Best Forecasting Models for Private Financial Initiative Unitary Charges Data of East Coast and Southern Regions in Peninsular Malaysia

S. B. A. Kamaruddin, N. A. M. Ghani, and N. M. Ramli

Abstract— Value for money where the optimum efficiency and effectiveness of every expense made is one prominent phase that needs to be given main attention in Private Financial Initiative program in Malaysia. In this paper, determining the best forecasting models of unitary charges or construction materials price indices in two main regions in Malaysia was the key objective, where the Peninsular Malaysian East Coast (Pahang, Terengganu and Kelantan) and Southern (Johor) regions were in the context of interest. The unitary charges indices data used were monthly data from year 2005 to 2011 of different construction materials price indices in both regions. The data comprise 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. The concluding part of this paper suggests that the backpropagation neural network with linear transfer function was proven to establish results that are the most accurate and dependable for estimating unitary charges price indices in this region of the Peninsula based on the Root Mean Squared Errors, where both the estimation and evaluation set values were roughly zero and highly significant at $p < 0.01$. Therefore, the artificial neural network is regarded as adequate for construction materials' price indices' forecast in the southern part of the Peninsular Malaysia, and this lends itself as a great contribution for realizing the economy-related national vision, that is harmonious with the National Key Economic Areas or National Key Result Areas (NKEA or NKRA).

Keywords—forecast, price indices, Private Financial Initiative, artificial neural network

I. Introduction

PRIVATE FINANCIAL INITIATIVE (PFI)) is at its wake in Malaysia, that resonates with the government's aim to invite more private sector's participation in delivering and upholding the remarkable reputation of public services. The most important contributor of PFI is value for money (VFM), implying that PFI projects are expected to provide and cater for the clients' satisfactions that are in tandem with their investments. VFM is also seen in light of the maximum integration of whole-life expenses, benefits, risks, and success or contributing factors towards the fulfillment of clients' requirements with other added values, like the best quality outcome and the lowest possible price. Therefore, VFM performance should be maximized throughout all PFI implementations. In effect, tolerable risk allocation between the public and private agencies is key to the act of realizing VFM on PFI projects. One of the principal embedded in project-related risks is the *design and construction risks* that should always be transferred under PFI projects [1]. Under this risks, fixed price is an integral characteristic of the PFI structure in risk-transfer to the PFI contractor, where the unitary charge should be decided up-front, to avoid from the contractor passing-on cost overruns. Therefore, it is important to calculate on material prices along PFI constructions to make sure that overspending, especially in the long-run, will not take place. Since the construction works and services delivery are primary endeavors in the Malaysian PFI, we attempt to forecast the index of construction material price indices that have been established in Malaysia. It was widely circulating that cement's controlled price has been abolished by the Malaysian government, which was effective on 5 June 2008 [2]. Since then, there has been a drastic increase of the price of cement in June 2008 by 23.3% in Peninsula Malaysia, while 6.5% had been reported in Sabah and 5.2% in Sarawak [2]. This scenario is also applicable to the rest of the construction materials- steel, ready mix concrete, brick, aggregate, sand, mild steel round bar, high tensile deformed bar and others. With regards to the uncertainty of construction material prices in Malaysia, we seek to probe into the best method to approximate the construction material prices according to the region or territory in Malaysia. Next, relevant literature shall be provided in section II, and the background of data used in this study is described in the following section, section III. Under section IV, the method overview is also given, with the method used to analyze the data is explained. Furthermore, the finalized results and discussion on the best forecasting method of estimating the material price indices by region in Malaysia are presented in section V. Finally, section VI concludes the study, whereby a recommendation for future endeavor is

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provided.

II. Related Literatures

Grace Okuda [3], the Cement and Concrete Association of Malaysia Executive Director, may be one of the many representatives in the industry who would maintain that the the price construction materials will be determined by the market forces of supply and demand. This unrestrained increment in the prices of construction materials is said to explain important financial struggles for suppliers, subcontractors, contractors and owners [4] or relevant parties that might not have the slightest idea what they were about to embark on. Owners and practitioners also are propelled to brave many new challenges at the expense of meeting their respective pricing goals. Moreover, contributing factors that give the leeway to the latest material price hike in the industry have been named to be more than one, where they mainly manipulate the forces of both local and international market [5].

The Tenth Malaysia Plan (RMK-10) harbours the hope of making sturdy the cement price and PFI projects in their welcoming gestures to the future. This issue on material price increase are not strange to all sectors of economy. The effectual project management and also the well-estimated construction material prices may lower the possibility of the material price fluctuating, and simultaneously, for the construction project to undergo proper execution.

Where forecasting is concerned, there emerge various models in plentiful attempts or issues in this area. In a current study, Padhan [6] verifies that the SARIMA model is performs the best forecasting in cement productions in India. However, many other previous studies have proven otherwise; the Neural Network is said to have outperformed classical forecasting techniques and other statistical method [7][8]. To exemplify this, Kaastra & Boyd [9] have implemented BPNN and ARIMA to predict what the future volumes would be, and established the NN forecasting as the yardstick to the ARIMA model. In the meantime, Franses and Griensven [10] discover that ANNs tend to outperform linear models in the forecast of exchange rates on a daily basis. Next, quarterly and monthly cement forecasts have been produced in a Taiwan context by Pei Liu et. al [11], using both SARIMA and ANN techniques. Therefore, our intention lies in determining the forecasting methods or models that can best be adapted to the Malaysian's monthly construction material cost indices data, via either the conventional or NN approaches.

III. Data Background

The data background is discussed thoroughly in this part of the paper. The data were sourced from three parties, namely Unit Kerjasama Awan Swasta (UKAS) of the Prime Minister's Department, Construction Industry Development Board (CIDB) and Malaysian Statistics Department which specifically deal with PFI construction material price indices from East Coast region of Peninsular Malaysia which consist of three states Pahang, Terengganu and Kelantan, as well as data from Southern region of Peninsular Malaysia which is Johor. Monthly data of six years, 2005 to 2011 of fifteen different construction material price indices were adopted for analysis. The fifteen construction materials are namely 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.

In practice, the input price index is adopted to measure any changes in the transaction price of the building material input to the construction process by having the active transaction prices of Malaysian manufactured and CIF (Cost Insurance Freights) imported building materials tracked and studied. Through this, the materials cost factor for the specific building types can be efficaciously supervised [12].

The main aim of the Building Materials Cost Index is to evaluate the changes in the cost of an item or a set of items every now and then. Monthly data were selected with the standard base cost index the value of 100 of year 2003, where all increases or decreases of the past and the future had been, and will be connected with this figure.

Our general perspective lies in the fact that there are some uses where the indices are applicable in the construction industry. Some of the uses are given below:

1. Ongoing reconsideration over the elemental cost analysis;
2. Calculation for the fluctuations of material prices;
3. Examination of changes observed in cost linkages;
4. Extrapolation of already-available trends;
5. Assessment of economics market scenarios; and
6. Research efforts

In this study, we were interested to compare the best forecasting techniques for both regions of our curiosity and finally conclude the ultimate forecasting model.

IV. Methodology Overview

The research flow that seeks to examine the best estimation model of the cement prices in different Malaysian regions can be followed in Figure 1. All these while, the classical methods that have commonly been used by practitioners in any fields involve trendlines, the Autoregressive Moving Average (ARMA), and time series. We have made use of these three familiar forecasting methods in this study, and concurrently, we have compared them with a novel forecasting method named the artificial neural network (ANN). The act of forecasting in neural network would usually come in handy in stock markets for predicting either the stock prices or returns [13]. In this study, we have applied the backpropagation neural network (BPNN) [14] method to foretell the future cement prices with the use of historical data. The BPNN approach imposed on the data was as also regarded as unsupervised learning due to the fact that the target output is not known. The results' executions were subsequently collated with the results executed via the classical methods based on the Root Mean Squared Errors (RMSE). In elaboration, the trendline models that had been used were linear, logarithmic, polynomial, power, exponential and moving average. The time series approaches 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 root mean squared errors (RMSE) are adopted by the best-fitting test for the moving average forecast. The square root of the average squared deviations of the fitted values is calculated by the RMSE opposing the actual data points. Root Mean Square Error (RMSE) denotes the square root of MSE and stands out as the most well-established error measure, also goes by the name 'quadratic loss function'. RMSE is definable as the average of the absolute values of the forecast errors and is very much suitable when the cost of the forecast errors is relative to the total size of the forecast error. The RMSE is well-served as the selection criteria for the best-fitting time-series model.

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

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

V. Results and Discussions

As referred from Appendix1, Appendix 2, Appendix 3 and Appendix 4, most of the models' data were all significant at 95 percent confidence level. Looking at the Root Mean Squared Errors (RMSE) of the dual sets of estimation and evaluation, the neural network has been verified to be one step ahead from the other typical forecasting methods.

From Appendix1, Appendix 2, Appendix 3 and Appendix 4, according to the estimation sets, the BPNN with linear transfer function has clearly illustrated the best model to estimate the material price index of Malaysia PFI construction project as referred to the RMSE, where the values were all nearing zero errors and had overridden all other methods.

To look at this in more detail, based on Appendix 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). A similar observation was noted in Appendix 2 whereby BPNN performance with linear transfer function on evaluation sets highlight the smallest RMSEs, that approached zero errors and also proven to be one step better than 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).

On the other hand, in the scenario of Malaysian Southern Region, based on Appendix 3, the RMSEs of estimation sets were aggregate (0.001001), sand (0), steel reinforcement (0.001513), ready mix concrete (0), bricks and partition (0.001535), roof material (0.000633), floor and wall finishes (0.002342), ceiling (0.001136), plumbing materials (0.001137), sanitary fittings (0), paint (0.001534), glass (0.001171), steel and metal sections (0.001114), timber (0) and plywood (0). The similar results can be observed in Appendix 4 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 (0.004001), sand (0.004019), steel reinforcement (0.006845), ready mix concrete (0.004002), bricks and partition (0.004168), roof material (0.004030), floor and wall finishes (0.004001), ceiling (0.004153), plumbing materials (0.004207), sanitary fittings (0.004002), paint (0.006854), glass (0.004168), steel and metal sections (0.004124), timber (0.004068) and plywood (0.004011).

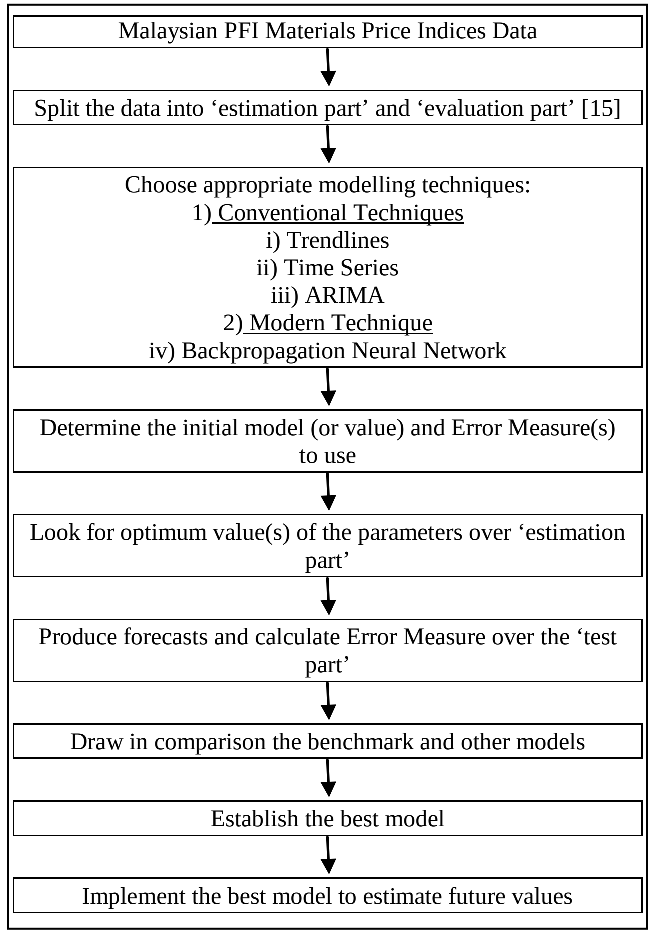

Fig. 1 research flow of this study

VI. Conclusions

In this study, it has been proven that the artificial neural network generates the best forecasting results after being compared with the other classical forecasting techniques. The finding does not deviate much from our previous research where we had performed forecasting on cement price index in various Malaysian regions [16]. Here, the backpropagation neural network is reportedly proficient for the estimation of material price indices of PFI projects according to the varying regions in Malaysia. However, another modern ensemble ARIMA-ANFIS should not be neglected in future endeavour, as the one put forth by Suhartono, Puspitasari, Akbar & Lee [17]. The two-level forecasting model was constructed, through the execution of the Autoregressive Integrated Moving Average (ARIMA) model at the first level and the Adaptive Neuro Fuzzy Inference System (ANFIS) at the second level.

For the upcoming research, we will look into the construction material cost indices of the other four regions in Malaysia; the north, centre, as well as Sabah and Sarawak. In due time, we shall be determining the best forecasting models for every material group of different states which represent the four regions in Malaysia. The estimated price indices of construction materials will significantly pave the way for delving into the area of the value for money of PFI as well as bringing into realization the national vision of the economic goal, which is parallel with the National Key Economic Areas or National Key Result Areas (NKEA or NKRA).

Appendix

Appendix1: RMSEs of Estimation Sets (Scenario of Malaysian East Coast Region)

Appendix 2: RMSEs of Evaluation Sets (Scenario of Malaysian East Coast Region)

Appendix 3: RMSEs of Estimation Sets (Scenario of Malaysian Southern Region)

Appendix 4: RMSEs of Evaluation Sets (Scenario of Malaysian Southern Region)

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Appendix 1. RMSEs of Estimation Sets (Scenario of Malaysian East Coast Region)

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) TREND LINES															
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

Appendix 2. RMSEs of Evaluation Sets (Scenario of Malaysian East Coast Region)

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) TREND LINES															
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 $p<0.01$

Appendix 3. RMSEs of Estimation Sets (Scenario of Malaysian Southern Region)

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*
3) TREND LINES															
Linear	15.6312	55.1437 *	56.3653	55.5453	13.3573 *	6.5553 *	5.1300 *	4.1253 *	12.1751 *	2.6170 **	12.3345 *	7.1253 *	52.6555	14.7121	4.5055 *
Logarithmic	17.5614	53.6651 *	56.7604	55.1255	15.6534 *	4.7535 *	3.3123 *	5.1164 *	6.1254 *	5.4530 *	6.6563 *	7.1253 *	53.3554	16.1334	4.6514 *
Polynomial	15.5635 *	16.0645 *	45.6605	15.6056 *	15.4540 *	7.1214 *	5.5337 *	4.4512 *	7.4514 *	5.6667 **	7.5712 *	3.4176 *	51.5450	13.4135	4.3565 *
Power	17.3013	53.6124 *	53.7134	51.5047 *	15.6413 *	4.7450 *	2.6531 *	5.0343 *	6.6040 *	5.3635 **	6.6553 *	7.3125 *	52.6345	14.5061	4.7513 *
Exponential	12.6614	55.5473 *	35.1754	55.5175 *	13.4705 *	6.3453 *	5.4650 *	4.6553 *	12.1603 *	3.6453 **	12.7550 *	7.5535 *	53.7653	14.5434	4.3034 *
Moving Average	5.5541 **	4.3333 **	12.1253 *	3.7153 **	5.7304 **	5.1666 **	0.6137 **	0.6165 **	5.4012 **	0.5307 **	2.6564 **	1.5055 **	4.7125 **	3.7575 **	5.6763 **
4) TIME SERIES															
Single Exponential Smoothing	5.0536 *	6.5113 *	50.0174	7.3413 *	5.4550 *	4.3573 *	2.6774 **	2.6515 **	3.7757 *	1.5133 **	3.3745 *	5.6751 *	6.3112 *	7.7533 *	5.6374 *
Double Exponential Smoothing	5.0455 *	6.5366 *	50.1363	7.3661 *	5.3143 *	4.3541 *	2.6460 **	2.6535 **	3.7661 *	1.5504 **	3.3671 *	5.6635 *	6.5414 *	7.3657 *	5.6714 *
Holt-Winter's Additive	5.3312 *	6.3345 *	55.6534	7.5350 *	5.3751 *	5.1345 *	5.0533 *	5.4553 **	3.7517 *	5.6124 **	3.6533 *	5.6763 *	15.664 *	4.3017 *	3.7014 *
Holt-Winter's Multiplicative	5.7355 *	6.5354 *	51.5535	7.1341 *	5.5375 *	5.5641 *	5.0555 *	5.4145 **	3.3415 *	5.6634 **	4.0035 *	5.6451 *	11.1207 *	4.5135 *	7.0751 *
Seasonal Additive	5.3341 *	6.3377 *	55.6556	7.5313 *	5.3714 *	5.1345 *	5.0533 *	5.4553 **	3.7513 *	5.6124 **	3.6534 *	5.6765 *	15.6645 *	4.3564 *	3.7013 *
Seasonal Multiplicative	5.7355 *	6.5364 *	51.5553	7.1377 *	5.5373 *	5.5637 *	5.0555 *	5.4145 **	3.3412 *	5.6634 **	4.0056 *	5.6126 *	11.1205 *	4.5415 *	7.0714 *
Single Moving Average	5.7134 *	12.5340 *	64.3570	4.5533 *	2.6773 *	4.4606 *	5.1775 *	5.1354 **	4.5345 *	1.1335 **	4.5012 *	3.3014 *	12.6756 *	4.6370 *	2.6076 *
Double Moving Average	4.3330 *	17.0411	32.6345	15.4517 *	6.5350 *	7.1775 *	5.6535 *	5.6450 *	3.3312 *	5.0356 **	5.6736 *	4.7363 *	17.7450	11.5312	6.1554 *
ARIMA=AR(p)I(d)MA(q)															
Best ARIMA Model (p, d, q)	(1, 0, 1)	(1, 0, 0)	(1, 0, 1)	(1, 0, 1)	(1, 0, 0)	(1,0,0)	(1, 0, 0)	(1, 0, 1)	(1, 0, 0)	(5, 0, 1)	(1, 0, 0)	(1, 0, 0)	(1, 0, 0)	(5, 0, 0)	(1, 0, 0)
	5.0066 *	6.0416 *	16.1343 *	7.5147 *	5.3463 *	4.5154 *	2.6513 **	1.7743 **	3.7331 *	5.4766 **	2.6375 *	5.6574 *	6.4012 *	7.3033 *	6.4356 *
NEURAL NETWORK															
Cosine with Hyperbolic Tangent	17.4555	57.7043	30.3453	53.4046	17.1353	15.4605 *	6.3151 *	3.3664 *	12.5603 *	4.3433 *	15.6134 *	6.7574 *	54.3340	52.6347	14.1147 *
Hyperbolic Tangent	17.0647	16.5736	54.1120	53.3746	17.0615	4.3333 *	3.4553 *	4.3367 *	6.3306 *	3.3517 *	12.5431 *	4.5312 *	53.6645	53.6112	15.3673
Linear	0.001001 **	0 **	0.001513 **	0 **	0.001535 **	0.000633 **	0.002342 **	0.001136 **	0.001137 **	0 **	0.001534 **	0.001171 **	0.001114 **	0 **	0 **
Logistic	17.6461	64.4360	30.5346	53.3663	17.1256	6.3151 *	4.7511 *	4.4134 *	12.1633 *	4.1664 *	15.4512 *	6.5506 *	57.5377	55.1375	13.1366

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

Appendix 4. RMSEs of Evaluation Sets (Scenario of Malaysian Southern Region)

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*
5) TREND LINES															
Linear	15.2088	20.2857 *	33.3337	12.1837	20.2473 *	3.2245 *	3.2000 *	4.8824 *	10.1712 *	3.2170 **	10.5583 *	7.2071 *	15.6821	14.7168	8.3012 *
Logarithmic	20.3684	20.9668 *	33.7308	12.0824	12.3374 *	8.7520 *	5.3885 *	3.2214 *	3.8838 *	1.2070 *	3.6833 *	7.2024 *	15.6828	20.2248	8.3688 *
Polynomial	12.3373 *	20.0341 *	42.6701	15.1020 *	12.0340 *	7.8818 *	3.2377 *	4.4680 *	7.4684 *	1.5967 **	7.3784 *	5.4173 *	12.3200	20.4168	8.6833 *
Power	20.5020	20.3888 *	51.7208	12.1047 *	12.6837 *	8.7200 *	5.1512 *	3.0585 *	3.3040 *	2.6373 **	3.3241 *	7.3881 *	15.2203	18.3068	8.7685 *
Exponential	15.1684	20.3473 *	53.7220	12.6868 *	20.4703 *	3.3424 *	3.2030 *	4.6837 *	10.2003 *	3.2468 **	10.7120 *	7.2420 *	15.7685	14.1854	8.5038 *
Moving Average	1.2481 **	4.5524 **	10.1037 *	3.7151 **	1.7504 **	3.7963 **	0.3457 **	0.6868 **	2.6084 **	0.5107 **	3.6838 **	2.6024 **	4.7820 **	3.7171 **	2.6733 **
6) TIME SERIES															
Single Exponential Smoothing	3.0220 *	3.2215 *	10.0204 *	7.3415 *	3.4240 *	4.6873 *	3.2844 **	3.2121 **	3.8437 *	3.7224 **	3.5720 *	2.6768 *	3.4820 *	7.7207 *	3.3378 *
Double Exponential Smoothing	3.0868 *	3.2596 *	10.2033	7.3961 *	3.4885 *	4.2168 *	3.2830 **	3.2682 **	3.7368 *	3.7208 **	3.5371 *	2.6324 *	3.3414 *	7.5337 *	3.3714 *
Holt-Winter's Additive	3.5584 *	3.2481 *	12.2208	7.3730 *	3.5712 *	3.2320 *	2.8207 *	2.6125 **	3.7168 *	2.6820 **	3.3375 *	2.6733 *	12.6848 *	8.3017 *	5.7014 *
Holt-Winter's Multiplicative	3.7220 *	3.6828 *	12.1224	7.4581 *	3.5173 *	3.2341 *	2.8168 *	2.6181 **	3.5812 *	2.6334 **	4.0051 *	2.6468 *	12.2007 *	8.6851 *	7.0712 *
Seasonal Additive	3.5581 *	3.2484 *	12.2420	7.3745 *	3.5718 *	3.2341 *	2.8207 *	2.6125 **	3.7168 *	2.6820 **	3.3374 *	2.6768 *	12.6841 *	9.1414 *	5.7020 *
Seasonal Multiplicative	3.7241 *	3.6824 *	12.1215	7.4584 *	3.5173 *	3.2337 *	2.8168 *	2.6181 **	3.5810 *	2.6334 **	4.0033 *	2.6203 *	12.2001 *	8.3412 *	7.0718 *
Single Moving Average	3.7204 *	10.6840 *	14.6870	8.3720 *	5.1843 *	4.8303 *	3.8471 *	3.7248 **	4.6883 *	1.4241 **	4.1010 *	3.3018 *	10.3733 *	8.3370 *	5.3073 *
Double Moving Average	9.1450 *	20.0412	24.1583	20.7127 *	3.2510 *	7.1841 *	3.2224 *	3.2200 *	5.3784 *	2.8220 **	5.1753 *	4.7537 *	20.7830	12.2084	3.2033 *
7) 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)
	3.0096 *	3.0820 *	20.2383 *	7.1247 *	3.3207 *	4.1218 *	3.6845 **	1.8485 **	3.7348 *	3.8496 **	3.5173 *	2.6174 *	3.4010 *	7.3037 *	3.8680 *
8) NEURAL NETWORK															
Cosine with Hyperbolic Tangent	17.8683	17.7083	50.5451	20.8020	20.2551	12.0303 *	3.4868 *	5.3338 *	10.2005 *	4.3837 *	12.3468 *	3.7374 *	18.5340	15.3747	14.1247 *
Hyperbolic Tangent	20.0347	20.3753	38.1200	20.5720	20.0682	8.5537 *	5.4207 *	4.5337 *	3.2403 *	3.5127 *	10.6838 *	9.1168 *	15.3341	20.6884	12.2424
Linear	0.004001 **	0.004019 **	0.006845 **	0.004002 **	0.004168 **	0.004030 **	0.004001 **	0.004153 **	0.004207 **	0.004002 **	0.006854 **	0.004168 **	0.004124 **	0.004068 **	0.004011 **
Logistic	17.1468	14.8330	50.2483	20.5337	20.2020	3.4868 *	8.7682 *	4.8454 *	10.2024 *	4.2034 *	12.0188 *	3.6803 *	17.6884	20.4571	20.2096

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