Jurnal Teknologi

Full Paper

THE IMPROVED BPNN-NAR AND BPNN-NARMA MODELS ON MALAYSIAN AGGREGATE COST INDICES WITH OUTLYING DATA

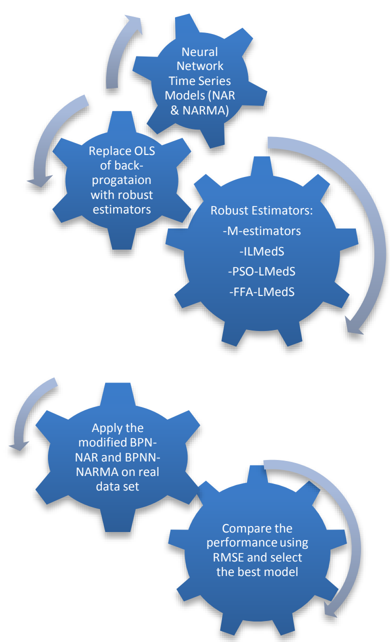
Saadi Ahmad Kamaruddin[a], Nor Azura Md Ghani[b]*, Norazan Mohamed Ramli[b]

[a]Computational and Theoretical Sciences Department, Kulliyyah of Science, International Islamic University Malaysia, Malaysia
[b]Center for Statistical and Decision Sciences Studies, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, Malaysia

Article history
Received
26 November 2015
Received in revised form
14 January 2016
Accepted
10 October 2016

*corresponding author
azura@tmsk.uitm.edu.my

Graphical abstract



Abstract

Neurocomputing have been adapted in time series forecasting arena, but the presence of outliers that usually occur in data time series may be harmful to the data network training. This is because the ability to automatically find out any patterns without prior assumptions and loss of generality. In theory, the most common training algorithm for Backpropagation algorithms leans on reducing ordinary least squares estimator (OLS) or more specifically, the mean squared error (MSE). However, this algorithm is not fully robust when outliers exist in training data, and it will lead to false forecast future value. Therefore, in this paper, we present a new algorithm that manipulate algorithms firefly on least median squares estimator (FFA-LMedS) for Backpropagation neural network nonlinear autoregressive (BPNN-NAR) and Backpropagation neural network nonlinear autoregressive moving (BPNN-NARMA) models to reduce the impact of outliers in time series data. The performances of the proposed enhanced models with comparison to the existing enhanced models using M-estimators, Iterative LMedS (ILMedS) and Particle Swarm Optimization on LMedS (PSO-LMedS) are done based on root mean squared error (RMSE) values which is the main highlight of this paper. In the meanwhile, the real-industrial monthly data of Malaysian Aggregate cost indices data set from January 1980 to December 2012 (base year 1980=100) with different degree of outliers problem is adapted in this research. At the end of this paper, it was found that the enhanced BPNN-NARMA models using M-estimators, ILMedS and FFA-LMedS performed very well with RMSE values almost zero errors. It is expected that the findings would assist the respected authorities involve in Malaysian construction projects to overcome cost overruns.

Keywords: BPNN, NAR, NARMA, firefly algorithm, least median squares

1.0 INTRODUCTION

Financial Initiatives (PFI) is now a trend in Malaysia, as it is consistent with the government's promoting greater private sector's involvement in upholding the reputation of public services. The most vital contributor of PFI is value for money (VFM), where optimal quality of construction projects with respect to client's satisfaction and investments are eventually achieved successfully. It is crucial to calculate on material prices that are incurred throughout the PFI constructions to ensure that overspending will not occur. Since the construction works and service delivery are the leading agenda in the Malaysian PFI, attempts have been made to predict the existing index of construction material price indices in Malaysia. It was well established that cement's controlled price has been obliterated by the Malaysian government, starting on 5 June 2008 [1]. Since then, there was a dramatic increase of the cement price in June 2008 which is by 23.3% in Peninsula Malaysia, while 6.5% was reported in Sabah and 5.2% in Sarawak [1].

In the mean while, Malaysian government had implemented Goods and Services Tax (GST) throughout the nation since 1st April 2015. Goods and Services Tax (GST) is a multi-stage tax on domestic consumption. GST is charged on all taxable supplies of goods and services in Malaysia except those specifically exempted. GST is also charged on importation of goods and services into Malaysia [2]. Due to the implementation of this new policy in Malaysia, developers are mainly hit by the cost of raw materials [3]. The worse impact is, industry players and experts expect the prices of residential properties to rise 2% to 4% post-GST despite the fact that such properties are not subject to the GST. Therefore, with the implementation with GST, coupled with the tougher operating environment, property developers are likely to strategies to buffer any negative impact.

The price increment is also applicable to the remaining construction materials- steel, ready mix concrete and several others [4]. As construction material prices in Malaysia have been met with uncertainty, the best method has been probed to give estimation of the construction material prices according to the central region of Malaysia. Next, the related literature is presented in section II, and the background of data used in this study is described briefly in section III. In section IV, the method overview is also supplied, and the method used to analyze the data explained. Next, the finalized results and discussion on the best forecasting approach for estimating the material price indices according to Malaysian regions are presented in section V. Finally, section VI contains the conclusion of the study, plus a recommendation for future works.

The direct idea of making the conventional neural network learning algorithm more powerful towards outlying data is by substituting the mean square error (MSE) with a different symmetric and continuous cost function. This will result in a nonlinear influence function [5] with the capability to cater for the influence of large errors. This can only be performed by making the loss functions robust using the statistical robust methods to reduce the impact of outliers issue [5,6], where the usual outliers occurrence in routine data ranges up to10% or even more [5-7]- this is the primary subject of this paper.

ANNs serves to be the object of interest of this research as they have proven to be effective in many scientific areas [8]. This is reasoned by the ability of the popular feedforward neural networks as a universal function approximator [6]. Most of the previous studies seek to improve the learning algorithm of feedforward neural networks by adapting the M-estimators predominantly.

In 1996, Liano [9] had introduced the LMLS (Least Mean Log Squares) method. He had introduced the logistic error function by forming an assumption of the errors generated using the Cauchy distribution. This contribution has inspired other authors to create some more competent functions. The idea of M-estimators by Hampel [10] had been continued by Chen and Jain [11] as they developed a new error criterion called Hampel's hyperbolic tangent, where β estimator was used to define the size of residuals assumed to be outliers.

Hector et al. [12] found that a robust algorithm for nonlinear autoregressive (NAR) models using the generalized maximum likelihood (GM) type estimators had outperformed the least squares method in managing the outliers. In a study by Chuang and Su [13], the annealing scheme was applied to reduce the value of β with the training progress. There were also approaches that also have performance functions based on the tau-estimators [14] and the LTS (Least Trimmed Squares) estimator, while the start-up data analysis with the MCD (Minimum Covariance Determinant) estimator was suggested [5]. El-Melegy et al. [6] have presented the Simulated Annealing for Least Median of Squares (SA-LMedS) algorithm, as they applied the simulated annealing technique to mitigate the performance measured by the median of squared residuals. Some efforts to make the learning methods of radial basis function networks more powerful, following the approaches for the sigmoid networks, have also been exercised [15, 16]. The latest robust learning methods to be mentioned are robust co-training based on the canonical correlation analysis as put forth by Sun and Jin [17], and robust adaptive learning using linear matrix inequality techniques [18].

In a paper written by Rusiecki [5], a new robust learning algorithm based on the iterated Least Median of Squares (LMedS) estimator was introduced. This new approach is much more effective and remarkably faster than the SA-LMedS method [6]. It also achieves better resistance to flawed training data. To ensure the robustness of the training process, not only that the performance function is modified, but also data suspected to be outliers were removed iteratively. Moreover, an approximate method to minimise the LMedS error criterion was proposed.

However, it is clear that all these works had given focus only on the NAR model. None of the works had considered using a robust approach in improving the NARMA model. The overall performance of the NARMA model is better than the NAR model [19]. It is the novelty of the approach that the existing robust estimators will be implemented on BPNN of the NARMA models. Another new factor of the research is translated in the extension of study towards the use of particle swarm optimization (PSO) to minimise the LMedS error criterion as begun by Shinzawa et al. [20], with adaptation of the NARMA model.

PSO developed by Eberhart and Kennedy [21], is a stochastic search method which took some inspiration from the act of the birds flocking. Similar to the genetic algorithm (GA), PSO is a population-based optimization tool that looks for optima by updating generations [21-25]. However, not like the GA, no evolution operators were included by the PSO [26]. As compared to GA, a striking advantage of PSO is that its algorithm has an extremely simple concept, computation costs are not high and only few adjustable parameters are required.

Moreover, Xin-She Yang in 2007 from Cambridge University developed a new metaheuristic algorithm, namely firefly (FFA) algorithm [29-34]. The firefly algorithm was found to perform better compared to particle swarm optimization in handling high level of noise [35]. In this study, we introduce a new approach to robustify the backpropagation learning algorithm of nonlinear neural network time series models using FFA-LMedS estimator. This paper aims to compare the performance of MSE, M-estimators, ILMedS, PSO-LMedS and FFA-LMedS in backpropagation algorithm of both BPNN-NAR and BPNN-NARMA models.

2.0 METHODOLOGY

The data were compiled from three different sources namely Unit Kerjasama Awam Swasta (UKAS) of Prime Minister's Department, Construction Industry Development Board (CIDB) and Malaysian Statistics Department which had endorsed the PFI construction material price indices for the Central region of the Peninsula which consists of three states Kuala Lumpur Federal Territory, Selangor, Negeri Sembilan and Melaka. The real-industrial monthly data of Malaysian Aggregate cost indices from January 1980 to December 2012 (base year 1980=100) were adapted, with outliers 3.9 percent of the overall data set.

Table 1 exhibits the summary statistics of the variable of interest. The total N=408 (12 months x 34 years) from January 1980 to 2013 (base 1980=100). The mean of aggregate is 113.7731, and the standard deviation is 7.63405. The variable is positively skewed with 1.409 skewness value. Based on the Jarque-Bera test for normality, the variable is highly significant at 99% confidence interval; aggregate (J-B=0.873, p=0.000). The variable of interest suffers from outliers problem as can be seen in Figure 1.

Table 1 Summary statistics of the malaysian cost indices Data

Notation	N	Mean	Std. Dev.	Max	Min	Skewness	Kurtosis	J-B
Agg	408	113.7731	7.63405	140.63	99.2	1.409	2.803	0.873 **

Note: * and **indicate significance at the 5% and 1% levels respectively.

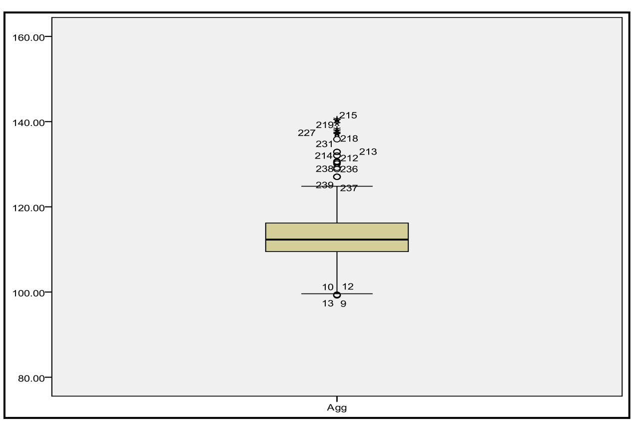


Figure 1 The boxplot of malaysian aggregate cost indices data

The flowchart of the research can be seen in Figure 2 Here, the existing robust estimators on backpropagation neural network were implemented. To answer the main objective of the study, the possible robust estimators hybrid in nonlinear autoregressive (NAR) and nonlinear autoregressive moving average (NARMA) of neural network time series were done using MATLAB R2012a. At this step, MATLAB scripts or codings were written parallel to the mathematical formulation done earlier. After that, the performance of the proposed robustified neural network models were compared using real life data using the standard performance measures (RMSE). The best comparative results were drawn here where the best model was chosen. The basic BPNN-NAR formulation can be represented as below;

The basic BPNN-NAR formulation can be represented as below;

$$H(x) = purelin\left[\sum_{j=1}^{m} w_{jk}\left[\tanh\left(\sum_{i=1}^{l} w_{ij}\left[x(t-1), x(t-2),..., x(t-n_y)\right] + \varepsilon(t)\right)\right]\right] \quad (1)$$

The finalized BPNN-NARMA formulation can be represented as below;

$$H(x) = purelin\left[\sum_{j=1}^{m} w_{jk}\left[\tanh\left(\sum_{i=1}^{l} w_{ij}\begin{bmatrix}[x(t-1), x(t-2),..., x(t-n_y), \\ \varepsilon(t-1), \varepsilon(t-2),..., \varepsilon(t-n_\varepsilon)] + \varepsilon(t)\end{bmatrix}\right)\right]\right] \quad (2)$$

where

$H(x)$ is the estimated model,
$x(t-1), x(t-2),\ldots, x(t-n_y)$ are lagged input terms,
$\varepsilon(t-1), \varepsilon(t-2),\ldots\varepsilon(t-n_\varepsilon)$ are lagged residual terms, and the lagged residual terms are obtained recursively after the initial model (based on the input and output terms) is found.
Hence, $\varepsilon(t)$ are the white noise residuals.
l is the input neurons with index i
m is the hidden neurons with index j
n is the output neurons with index k

A) Robust Backpropagation Algorithm

The most important part of the study is the mathematical formulation improvement part of backpropagation neural network algorithm using statistical robust estimators. To make robust the traditional backpropagation algorithm based on the M-estimators concept for reducing outlier effect, the squared residuals ε_i^2 in the network error by another function of the residuals

$$E = \frac{1}{N}\sum_{i}^{N}\varepsilon_i^2 , \quad (3)$$

and this yields,

$$E = \frac{1}{N}\sum_{i}^{N}\rho(\varepsilon_i), \quad (4)$$

where N is the total number of samples available for network training. We are deriving the updating of the network weights based on the gradient decent learning algorithm. To prevent the loss of generality, a feedforward neural network with one hidden layer will be implemented in this study. The weights from the hidden neurons to output neurons, $W_{j,i}$ are expressed as

$$\Delta W_{j,i} = -\alpha\frac{\partial E}{\partial W_{j,i}} = -\frac{\alpha}{N}\sum_{i}^{N}\frac{\partial\rho(\varepsilon_i)}{\partial W_{j,i}}$$

$$= -\frac{\alpha}{N}\sum_{i}^{N}\varphi(r_i).\frac{\partial f_j}{\partial net_j}.O_i, \quad (5)$$

where α is a user-supplied learning constant, O_h is the output of the i^{th} hidden neuron, $O_j=f_j(net_j)$ is the output of the j^{th} output neuron, $net_j=\sum_i W_{ji}O_i$ is the induced local field produced at the input of the activation function associated with the output neuron (j), and f_j is the activation function of the neurons in the output layer. In this paper, a linear activation function (purelin) is used in the output layer's neurons. The weights from the input to hidden neurons $W_{j,i}$ are updated as

$$\Delta W_{ji} = -\alpha\frac{\partial E}{\partial W_{ji}} = -\frac{\alpha}{N}\sum_{i}^{N}\frac{\partial\rho(\varepsilon_i)}{\partial W_{j,i}}$$

$$= -\frac{\alpha}{N}\sum_{i}^{N}\sum_{j}\varphi(r_i).\frac{\partial f_j}{\partial net_j}.W_{j,i}.\frac{\partial f_i}{\partial net_i}.I_i, \quad (6)$$

where I_i is the input to the ith input neuron, $net_j=\sum_i W_{j,i}O_i$ is induced local field produced at the input of the activation function associated with the hidden neuron (i), and f_j is the activation function of the neurons in the hidden layer. We have the intention to use the tan-sigmoid function as the activation function for the hidden layer's neurons because of its flexibility.

The least-median-of-squares (LMedS) method estimates the parameters by solving the nonlinear minimization problem

$$\min\ med_i\ \varepsilon_i^2 \quad (7)$$

That is, the estimator must produce the smallest value for the median of squared residuals computed for the entire data set. It appears that this method is very robust to false matches and also to outliers owing to bad localization [6]. Not like the M-estimators, however, the LMedS problem cannot be reduced to a weighted least-squares problem. It is perhaps not doable to jot down a straightforward formula for the derivative of LMedS estimator. Hence, deterministic algorithms may not be able to function to minimize that estimator. The Monte-Carlo technique [7, 27] has been practised to solve this problem in some non-neural applications. Stochastic algorithms are also identified as the optimization algorithms which use random search to attain a solution. Stochastic algorithms are thus relatively slow, but there is likelihood that it will find the global minimum. One quite popular optimization algorithm applied to minimize an LMedS-based network error is simulated annealing (SA) algorithm. SA is a superb algorithm because it is relatively general and it has the tendency not to get stuck in either the local minimum or maximum [6]. However, [5] discovers that iterated LMedS tends to outperform the SA-LMedS. Table 2 shows the stopping criterion considered in this research. Figure 2 shows the experimental flowchart of the proposed robust BPNN-NAR and BPNN-NARMA models.

3.0 RESULT AND DISCUSSION

Table 3 shows the comparisons of performance results of robustified nonlinear autoregressive and nonlinear autoregressive moving average of artificial neural network time series models on Malaysian Aggregate Materials cost indices data respectively. The results are based on the different parameter settings combinations in both BPNN-NAR and BPNN-NARMA models.

Table 4 represents the model validation results of ordinary and modified backpropagation algorithms on Malaysian Aggregate Price Index Data using Moving Block Bootstrap. All in all, the results observed in Table 3 are reliable since the bootstrap results are better than the results observed in Table 3.

4.0 CONCLUSION

In this particular study, nonlinear time series neural network models were used; NAR and NARMA models to cope the uncertainty of the future [28]. Since the presence of outliers are impossible to be avoided in real data set, training feedforward neural networks by the popular backpropagation algorithm may produce wrong and inaccurate models because the original MSE learning algorithm is not robust, and as a result, a loss of efficiency [36]. Therefore, there is a need to replace the MSE cost function with another robust cost functions such as M-estimators, ILMedS, PSO-LMedS and FFA-LMedS.

In future endeavour, FFA-LMedS shall be experimented on real-world-data which consist of 30% to 50% outlying data. The proposed robust algorithms for training neural networks may be possible to be adapted various fields of artificial intelligence, system identification, pattern recognition, machine learning, quality control and optimization and scientific computing.

Table 2 Stopping Criteria

MATLAB Terms	Values	NN Terms
net.trainParam.epochs	1000	Maximum number of epochs to train
net.trainParam.goal	0	Performance goal
net.trainParam.max_fail	6	Maximum validation failures
net.trainParam.min_grad	1e^-7	Minimum performance gradient
net.trainParam.mu	0.001	Initial μ
net.trainParam.mu_dec	0.1	μ decrease factor
net.trainParam.mu_inc	10	μ increase factor
net.trainParam.mu_max	1e^10	Maximum μ

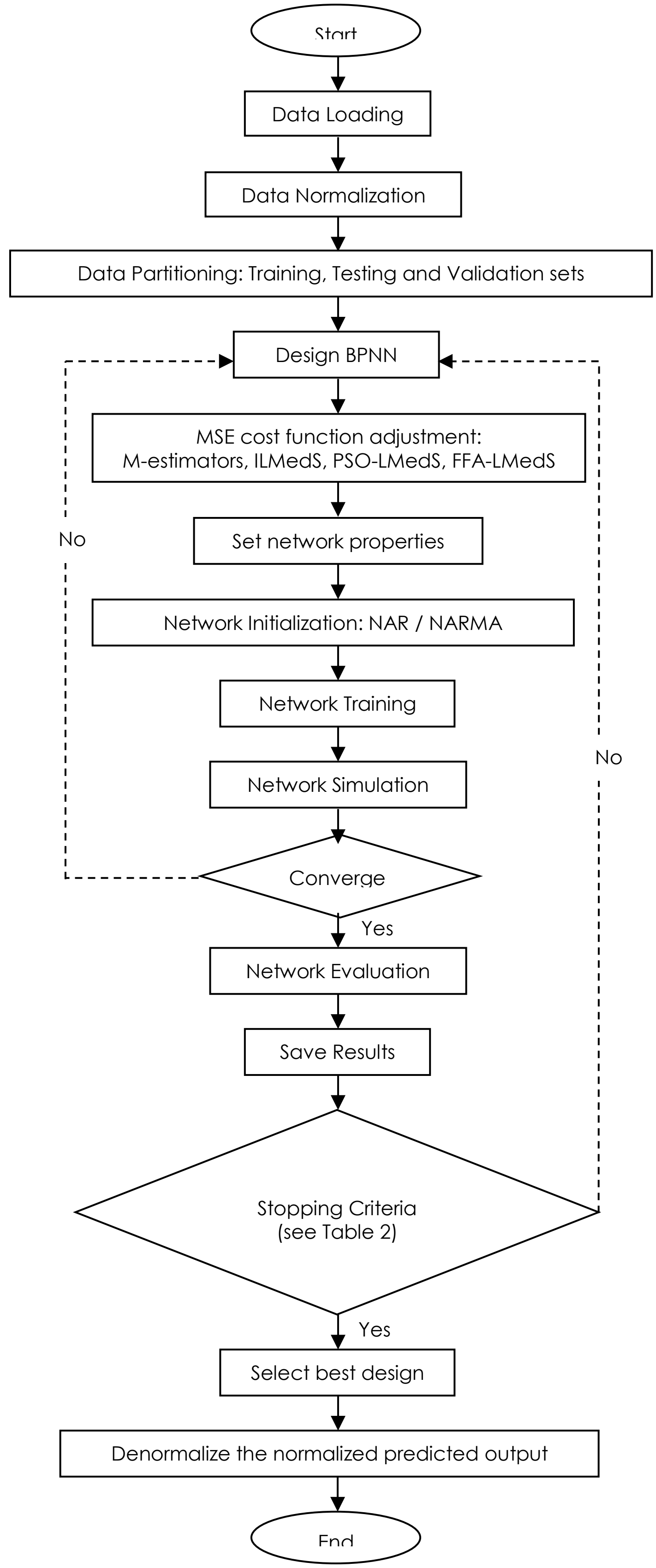


Figure 2 Flowchart of proposed robust BPNN-NAR and BPNN-NARMA

Table 3 Comparison of the best results of ordinary and modified back propagation algorithms on Malaysian aggregate price index data

Input Lags	Error Lags	Hidden Nodes	NAR						NARMA					
			RMSE	MSE	AIC	MAPE	MAD	R^2	RMSE	MSE	AIC	MAPE	MAD	R^2
MSE														
10	10	20	1.877	0.079	39.972	547.179	1.106	0.905	2.726	0.115	58.052	794.677	1.607	0.869
M-estimators (L2)														
15	15	25	0.123	0.005	2.619	35.857	0.073	0.978	0.013	0.001	0.277	3.790	0.008	0.983
M-estimators (L1)														
15	15	25	0.123	0.005	2.619	35.857	0.073	0.978	0.013	0.001	0.277	3.790	0.008	0.983
M-estimators (L1-L2)														
10	10	20	0.053	0.002	1.129	15.450	0.031	0.981	0.006	0.000	0.128	1.749	0.004	0.983
M-estimators (LP)														
25	25	40	0.040	0.002	0.852	11.661	0.024	0.982	0.002	0.000	0.043	0.583	0.001	0.984
M-estimators (Fair)														
15	15	25	0.074	0.003	1.576	21.572	0.044	0.981	0.006	0.000	0.128	1.749	0.004	0.983
M-estimators (Huber)														
15	15	20	0.006	0.000	0.128	1.749	0.004	0.983	0.000	0.000	0.000	0.000	0.000	0.996
M-estimators (Cauchy)														
25	25	40	0.094	0.004	2.002	27.403	0.055	0.980	0.094	0.004	2.002	27.403	0.055	0.980
M-estimators (Geman-McClaure)														
15	15	25	0.072	0.003	1.533	20.989	0.042	0.981	0.006	0.000	0.128	1.749	0.004	0.983
M-estimators (Welsch)														
15	15	20	0.015	0.001	0.319	4.373	0.009	0.983	0.000	0.000	0.000	0.000	0.000	0.998
M-estimators (Tukey)														
20	20	35	0.070	0.003	1.491	20.406	0.041	0.981	0.002	0.000	0.043	0.583	0.001	0.984
Iterated Least Median Square (ILMedS)														
15	15	20	0.053	0.002	1.129	15.450	0.031	0.981	0.003	0.000	0.064	0.875	0.002	0.984

Particle Swarm Optimization on Least Median Square (PSO-LMedS)

Input Lags	Error Lags	Hidden	Swarm Size	Itera-tion	NAR						NARMA					
					RMSE	MSE	AIC	MAPE	MAD	R^2	RMSE	MSE	AIC	MAPE	MAD	R^2
15	15	40	40	20	0.005	0.000	0.106	1.458	0.003	0.983	0.005	0.000	0.106	1.458	0.003	0.983
Firefly Algorithm on Least Median Square (FFA-LMedS)																
15	15	20	20	20	0.007	0.003	1.491	20.406	0.041	0.981	0.002	0.000	0.043	0.583	0.001	0.984

Table 4 Model validation results of ordinary and modified back propagation algorithms on Malaysian aggregate price index data using moving block bootstrap

Input Lags	Error Lags	Hidden Nodes	NAR						NARMA					
			RMSE	MSE	AIC	MAPE	MAD	R^2	RMSE	MSE	AIC	MAPE	MAD	R^2
MSE														
10	10	20	1.727	0.073	34.376	514.348	1.040	0.907	2.535	0.102	49.925	754.943	1.478	0.872
M-estimators (L2)														
15	15	25	0.113	0.005	2.252	33.706	0.069	0.980	0.012	0.001	0.238	3.601	0.007	0.986
M-estimators (L1)														
15	15	25	0.113	0.005	2.252	33.706	0.069	0.980	0.012	0.001	0.238	3.601	0.007	0.986
M-estimators (L1-L2)														
10	10	20	0.049	0.002	0.971	14.523	0.029	0.983	0.006	0.000	0.110	1.662	0.004	0.986
M-estimators (LP)														
25	25	40	0.037	0.002	0.733	10.961	0.023	0.984	0.002	0.000	0.037	0.554	0.001	0.987
M-estimators (Fair)														
15	15	25	0.068	0.003	1.355	20.278	0.041	0.983	0.006	0.000	0.110	1.662	0.004	0.986
M-estimators (Huber)														
15	15	20	0.006	0.000	0.110	1.644	0.004	0.985	0.000	0.000	0.000	0.000	0.000	0.999
M-estimators (Cauchy)														
25	25	40	0.086	0.004	1.722	25.759	0.052	0.982	0.087	0.004	1.722	26.033	0.051	0.983
M-estimators (Geman-McClaure)														
15	15	25	0.066	0.003	1.318	19.730	0.039	0.983	0.006	0.000	0.110	1.662	0.004	0.986
M-estimators (Welsch)														
15	15	20	0.014	0.001	0.274	4.111	0.008	0.985	0.000	0.000	0.000	0.000	0.000	1.000
M-estimators (Tukey)														
20	20	35	0.064	0.003	1.282	19.182	0.039	0.983	0.002	0.000	0.037	0.554	0.001	0.987
Iterated Least Median Square (ILMedS)														
15	15	20	0.049	0.002	0.971	14.523	0.029	0.983	0.003	0.000	0.055	0.831	0.002	0.987

Particle Swarm Optimization on Least Median Square (PSO-LMedS)

Input Lags	Error Lags	Hidden	Swarm Size	Itera-tion	NAR						NARMA					
					RMSE	MSE	AIC	MAPE	MAD	R^2	RMSE	MSE	AIC	MAPE	MAD	R^2
15	15	40	40	20	0.005	0.000	0.091	1.371	0.003	0.985	0.005	0.000	0.091	1.385	0.003	0.986
Firefly Algorithm on Least Median Square (FFA-LMedS)																
15	15	20	20	20	0.006	0.003	1.282	19.182	0.039	0.983	0.002	0.000	0.037	0.554	0.001	0.987

Acknowledgement

Special thanks also go to Universiti Teknologi MARA and Malaysian Ministry of Education (MOE) for supporting this research under the Research Grant No. 600-RMI/FRGS 5/3 (137/2014) and No. 600-RMI/DANA 5/3/CIFI (65/2013). Additionally, appreciation to International Islamic University Malaysia and MOHE for the research grant awarded to this project, RIGS 16-092-0256.

References

[1] Foad, H. M. and Mulup, A. 2008. *Harga Siling Simen Dimansuh 5 Jun,* Utusan, Putrajaya, 2nd June.

[2] Goh, J. 2015. Developers Strategizing to Buffer GST Impact, *The Edge Malaysia, MSN News*, 9th February.. 27.

[3] Royal Malaysian Customs. 2014. *Good and Sevices Tax: Guide on Construction Industry*, 29th October, pp. 1-27.

[4] S. B. A. Kamaruddin, N. A. M. Ghani and N. M. Ramli. 2014. Best Forecasting Models for Private Financial Initiative Unitary Charges Data of East Coast and Southern Regions in Peninsular Malaysia. *International Journal of Economics and Statistics.* 2

[5] A. Rusiecki. 2012. Robust Learning Algorithm Based on Iterative Least Median of Squares, *Neural Process Lett.* 36: 145-160.

[6] M. T. El-Melegy, M. H. Essai and A. A. Ali. 2009. Robust Training of Artificial Feedforward Neural Networks, *Found Comput Intell 1, Springer, Berlin, Heidelberg.* 1: 217–242.

[7] Z. Zhang. 1997. Parameter Estimation Techniques: A tutorial with Application to Conic Fitting, *Image and Vision Computing.* 15(1): 59-76.

[8] P. Sugunnasil, S. Somhom, W. Jumpamule and N. Tongsiri, 2014. Modelling A Neural Network Using An Algebraic Method, *ScienceAsia. 40*: 94-100.

[9] K. Liano, 1996. Robust Error Measure for Supervised Neural Network Learning with Outliers, *IEEE Trans. Neural Networks 7*: 246-250.

[10] F. R. Hampel, E. M. Ronchetti, P. J. Rousseeuw and W. A. Stahel 1986. *Robust Statistics, The Approach Based On Influence Functions,* Wiley, New York

[11] D. S. Chen and R. C. Jain. 1994. A Robust Back Propagation Learning Algorithm for Function Approximation, *IEEE Trans Neural Netw. 5:* 467–479.

[12] A. Hector, M. Claudio and S. Rodrigo, *2002.* Robust Estimator for the Learning Process in Neural Network Applied in Time Series, *ICANN 2002, LNCS.* 1080-1086.

[13] C. Chuang, S. Su and C. Hsiao. *2000.* The Annealing Robust Backpropagation (ARBP) Learning Algorithm, *IEEE Trans Neural Netw. 1:* 1067–1076.

[14] A. V. Pernia-Espinoza, J. B. Ordieres-Mere, F. J. Martinez-de-Pison and Gonzalez-Marcos. *2005.* A TAO-Robust Backpropagation Learning Algorithm, *Neural Networ. 18:* 191–204.

[15] C. C. Chuang, J. T. Jeng and P. T. Lin; 2004; Annealing Robust Radial Basis Function Networks for Function Approximation with Outliers, *Neurocomputing* 56: 123–139.

[16] S. V. A. David, 1995. Robustization of A Learning Method for RBF Networks, *Neurocomputing* 9: 85–94.

[17] S. Sun and F. Jin. 2011. Robust co-training, *International Journal of Pattern Recognition Artificial Intelligence.* 25(7): 1113–1126.

[18] X. Jing. 2012, Robust Adaptive Learning of Feedforward Neural Networks via LMI Optimizations, *Neural Networks*. 31: 33-45.

[19] G. M. Bruna. 1994.. *Short Term Load Forecasting Using Non-Linear Models, Master Thesis Report, Measurement and Control Section ER, Electrical Engineering*, Eindhoven University of Technology, The Netherlands, August 1994.

[20] H. Shinzawa, J. H. Jiang, M. Iwahashi and Y. Ozaki. 2007. Robust Curve Fitting Method for Optical Spectra by Least Median Squares (LMedS) Estimator with Particle Swarm Optimization (PSO). *Analytical Science.,* 23(7): 781-785.

[21] J. Kennedy and R. Eberhart. 1995. Particle Swarm Optimization, *Proceedings of IEEE International Conference on Neural Network. 4*(2): 1942-1948.

[22] Y. Shi and R. Eberhart. 1998. A Modified Particle Swarm Optimizer, *Evolutionary, Proceedings of IEEE World Congress on Computational Intelligence*. 69-73.

[23] M. Clerc and J. Kennedy. 2002. The Particle Swarm-Explosion, Stability, and Convergence in A Multidimensional Complex Space, *IEEE Transactions on Evolutionary Computation, 6(1*): 58-73.

[24] R. C. Eberhart and Y. Shi. *2001.* Particle Swarm Optimization: Developments, Applications and Resources, *Proceedings of the 2001 Congress on Evolutionary Computation.* 81-86.

[25] J. Yu, S. Wang and L. Xi, 2008. Evolving Artificial Neural Networks Using an Improved PSO and DPSO, *Neurocomputing*, 71(4): 1054-1060.