with the GA-based optimization, other learning algorithms might also prove effective in place of ANN. We believe that there is great potential for further research with the optimization using the GA for other AI techniques including case-based reasoning and support vector machines. For future work, we intend to apply the proposed model to more complicated areas in accounting including cost estimation, cost allocation to specific departments, and the mitigation of the linear assumption in cost-volume-profit (CVP) analysis.

References


