Contributed paper

Cost model development using artificial neural networks

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Keywords

Costs, Modelling, Development, Taguchi methods, Neural networks

Abstract

In order for the aerospace industry to achieve success in export markets through the provision of high levels of product choice, it will need to develop and economically use many new materials and manufacturing processes. Examines how the constraints imposed by changing market trends affect the identification of "cost estimating relationships" and investigates their relative benefits and limitations in terms of their effects on the overall cost model development process. A method of establishing cost estimating relationships that appears to offer benefits to the cost modelling process is that of artificial neural networks (ANNs). Using the Taguchi method, a series of experiments have been undertaken to select an appropriate network for the "turning process". The estimation accuracy and robustness of cost models developed using suitable ANN structures have then been examined under varying conditions in order to identify guidelines

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Introduction

Market trends suggest that the UK aerospace industry (De Rosa, 1999; Stalk and Hout, 1990), in order to secure significant future export sales, will need to increase the complexity of its product development and manufacturing process. To support this there is a growing interest in developing cost models that are able to forecast the behaviour of various cost categories accurately, where such cost models can be used as an essential part of the design process at all stages through the product life-cycle, for example allowing detailed cost-performance trade-offs to be made.

A potential constraint to providing this support for product and process development in an effective and timely manner is the cost modelling process itself. The main tasks involved in the development of a cost model, i.e. data identification, data collection and data analysis, will all be affected by the constraints placed on the cost estimating and cost modelling processes as indicated in Table I.

Of particular concern are the mathematical modelling techniques used to establish the "cost estimating relationships" (CERs), which form the basis of cost models. The characteristics which describe these CERs are shown in Figure 1 (Stockton *et al.*, 1998).

Ideally, an effective data analysis technique, such as artificial neural networks, must assist in enabling the constraints to the development of cost models to be overcome and in addition be capable of meeting the user needs in terms of the required characteristics of the cost model.

Cost model levels

Within the aerospace industry, significant technical changes, are taking place in response to the need to cut costs, product development time, and manufacturing time. The basic levels of cost models employed are as follows:

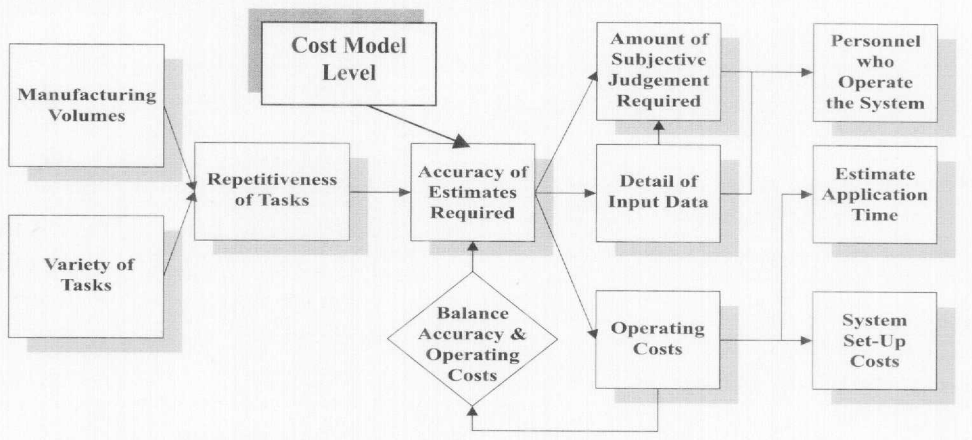
- *High level model.* Where relatively simple data inputs are required to yield costs for complete subsystems or whole products. A low level of cost detail is provided by such models. These models are normally used at strategic or concept decision-making stages and typical inputs would be in terms of the expected weight or

Aircraft Engineering and Aerospace Technology
Volume 73 · Number 6 · 2001 · 536–541

Table I Effect on cost model development tasks

Cost model development tasks	Limitations on cost estimating/modelling process: Greater number of cost models required	Less historical cost data available	Less time available to develop models	Greater product and process complexity	Less process expertise available
Data identification	✓	✓		✓	✓
Data collection	✓	✓	✓	✓	✓
Data analysis	✓	✓	✓	✓	✓

Figure 1 Inter-relationships between cost model characteristics



dimensions of a product. Ballpark estimates would then be output suitable for quickly establishing the viability of alternative concepts.

- *Low level model.* Requires in-depth examination of the process or product to be costed. The detailed activities of the manufacturing process must be identified for each individual component that makes up a product and the relationships between these activities and the cost resources required to perform them. Low level models tend to be highly accurate and are used for such functions as the detailed costing of components or comparison of alternative detailed designs. In order to develop low level manufacturing process cost models, a thorough understanding of the manufacturing processes involved is required. They are based on a detailed estimation of the main manufacturing cost categories such as material use, fabrication and assembly.
- *Heuristic/rule of thumb model.* These models involve cost estimators and/or process experts providing subjective estimates of the relationships between products and/or processes and their costs. The accuracy of such models depends on the levels of experience and bias of the persons making the estimates.

Cost model development process

At each of the above levels, cost models can be described in terms of the common set of characteristics shown in Figure 1. It is these characteristics, e.g. estimation accuracy, level of detail of input and output data, estimate application time, and their interactions that largely determine the individual tasks involved in the cost model development process.

The basic tasks involved in developing cost models are data identification, data collection and data analysis. At all stages in the process, decisions need to be made concerning the relevant data that needs to be collected and how this data collection process will take place. In addition, the data analysis techniques used to establish valid process time estimating relationships within the data need to be selected and applied.

Previous work (Stockton and Wang, 1999) outlined how several advanced modelling techniques, including artificial neural networks, could potentially provide methods for successfully overcoming the constraints to

Aircraft Engineering and Aerospace Technology
Volume 73 · Number 6 · 2001 · 536–541

the development of cost models. In order to achieve this aim these methods must assist in:

- identifying cost drivers and their relative importance;
- significantly reducing the amount of data required to establish models;
- reducing the required accuracy of input data and where possible enable greater levels of qualitative data to be used;
- removing the need to establish the variables that constitute the cost drivers;
- removing the need to know prior to data analysis the form of the cost function; and
- increasing the number of variables that can be considered within the cost model.

Artificial neural networks

An artificial neural network (ANN) (Bode, 1998; De la Garza and Rouhana, 1995; Shtub and Zimerman, 1993) consists of a number of computer processing elements of the type shown in Figure 2 (Wang, 2000).

These processing elements are arranged in layers (Wang and Stockton, 2000). They represent a mathematical model of the physical processes that take place in brain cells. In an ANN, a processing element (PE) has many input paths and combines, normally by a simple summation, the values of these input paths. The combined input within a PE is then modified by a transfer function.

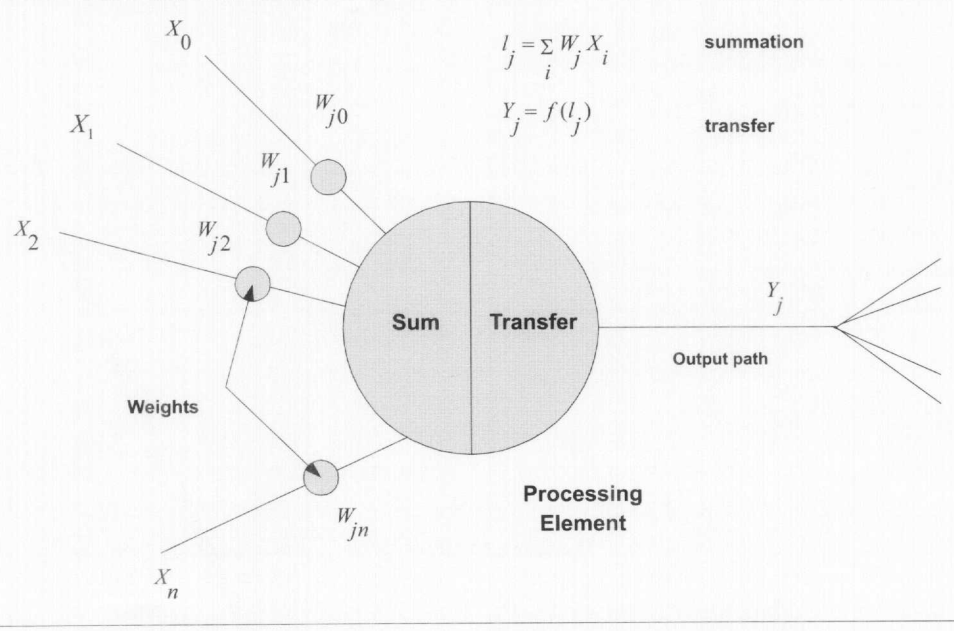
The values output from transfer functions are generally passed directly to the output paths of PEs. These paths can be connected to input paths of other PEs through connection weights, which correspond to the synaptic strength of the neural connections. Since each connection has a corresponding weight, the signals on the input lines to a PE are modified by these weights prior to being summed, i.e. to produce a weighted summation.

Development of turning cost model

Within the aerospace industry, there are a wide variety of turning processes undertaken. With respect to the turning process, Boothroyd and Reynolds (1989) developed a detailed cost model. A spreadsheet-based version of this model was created and used to generate the costing information that trained and tested the ANN cost models. The objective of the research was to examine the ability of ANNs to develop such models. By using the model developed by Boothroyd and Reynolds (1989), the performance of an ANN in predicting these relationships could be measured with a high level of certainty. This model was chosen as suitable for use within the experimentation since it contained a relatively large number of predictor variables (i.e. 16), and both linear and non-linear relationships between these variables and process costs.

The experiments listed in Tables II and III were carried out to determine the effects on

Figure 2 Artificial neural network processing element



Aircraft Engineering and Aerospace Technology
Volume 73 · Number 6 · 2001 · 536–541

Table II Number of hidden layers experimentation

Experiment numbers	Number of layers	Number of PEs per layer	Model types tested
1-20	1	1-10	Best ANN, worst ANN
21-40	2	1-10	Best ANN, worst ANN
41-60	3	1-10	Best ANN, worst ANN

Table III Number of PEs per layer experimentation

Experiments numbers	Number of PEs per layer	Number of layers	Model types tested
1-6	1	1, 2, 3	Best ANN, worst ANN
7-12	2	1, 2, 3	Best ANN, worst ANN
13-18	10	1, 2, 3	Best ANN, worst ANN

the accuracy of ANN based cost estimating models, of both:
- the number of hidden layers within ANN structures; and
- the number of processing elements per layer.

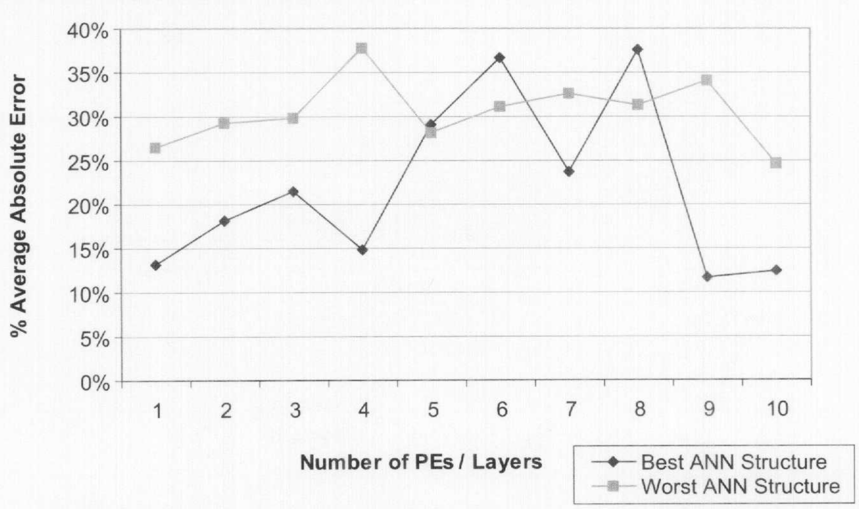
Results analysis

In order to identify the relative effect on cost modelling estimating accuracy of the number of processing elements per layer, the experiments listed in Table II and Table III were carried out. The results obtained are shown in Figures 3 to 6. For all experiments the maximum training (i.e. 750 data points) and maximum testing (i.e. 350 data points) sets were used.

From Figures 3 to 6 the following effects can be observed.

- Where networks contain one hidden layer, Figure 3, the estimating ability of the resulting ANN models can be erratic, i.e. there is no discernible trend in estimating accuracy as number of PEs per layer increases. There is also a large variation in estimating accuracy, i.e. between 12 per cent and 37 per cent.
- Where networks contain two hidden layers, Figure 4, there is an initial increase in estimating accuracy from one PE/layer to two PEs/layer but thereafter there is no discernible difference when additional PEs are introduced. There is also, when two or more PEs/layer are used, a marked decrease in variability of estimating accuracy, i.e. between 9 per cent and 20 per cent.
- Where networks contain three hidden layers, Figure 5, again there is an initial increase in estimating accuracy from three PEs/layer to four PEs/layer but thereafter again there is no discernible difference when additional PEs are introduced. Again there is, when four or more PEs/layer are used, a decrease in variability of estimating accuracy, i.e. between 7 per cent and 17 per cent.
- In Figure 6 the relative effect of varying the number of PEs/layer is compared between one-layer, two-layer and three-layer networks. Overall the three-layer network provides the highest estimating accuracy.

Figure 3 Effect of number of PEs/layer – one layer



Aircraft Engineering and Aerospace Technology
Volume 73 · Number 6 · 2001 · 536–541

Figure 4 Effect of number of PEs/layer – two layers

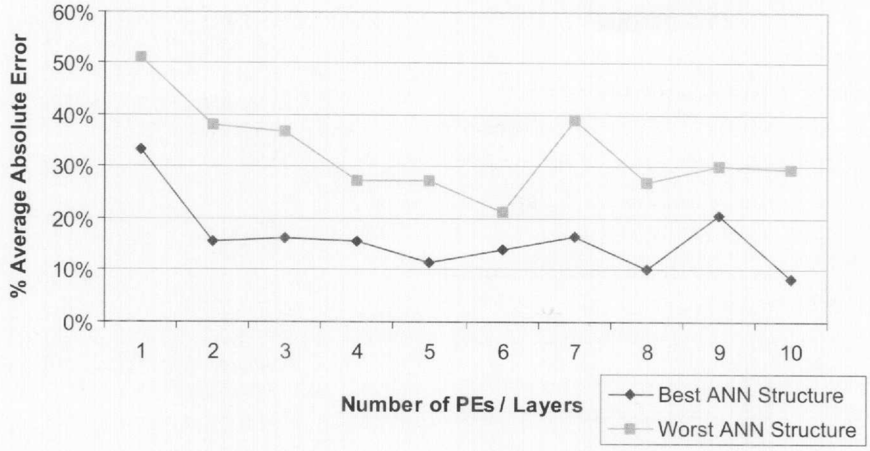


Figure 5 Effect of number of PEs/layers – three layers

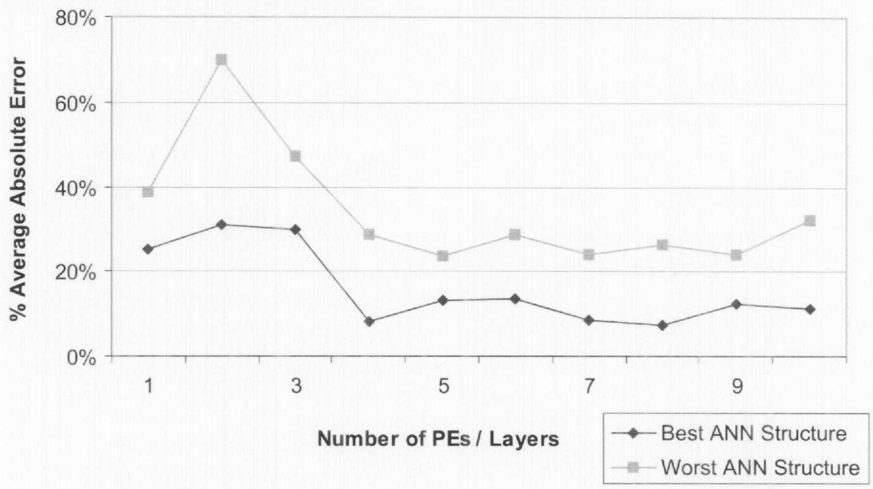
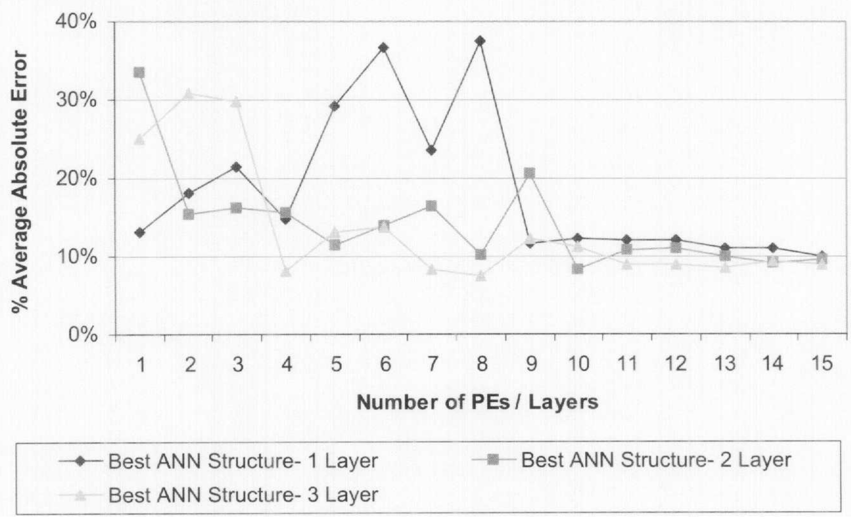


Figure 6 Effect of number of PEs/layer with three layers



Aircraft Engineering and Aerospace Technology
Volume 73 · Number 6 · 2001 · 536–541

Summary

It has been identified that global market trends are resulting in the need for manufacturing organisations to offer great changes in their products. In order to support this, the quantity and quality of cost models will need to be greatly increased. As an alternative method of establishing cost models, neural networks have been examined to establish suitable structures for cost models. Experimental studies undertaken to compare alternative ANN structures have yielded marked differences in their estimating accuracy, hence demonstrating the importance of ensuring that suitable ANN structures are used. This is particularly important when deciding the number of layers and number of processing elements per layer to include in the ANN model since experiments have shown that in general, increasing the number of processing elements per layer and decreasing the number of layers within an ANN model leads to an increase in estimating accuracy.

References and further reading

Bode, J. (1998), "Neural networks for cost estimation", *Cost Engineering*, Vol. 40 No. 1, pp. 25-31.

Boothroyd, G. and Reynolds, C. (1989), "Approximate cost estimates for typical turned parts", *Journal of Manufacturing Systems*, Vol. 8 No. 3, pp. 185-93.

De la Garza, J.M. and Rouhana, K.G. (1995), "Neural networks versus parameter-based applications in cost engineering", *Journal of Cost Engineering*, Vol. 37 No. 2, pp. 14-18.

De Rosa, C. (1999), *Customer Trade: The Next Industrial Revolution*, Symix Systems, Dartmund.

Shtub, A. and Zimerman, Y. (1993), "Neural-network-based approach for estimating the cost of assembly systems", *International Journal of Production Economics*, Vol. 32 No. 2, pp. 189-207.

Stalk, G.H. and Hout, T.M. (1990), *Competing against Time: How Time Based Competition Is Reshaping Global Markets*, Free Press, New York, NY.

Stockton, D.J. and Wang, Q. (1999), "Applying advanced modelling techniques to cost estimating", Conference of Association of Cost Engineers: Engineering Manufacturing Committee, March, De Monfort University, Leicester.

Stockton, D.J., Forster, R. and Messner, B. (1998), "Developing time estimating models for advanced composite manufacturing processes", *Aircraft Engineering and Aerospace Technology*, Vol. 70 No. 6, pp. 445-50.

Taguchi, G. (1987), *System of Experimental Design: Engineering Methods to optimise Quality and Minimise Costs*, Vols 1 and 2, UNIPUB/Kraus International Publications, White Plains, NY.

Wang, Q. (2000), "Improving the cost model development process using neural networks", PhD thesis, De Montfort University, Leicester.

Wang, Q. and Stockton, D.J. (2000), "Process cost modelling using neural networks", *International Journal of Production Research*, Vol. 38 No. 16, pp. 3811-21.