The role of neural networks in early stage cost estimation in the 21st century

THE ROLE OF NEURAL NETWORKS IN EARLY STAGE COST ESTIMATION IN THE 21ST CENTURY

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The impact of technology on all areas of science and industry in the latter half of the twentieth century has been enormous, and the building industry has been no exception. However, early stage cost estimation has been little affected by these advances in comparison to most of the rest of the industry, and is still largely based on a combination of simple models and professional judgement.

This paper reports how research currently being undertaken at UMIST could change this practice significantly. A neural network model which is able to estimate the total cost of construction to the client is being developed. This model considers forty variables which define the project at this early stage. Some of these variables would not usually be considered within the estimation of the cost. Perhaps most significantly, by including procurement it is able to evaluate the cost of different procurement routes inclusive of the client's administrative costs.

How the neural network improves on existing modelling techniques by its use of existing project data is explained, and its role in early stage cost estimation in the 21st century outlined.

Keywords: cost modelling, early stage estimating, neural networks, procurement.

1 INTRODUCTION

The construction industry has proved itself very slow to adopt new techniques for early stage cost estimation. Many new techniques have been developed in recent years, and yet they have largely been ignored. Research undertaken by Fortune (Fortune 1994) showed that many significant early cost estimation techniques were not used. The principal reason was that estimators, though aware of such techniques, do not understand how to use them. Another problem with the adoption of such techniques, according to Ross (Ross, 1998), is that estimators tend to be unwilling to adopt techniques which do not allow some form of professional judgement to be incorporated, something which newer techniques tend not to be able to do. However, this continued reliance on traditional, judgement based techniques has lead to some dissatisfaction with early stage cost estimating among construction clients (Fortune, 1994), whose expectations of this process are increasing all the time.

This has placed pressure on the industry, and may be a significant factor in providing the paradigm shift called for by Brandon (Brandon, 1982). Yet the results of more recent research (Ross, 1998) indicate that there is little evidence of any increase in the use of these techniques. This would suggest that the current mood of looking forward to the new millennium and adopting new ideas has failed to infect the practice of early stage cost estimation.

In addition to not looking forward, it has also been identified that estimators tend not to look back to past performances. Lowe (1996) found very little monitoring of the performance of estimators, a fact that was also observed by Birnie (1993). This means that it is very difficult for estimators to form any objective opinion of their own estimating capacity. Both Lowe (1996) and Skitmore (1990) found that while the level of accuracy perceived by the early stage estimator was less than 10%, the actual accuracy achieved was greater than 20%, suggesting that estimators have an unrealistically high opinion of the quality of their estimating ability. This conclusion was also drawn by Birnie (1993).

The fact that there is no feedback to the estimators is of great concern. Not only might it cause estimators to unwittingly mislead clients as to the accuracy of their estimates, but it also prevents the objective evaluation of new techniques. If an estimator is faced with a new technique and is not used to obtaining the kind of feedback which would permit the objective evaluation of the new technique, then there is no option but to base opinions upon more subjective criteria. This creates an obstacle to the objective evaluation of new techniques.

Having said this, a model is currently under development at UMIST which could provide a new technique for cost estimating which not only aims to be more accurate than former cost estimation models, but also which requires, as part of its implementation, the feedback of the estimator's performance. Using a neural network model and a large set of past projects, this model would be able to arrive at accurate forecasts of the cost of a building. In addition to this, the output of a fully developed model would provide information which would inform the estimator’s employment of professional judgement in providing a final cost forecast. This is achieved through the provision of a cost distribution for a proposed project.

2 A PREDICTIVE MODEL OF THE TOTAL COST OF CONSTRUCTION

The aim of the early stage estimating procedure is twofold. Its primary function is to provide the client with a comparative cost of different options through a “what if” analysis. In particular, the research aims to provide an objective indication of the cost of different procurement routes. The model enables the objective comparison of the cost to the client of different procurement routes.

While existing research has determined differences between the costs of the different procurement routes, it has aimed to determine a single figure for the difference for projects as a whole. No attempt has been made to provide a difference for a specific project (Duff, 1998). Furthermore, no previous research has determined the cost to the client using any objective method.

The absence of such a technique is significant. It means that the client's advisors have no means of providing an objective measure of the cost of following different procurement routes. The client must depend upon the judgement of the advisors, which is based on their own perception of both the project and the different procurement routes, and is hence subject to their opinions and prejudices. The predictive model will prevent this by allowing the client's advisors to obtain an objective comparison of the costs the procurement routes for a specific project.

The second aim of the predictive model was to provide the client with an objective forecast of the overall building cost. Both of these aims will be realised through the development of a predictive model of the total cost of construction. Any predictive model which estimates the cost of a building must not only consider its physical characteristics, but must also be able to model the complex and little understood interrelationships which exist between all the cost significant variables at this early stage of the project. In a pilot study to the current development (Duff), the ability to model these relationships was assessed for a number of techniques. Thirty-nine cost significant variables were identified, and a neural network model was found to be the most appropriate technique. This was for the following reasons.

- Neural networks, unlike linear regression, are able to model interdependencies between input data which will inevitably occur when considering construction cost significant variables. For example, the model variables - such as number of storeys, gross floor area and number of lifts - will almost certainly be correlated.

- Neural networks can deal more readily with non-linear relationships.

- Neural networks can, more effectively than regression, handle incomplete data sets. This is important because it is difficult to guarantee that complete data sets will be always be available.

2.1 The neural network

The number of variables used in the model has now been expanded beyond those identified in the pilot study by the inclusion of a variable to indicate the complexity of the shape of the building. Thus, there are now forty cost significant variables. These variables include variables relating to the proposed contract type as well as details of the physical characteristics of the building, the construction and the services.

The neural network under development for the project will be trained using existing data from around 500 projects. Once properly trained the neural network will be able to predict the total cost of a building. The resulting model will, in the first instance, have two applications. The first of these is as a tool to help estimators see how much the building would be expected to cost, based on past projects. The second application is as a comparative tool. It would provide an indication of how much a project's cost would vary if part of the specification were changed (for example, the cost of increasing the floor are or reducing the number of lifts).

However, these neural networks would only provide a single deterministic value of the cost. While this is useful, it supplies only an indication of how much such a project would cost, on average. In reality, a project's final cost can only be forecast to a limited certainty, and a deterministic value fails to represent this fact. Of course, it would be fairly straightforward to supply a single error value, indicating how accurate, on the whole, the neural network is, by testing it against some existing data. This would indicate the amount to which the actual cost of a project will vary from the forecast cost. However, it only gives an indication of how much it would vary on average for any project, rather than providing a value specific to a given project.

This measure would be valid and useful if the variation of actual cost from forecast cost can be expected to remain constant from one project type to another. However, this will not necessarily be the case. There are two solutions to this problem. The first is to determine how accurate the estimate provided by the neural network is for broad types of project. The second and more accurate method would be to determine the level of accuracy of the estimate for each project. This could be achieved by using a stochastic neural network which yields, as its output, not a single value, but a distribution. While the model currently under development is a deterministic one, it is very likely that a stochastic neural network might be developed in the future.

2.2 Implementation of the model

The model will have a direct application in industry in two ways. Firstly, it will provide a means of comparing the cost of different options. This allows a "What if?" analysis to be performed. This ability would be invaluable, as it not only provides indications of cost increases or decreases with changes in building specification, but also how changing different project strategic variables, such as the procurement route or tendering strategy, might be expected to affect the cost.

The output of the deterministic model would be useful for a direct comparison of the expected costs. However, it would not be able to indicate whether there are variations in the cost-risk implications for different choices. In order to obtain this information a stochastic model would be required. The stochastic model would provide a distribution, rather than a single value. Thus differences in the distribution between different choices could be observed, and the cost-risk implications evaluated.

The second way in which the model would be applied is to obtain a benchmark figure of the total cost of the project to the client. This figure is based on past projects, and is therefore an objective measure of how much the project would be expected to cost. The estimator could then decide how much the actual cost of the project is likely to vary from the cost indicated by the model and adjust the figure accordingly. This judgement would have two elements: how accurately the project specified matches the actual project, and how the output from the model matches the results obtained by other techniques.

When defining the project for the model, the estimator will be aware that the specification used by the model may not wholly describe the project. The model is defined by 40 cost significant variables which are common to all buildings. However, there may be other cost significant factors which are specific to the particular project, and to the needs of the particular client. For example, the project might be ecologically sensitive, with the possibility of disruption by environmental campaigners. The estimator would therefore have to estimate how significantly this factor might affect the cost, using his or her professional judgement.

In addition to this, there may be also be differences between the actual project and the project specified arising from problems with the determination of subjective variables such as quality. If the quality, for example, uses a five-point scale running from very low to very high, the estimator might specify that the quality is *high*. However, the estimator, knowing what type of project is usually specified as being *high*, might feel that the project is actually somewhere between *medium* and *high*, but closer to *high*. In this circumstance, the estimator would have to observe the cost of the project both at *medium* and *high* qualities, and select a value between using professional judgement.

The amount of information provided by the deterministic model which might aid the estimator in exercising this judgement is limited. All the model produces is a single value. Of course, a general measure of accuracy for the neural network is available, and this indicates how much, on average, the network's predictions vary from the actual cost of the project. This provides the estimator with an approximate indication of by how much projects with the same specification typically vary in cost. However, this can be improved upon by implementing a neural network whose output is a distribution, rather than a single value. This would provide the estimator with a much more accurate indication of by how much the project might vary. The estimator has not only a mean cost for projects of this specification, but also upper and lower limits. This gives the estimator a quantitative value of how much the estimate can reasonably be varied from the mean.

As well as determining how much the cost is likely to vary from the estimate provided by the model, the estimator could also consider the results of other estimating techniques in the determination of the estimated cost. Thus the model becomes one of the tools that the estimator will use in the early stage cost estimation. When determining the actual forecast cost, the estimator will use the estimates from both the model and a number of other techniques, as well as the fact that the actual cost is expected to be either higher or lower than the cost forecast by the model.

Of course, this process may not just be a one off selection, but where there is significant disparity between the predictions, the estimator may wish to see if they can be explained before making the final estimate. If any explanation can be found, then there are two possible causes: a poor model, or the fact that one model is more suited to the particular type of project than another. If the disparity is caused by poor modelling then it can be fixed. If it is caused by one model being more suited to the task in hand than another, then this fact can be taken into account when making the final estimate. In either case, the accuracy of the estimate is improved.

In the longer term, use of the model may also have other positive benefits. Not only will using the model add a more objective model to the estimator's "toolbox" of analytical techniques, but the model will also ensure proper feedback of the estimator's performance. This is ensured by the fact that the model will require lots of up to date data for training an accurate network. Thus, the final project data will have to be collected, thus putting the structures in place which will allow the performance of early stage estimation to be evaluated. This feedback will help the estimators to have a realistic idea of how accurately they can estimate. It will also provide them with an opportunity to evaluate which modelling techniques have been most appropriate for a particular project, and hence influence the confidence they place in each technique. This would allow estimators to make an informed choice as to the confidence placed in each of the estimating techniques they use.

Thus, the use of the predictive model has great potential not only for providing objective comparisons between the coast different options for the project - including the procurement route - or for providing an accurate benchmark estimate for the cost of the project. It could also, provided it is implemented carefully, play a key role in improving the accuracy the early stage estimation of the cost of a project into the next millennium.

3 NEURAL NETWORKS AND THE COMING MILLENIUM

The potential benefits of using a neural network for early stage cost estimation have already been outlined. However, the use of neural networks is not restricted merely to this small subset of cost estimation. The fact that they can model complex relationships between a number of significant variables without those relationships having to be identified or quantified makes them highly suitable for many other areas of project planning. It is likely that this scope will be capitalised on, and that neural networks could become quite common among planning and estimation tools in the coming millennium.

3.1 Expansions and acceptance of technology

It has already been shown how the predictive model for early cost estimation should become part of the estimator's toolbox. O'Brien (1992) explains that estimators tend not to depend on one technique, but to use a number of techniques, and then apply critical judgement to obtain an estimate. This applies not only to early stage cost estimation, but to the practice of estimating in general. This means that wherever neural networks are shown to be accurate predictive models, they must surely be incorporated into the estimator's toolbox. This incorporation would, as for the early stage forecasting model, encourage feedback of the accuracy of the estimates made, and hence improve the estimator's performance.

This value of feedback in evaluating the efficacy of techniques is not, however, restricted to existing techniques. The same critical judgement which might be applied to techniques that estimators already use widely might also be applied to any new techniques which emerge. Research into estimation will continue, and will almost certainly continue to yield new techniques. If feedback structures are already in place, then estimators will be much more equipped to evaluate the performance for themselves. This not only provides a much more objective criterion for the rejection or acceptance of a model, but also provides the researcher with a clear indication that the new model does not perform. If a model is not used widely then it is because it does not yield sufficiently accurate estimates, rather than because of industry prejudice. It should therefore either be improved or scrapped.

This process not only provides for the expansion of neural network models the practice of estimating, but also provides the structure for new technology to be accepted more readily, where appropriate. This should permit the accuracy, and hence the quality, of estimating to be consistently increased in the future.

4 CONCLUSIONS

The process and quality of estimating, particularly early stage estimating, has largely failed to meet up to the expectations of the late twentieth century. Estimators tend to consider their estimates more accurate than they are, and use this opinion to justify their rejection of new techniques. However, it has been shown how research currently underway at UMIST could lead the way to a radical change in the practice of early stage cost estimation.

A model is being developed which will be able to predict the final cost of a building using only information typically available at the early stage. This model is objective, as it uses past project data to make its estimates. It has been shown how such a model could form an invaluable tool for the early stage cost estimator. This arises both from the provision of objective information, and the process of feedback of information which implementation of the model would engender.

Furthermore, it has been determined that neural networks would be suitable for other estimating problems, and that the resultant feedback could create an industry which is far more responsibly receptive to new technologies.

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