Estimating Construction Materials Price Indices of Private Financial Initiative in Malaysian East Coast Region

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Abstract: - The major phase that needs to be given main attention in Private Financial Initiative program in Malaysia is value for money, where optimum efficiency and effectiveness of each expense are successfully attained. In this paper, estimating unitary charges or materials price indices in each region in Malaysia was the key objective. Here, we aim to discover the best forecasting method to estimate unitary charges price indices of construction industry in the East Coast region of Peninsular Malaysia (Johor). The unitary charges indices data used were monthly data from year 2005 to 2011 of different construction materials price indices in the East Coast region Peninsular Malaysia. The data were the price indices of aggregate, sand, steel reinforcement, ready mix concrete, bricks and partition, roof material, floor and wall finishes, ceiling, plumbing materials, sanitary fittings, paint, glass, steel and metal sections, timber and plywood. Finally, two-layer backpropagation neural network with linear transfer function was found to produce the most accurate and reliable results for estimating unitary charges price indices in East Coast region Peninsular Malaysia based on the Root Mean Squared Errors, where the values for both estimation and evaluation sets were approximately zero and highly significant at $p < 0.01$. Therefore, artificial neural network is sufficient to forecast construction materials price indices in south region of Penisular Malaysia, and this is such a contribution towards realizing the national vision of economical goal, in line with National Key Economic Areas or National Key Result Areas (NKEA or NKRA).

Key-Words: - forecast, price indices, construction, Private Financial Initiative, artificial neural network

1 Introduction

Financial Initiatives (PFI) is just about to germinate in Malaysia akin to the government's aim which is to increase the participation of the private sector in delivering significant eminence of public services. The most important contributing factor of PFI is value for money (VFM), meaning that PFI projects are expected to offer and fulfill the clients' satisfactions parallel to their investments. VFM is known as the maximum amalgamation of whole-life expenses, benefit, risks, and success or contributing factors in order to satisfy clients' requirements with best quality outcome and minimum possible price. Therefore, the performance of VFM should be maximized along all PFI implementations. Consequently, tolerable risk allocation between the public and private sectors is the key to realizing VFM on PFI projects. One of the principal project-related risks is the *design and construction risks* which should always be transferred under PFI projects [1]. Under this risks, fixed price is one key features of the PFI structure in transferring the risks to the PFI contractor, where the unitary charge should be agreed up-front, preventing the contractor from passing-on cost overruns. Therefore, estimating material prices along PFI constructions is important in order to prevail over long term overspending. Since the construction works and services delivery are the major endeavors in the Malaysian PFI, we aim to forecast the index of construction material price indices in Malaysia. It is well known that cement controlled price has been cancelled by Malaysian government, commencing 5 June 2008 [2]. Since that cancellation, price of cement had increased dramatically in June 2008 by 23.3% at Malaysia, whereas 6.5% in Sabah and 5.2% in Sarawak [2]. This scenario then repeated on many other construction materials such as steel, ready mix concrete, brick, aggregate, sand, mild steel round bar, high tensile deformed bar and others. In the sense of the uncertainty of construction material prices in Malaysia, we attempted to ferret out the best method to estimate construction material prices by regions in Malaysia. Subsequently, section II discusses on the related literatures, and section III describes the background of data used in this study. Under section IV, an overview of the methods used to analyze the data is well explained. Furthermore, section V presents the finalized results and discussion on the best forecasting method to estimate material price indices by regions in Malaysia. Finally, section VI presents a short wrapping up of the study and a recommendation for future endeavor.

2 Related Literatures

Cement and Concrete Association of Malaysia executive director, Grace Okuda [3] agrees that market forces of supply and demand will determine the price construction materials. This uncontrolled escalation of constructions material price in the construction industry has caused significant financial hardships for unprepared suppliers, subcontractors, contractors and owners [4]. It is also forcing owners and practitioners alike to confront new challengers in reaching their individual pricing goal. Moreover, there are many contributing factors to the recent material price spiking in the construction industry, mainly involve both local and international market forces [5].

The Tenth Malaysia Plan (RMK-10) is expected to stabilize the cement price and PFI projects in the effort of welcoming the future. This material price escalation issues are normal phenomena for all economy sector. The effective project management and proper estimation of construction material prices may reduce the effect of material price fluctuations, and at the same time, construction project can be executed properly.

In the forecasting area, there exist various models in numerous forecasting attempts or issues. In a current study, Padhan [6] found that SARIMA model performed the best in forecasting cement productions in India. However, many previous studies have proven that Neural Network outperforms classical forecasting techniques and other statistical method. For example, Kaastra & Boyd [7] implemented BPNN and ARIMA to forecast future forecasting volumes, and established NN forecasting as benchmark to the ARIMA model. In the meanwhile, Franses and Griensven [8] found that ANNs outperform linear models for forecasting daily exchange rates. In a study, Pei Liu et.al [9] establishes quarterly and monthly cement forecast in Taiwan context using SARIMA and ANN techniques. Therefore, we also intend to determine the forecasting methods or models that best suit the Malaysian's monthly construction material cost indices data, whether conventional or NN approaches.

3 Data Background

In this section, the data background is discussed. The data were collected from three different sources which are, Unit Kerjasama Awan Swasta (UKAS) of Prime Minister's Department, Construction Industry Development Board (CIDB) and Malaysian Statistics Department which specified on PFI construction material price indices from East Coast region of Peninsular Malaysia which consist of three states Pulau Pinang, Kedah and Perlis. Monthly data from year 2005 to 2011 of fifteen different construction material price indices were used. The fifteen construction materials are aggregate, sand, steel reinforcement, ready mix concrete, bricks and partition, roof material, floor and wall finishes, ceiling, plumbing materials, sanitary fittings, paint, glass, steel and metal sections, timber and plywood.

Practically, input price index is used to measure changes in the transaction price of building material input to the construction process by tracking movements of transaction prices of Malaysian manufactured and CIF (Cost Insurance Freights) imported building materials. By this way, the materials cost factor for the selected building types can be monitored effectively [10].

The main purpose of the Building Materials Cost Index is to measure changes in the cost of an item or group of items from time to time. Monthly data were chosen with standard base cost index the value of 100 of year 2003, where all past and future increases or decreases being related to this figure.

In general, there are several of uses to which these indices are applicable in the construction industry. Some of them are as follows:

1. Continuous revision of elemental cost analysis;
2. Calculation for material price fluctuations;
3. Examination of changes in cost relationships;
4. Extrapolation of existing trends;
5. Assessment of economics market conditions; and
6. Research endeavours

In this study, we are interested to Malaysian PFI material price indices values in the future. In this particular study, we try to estimate the material price indices using the best model starting from January 2012 to January 2013.

4 Overview of the Methodology

The research flow to determine the best estimation model of the cement prices in different regions in Malaysia can be seen in Figure 1. Practically, the classical methods that are commonly used by practitioners in any fields involve trendlines, Autoregressive Moving Average (ARMA), and time series. We adapted these three common forecasting methods in this study, and at the same time we compared those methods with a modern forecasting method called artificial neural network (ANN). In forecasting world, neural network is usually used in stock markets to predict either stock prices or returns. In this study, we applied backpropagation neural network (BPNN) method to forecast the future cement prices using historical data. The BPNN approach implemented on the data was known as unsupervised learning due to unknown target output. The results executions were then compared with the results executed using classical methods based on Root Mean Squared Errors (RMSE). To be detailed, the trendline models used were linear, logarithmic, polynomial, power, exponential and moving average. Then time series approach applied were single exponential smoothing, double exponential smoothing, Holt-Winter's additive, Holt-Winter's multiplicative, seasonal additive, seasonal multiplicative, single moving average and double moving average. The best-fitting test for the moving average forecast uses the root mean squared errors (RMSE). The RMSE calculates the square root of the average squared deviations of the fitted values versus the actual data points. Root Mean Square Error (RMSE) is the square root of MSE and is the most popular error measure, also known as the quadratic loss function. RMSE can be defined as the average of the absolute values of the forecast errors and is highly appropriate when the cost of the forecast errors is proportional to the absolute size of the forecast error. The RMSE is used as the selection criteria for the best-fitting time-series model.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i-1}^{N}(y_i - \hat{y}_i)^2} \qquad (1)$$

where y_i represents a vector of N predictions and $\hat{y}_i$ denotes the vector of actual values.

5 Overview of the Methodology

Based on Table 1 and Table 2, most of the models data were all significant at 95 percent confidence level. Based on the Root Mean Squared Errors (RMSE) of both estimation and evaluation sets, neural network has been proven to outperform the other conventional forecasting methods.

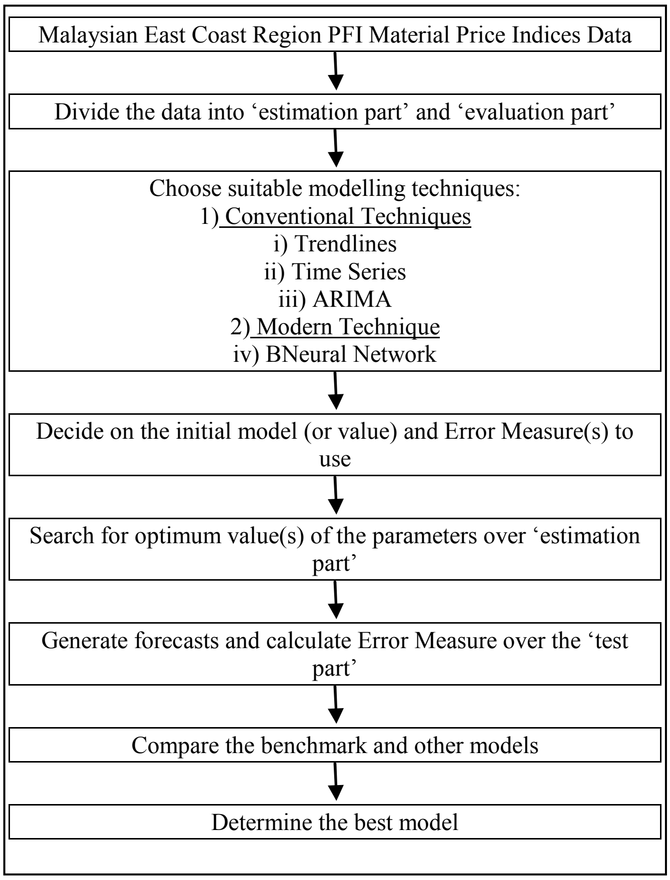

Fig. 1 Flow of methods implementation in this study

From Table I, using the estimation sets, it can be clearly seen that BPNN with linear transfer function showed the best model to estimate the material price index of Malaysia PFI construction project based on the RMSE, where the values were all almost zero errors and outperformed all other methods.

To be detailed, from Table 1, the RMSEs of estimation sets were aggregate (1.23001), sand (0), steel reinforcement (1.23786), ready mix concrete (0), bricks and partition (1.23232), roof material (0), floor and wall finishes (0), ceiling (1.23868), plumbing materials (1.23867), sanitary fittings (0), paint (1.23734), glass (1.23171), steel and metal sections (1.23114), timber (0) and plywood (0). The similar can be observed in Table 2 whereby the performance of BPNN with linear transfer function on evaluation sets showed the smallest RMSEs, nearing zero errors and outperformed other methods. For instance, aggregate (1.4681), sand (1.4019), steel reinforcement (1.4345), ready mix concrete (1.4682), bricks and partition (1.4314), roof material (1.4030), floor and wall finishes (1.4681), ceiling (1.4363), plumbing materials (1.4567), sanitary fittings (1.4682), paint (1.4354), glass (1.4314), steel and metal sections (1.4324), timber (1.4014) and plywood (1.4011). Table 3 shows the estimation values of material price indices using BPNN with linear transfer function different regions in Malaysia from January 2012 to January 2013, prediction of the 84^{th} to 96^{th} periods.

6 Conclusion

In this particular study, artificial neural network is proven to produce the best forecasting results compared to the other classical forecasting techniques. The finding is parallel to our previous research where we did forecasting on cement price index by different regions in Malaysian [11]. In this study, two-layer backpropagation neural network is proven proficient to estimate material price indices of PFI projects with respect to the different regions Malaysia. However, other modern ensemble ARIMA-ANFIS should be given an attention in the future attempt, such one that has been proposed by Suhartono, Puspitasari, Akbar & Lee [12]. The two-level forecasting model was developed by implementing Autoregressive Integrated Moving Average (ARIMA) model on the first level and Adaptive Neuro Fuzzy Inference System (ANFIS) on the second level.

For further endeavor, we will examine the construction material cost indices of the other four different regions in Malaysia which are north, south, west and Sabah Sarawak. We will soon determine the best forecasting models for every material group of different states in the four regions in Malaysia. The estimated price indices of construction materials will contribute significantly to the value for money of PFI as well as realizing the national vision of economical goal, in line with National Key Economic Areas or National Key Result Areas (NKEA or NKRA).

Acknowledgement

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Table 1. RMSEs of Estimation Sets

FORECASTING METHOD	THE ROOT MEAN SQUARED ERRORS (RMSE) AND SIGNIFICANCE LEVEL OF EACH METHOD IMPLEMENTED														
	Aggregate	*Sand*	*Steel Reinforce-ment*	*Ready Mix Concrete*	*Bricks and Partition*	*Roof Material*	*Floor and Wall Finishes*	*Ceiling*	*Plumbing Materials*	*Sanitary Fittings*	*Paint*	*Glass*	*Steel and Metal Sections*	*Timber*	*Plywood*
1) TRENDLINES															
Linear	24.8374	62.1837	78.3873	86.2873	86.3286	8.6273 *	7.8600 *	4.7473 *	10.1721 *	3.2170 **	10.1787 *	7.4423 *	23.7862	14.7441	8.7086 *
Logarithmic	17.7814	23.8671	78.7808	86.7421	24.8734	8.7237 *	3.3743 *	7.1244 *	8.7478 *	2.4730 *	8.8283 *	7.4473 *	23.3868	18.8638	8.8718 *
Polynomial	24.7837	18.0842	42.8602	24.8028	24.8740	7.7418 *	7.2177 *	4.4710 *	7.4714 *	2.6867 **	7.2184 *	3.4178 *	21.7470	86.4862	8.3287 *
Power	17.3086	23.7474	23.7868	21.2047	24.8486	8.7470 *	3.8631 *	7.0383 *	8.8040 *	2.3837 **	8.8723 *	7.3742 *	23.7347	18.7081	8.2186 *
Exponential	86.2814	62.7473	32.1214	86.7172	86.4707	8.3473 *	7.4870 *	4.8623 *	10.1803 *	3.2423 **	10.7860 *	7.7237 *	23.7823	14.2834	8.3038 *
Moving Average	2.2181 **	4.1717 **	10.1073 *	3.7243 **	2.7304 **	2.1868 **	2.4867 **	2.4182 **	2.8084 **	0.2307 **	3.6274 **	1.7021 **	4.7847 **	3.7622 **	2.8783 **
2) TIME SERIES															
Single Exponential Smoothing	7.0738 *	8.2186 *	20.0174	7.3486 *	7.4210 *	4.3623 *	3.6274 **	3.8624 **	3.2121 *	1.2863 **	3.3747 *	2.8211 *	8.4844 *	7.7217 *	7.8378 *
Double Exponential Smoothing	7.0872 *	8.2386 *	20.8683	7.3861 *	7.4743 *	4.3741 *	3.2740 **	3.8632 **	3.2141 *	1.8608 **	3.3871 *	2.7437 *	8.7414 *	7.3821 *	7.8714 *
Holt-Winter's Additive	7.1784 *	8.1782 *	86.6738	7.7370 *	7.3721 *	7.8647 *	2.0217 *	2.8863 **	3.7217 *	2.6844 **	3.8717 *	2.8783 *	24.6248 *	8.3017 *	3.7014 *
Holt-Winter's Multiplicative	7.7321 *	8.2328 *	21.8637	7.8681 *	7.2321 *	7.2841 *	2.0622 *	2.8182 **	3.3824 *	2.6834 **	4.0032 *	2.8471 *	11.4407 *	8.7862 *	7.0721 *
Seasonal Additive	7.1781 *	8.1721 *	86.6728	7.7386 *	7.3718 *	7.8642 *	2.0217 *	2.8863 **	3.7286 *	2.6844 **	3.8734 *	2.8782 *	24.6242 *	8.3724 *	3.7086 *
Seasonal Multiplicative	7.7372 *	8.2324 *	21.8623	7.8621 *	7.2373 *	7.2837 *	2.0622 *	2.8182 **	3.3810 *	2.6834 **	4.0078 *	2.8448 *	11.4402 *	8.7424 *	7.0718 *
Single Moving Average	7.7864 *	10.2340 *	24.3620	8.7217 *	3.6273 *	4.7408 *	2.1212 *	2.8678 **	4.2387 *	1.8632 **	4.2010 *	3.3018 *	12.4218 *	8.8370 *	3.7078 *
Double Moving Average	8.1730 *	17.0411	17.2387	24.4217 *	8.2320 *	7.1212 *	2.8237 *	2.8470 *	3.1784 *	2.0378 **	2.8738 *	4.7383 *	17.7870	11.2384	8.2474 *
ARIMA=AR(p)I(d)MA(q)															
Best ARIMA Model (p, d, q)	(1, 0, 0)	(1, 0, 0)	(2, 0, 1)	(1, 0, 1)	(1, 0, 0)	(1,0,0)	(1, 0, 0)	(1, 0, 1)	(1, 0, 0)	(1, 0, 1)	(1, 0, 0)	(1, 0, 0)	(1, 0, 0)	(2, 0, 0)	(1, 0, 0)
	7.8381 *	8.0818 *	18.8683	7.2147 *	7.3483 *	4.8648 *	3.6286 **	1.2183 **	3.7348 **	2.4786 **	3.2321 **	2.8624 **	8.4010 *	7.3017 *	8.9233 *
NEURAL NETWORK															
Cosine with Hyperbolic Tangent	17.8762	62.7083	30.3423	23.8048	17.8623	24.7407	8.4871 *	3.3748 **	10.2803 *	4.3817 *	24.6864 *	8.2174 *	28.1740	23.7347	14.1147 *
Hyperbolic Tangent	17.0847	18.2868	78.1440	23.3748	17.0824	8.1717 *	3.4623 **	4.1787 *	8.1708 *	3.3217 **	10.7448 *	8.7344 *	23.7442	23.8184	24.2173
Linear	1.23001 **	0 **	1.23786 **	0 **	1.23232 **	0 **	0 **	1.23868 **	1.23867 **	0 **	1.23734 **	1.23171 **	1.23114 **	0 **	0 **
Logistic	17.2481	24.8380	30.7374	23.3743	17.1028	8.4871 *	8.2111 *	4.8864 *	10.1817 *	4.1744 *	24.8274 *	8.7208 *	62.2321	62.8672	86.8686

*significant at p<0.05, **significant at p<0.01

Table 2. RMSEs of Evaluation Sets

FORECASTING METHOD	THE ROOT MEAN SQUARED ERRORS (RMSE) AND SIGNIFICANCE LEVEL OF EACH METHOD IMPLEMENTED														
	Aggregate	*Sand*	*Steel Reinforce-ment*	*Ready Mix Concrete*	*Bricks and Partition*	*Roof Material*	*Floor and Wall Finishes*	*Ceiling*	*Plumbing Materials*	*Sanitary Fittings*	*Paint*	*Glass*	*Steel and Metal Sections*	*Timber*	*Plywood*
1) TRENDLINES															
Linear	36.5697	32.9857	34.7335	32.1835	56.2473	2.9245 **	3.5668 **	4.9724 *	56.1732	3.5670 **	56.5583	7.5651 *	36.1456	14.7314	8.3032 *
Logarithmic	14.7144	56.9614	33.7308	32.0824	32.3354	8.7556 *	5.3975 *	2.9564 *	3.9738 *	1.5650 **	3.1433 *	7.1424 *	36.1428	32.9248	8.3148 *
Polynomial	32.3353	56.0341	43.2701	36.1456	32.0340	7.9718 *	2.9357 **	4.4140 *	7.4144 *	1.5967 **	7.3784 *	5.4173 *	32.3560	56.4314	8.1433 *
Power	56.5056	14.7978	51.7568	32.5647	32.1435	8.7560 *	5.3632 *	3.0585 *	4.7040 *	3.1453 **	4.7241 *	7.3971 *	36.2563	18.3014	8.7145 *
Exponential	36.3144	14.7473	52.4256	32.1414	56.4703	4.7424 *	3.5630 **	4.1435 *	56.5603	3.2414 **	56.7320	7.2456 *	36.7145	14.1854	8.5038 *
Moving Average	1.2481 **	4.5524 **	56.2565	3.7361 **	2.7504 **	3.4963 **	3.3457 **	3.1414 **	3.2084 **	2.5567 **	3.1438 **	3.2024 **	4.7856 **	3.7171 **	3.2733 **
2) TIME SERIES															
Single Exponential Smoothing	3.0256 **	2.9146 **	56.0564	7.3436 *	3.4240 **	4.1473 *	3.2294 **	3.1456 **	3.2437 *	2.4224 **	3.5756 **	3.2714 **	3.4856 **	7.7565 *	4.7378 *
Double Exponential Smoothing	3.0814 **	2.9596 **	56.5633	7.3961 *	3.4975 **	4.1414 *	3.2830 **	3.5642 **	3.7314 *	2.4208 **	3.5371 **	3.1424 *	4.7414 *	7.5337 *	4.2414 *
Holt-Winter's Additive	3.5584 **	3.2481 **	32.2568	7.3530 *	3.5732 **	2.9356 **	2.8565 **	3.1425 **	3.7314 *	3.2856 **	4.7355 *	3.2733 *	32.1448	8.3017 *	5.7014 *
Holt-Winter's Multiplicative	3.7256 **	3.1428 **	32.3224	7.4581 *	3.5173 **	2.9341 **	2.8314 **	3.5681 **	3.5832 *	3.1434 **	4.6851 *	3.2414 *	32.5680	8.1451 *	7.8032 *
Seasonal Additive	3.5581 **	3.2424 **	32.2456	7.3545 *	3.5718 **	2.9341 **	2.8565 *(*	3.1425 **	3.7314 *	3.2856 **	4.7354 *	3.2714 *	32.1441	9.1414 *	5.7056 *
Seasonal Multiplicative	3.7241 **	3.1424 **	32.3146	7.4524 *	3.5173 **	2.9337 **	2.8314 **	3.5681 **	3.5856 *	3.1434 **	4.6833 *	3.2563 *	32.5601	8.3432 *	7.8018 *
Single Moving Average	3.7564 **	56.1440	14.1470	8.3556 *	5.3243 *	4.8303 *	2.4241 **	2.4248 **	4.1483 *	1.4241 **	4.1456 *	4.7018 *	56.3733	8.3370 *	5.3803 *
Double Moving Average	9.1450 *	56.0432	24.3683	32.4327	2.9556 **	7.3241 *	2.9224 **	2.9560 **	5.3584 *	2.8256 **	5.1753 *	4.7535 *	56.7830	32.5684	2.9033 **
3) ARIMA=AR(p)I(d)MA(q)															
Best ARIMA Model (p, d, q)	(1, 0, 0)	(1, 0, 0)	(2, 0, 1)	(1, 0, 1)	(1, 0, 0)	(1,0,0)	(1, 0, 0)	(1, 0, 1)	(1, 0, 0)	(1, 0, 1)	(1, 0, 0)	(1, 0, 0)	(1, 0, 0)	(2, 0, 0)	(1, 0, 0)
	3.6896 *	3.0856 *	32.9383	7.3247 *	4.7565 *	4.3568 *	3.1445 **	1.2485 **	3.7348 **	2.4796 **	3.5173 **	3.5674 **	3.4056 *	7.3035 *	3.8140 **
4) NEURAL NETWORK															
Cosine with Hyperbolic Tangent	17.8143	17.7083	50.5451	56.8056	32.9551	32.0303	3.4814 **	5.3338 *	56.5605 *	4.3835 *	32.3414	3.7374 **	18.5340	36.3547	14.3247
Hyperbolic Tangent	56.0347	14.2453	38.3560	56.5756	56.0142	8.5535 *	5.4565 *	4.5337 *	3.2403 *	3.5327 *	56.1438 *	9.1314 *	36.3341	56.1484	32.2424
Linear	1.4681 **	1.4019 **	1.4345 **	1.4682 **	1.4314 **	1.4030 **	1.4681 **	1.4363 **	1.4567 **	1.4682 **	1.4354 **	1.4314 **	1.4324 **	1.4014 **	1.4011 **
Logistic	17.1414	14.8330	50.2483	56.5335	32.9056	3.4814 **	8.7142 *	4.8454 *	56.1424 *	4.5634 *	32.0197	3.1403 **	17.1424	56.4571	56.5696

*significant at $p<0.05$, **significant at $p<0.01$

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Table 3. Estimated Material Price Indices in East Coast Region of Malaysia from January 2012 to January 2013 using BPNN

PREDICTED PERIOD	**CONSTRUCTION MATERIAL PRICE INDICES PREDICTION USING BACKPROPAGATION NEURAL NETWORK**														
	Aggregate	**Sand**	**Steel Reinforce -ment**	**Ready Mix Concrete**	**Bricks and Partition**	**Roof Material**	**Floor and Wall Finishes**	**Ceiling**	**Plumbing Materials**	**Sanitary Fittings**	**Paint**	**Glass**	**Steel and Metal Sections**	**Timber**	**Plywood**
JAN 2012	132.6722	134.3313	181.5322	155.9518	114.1371	129.7637	129.3834	134.7077	132.6275	113.8478	129.2163	134.3531	107.0752	145.9573	182.6393
FEB 2012	132.6324	134.3343	178.5147	151.2598	145.8134	129.1313	129.2213	129.2249	131.5284	113.9355	129.2563	134.4147	107.0752	147.1413	183.5237
MARCH 2012	131.2639	134.3769	181.5137	151.2598	145.3276	129.2474	129.1496	129.8433	131.4283	129.8474	129.2752	134.4938	172.5229	148.1473	184.1246
APRIL 2012	131.2547	134.3078	183.5514	152.7684	145.1435	129.3147	129.1475	129.3553	132.6332	129.1376	129.8329	134.5362	172.8628	149.4763	184.7147
MAY 2012	131.2156	134.1427	181.5964	152.2538	145.2522	129.4593	129.5534	129.1372	131.1414	134.2571	129.8334	134.3415	172.7256	243.3563	191.8342
JUNE 2012	132.5633	134.1455	182.3254	154.1512	145.4738	129.5514	129.4795	129.2813	132.1353	129.6529	129.7684	134.7133	172.7256	213.1412	185.3783
JULY 2012	132.1375	134.1483	183.3733	155.7135	145.5651	129.3522	129.7848	129.3722	132.8384	134.3783	129.3749	134.7841	172.7956	242.6281	183.1071
AUG 2012	132.8714	134.3211	184.7214	155.7135	145.5832	129.7563	129.8722	129.5147	135.6214	134.5424	129.3118	134.7613	173.0713	246.0768	181.3459
SEPT 2012	132.8137	134.3149	176.8495	155.5371	145.0772	129.8414	129.3128	129.3279	135.8107	129.6472	129.7683	134.6356	174.2625	245.2137	185.1614
OCT 2012	132.8147	134.3247	183.8375	155.2453	145.8379	129.9472	129.6355	129.7421	135.7514	134.7293	129.7652	134.7242	172.5956	253.3458	188.1373
NOV 2012	135.9847	134.3263	196.9147	155.2453	145.9184	129.3262	129.1474	129.7614	135.3578	129.2213	129.0713	113.3472	178.0707	256.1341	188.7507
DEC 2012	135.6263	134.3149	137.7253	155.7135	145.9389	129.6319	129.3476	129.9733	135.5341	129.8134	129.1298	113.1147	182.4947	260.5754	191.1459
JAN 2013	135.9114	134.4745	142.3837	155.5371	114.3237	129.2147	129.4596	129.3838	135.5613	129.3337	129.1298	113.1728	184.1914	265.3793	193.1371

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