BESPOKE PRECAST PRODUCTIVITY ESTIMATION WITH NEURAL NETWORK MODEL

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Bespoke precast-concrete components are custom made for construction projects. The variety of product designs results in requiring different manufacturing time. To estimate the productivity of four precast routines, this study identifies twenty influential factors based on the difficulty in product designs and manpower. These influential factors are such as nominal height, length, and width, tiling area, the number of curves, the number of embedded parts, concrete strength, slump, reinforcement weight, and the number of different bar shapes, etc. Productivity estimation models are formulated using two techniques: neural network (NN) and multivariable linear regression (MLR). The estimation performance from both techniques is measured with three statistical values, namely absolute percentage error, mean square error, and correlation coefficient. The experimentation results show that MLR gives insignificantly better performance than NN. However, standardised residuals from the NN are distributed in the narrower range than the ones from the MLR.

Keywords: bespoke precast-concrete production, multivariable linear regression, neural network, productivity estimation.

INTRODUCTION

Estimation is a necessary assignment in construction management. It includes cost (bid preparation, budget), time (productivity, project schedule), or quality estimation. Despite from that, the estimation is complicated, intuitive and approximate. For the productivity estimation, there can be so many factors that influence the productivity of construction tasks because the tasks involve long sequential processes, craftsmanship, many materials and tools, and changeable site conditions. Some of the factors are easily recognised; some of them may not. Also, the extent of these factors affect the productivity is difficult to identify. To avoid these problems, an empirical estimation technique has been used. The technique is based on estimators' experience to consider current task conditions and to adjust a standard productivity figure in a handbook for a suitable value. It is a simple technique but lacks of consistency and learning from the past cases (Chao and Skibniewski, 1994).

For bespoke precast-concrete production, precast components are custom made for a construction project. The construction tasks are brought into a factory where there is a controlled working environment. The productivity estimation of precast manufacturing is strongly required for arranging a production schedule. Factors that are identified to affect the productivity are the difficulty in custom product designs. This paper reports a study of the estimation of bespoke precast productivity using two computing techniques: neural network (NN) and multivariable linear regression (MLR). The productivity model with neural network is developed for bespoke precast

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production named BPPE-NN. The performance of the BPPE-NN model is reported and compared with the MLR model.

AVAILABLE PRODUCTIVITY ESTIMATION TECHNIQUES

The productivity estimation is based upon the assumption that there are certain relationships between a set of influential factors and productivity in the past events. Therefore, the productivity of the future events can be estimated by determining these relationships and specifying values for the influential factors. This section investigates available techniques of determining the relationships.

The first technique is statistic-based called the multivariable linear regression. It attempts to map the relationships between the influential factors and the productivity with the explicit mathematical functions. The mapping functions are initially presumed and later evaluated. They could be linear functions (multivariable linear regression) or non-linear functions (multivariable non-linear regression). However, the statistical technique could oversimplify the relationships comparing with the neural network technique (Sonmez and Rowings, 1998; Yeh, 1998; Smith, 1999; Leung et al., 2001).

The second technique that has been widely used in recent research for identifying the relationships is the neural network. The neural network technique imitates a pattern recognition process of a human brain (Wasserman, 1989; Rumelhart et al., 1986). Rather than identifying explicit functions for the relationships, the neural network technique leaves the relationships in a ‘black box’. The network ‘learns’ to map the input patterns with the output patterns during the training process and subsequently is applied to new and unseen data. The advantages of neural network over the statistical technique are the ability to capture complex multivariable non-linear relationships, and interrelationships among influential factors. Many applications of neural network in construction research have been found including the estimation of cost, quality, and productivity ([Cost] Chua et al., 1997; Hegazy and Ayed, 1998; Adeli and Wu, 1998; Yeh, 1998; [Quality] Lai and Serra, 1997; Liu, 1997; [Productivity] Chao and Skibniewski, 1994; Portas and AbouRizk, 1997; Sonmez and Rowings, 1998; Leung, et al., 2001; AbouRizk et al., 2001).

Previous productivity estimation studies showed influential factors largely based on the working environment (such as, temperature, site condition, or equipment setting, etc) with little attention to designs. Since their models were the construction tasks which executed on site. On the other hand, this study proposes a productivity estimation model for precast manufacturing tasks. The precast manufacturing tasks are generally similar to the construction tasks but they are executed in a different, more controllable environment. The next section is the investigation of the bespoke precast production to identify the influential factors and develop the productivity estimation model.

BESPOKE PRECAST PRODUCTIVITY MODEL FORMULATION

In this research study, bespoke precast-concrete manufacturing is modelled with the neural network. The developed model is named as ‘Bespoke Precast Productivity Estimation with Neural Network Model’ (BPPE-NN). The target productivity values of the estimation are specified. The influential factors affecting productivity of these routines are identified. The neural network is then formulated with suitable network architecture. The other network’s details, such as normalising (scaling) input and

output data, configuration and parameters, and the criteria for measuring the network's performances, are also explained.

Bespoke Precast-Concrete Manufacturing

Four main routines of the bespoke precast-concrete manufacturing, namely '*mould preparation*', '*casting*', '*mould stripping*', and '*finishing*' are considered in the BPPE-NN. Planners need to estimate processing times or durations of these routines in order to arrange a production schedule. Therefore, the productivity of the routines is defined in terms of durations for accomplishing the routines and these terms are the values to be estimated (see Equation 1). The duration of a routine starts counting when an ongoing product is handed over to the crew, and stops when it is passed to a consecutive routine. This is a theoretical definition as in practice there could be a slight overlapping time between two consecutive routines.

Equation 1: $(Duration)_i = (WorkOutput)_i / (Productivity)_i$

Where: i is the identity for a routine of a product; and $(WorkOutput)_i$ *is a known variable.*

Bespoke precast products are custom made. New and unseen product designs are always expected; for example, one construction project may require more than a hundred different designed products. Each of them requires different durations for those routines. These figures are the values to be estimated.

Productivity Influential Factors

It is difficult to exhaustively determine all factors affecting labour productivity. Many productivity models have proposed different sets of these factors. Russell (1993) considered factors, such as weather, site conditions, owner/consultants, design/drawings, work force, availability of materials, tools, equipment, and schedule. Sonmez and Rowings (1998) developed productivity models for concrete pouring, formwork, and concrete finishing tasks with NN. Their influential factors were quantities, job type, crew size, overtime, percent labourer, temperature, humidity, precipitation, and concrete pump. AbouRiszk et al. (2001) identified 33 influential factors affecting labour production rate under nine groups including construction project characteristics, site, labour, equipment, project difficulty, activity conditions, quantity, design, and activity difficulty. Thomas et al. (2003) identified demotivators and their effects on the productivity of workers in civil engineering projects. Most significant demotivators are material availability, overcrowded work areas, and rework. Srinavin and Mohamed (2003) have proposed a relationship model between construction worker productivity and thermal environment.

Yeh (1998) suggested that if an influential factor has a very small variation (considered as a constant rather than a variable), their effects could be very small and could be neglected from a model. In this way, the controlled environment within a precast concrete factory should remove a number of the influential factors. However, in a *bespoke* precast production, there is a large variation of product designs. Therefore, the difficulties in product designs should contribute important influences. In this BPPE-NN, 20 influential factors that affect the productivity of the precast routines are categorised into three main groups namely product shape, materials, and manpower.

A precast product design is extracted 16 characteristics from its shape, and materials. They are as the following:

- '*Nominal height*' is the vertical dimension, '*nominal length*' is the longer horizontal dimension, and '*nominal width*' is the other horizontal dimension of a product.
- '*Base area*' is the area that is on the bottom when a product is being cast; normally it equal to length multiplied by width.
- '*Top surface area*' is the area that are on the top and do not contact with the mould.
- '*Dropping area*' is the area that a panel has dropped its nominal height.
- '*Finishing area*' is the area of concrete finishing area on the top surface area.
- '*Tiling area*' is the area that is pasted with tiles.
- '*Volume*' is the total concrete volume of a product.
- '*Weight*' is a weight of a product calculated from a concrete weight and all embedded parts' weights.
- '*Number of curves*' is the counting number of curve surfaces along a product's shape; for example, a curve surface of a window, or a curve surface of a balcony.
- '*Number of embedded parts*' is counted from all embedded parts, which are not reinforcement, such as lifting point blockouts, duct blockouts.
- '*Concrete strength*', and '*slump*' of the used concrete are determined.
- '*Reinforcement weight*', and '*number of different bar shapes*' are determined from the bar list table provided on a product design drawing.

The four remaining factors come from '*the number of workers*' on each routine, i.e. mould preparation, casting, mould stripping, and finishing that have been used on that product. Information of shapes and materials of a product is obtained from a product shop-design as shown in Figure 1. For manpower information, the numbers of workers on each of four routines can be obtained from a factory daily-report. The sample data-sets of the 50 different precast products were collected from a leading bespoke precast-concrete manufacturer in UK. These data-sets are used for designing architecture and evaluating performance of BPPE-NN.

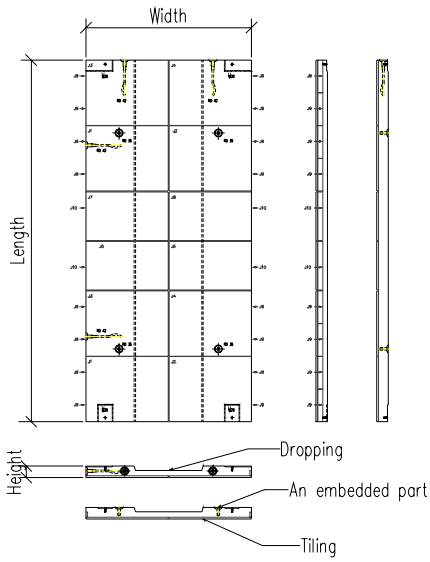


Figure 1 Information from a shape of a precast product design

BPPE-NN's Architecture Development

The common practice of designing NN's architecture is through trial-and-error. The first step is to develop the NN with a common architecture and rule-of-thumb settings, then evaluate the NN's performance, and adjust the parameters to improve the NN's performance. Fundamental knowledge and common terms of NN can be obtained from Wasserman (1989) and will not be detailed in this paper. Chua et al. (1997) suggested that the number of processing elements (PEs) in the hidden layers is usually bounded by the number of input and output processing elements. If too many hidden PEs are used, the network will form a rigid pattern on the training samples so that it will not generalise (over-training) and tends to memorise the training samples. Figure 2 shows the flowchart of the BPPE-NN's architecture design with a trial-and error procedure.

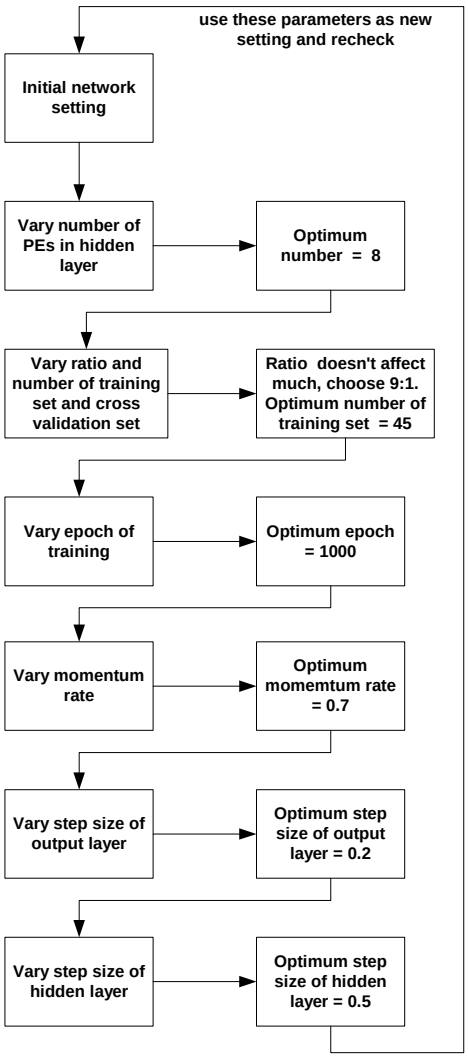


Figure 2 Trial-and-error design of the BPPE-NN's architecture

Through the trail-and-error, the multi layer perceptrons (MLP) with feedforward and back-propagation train is finally selected as the BPPE-NN architecture. The BPPE-NN has full connection of three layers. The hidden layer with the optimum number of hidden PEs is 8. The input layer has 20 PEs for all of the influential factors, and the output layer has 1 PE for each estimated value. The BPPE-NN is divided into four

networks for four estimated outputs. Commercial software used in the study is '*Neural Solutions*' (NeuroDimension, Inc.) to perform calculations and analyses.

The transfer function of processing elements (PEs) is the hyperbolic tangent (tanh). All data, both inputs and desired outputs, are normalised before used because the transfer function, the hyperbolic tangent, is sensitive to inputs within range (-1, 1) and its outputs are within range (-1, 1). The following normalising formula has been used:

Equation 2: $d_i = (A_i \times D_i) + C_i$

Where: d_i *is a normalised value;* D_i *is an actual value;*

$A_i = (UB - LB)/(D_i^{\max} - D_i^{\min})$; $C_i = UB - A_i \times D_i^{\max}$; $D_i^{\max}$ *and* $D_i^{\min}$ *are the maximum and minimum values found within a data set channel i; and UB and LB are the upper bound and lower bound values entered to the PEs.*

Network outputs are later denormalised using the same Equation (2). The final networks of BPPE-NN use the momentum learning rule method with the momentum rate = 0.7, the step size of output layer = 0.2, and the step size of hidden layer = 0.5.

Performance Measurement

Adeli and Wu (1998) mentioned that the best estimate could be defined as the estimate that minimizes the average error between the actual and estimated outputs. Many statistical values are used to quantify the estimation error, such as the absolute percentage error (APE), the mean square error (MSE), and the correlation coefficient (r). These are used for quantifying the error in the BPPE-NN. They are defined by the following Equations (3)-(5). The BPPE-NN's performance is measured at both training and testing stages:

Equation 3: $$APE = \frac{\sum_{i=0}^{N} (d_i - y_i)/d_i}{N} \times 100$$

Equation 4: $$MSE = \frac{\sum_{i=0}^{N} (d_i - y_i)^2}{N}$$

Equation 5: $$r = \frac{\frac{1}{N}\sum_{i=0}^{N} (d_i - \mu_d)(y_i - \mu_y)}{\sigma_d \times \sigma_y}$$

Where: N *= number of exemplars in the data set;* y_i, d_i *= network output and desired output for exemplar i, respectively;* μ_y, μ_d *= mean of network output and desired output data-sets, respectively;* σ_y, σ_d *= standard deviation of network output and desired output data-sets, respectively.*

Yeh, 1998 noted that the NN's performance could be measured by the learning speed (efficiency) and generalisation capability (accuracy) of the network. From the BPPE-NN's architecture design, the network parameters have been set with the optimum values to ensure the efficiency of learning process. Also cross validation method has been used to control the generalisation of the networks.

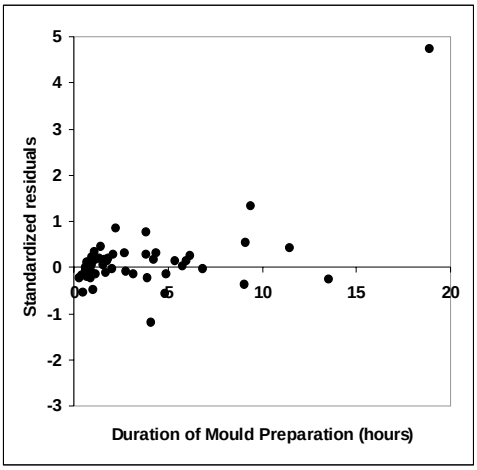
BPPE-NN's Training and Results

The data-sets are randomly divided into a 'training' set (45 data-sets), and a 'testing' set (5 data-sets). The BPPE-NN is trained with data from the training set while the testing set is applied during the training procedure to check the learning performance. '*Cross validation*' method is to test the NN with some data taken from the testing set and while it is being trained. The training procedure will be terminated if the error from the cross validation increases. The cross validation can prevent the NN memorising the training data patterns. Another setting is to reduce the size of BPPE-NN by separating the model into four networks for the four outputs so that they can 'learn' faster.

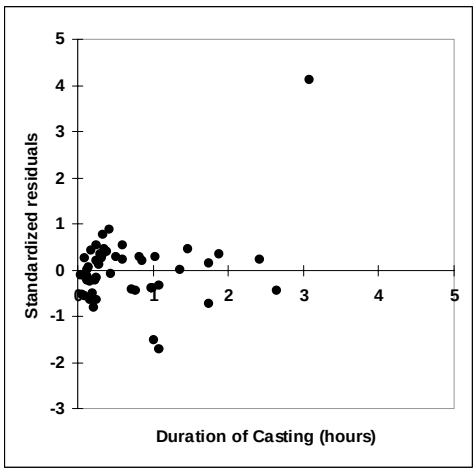
The BPPE-NN is trained with three repeated run times to collect the best result. Then the testing set is reselected ten times for different data-sets to cover all sample data-sets. This strategy of reselection of testing set is proposed and named as the 'rotating testing set' method. The idea is to use the sample data-sets for a training set as many as possible without scarifying the generalisation of the testing results. Even there is a small amount of testing set on a network training run, the testing set will be reselected on the next run and then cover all the sample data-sets. Results from the BPPE-NN's training procedure are shown in Table 1. Graphs of the actual (desired output) and standardised residuals of the estimated (output) durations of four precast routines are shown in Figure 3.

Table 1 BPPE-NN's training results

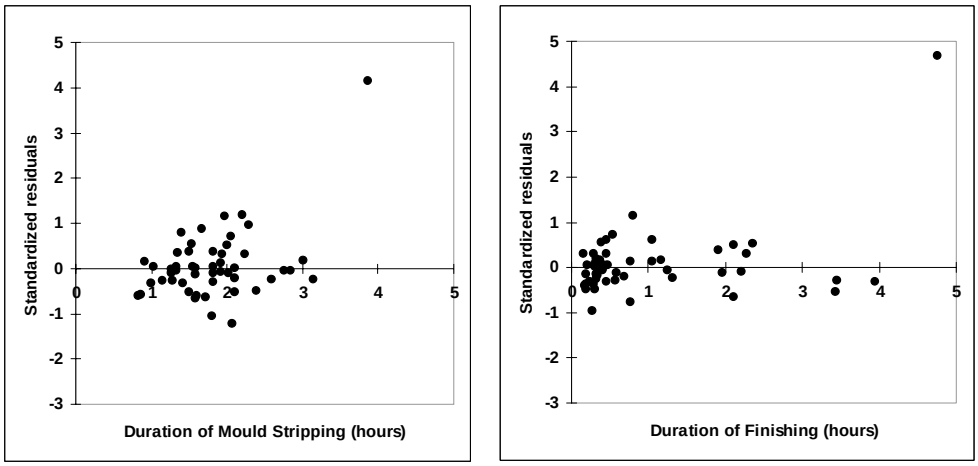
Average of All Runs	Mould Preparation		Casting		Mould Stripping		Finishing	
	Training	Cross Validation	Training	Cross Validation	Training	Cross Validation	Training	Cross Validation
Minimum normalised MSEs	2.86E-04	5.35E-03	2.06E-04	1.14E-03	1.70E-04	3.96E-03	2.83E-04	1.29E-03
Final normalised MSEs	2.86E-04	8.66E-03	2.06E-04	1.54E-03	1.70E-04	4.65E-03	2.83E-04	1.85E-03



(a) Mould preparation



(b) Casting



(c) Mould stripping (d) Finishing

Figure 3 Graphs of actual values and standardised residuals from BPPE-NN

The BPPE-NN's training results show in all cases that the minimum and final MSEs of the training hold the same values while the final MSEs of cross validation are larger than the minimum MSEs of cross validation. When the training MSEs gradually reduced, there is no reduction in the cross validation MSEs. This meant the networks started memorising the training patterns. The training run is forced to end soon after that and the networks' weights are taken from the epoch that gives the smallest cross validation MSEs. The networks are poorly generalised, as there is a large difference between training and cross validation MSEs in all cases. The estimation results indicate that most (90%-95%) standardised residuals are narrowly distributed within the range (-1, 1). However, there is one data-set with a result significantly outside the range as shown in Figure 3 (a) to (d). That data-set affects the average performance of BPPE-NN. It is suspected that there was a mistake when recording this data-set or there is a fault extrapolation from the out-of-range data-set.

MULTIVARIABLE LINEAR REGRESSION

Bespoke precast productivity is also modelled using the multivariable linear regression (MLR) technique. The relationships between each productivity value and all influential factors are described by Equation (6) below:

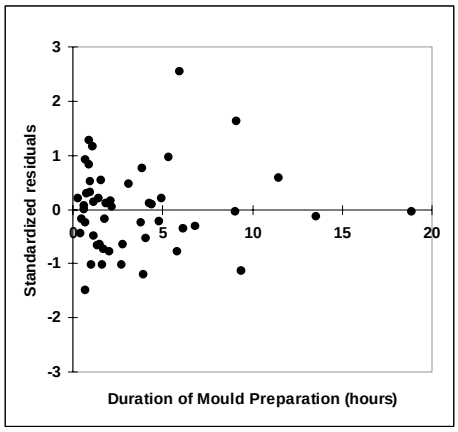
Equation 6: $y = A_0 + \sum_{i=1}^{n} A_i x_i$

Where: y is an estimated output variable; x_i *is a variable of an influential factor i;* A_i *is a coefficient;* A_0 *is a constant or an intercept; and n is the number of influential factors.*

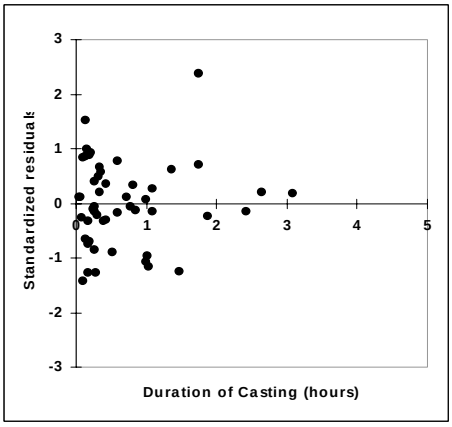
Results from the multivariable linear regression are shown in Table 2. Graphs of the actual values and the standardised residuals of four precast routines are show in Figure 4.

Table 2 Parameters from MLR

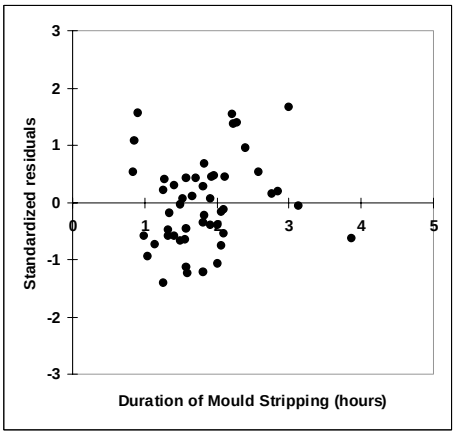
i	Parameter	Mould preparation			Casting			Mould stripping			Finishing		
		A_i	t	Pr > t	A_i	t	Pr > t	A_i	t	Pr > t	A_i	t	Pr > t
0	Intercept	*-4.06*	-2.91	0.007	*-0.25*	-0.97	0.339	*-1.17*	-2.24	0.033	*-0.22*	-0.81	0.423
1	Height	*1.03*	3.12	0.004	*0.04*	0.70	0.489	*0.72*	5.78	< 0.0001	*0.05*	0.75	0.457
2	Length	*0.73*	4.23	0.000	*0.05*	1.61	0.119	*0.04*	0.58	0.567	*0.00*	-0.13	0.896
3	Width	*0.96*	2.33	0.027	*-0.02*	-0.23	0.820	*0.16*	1.03	0.313	*-0.04*	-0.45	0.655
4	Base area	*-0.63*	-2.86	0.008	*-0.04*	-0.89	0.381	*-0.09*	-1.10	0.281	*0.01*	0.14	0.894
5	Volume	*-1.00*	-1.01	0.321	*0.06*	0.36	0.723	*-0.03*	-0.09	0.927	*-0.27*	-1.41	0.170
6	Weight	*0.00*	1.23	0.228	*0.00*	-0.19	0.852	*0.00*	0.66	0.515	*0.00*	2.54	0.017
7	No. of curve	*0.42*	1.98	0.057	*0.00*	0.03	0.978	*0.14*	1.71	0.098	*0.08*	1.98	0.058
8	No. of blockout	*0.09*	1.01	0.319	*0.01*	0.69	0.496	*0.13*	3.68	0.001	*0.04*	2.47	0.019
9	Surface area	*0.20*	1.94	0.062	*0.01*	0.41	0.684	*-0.05*	-1.26	0.218	*0.06*	3.04	0.005
10	Dropping area	*1.07*	11.39	< 0.0001	*0.00*	0.19	0.848	*0.31*	8.85	< 0.0001	*0.08*	4.39	0.000
11	Finishing area	*-0.07*	-1.00	0.325	*0.08*	6.70	< 0.0001	*-0.03*	-1.14	0.264	*0.10*	7.15	< 0.0001
12	Strength	*0.00*	-0.39	0.699	*0.00*	1.03	0.314	*0.00*	-0.65	0.524	*0.00*	0.32	0.754
13	Slump	*-0.05*	-1.43	0.164	*-0.03*	-5.10	< 0.0001	*-0.02*	-1.96	0.060	*-0.01*	-1.04	0.306
14	Tiling area	*0.49*	3.50	0.002	*0.05*	2.14	0.041	*0.07*	1.32	0.197	*0.14*	5.11	< 0.0001
15	Rein.by weight	*0.02*	3.25	0.003	*0.01*	6.84	< 0.0001	*0.00*	-2.25	0.032	*0.00*	-1.15	0.261
16	No.of diff.shape	*0.10*	2.41	0.022	*0.02*	2.44	0.021	*0.01*	0.77	0.449	*0.00*	0.17	0.864
17	MP of mould prep.	*0.38*	3.90	0.001	*0.03*	1.61	0.117	*0.04*	1.09	0.285	*0.01*	0.57	0.572
18	MP of casting	*0.16*	1.62	0.116	*0.06*	3.47	0.002	*-0.01*	-0.39	0.699	*-0.02*	-0.92	0.366
19	MP of mould strip.	*-0.12*	-1.29	0.206	*-0.02*	-1.14	0.262	*0.46*	13.26	< 0.0001	*-0.02*	-1.36	0.185
20	MP of finishing	*0.35*	1.72	0.097	*0.00*	-0.03	0.977	*-0.02*	-0.27	0.785	*0.17*	4.33	0.000



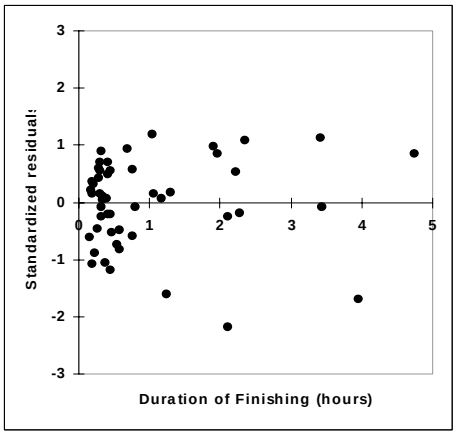
(a) Mould preparation



(b) Casting



(c) Mould stripping



(d) Finishing

Figure 4 Graphs of actual values and standardised residuals from the MLR

The parameter results from the MLR show that the ‘dropping area’ parameter has the most significant relationship with the ‘moulding preparation’ routine because it had the biggest t-value and the least p-value. In similar ways, ‘reinforcement by weight’, ‘finishing area’, and ‘slump’ parameters have the most significant relationships to the ‘casting’ routine; ‘height’ and ‘dropping area’ to the ‘mould stripping’; and ‘finishing area’ and ‘tiling area’ to the ‘finishing’. The estimation results show that 75%-80% of all standardised residuals are distributed within the range (-1, 1).

RESULT COMPARISONS

The estimation performances of the two techniques are compared using three error measurements as shown in Table 3. It can be seen that the MLR technique gives insignificantly better results than the NN technique in almost all comparisons. The NN technique only gives slightly better APEs in the ‘casting’ and the ‘mould stripping’ routines. However, standardised residuals from the NN are distributed in the narrower range than the ones from the MLR. This means NN can give ‘more often’ precise estimated values. Finally, in terms of calculation complexity the MLR technique is less complicated and requires less computation time than the NN.

Table 3 Estimation performances of the MLR and NN techniques

Mould Preparation		
Measurement	NN	MLR
APE	17.4	14.0
MSE	0.669	0.083
r	0.981	0.997
Casting		
Measurement	NN	MLR
APE	13.4	16.8
MSE	0.005	0.003
r	0.995	0.997
Mould Stripping		
Measurement	NN	MLR
APE	4.0	5.6
MSE	0.015	0.012
r	0.981	0.984
Finishing		
Measurement	NN	MLR
APE	10.5	8.8
MSE	0.013	0.003
r	0.995	0.999

CONCLUSIONS

This paper reported the study of the bespoke precast productivity estimation. The productivity models have been formulated and verified with sample data-sets. Four productivity values for four main bespoke precast manufacturing routines are estimated. Twenty influential factors are identified based on the variations in precast product designs and the number of workers on each routine. The NN and MLR techniques are used for modelling and their results are then compared. The ‘rotating testing set’ method has been used in the network training process.

The results from the experimentation are different from the other research that the estimation performance of the MLR model is slightly better than that of the NN model. It is concluded that BPPE-NN is comparable to the MLR model. They can be implemented together as BPPE-NN will give more often precise estimated values while the MLR model will help cross examine the results and to alert the fault extrapolation from BPPE-NN. However, the reliability of both models much depends on the exhaustiveness of influential factors, and an amount and the representativeness of historical data.

In a long-term implementation, the BPPE-NN is based on a large amount of historical data. Its estimation performance is anticipated to be better and better because its ability to be generalised to match future cases. Also, the BPPE-NN supports the automation in the estimation process and integrates data to product design process. Precast-concrete manufacturers potentially benefit from the model through the more accurate but less effortful estimation.

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