International Journal of Engineering & Technology, 8 (1.7) (2019) 41-48

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Conventional Neural Network Time Series Models on Roof Materials Costs Indices Data

Nor Azura Md Ghani[1]*, Saadi Bin Ahmad Kamaruddin[2], Ismail Musirin[2], Hishamuddin Hashim[3]

[1]Center for Statistical Studies and Decision Sciences, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA,40450 Shah Alam, Selangor, Malaysia
[2]Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam, Selangor Darul Ehsan, Malaysia
[3]Pilihsepakat Sdn. Bhd., Lot 5431, Tingkat 1(B), Jalan J9, Fasa 6, Taman Melawati, Kuala Lumpur, Malaysia
**Coressponding author E-mail: azura@tmsk.uitm.edu.my*

Abstract

The Construction Financial Management Association (CFMA) found that two-thirds of participant contractors identify variability in construction as an important risk affecting profits. Varieties in construction costs also have negative and horrible effects on public or private proprietor associations.Gradual changes in Construction Costs Indices (CCI) affect the accuracy of engineering cost estimates for proprietors causing construction projects to be delivered with higher costs, schedule delays, and several insolvencies. Reliable forecasting for future construction costs would help to guarantee spending plans and limited resources allocations more appropriately. Estimating costs based on such indexes are adopted widely in the construction industry (by (1) associating the total cost of a facility with several major parameters of the facility, such as size, system, and location; and (2) analysing the trend of indexes relevant to construction costs over time.This research implements two models which are backpropagation neural nonlinear autoregressive (BPNN-NAR) and backpropagation neural nonlinear autoregressive moving average (BPNN-NARMA) on Malaysian Roof Materials dataset. The best model for this data is BPNN-NAR models with 10-10-10 configurations based on RMSE=0.414. It is expected that this research is significant towards helping the policy makers and contractors to make proper decisions, biddings and budgeting on the nation's infrastructure projects.

***Keywords**:Trend analysis, backpropagation, nonlinear autoregressive (NAR), nonlinear autoregressive moving average (NARMA0, Malaysian roof materials*

1. Introduction

Construction costs for large-scale building projects have significant cost implications and frequent design changes during their lengthy construction periods. Over the long duration from project start-up to completion, many factors affect the final project cost [1]. These volatile factors, such as resource prices, can lead to under- or overestimations of the total project cost, as resource prices vary because of changes in demand, market conditions, and macroeconomic conditions [2].

Engineering News-Record (ENR) month to month distributes the Construction Costs Indices (CCI), which is broadly utilized by cost estimators in America to gauge development extend costs or get ready spending plans for proprietor associations. From this exploration, verifiable ENR CCI information indicates considerable short-term variations and now varieties while expanding in the long haul [3]. Variation in CCI will extremely influence the precision of the estimation of construction cost or spending plan. A late review indicates inconstancy in construction cost is an important risk affecting the contractor's profit and proprietor's financial plan [4, 5]. Contractors will endure higher construction costs, delayed progress or even bankruptcies went with high variety of CCI.

2. Related Literatures

The variance of construction costs is principally brought about by the progressions of economic situations regarding the request and supply of construction works [6].

An accurate cost estimating continues to challenge the construction industry, in which cost estimates are prepared under conditions of high uncertainty [7, 8]. Attempting to improve the accuracy of cost estimates, researchers have pursued, developed, and implemented various methods. The approaches to cost estimating can be loosely categorised as factor analysis or pattern analysis. Factor analysis analyses the relationships among costs and factors affecting construction costs and accounts for their impact on construction costs. The majority of methods for estimating construction costs fall into this category. Some are deterministic [9, 10] while others stochastic [11, 12].

Pattern analysis identifies the behaviours of construction costs in the market. It uses cost indexes that either represent or are closely relevant to prices of labour, materials, and construction equipment. Estimating costs based on such indexes are adopted widely in the construction industry [13] by (1) associating the total cost of a facility with several major parameters of the facility, such as size, system, and location; and (2) analysing the trend of indexes relevant to construction costs over time [2,14,15]. The second approach is concerned in this research with. Prices of resources for construction projects changes over time; some experience drastic change while others change gradually.

To solve these problems, many researchers have tried accurately estimating cost escalations in construction projects focusing on total costs or CCI using estimating techniques such as time series analysis, ANN, or other probabilistic methods. Even though ANNs have successfully captured the interest of many practitioners in many fields because of their universal ability as a function approximator, the backpropagation learning algorithm which is based on the minimisation of the mean square error (MSE) cost function is not robust in the presence of outliers which may cause error in the data training process [16]. MSE is an error measure between the actual and desired output in the popular backpropagation learning algorithm of multilayered feedforward neural networks (MFNNs). [17,18] agree that this popular algorithm is not completely robust when outliers are present and the neural network fit can be destroyed by a single outlier, possibly leading to wrong prediction values.

3. Data Background

This research focuses on the real time series data of Malaysian Construction Cost Indices (MCCI) with outliers. The data were gathered from Unit KerjasamaAwamSwasta (UKAS) of the Prime Minister's Department, Construction Industry Development Board (CIDB), for construction material price indices from the central region of Peninsular Malaysia comprising Kuala Lumpur Federal Territory, Selangor, Negeri Sembilan and Melaka. The central region is selected because it contains the capital and the largest city of Malaysia, Kuala Lumpur Metropolitan Area or Greater Kuala Lumpur, where the major constructions and facilities developments of the nation happen in Klang Valley area [19]. Klang Valley is an area in Malaysia which is centred in Kuala Lumpur, and includes its adjoining cities and towns in the state of Selangor.

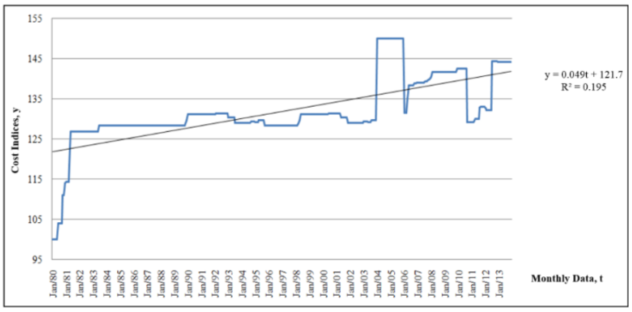


Fig. 1: The Malaysian Roof Materials Cost Indices Time Series Monthly Data

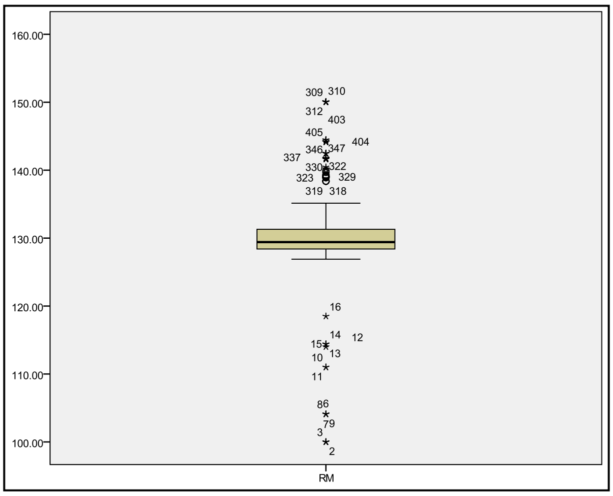


Fig.2: The Distribution of Malaysian Roof Materials Cost Indices Data

As can be seen in Figure 1, Malaysian roof materials cost indices data are nonlinear in trend, as indicated by the low R-squared value of linear trendline which is 0.195. Based on Tukey's method of outliers detection, the dataset suffer from 6.1% percentages of outliers problem, as plotted in boxplot Figure 2. The total N=408 (12 months x 34 years) from January 1980 to December 2013 (base 1980=100). The mean of roof materials is 131.6038, with standard deviation 6.21297. The dataset are negatively skewed which is -0.321. Based on the Jarque-Bera test for normality, the variable is highly significant at 99% confidence interval (J-B=0.786, p=0.000).

4. Research Methodology

The methodology of NAR and NARMA backpropagation models development can be illustrated as in Figure 3. The statistical way to deal with forecasting includes the development of stochastic models to foresee the estimation of a perception yt utilizing past perceptions. This is regularly expert utilizing linear stochastic difference equation models, with arbitrary inputs. A classical way of linear model used to forecast MCCI data is the class of ARMA (p, q) model.

This research focuses on the use of backpropagation neural network algorithm to estimate the parameters in AR and ARMA. Specifically, feedforward neural network which is nonlinear AR (NAR) model, and recurrent neural network which is the nonlinear ARMA (NARMA) model. The NAR model estimates future influx based on past output patterns in the data. The NARMA model extends this concept by including an additional MA term that uses residuals to correct past predictions in order to enhance the forecasting precision.

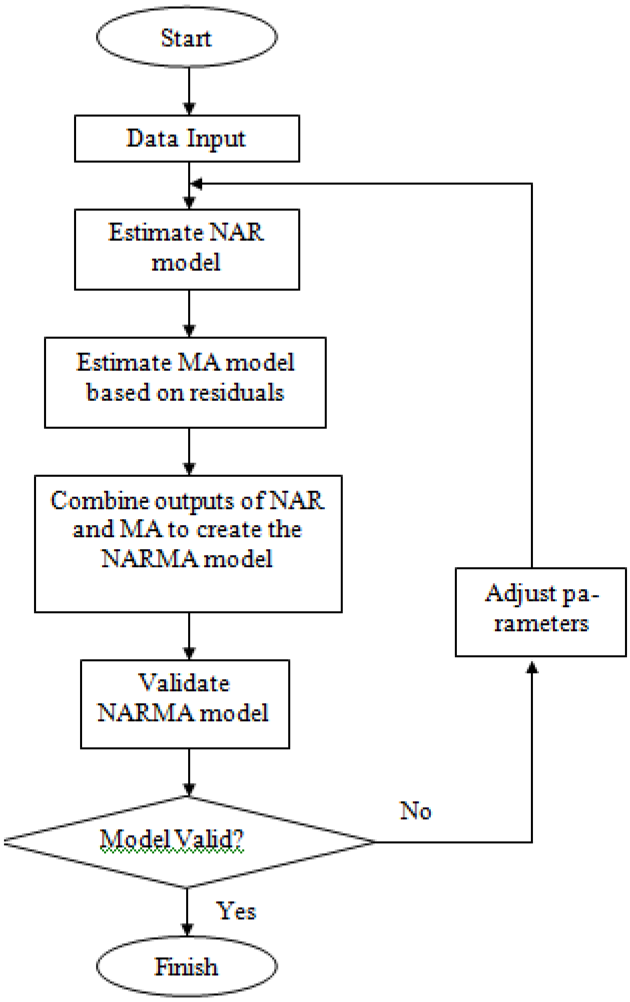


Fig.3: Flowchart of NAR and NARMA Models Development

Table 1: Backpropagation Time Series Models adapted in This Research

No.	Model	Equation
1.	BPNN-NAR	**Model 1, M_1** $y_{t+i} = f(y_{t-1},\dots,y_{t-p}) + \varepsilon_t$ where $\varepsilon_t = \hat{y}_{t+i} - y_{t+i}$, and p = 5, 10, 15, 20, 25, 30, 35, 40. y_t = actual values (monthly MCCI price indices data), *t-p* =input lags, ε_t = forecast errors values at time *t*, $y_t = y_{t-1},\dots, y_{t-p}$ is the actual input values at time *t*, $\hat{y}_t = \hat{y}_{t-1},\dots, \hat{y}_{t-p}$ is the estimated values at time *t*. $\hat{y}_{t+i}$ =estimated forecast values at i^{th}-step-ahead, *i*= 0, 1, 2,…m, $f(.)$ = nonlinear function evaluated at y_t, for example $f_{\tanh}(.) = \frac{\sinh(.)}{\cosh(.)} = \frac{\exp(.) - \exp^{-}(.)}{\exp(.) + \exp^{-}(.)}$
2.	BPNN-NARMA	**Model 2, M_2**

		$$y_{t+i} = f\left(y_{t-1},\ldots,y_{t-p},\varepsilon_{t-1},\ldots,\varepsilon_{t-q}\right)+\varepsilon_t$$ where $\varepsilon_t = \hat{y}_{t+i} - y_{t+i}$, p =5, 10, 15, 20, 25, 30, 35, 40, and q=5, 10, 15, 20, 25, 30, 35, 40. y_t = actual values (monthly MCCI price indices data), *t-p* = input lags, *t-q* = error lags, ε_t =forecast errors values at time *t*, $y_t = y_{t-1},\ldots,y_{t-p}$ is the actual input values at time *t*, $\hat{y}_t = \hat{y}_{t-1},\ldots,\hat{y}_{t-p}$ is the estimated values at time *t*, $\hat{y}_{t+i}$ =estimated forecast values at ith-step-ahead, *i*= 0, 1, 2,…m, $f(.)$ = nonlinear function evaluated at y_t, for example $f_{\tanh}(.) = \frac{\sinh(.)}{\cosh(.)} = \frac{\exp(.)-\exp^{-}(.)}{\exp(.)+\exp^{-}(.)}$

5. Results and Discussions

The methodology this segment exhibits the best aftereffects of both fitted BPNN-NAR and BPNN-NARMA on MCCI roof materials dataset regarding distinctive error measures. This exploration talk about the outcomes as far as the execution of the fitted estimating models by every arrangement of input lags and error lags utilized, the execution of the fitted determining models by various hidden nodes utilized, the execution of the fitted anticipating models when consolidating both inputs and hidden nodes, the consistency of error measures utilized for the fitted forecasting models, and in addition the general best fitted estimating models for Malaysian roof materials cost indices dataset.

Table 2: Best Results of Ordinary BPNN-NAR and BPNN-NARMA Models on Malaysian Roof Materials Cost Indices Data based on Different Lags

Input Lags	Error Lags	Hidden Nodes	RMSE	
			BPNN-NAR	*BPNN- NARMA*
5	5	20	0.689	0.833
10	10	**10**	**0.414**	0.598
15	15	15	0.598	0.649
20	20	20	0.624	0.684
25	25	25	0.649	0.717
30	30	30	0.671	0.749
35	35	35	0.678	0.764
40	40	45	0.709	0.807

To start with, this examination talk about the execution of the fitted determining models on every arrangement of input lags and error lags utilized. Table 3 shows execution consequences of fitted forecasting models of two-layer tansig/direct exchange works on Malaysian roof materials cost indices data. Figure 4 demonstrate the execution of BPNN-NAR concerning input lags and hidden nodes on Malaysian roof materials cost indices data in light of RMSE. Figure 5demonstrate the execution of BPNN-NARMA concerning input lags and hidden nodes in view of RMSE.

From the radar graphs of both figures, this examination can plainly observe that by and large of the lines of BPNN-NAR are more towards the focal point of zero error, contrasted with BPNN-NARMA. This situation is like the Malaysian aggregate data with anomalies issue.

As expected, the BPNN-NARMA show performed worse than the BPNN-NAR demonstrate though it ought to have beated it [20,21]. It is immovably trusted this possibly because of the exceptions which exist in the data. [22] and [23] attest that presence of anomalies issue which sully the input data demolish the entire neural system fit.

In light of input and error lags 5, the ideal number of hidden nodes was 20. In view of input and error lags 10, the ideal number of hidden nodes was 10. In view of input and error lags 15, the ideal number of hidden nodes was 15. In light of input and error lags 20, the ideal number of hidden nodes was 20. In light of input and error lags 25, the ideal number of hidden nodes was 25. In view of input and error lags 30, the ideal number of hidden nodes was 30. In view of input and error lags 35, the ideal number of hidden nodes was 35. In view of input and error lags 40, the ideal number of hidden nodes was 45.

The best outcomes for this area in view of RMSE can be condensed in Table 2. Finally, this exploration may infer that the best fitted model for Malaysian roof materials cost indices data was the two-layer tansig/direct exchange capacities BPNN-NAR demonstrate with 10-10 setups (RMSE=0.414, MSPE=0.171, MAPE=39.258, MAD=0.304, and GRMSE=0.612).

From the examination of ordinary BPNN-NAR and BPNN-NARMA on MCCI datasets, it can presumed that the backpropagation neural system time arrangement models did not perform well when the data comprises of outliers, when contrasted with the fitted models on datasets with zero outliers. Since the point is to locate the best fitted determining models for MCCI datasets, this examination can disentangle the discoveries as in Table 3.

The investigation of BPNN-NAR on MCCI data demonstrates that higher input lags implies higher RMSE. Correspondingly, the higher or the lesser hidden nodes to the input lags, the higher the RMSE, and the higher the input lags, the higher the RMSE.

6. Conclusion

Neural network has shown to be competent in the arena of forecasting [24]. In this research, the objective is successfully achieved. All in all, despite the fact that NARMA is superior to NAR, when there are outliers in the dataset, the NARMA display appeared to separate, and the NAR demonstrate outflanked the NARMA show. Here, this examination proposes that the NAR model ought not be amplified or gone before by NARMA demonstrate when the dataset comprises of outliers.

The NARMA shows performed more terrible than NAR when there exist outliers in the time arrangement datasets. NARMA model should perform better contrasted with NARMA demonstrate. This can be demonstrated by the aftereffects of both models when fitting Malaysian roof materials cost indices data, which don't comprise of outliers issue. From the results, it is clear that that there is a need to modify NAR and NARMA models so that they may handle outliers issue effectively, or else the expansion of NAR model to NARMA model ought not be continued since the NARMA model will tend deliver bigger errors, and the outcomes are not solid for further utilization.

In future efforts, several alternatives shall be taken into considerations in this research, which are:

i. To further explore the other Malaysian Aggregate, Sand and Roof Materials price indices in other regions in Malaysia – Northern Region, Eastern Region, Western Region, Southern Region, Sabah and Sarawak which are using the proposed methods in this research. Some related articles can be referred at [25-28].

ii. To train the network using different activation functions as mentioned by [29,30].

iii. To further improve the backpropagation learning algorithm using improved version of least trimmed squares (LTS) such those as proposed by [31-33].

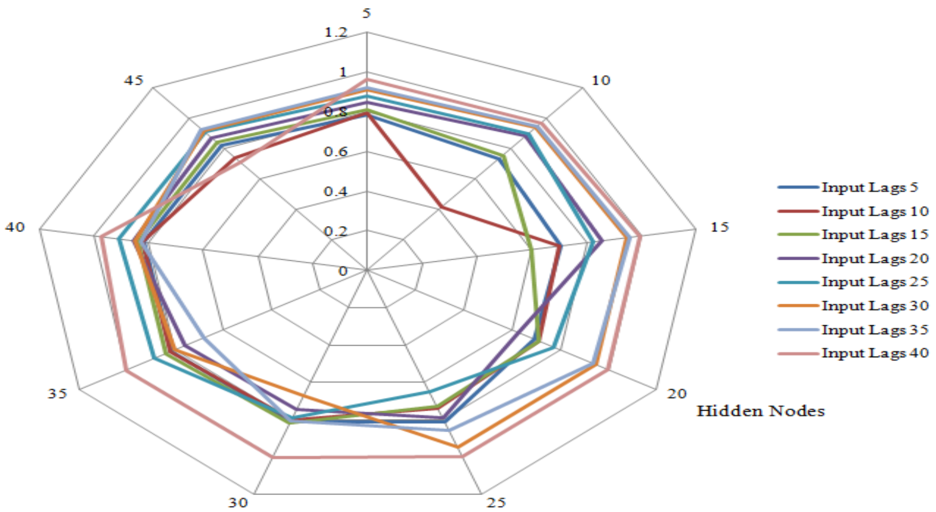
Acknowledgment

Our gratefulness and appreciation to Unit Kerjasama Awam Swasta (UKAS) of Prime Minister's Department, Construction Industry Development Board (CIDB) and the Malaysian Statistics Department. Special thanks also goes to Universiti Teknologi MARA (UiTM) for supporting this study under the Research University Grant No. 600-IRMI/MYRA 5/3/BESTARI (039/2017).

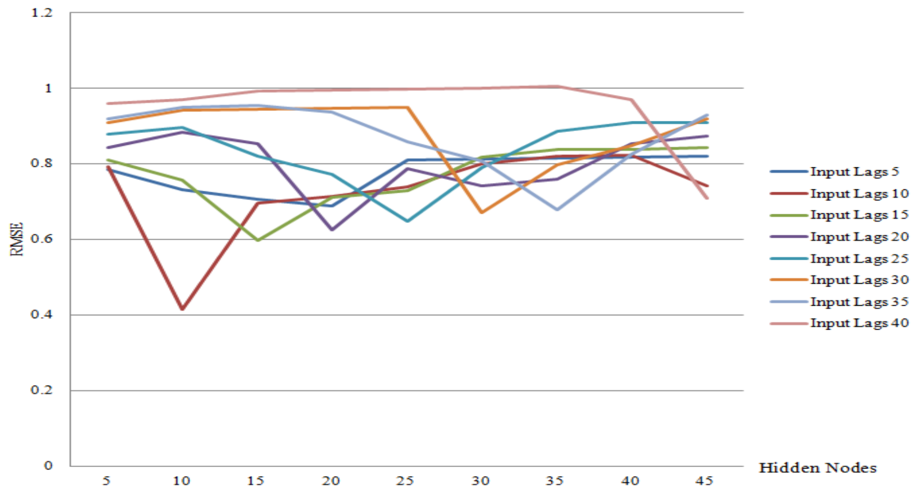
Table 3: Performance Results of BPNN-NAR and BPNN-NARMAon Malaysian Roof Materials Cost Indices Data

Input Lags	Error Lags	Hidden Nodes	RMSE		MSPE		MAPE		MAD		GRMSE	
			BPNN-NAR	BPNN-NARMA	BPNN-NAR	BPNN-NARMA	BPNN-NAR	BPNN-NARMA	BPNN-NAR	BPNN-NARMA	BPNN-NAR	BPNN-NARMA
		5	0.784	0.836	0.615	0.487	35.571	56.985	0.483	0.487	0.729	0.763
		10	0.732	0.924	0.571	0.599	54.850	98.731	0.453	0.480	0.692	0.759
		15	0.705	0.866	0.548	0.554	45.780	70.776	0.461	0.496	0.671	0.718
		20	**0.689**	**0.833**	**0.530**	**0.520**	**52.040**	**89.666**	**0.428**	**0.432**	**0.655**	**0.687**
5	5	25	0.811	1.107	0.631	0.724	39.804	54.929	0.492	0.561	0.746	0.877
		30	0.813	1.113	0.633	0.728	43.432	64.410	0.494	0.564	0.749	0.883
		35	0.815	1.119	0.635	0.732	47.060	74.638	0.495	0.568	0.751	0.888
		40	0.818	1.126	0.637	0.737	54.246	97.046	0.497	0.571	0.753	0.894
		45	0.820	1.133	0.639	0.741	50.760	85.886	0.498	0.574	0.755	0.899
		5	0.793	1.068	0.623	0.706	46.811	74.056	0.487	0.551	0.728	0.840
		10	**0.414**	**0.598**	**0.171**	**0.358**	**39.258**	**56.706**	**0.304**	**0.440**	**0.612**	**0.796**
		15	0.697	0.626	0.537	0.392	59.123	59.361	0.432	0.460	0.654	0.824
		20	0.713	0.848	0.555	0.528	55.565	90.517	0.465	0.436	0.670	0.691
10	10	25	0.740	0.883	0.578	0.562	53.459	80.958	0.457	0.500	0.690	0.724
		30	0.801	1.083	0.631	0.716	47.560	61.210	0.492	0.556	0.726	0.842
		35	0.820	1.128	0.639	0.734	47.701	61.582	0.497	0.566	0.745	0.884
		40	0.822	1.134	0.641	0.739	47.794	61.846	0.498	0.570	0.747	0.889
		45	0.741	1.026	0.573	0.662	56.843	73.726	0.477	0.546	0.690	0.824
		5	0.809	1.105	0.637	0.729	62.540	100.752	0.501	0.577	0.733	0.860
		10	0.756	0.967	0.592	0.622	71.421	101.275	0.470	0.498	0.696	0.776
		15	**0.598**	**0.649**	**0.428**	**0.340**	**84.116**	**134.754**	**0.445**	**0.449**	**0.659**	**0.703**
15	15	20	0.711	0.873	0.549	0.540	78.988	120.141	0.445	0.449	0.659	0.703
		25	0.728	0.908	0.568	0.575	74.235	107.344	0.478	0.515	0.675	0.736
		30	0.818	1.114	0.645	0.733	63.541	81.078	0.506	0.572	0.732	0.855
		35	0.837	1.159	0.654	0.752	63.728	81.572	0.511	0.583	0.751	0.897
		40	0.839	1.166	0.656	0.756	63.853	81.924	0.513	0.586	0.753	0.903
		45	0.842	1.172	0.658	0.760	63.979	82.276	0.514	0.589	0.755	0.909
		5	0.844	1.179	0.660	0.765	63.541	81.332	0.516	0.593	0.758	0.914
		10	0.883	1.237	0.686	0.797	64.748	83.136	0.532	0.613	0.785	0.950
		15	0.853	1.167	0.668	0.759	64.875	83.494	0.520	0.588	0.756	0.888
		20	**0.624**	**0.684**	**0.443**	**0.353**	**65.002**	**83.853**	**0.457**	**0.461**	**0.681**	**0.733**
20	20	25	0.788	1.019	0.613	0.645	84.890	136.164	0.484	0.512	0.719	0.810
		30	0.742	0.919	0.569	0.560	72.564	102.387	0.457	0.461	0.681	0.734
		35	0.759	0.955	0.588	0.596	85.462	138.022	0.492	0.529	0.698	0.768
		40	0.853	1.171	0.668	0.760	80.252	123.106	0.520	0.588	0.756	0.891
		45	0.873	1.218	0.678	0.780	75.423	110.042	0.525	0.599	0.776	0.936
		5	0.878	1.232	0.682	0.788	64.557	83.214	0.528	0.606	0.780	0.946
		10	0.896	1.241	0.697	0.800	65.784	85.059	0.544	0.626	0.787	0.938
25	25	15	0.820	1.065	0.633	0.667	65.913	85.423	0.496	0.525	0.740	0.840
		20	0.772	0.961	0.588	0.579	66.042	85.789	0.469	0.473	0.701	0.761
		25	**0.649**	**0.717**	**0.458**	**0.365**	**65.590**	**83.496**	**0.469**	**0.473**	**0.701**	**0.762**

		30	0.789	1.000	0.607	0.617	65.784	84.006	0.504	0.542	0.719	0.797
		35	0.887	1.225	0.691	0.785	65.913	84.369	0.533	0.603	0.779	0.924
		40	0.908	1.274	0.700	0.806	66.042	84.732	0.538	0.614	0.799	0.970
		45	0.910	1.282	0.702	0.811	86.249	137.739	0.540	0.618	0.801	0.976
		5	0.908	1.276	0.700	0.806	73.725	103.509	0.538	0.614	0.799	0.972
		10	0.941	1.327	0.721	0.833	99.159	159.448	0.550	0.630	0.821	1.001
		15	0.944	1.335	0.723	0.837	93.114	142.185	0.552	0.633	0.823	1.007
		20	0.947	1.342	0.725	0.842	87.511	127.066	0.554	0.637	0.825	1.014
30	30	25	0.949	1.350	0.727	0.847	74.904	96.027	0.555	0.640	0.828	1.020
		30	**0.671**	**0.749**	**0.470**	**0.375**	**75.125**	**96.611**	**0.478**	**0.482**	**0.718**	**0.787**
		35	0.798	1.003	0.603	0.596	75.273	97.027	0.478	0.482	0.718	0.788
		40	0.848	1.113	0.650	0.686	75.420	97.443	0.505	0.535	0.758	0.870
		45	0.918	1.276	0.709	0.807	74.904	96.327	0.543	0.614	0.797	0.955
		5	0.918	1.277	0.709	0.807	75.125	96.912	0.543	0.614	0.797	0.956
		10	0.949	1.344	0.728	0.839	76.703	99.177	0.554	0.632	0.817	1.001
		15	0.954	1.358	0.733	0.849	76.853	99.602	0.557	0.639	0.821	1.013
		20	0.937	1.316	0.725	0.833	100.36	161.591	0.559	0.644	0.804	0.974
35	35	25	0.857	1.131	0.659	0.695	85.793	121.569	0.510	0.540	0.757	0.873
		30	0.807	1.020	0.611	0.604	101.04	163.792	0.482	0.486	0.717	0.792
		35	**0.678**	**0.764**	**0.477**	**0.380**	**94.883**	**144.223**	**0.482**	**0.486**	**0.717**	**0.793**
		40	0.825	1.062	0.632	0.643	89.174	128.856	0.518	0.558	0.734	0.829
		45	0.928	1.299	0.718	0.818	76.327	97.317	0.548	0.620	0.796	0.961
		5	0.960	1.378	0.737	0.859	76.553	97.911	0.560	0.646	0.826	1.029
		10	0.970	1.361	0.746	0.850	78.160	100.201	0.565	0.639	0.824	0.997
		15	0.993	1.415	0.757	0.873	78.313	100.633	0.571	0.651	0.846	1.046
		20	0.995	1.423	0.759	0.878	77.778	99.477	0.572	0.655	0.848	1.052
40	40	25	0.998	1.432	0.761	0.883	78.007	100.083	0.574	0.659	0.851	1.059
		30	1.001	1.440	0.763	0.888	78.160	100.514	0.576	0.662	0.853	1.065
		35	1.004	1.448	0.766	0.893	78.313	100.946	0.578	0.666	0.856	1.072
		40	0.970	1.366	0.746	0.851	102.27	163.946	0.565	0.639	0.824	1.002
		45	**0.709**	**0.807**	**0.495**	**0.396**	**87.423**	**123.267**	**0.497**	**0.501**	**0.743**	**0.830**

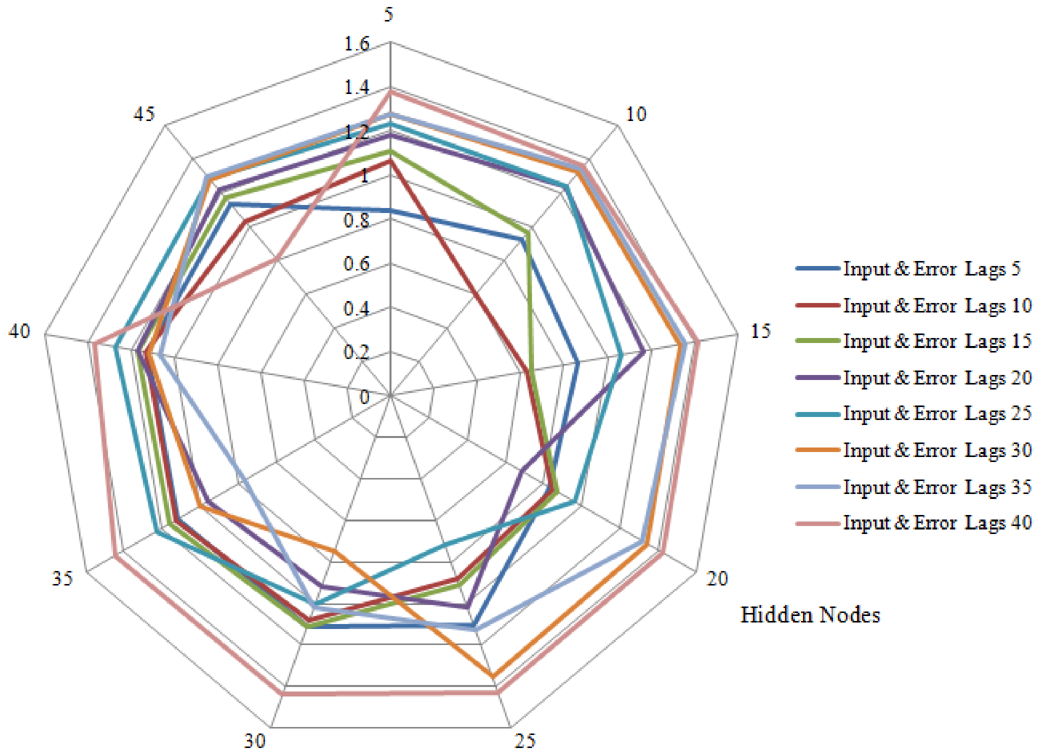


A.

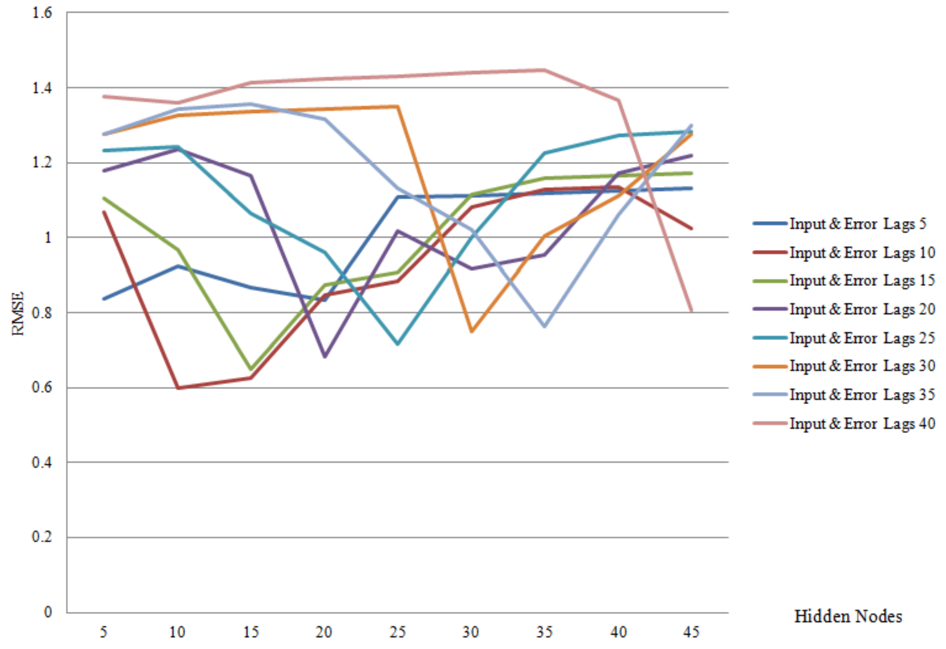


B.

Fig.4: P erformance of BPNN-NAR with Respect to Input Lags and Hidden Nodes on Malaysian Roof Materials Cost Indices Data based on RMSE



A.



B.

Fig. 5: Performance of BPNN-NARMA with Respect to Input Lags and Hidden Nodes on Malaysian Roof Materials Cost Indices Data based on RMSE

References

[1] Shane, J. S., Molenaar, K. R.,&Anderson, S.,& Schexnayder, C. (2009). Construction project cost escalation factors. Journal of Management in Engineering, 25(4), pp. 221-229.

[2] Williams, T. P. (1994). Predicting changes in construction cost indexes using neural networks. Journal of Construction Engineering and Management, 120(2), pp. 306–320.

[3] Ashuri, B. & Lu, J. (2010b). Forecasting ENR construction cost index: A time series analysis approach. Proceedings of Construction Research Congress 2010 & Innovation for Reshaping Construction Practice, 1(1), pp. 1345-1355.

[4] Ervin, E. (2007). How to protect profit as material prices rise. Puget Sound Business Journal, 1(1), pp. 1-7.

[5] Gallagher, J. P. (2008). Material Price Escalation: Managing the Risks. Construction eNewsletter.

[6] Wong, J. M., Ng, S. T. & Chan, A. P. (2010). Strategic planning for the sustainable development of the construction industry in Hong Kong. Habitat International, 34(2), pp. 256-263.

[7] Rao, G. N. & Grobler, F. (1997). Integrated analysis of cost risk and schedule risk. Proc., 4th Congress on Computing in Civil Engineering, pp. 1404–1411.

[8] Flood, I. (1997). Modeling uncertainty in cost estimates: A universal extension of the central limit theorem. Proc., 4th Congress on Computing in Civil Engineering, 1(1), pp. 551–558.
[9] Trost, S. M. & Oberlender, G. D. (2003). Predicting accuracy of early cost estimates using factor analysis and multivariate regression. ASCE Journal of Construction Engineering and Management, 129(2), pp. 198-204.
[10] Attalla, M. & Hegazy, T. (2003). Predicting cost deviation in reconstruction projects: Artificial neural networks versus regression. J. Constr. Eng. Manage., 129(4), pp. 405–411.
[11] Touran, A. (2003). Probabilistic model for cost contingency. Journal of Construction Engineering Management, 129(3), pp. 280–284.
[12] Doğan, S. Z., Arditi, D. & Günaydın, H. M. (2006). Determining attribute weights in a CBR model for early cost prediction of structural systems. J. Constr. Eng. Manage., 132(10), pp. 1092–1098.
[13] Diekmann, J. E. (1983).Probabilistic estimating: Mathematics and applications.J. Constr. Eng. Manage., 109(3), pp. 297–308.
[14] Koppula, S. D. (1981).Forecasting engineering costs: Two case studies. Journal Constr. Div., 107(4), pp. 733–743.
[15] Wilmot, C. G. & Cheng, G. (2003).Estimating future highway construction costs.Journal of Construction Engineering Management, 129(3), pp. 272–279.
[16] El-Melegy, M. T., Essai, M. H. & Ali, A. A. (2009). Robust training of artificial feedforward neural networks. Found Comput Intell 1, 1(1), pp. 217–242.
[17] Allende, H., Moraga, C. & Salas, R. (2002a). Artificial neural networks in time Series forecasting: A comparative analysis. Kybernetika, 38 (6), 685-707.
[18] Allende, H., Moraga, C. & Salas, R. (2002b). Robust estimator for the learning process in neural networks applied in time series. Proceedings of International Conference on Artificial Neural Networks, pp. 1080-1086.
[19] Mohit, M. A., Ibrahim, M. & Rashid, Y. R. (2010). Assessment of residential satisfaction in newly designed public low-cost housing in Kuala Lumpur, Malaysia. Habitat International, 34(1), pp. 18-27.
[20] Uilhoorn, F. E. (2016). Comparison of two non-convex mixed-integer nonlinear programming algorithms applied to autoregressive moving average model structure and parameter estimation. Engineering Optimization, 1(1), pp. 1-14.
[21] Ding, F., Wang, X., Chen, Q. & Xiao, Y. (2016). Recursive least squares parameter estimation for a class of output nonlinear systems based on the model decomposition. Circuits, Systems, and Signal Processing, 1(1), pp. 1-16.
[22] Piloto-Rodríguez, R., Sánchez-Borroto, Y., Lapuerta, M., Goyos-Pérez, L. & Verhelst, S. (2013). Prediction of the cetane number of biodiesel using artificial neural networks and multiple linear regression. Energy Conversion and Management, 1(65), pp. 255-261.
[23] Velo, A., Pérez, F. F., Tanhua, T., Gilcoto, M., Ríos, A. F. & Key, R. M. (2013). Total alkalinity estimation using MLR and neural network techniques.Journal of Marine Systems, 111, pp. 11-18.
[24] Haviluddin, H., & Jawahir, A. (2015). Comparing of ARIMA and RBFNN for short-term forecasting. International Journal of Advances in Intelligent Informatics, 1(1), 15-22.
[25] Ghani, N. A. M., Kamaruddin, S. B. A., Musirin, I., & Hashim, H. (2018). Results of Fitted Neural Network Models on Malaysian Aggregate Dataset. Bulletin of Electrical Engineering and Informatics, 7(2), 272-278.
[26] Ghani, N. A. M., Kamaruddin, S. B. A., Musirin, I., & Hashim, H. (2018). Conventional Neural Network Time Series Models on Sand Price Indices Dataset. International Journal of Engineering and Technology, 7(3.15), 11-15.
[27] Saadi Bin Ahmad Kamaruddin, Nor Azura Md Ghani, Norazan Mohamed Ramli,(2018). Consolidated Backpropagation Neural Network for Malaysian Construction Costs Indices Data with Outliers Problem. Pertanika J. Sci. & Technol., 26 (1): 353 – 366.
[28] Ghani, N. A. M., Kamaruddin, S. A., Ramli, N. M., Musirin, I., & Hashim, H. (2017). Enhanced BFGS Quasi-Newton Backpropagation Models on MCCI Data. Indonesian Journal of Electrical Engineering and Computer Science, 8(1), 101-106.
[29] Sibi, P., Jones, S. A. & Siddarth, P. (2013). Analysis of different activation functions using back propagation neural networks. Journal of Theoretical and Applied Information Technology, 47(3), pp. 1264-1268.
[30] Sofian, I. M., Affandi, A. K., Iskandar, I., & Apriani, Y. (2018). Monthly rainfall prediction based on artificial neural networks with backpropagation and radial basis function. International Journal of Advances in Intelligent Informatics, 4(2).
[31] Beliakov, G., Kelarev, A. & Yearwood, J. (2012). Derivative-free optimization and neural networks for robust regression. Optimization, 61(12), pp. 1467-1490.
[32] Alfons, A., Croux, C. & Gelper, S. (2013). Sparse least trimmed squares regression for analyzing high-dimensional large data sets. The Annals of Applied Statistics, 7 (1), pp. 226-248.
[33] Zioutas, G., Avramidis, A. & Pitsoulis, L. (2007). Penalized Trimmed Squares and A Modi-Fication of Support Vectors for Un-Masking Outliers in Linear Regression. REVSTAT–Statistical Journal, 5(1), pp. 115-136.