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Consolidated Backpropagation Neural Network for Malaysian Construction Costs Indices Data with Outliers Problem

Saadi Ahmad Kamaruddin[1], Nor Azura Md Ghani[2]* and Norazan Mohamed Ramli[2]

[1]*Computational and Theoretical Sciences Department, Kulliyyah of Science, International Islamic University Malaysia, 53100 Kuala Lumpur, Malaysia*
[2]*Centre for Statistical and Decision Sciences Studies, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 UiTM, Shah Alam, Selangor Malaysia*

ABSTRACT

Neurocomputing has been adjusted effectively in time series forecasting activities, yet the vicinity of exceptions that frequently happens in time arrangement information might contaminate the system preparing information. This is because of its capacity to naturally realise any example without earlier suspicions and loss of sweeping statement. In principle, the most widely recognised calculation for preparing the system is the backpropagation (BP) calculation, which inclines toward minimisation of standard slightest squares (OLS) estimator, particularly the mean squared mistake (MSE). Regardless, this calculation is not by any stretch of the imagination strong when the exceptions are available, and it might prompt bogus expectation of future qualities. In this paper, we exhibit another calculation which controls the firefly algorithm of least median squares (FFA-LMedS) estimator for neural system nonlinear autoregressive moving average (ANN-NARMA) model enhancement to provide betterment for the peripheral issue in time arrangement information. Moreover, execution of the solidified model in correlation with another hearty ANN-NARMA models, utilising M-estimators, Iterative LMedS and Particle Swarm Optimisation on LMedS (PSO-LMedS) with root mean squared blunder (RMSE) qualities, is highlighted in this paper. In the interim, the actual monthly information of Malaysian Aggregate, Sand and Roof Materials value was taken from January 1980 to December 2012 (base year 1980=100) with various levels of anomaly issues. It was found that the robustified ANN-NARMA model utilising FFA-LMedS delivered the best results, with the RMSE values having almost no mistakes at all in all the preparation, testing and acceptance sets for every single distinctive variable. Findings of the studies are hoped to assist the regarded powers including the PFI development tasks to overcome cost overwhelms.

Keywords: ANN, time series, robust backpropagation, firefly algorithm, least median squares

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E-mail addresses:
adi8585@yahoo.com (Saadi Ahmad Kamaruddin),
azura@tmsk.uitm.edu.my;
azura158@salam.uitm.edu.my (Nor Azura Md Ghani),
norazan@tmsk.uitm.edu.my (Norazan Mohamed Ramli)
*Corresponding Author

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INTRODUCTION

Private Financial Initiative (PFI) is currently a pattern in Malaysia as it is steady with the administration advancing more noteworthy private division's association in maintaining the notoriety of open administration. The most basic benefactor of PFI is value for money (VFM), where ideal nature of development tasks for customer's fulfilment and ventures in the long run are accomplished effectively. It is pivotal to figure on material costs that are brought about through PFI developments to guarantee that overspending will not happen. Since the development works and administration conveyance are the main motivations in the Malaysian PFI, endeavors have been made to foresee the current record of development material value files in Malaysia. It was settled that concrete's controlled cost has been wrecked by the Malaysian government, beginning on 5 June 2008 (Foad & Mulup, 2008). From that point on, there was a significant increment of the bond cost in June 2008, which was by 23.3% in Peninsula Malaysia, while this was 6.5% for Sabah and 5.2% in Sarawak (Foad & Mulup, 2008).

Malaysian government had executed Goods and Services Tax (GST) all through the country since 1 April 2015. Products and Services Tax (GST) is a multi-stage charge on local utilisation. GST is charged on every assessable supply of products and administrations in Malaysia, with the exception of those exempted. GST is likewise charged on importation of merchandise and administrations into Malaysia (Goh, 2015). Because of the GST implimention in Malaysia, engineers are principally hit by the expense of crude materials (Royal Malaysian Customs, 2014). The worst effect is, industry players and specialists expect the costs of private properties to rise 2% to 4% post-GST in spite of the way that such properties are not subject to the GST. In this way, with the execution with GST, combined with the harder working environment, property engineers are liable to methodologies to cradle any negative effect.

The value augmentation is additionally appropriate to the remaining development materials-steel, prepared blend concrete and a few others (Kamaruddin, Ghani, & Ramli, 2014). As development material costs in Malaysia have been met with vulnerability, the best strategy has been examined to give estimation of the development material costs as per the focal area of Malaysia. Next, the related writing is exhibited in the subsequent section, and the foundation of information utilised as a part of this study is depicted in the section that follows. Strategy review is additionally supplied, and the technique used to dissect the information clarified. Next, the concluded results and discourse on the best anticipating approach for evaluating the material value files, as indicated by Malaysian areas, are elaborated in result and discussion section. Finally, the conclusion of the study is elaborated at the end of the paper, together with recommendations for future work.

RELATED LITERATURE

The immediate thought of making the customary neural system learning calculation all the more effective towards remote information is by substituting the mean square errors (MSE) with an alternate symmetric and persistent cost capacity. This will bring about a nonlinear impact capacity (Rusiecki, 2012) with the ability to provide food for the impacts of extensive mistakes. This must be performed by making the misfortune capacities hearty utilising the factual vigorous strategies to lessen the effects of anomalies issue (Rusiecki, 2012; El-Melegy, Essai, & Ali, 2009), where typical exceptions include event in routine information ranges up to 10% or significantly more (Rusiecki, 2012; El-Melegy et al., 2009; Zhang, 1997), which is the essential subject of this paper.

ANNs serves to be the object of enthusiasm of this exploration as they have turned out to be compelling in numerous exploratory zones (Sugunnasil, Somhom, Jumpamule, & Tongsiri, 2014). This is contemplated by the capacity of the mainstream feedforward neural systems as a general capacity approximator (El-Melegy et al., 2009). The greater part of past studies have attempted to enhance adaptation so as to learn calculation of feedforward neural systems, the M-estimators, overwhelmingly.

In 1996, Liano (1996) presented the LMLS (Least Mean Log Squares) strategy. He presented the logistic mistake capacity by shaping a presumption of the blunders produced utilising the Cauchy appropriation. This commitment has motivated different creators to make some more equipped capacities. The thought of M-estimators by Hampel (Hampel, Ronchetti, Rousseeuw & Stahel, 1986) had been proceeded by Chen and Jain (Chen & Jain, 1994) as they added to another mistake basis called Hampel's hyperbolic digression, where β estimator was utilised to characterise the extent of residuals thought to be anomalies.

Hector, Claudio, and Rodrigo (2002) found that a vigorous calculation for nonlinear autoregressive (NAR) models utilising the summed up most extreme probability (GM) sort estimators beat the minimum squares technique in dealing with the exceptions. In a study by Chuang, Su, and Hsiao (2000), the toughening plan was connected to decrease the estimation of β with the preparation progress. There were likewise approaches that additionally have execution capacities taking into account the tau-estimators (Pernia-Espinoza, Ordieres-Mere, Martinez-de-Pison, & Gonzalez-Marcos, 2005) and the LTS (Least Trimmed Squares) estimator, while the start-up information examination with the MCD (Minimum Covariance Determinant) estimator was recommended (Rusiecki, 2012). El-Melegy et al. (2009) have exhibited the Simulated Annealing for Least Median of Squares (SA-LMedS) calculation, as they connected the reproduced strengthening procedure to relieve the execution measured by the middle of squared residuals. A few endeavours to make the learning techniques for outspread premise capacity organises all the more effective, after the methodologies for the sigmoid systems, have additionally been practiced (Chuang, Jeng, & Lin, 2004; David, 1995). The most recent vigorous learning strategies to be specified are powerful co-preparing in view of the authoritative connection examination, as set forth by Sun and Jin (2011), and hearty versatile learning utilising direct grid imbalance methods (Jing, 2012).

In a paper composed by Rusiecki (2012), another hearty learning calculation in view of the iterated Least Median of Squares (LMedS) estimator was presented. This new approach is a great deal more compelling and strikingly speedier than the SA-LMedS technique (El-Melegy et al., 2009). It likewise accomplishes better imperviousness to imperfect preparing information. To guarantee the power of the preparation process that the execution capacity is changed, information suspected to be exceptions is evacuated iteratively. A rough technique to minimise the LMedS blunder rule was proposed.

In any case, it is clear that each of these works has concentrated on the NAR model only. In other words, none of the works has considered utilising a strong methodology to enhance the NARMA model. The general execution of the NARMA model is superior to the NAR model (Bruna, 1994). It is the curiosity of the methodology that the current vigorous estimators are executed on BPNN of the NARMA models. Another new variable of the examination is interpreted in the augmentation of study towards the utilisation of molecule swarm advancement (PSO) to minimise the LMedS mistake standard, as started by Shinzawa, Jiang, Iwahashi and Ozaki (2007), with adjustment of the NARMA model.

PSO, created by Eberhart and Kennedy (1995), is a stochastic inquiry technique which takes motivation from the demonstration of winged animals rushing. Like the hereditary calculation (GA), PSO is a populace based enhancement apparatus that searches for optima by upgrading eras (Eberhart & Kennedy, 1995; Shi & Eberhart, 1998; Clerc & Shi, 2002; Eberhart & Shi, 2001; Yu, Wang, & Xi, 2008). Be that as it, unlike the GA, no development administrators were incorporated by the PSO (Goldberg, 1989). When contrasted with GA, a striking favourable position of PSO is that its calculation has a great basic idea, while calculation expenses are not high and only a couple of flexible parameters are required.

Also, in 2007, Xin-She Yang from Cambridge University added to another metaheuristic calculation known as the firefly (FA) calculation (Yang, 2008; Yang & Deb, 2009; Yang, 2009; Yang & He, 2013; Yang, 2010a; Yang, 2010b). The firefly calculation was found to perform better in comparison with molecule swarm advancement in taking care of the abnormal state of commotion (Pal, Rai & Singh, 2012). In this study, another methodology, with robustify the backpropagation learning calculation of nonlinear neural system time arrangement models, was used utilising FA-LMedS estimator. This paper includes the execution of LS, M-estimators, ILMedS, PSO-LMedS and FA-LMedS in the backpropagation calculation of both BPNN-NAR and BPNN-NARMA models.

DATA BACKGROUND

Information was incorporated from three unique sources of Unit Kerjasama Awam Swasta (UKAS) of Prime Minister’s Department, Construction Industry Development Board (CIDB) and Malaysian Statistics Department which have supported the PFI development material value records for the Central area of the Peninsula comprising four states of Kuala Lumpur Federal Territory, Selangor, Negeri Sembilan and Melaka. The genuine modern month-to-month information of Malaysian Aggregate, Sand and Roof Materials value records from January 1980 to December 2012 (base year 1980=100) were adjusted, with various rates of anomalies issues, 3.9%, 0% and 8.1% individually.

Table 1 displays the synopsis measurements of the variables of hobby. The aggregate N=408 (12 months × 34 years) was from January 1980 to 2013 (base 1980=100). The mean of sand is the most astounding (198.6969), trailed by rooftop materials (131.6038) and total (113.7731). Definitively, the cost of sand is the most exorbitant compared to rooftop materials and in total.

Table 1
Summary statistics of the construction materials price indices data

Notation	N	Mean	Std. Dev.	Max	Min	Skewness	Kurtosis	J-B
Aggregate	408	113.7731	7.63405	140.63	99.2	1.409	2.803	0.873**
Sand	408	198.6969	68.4966	287.88	100	0.143	-1.730	0.828**
Roof Materials	408	131.6038	8.21297	150.04	100	-0.321	3.508	0.786**

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

Likewise, sand demonstrates the most elevated standard deviation (68.4966) compared to the total (7.63405) and rooftop materials (8.21297). Both total and sand are emphatically skewed which are 1.409 and 0.143, respectively. However, rooftop materials are contrarily skewed (- 0.321). Be that as it may, taking into account the Jarque-Bera test for ordinariness, each of the three variables are very critical at 99% certainty interim; total (J-B=0.873, p=0.000), sand (J-B=0.828,p=0.000), and rooftop materials (J-B=0.786,p=0.000). The variables of interest experienced the ill effects of anomalies issues, as illustrated in Figure 1, Figure 2 and Figure 3, respectively.

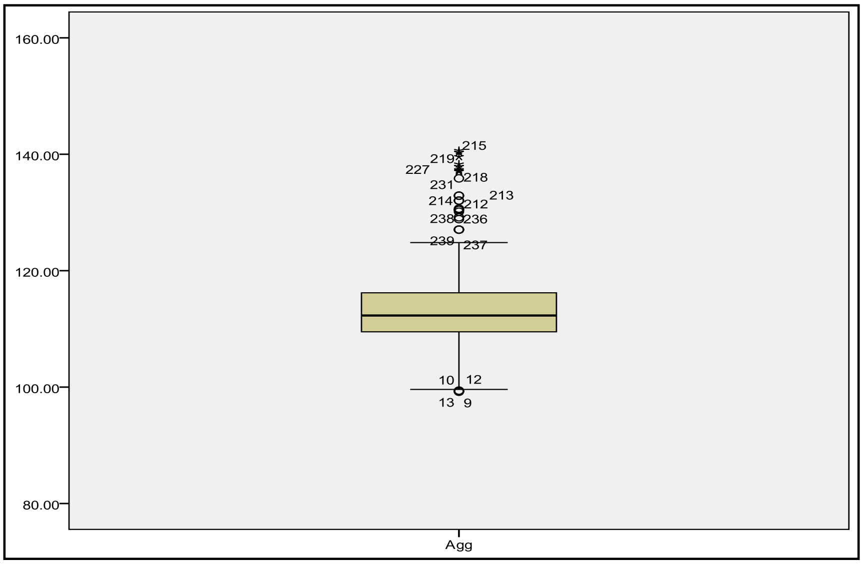

Figure 1. The boxplot of Malaysian Aggregate data

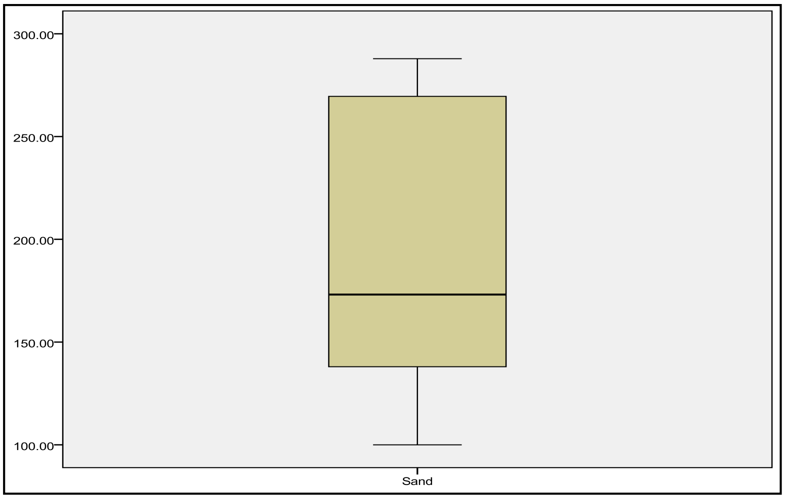

Figure 2. The boxplot of Malaysian Sand data

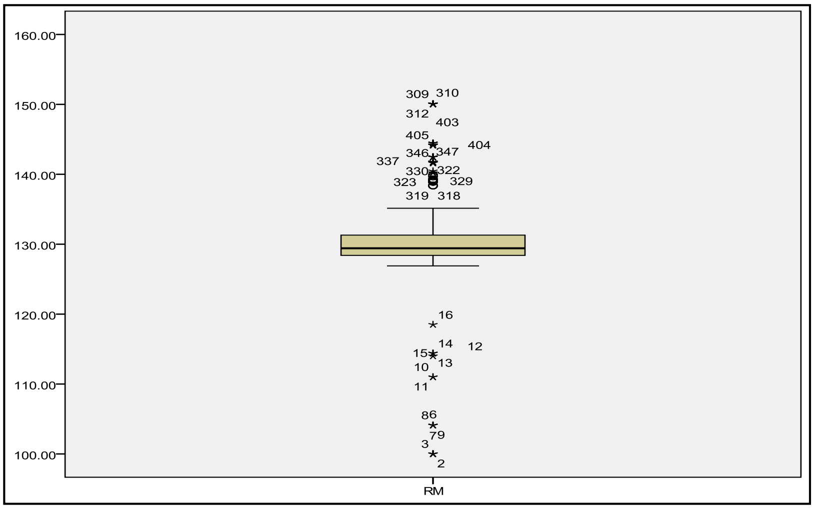

Figure 3. The boxplot of Malaysian Roof Materials data

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

METHODOLOGY

A flowchart of the examination is given in Figure 4. In the figure, the current vigorous estimators on backpropagation neural system are actualised. In order to obtain the primary target of the

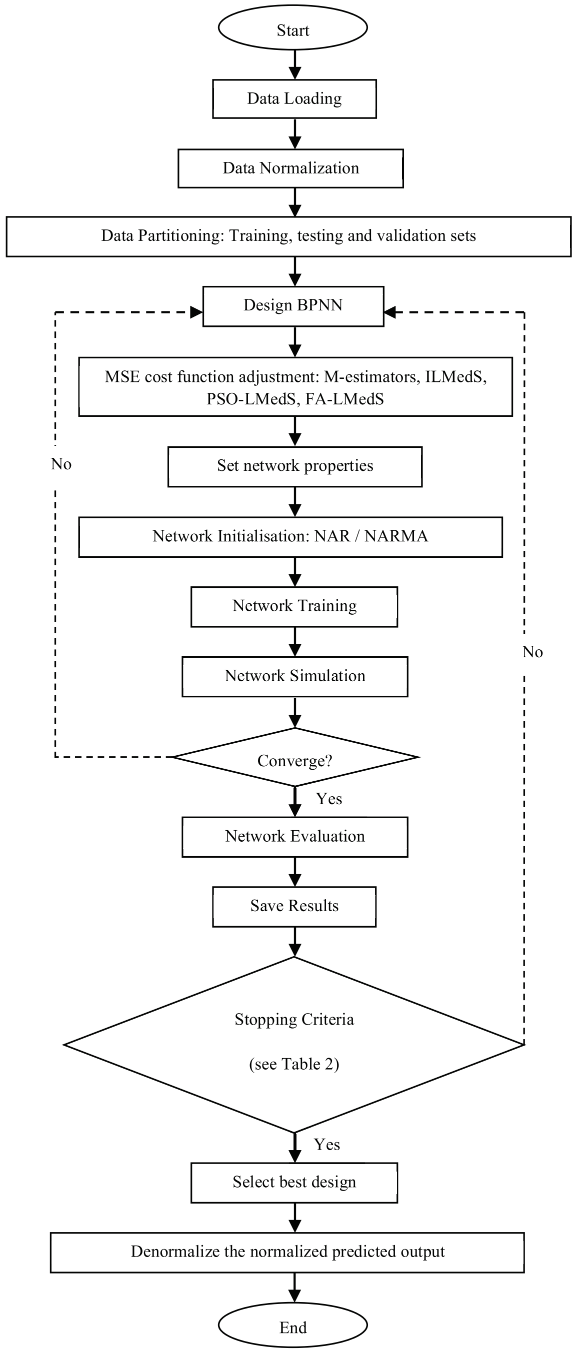

Figure 4. Flowchart of proposed robust backpropagationNN

study, the conceivable powerful estimators half breed in nonlinear autoregressive (NAR) and nonlinear autoregressive moving normal (NARMA) of neural system time arrangement were done using MATLAB R2012a. NARMA model was extended from NAR model by including the error terms as new inputs. At this stride, MATLAB scripts or codings were composed parallel to the numerical plan done prior to that. This was followed by execution of the proposed robustified neural system models, which were thought about utilising genuine information using standard execution measures (RMSE). The best relative results were drawn where the best model was picked. At the end of this examination, a programmed anticipating framework improvement was set up using MATLAB guide client interface (GUI) that had been effectively created. Finally, forecasts without bounds value lists of the Malaysian development material in the coming years before the best model were done at this stage. Details of the fundamental NAR-ANN are given below. The basic NAR-ANN formulation can be represented as follows:

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

The finalised NARMA-ANN formulation can be represented as follows:

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

where

H(x) is the estimated model,

x(t-1), x(t-2),…, x(t-ny) are lagged input terms,

ε(t-1), ε(t-2),…ε(t-nε) are lagged residual terms, and the lagged residual terms are obtained recursively after the initial model (based on the input and output terms) has been found.

Hence, ε(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

Robust Backpropagation Algorithm

The most essential part of the study is the scientific definition change a portion of backpropagation neural system calculation utilising measurable vigorous estimators. In order to make the customary backpropagation calculation effective in light of the M-estimators idea for lessening anomaly impact, the squared residuals ε_i^2 in the network error by another capacity of the residuals

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

and this yields,

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

where N is the total number of samples available for network training. The updated network weights was obtained based on the gradient descent learning algorithm. To prevent generality loss, a feedforward neural network, with one hidden layer, was implemented in this study. The weights from the hidden neurons to output neurons, Wj,i, are expressed as

$$\Delta W_{j,i} = -\alpha\frac{\partial E}{\partial W_{j,i}} = -\frac{\alpha}{N}\sum_{i}^{N}\frac{\partial\rho(\varepsilon_i)}{\partial W_{j,i}} \tag{5}$$
$$= -\frac{\alpha}{N}\sum_{i}^{N}\varphi(r_i).\frac{\partial f_j}{\partial net_j}.O_i,$$

where α is a user-supplied learning constant, Oh 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:

$$\Delta W_{ji} = -\alpha\frac{\partial E}{\partial W_{ji}} = -\frac{\alpha}{N}\sum_{i}^{N}\frac{\partial\rho(\varepsilon_i)}{\partial W_{j,i}} \tag{6}$$
$$= -\frac{\alpha}{N}\sum_{i}^{N}\sum_{j}\varphi(r_i).\frac{\partial f_j}{\partial net_j}.W_{j,i}.\frac{\partial f_i}{\partial net_i}.I_i,$$

where I_i is the input to the i^{th} input neuron, $net_j=\sum W_{j,i}O_i$ 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-square (LMedS) method estimates the parameters by solving the nonlinear minimisation problem.

$$minmed_i\ \varepsilon_i^2 \tag{7}$$

That is, the estimator must create the least worth for the least median squares figured for the whole information set. It creates the impression that this strategy is extremely hearty to false matches, particularly to anomalies inferable from terrible limitation (El-Melegy at al., 2009). Unlike the M-estimators, the LMedS issue can not be lessened to a weighted slightest squares issue. It is probably impossible to write a clear equation for the subordinate of LMedS estimator. Subsequently, deterministic calculation will not have the capacity to minimise that estimator.

The Monte-Carlo method (Zhang, 1997; Aarts, Korst, & Michiels, 2005) has been honed to take care of this issue in some non-neural applications. Stochastic calculations are likewise distinguished as the enhancement calculations which utilise arbitrary hunt to achieve an answer. Stochastic calculations are generally moderate, yet there is a probability that it will locate the worldwide least. One very well known improvement calculation to minimise a LMedS-based system blunder is mimicked toughening (SA) calculation. SA is an eminent calculation as it is moderately broad and has the inclination not to get stuck in either the neighbourhood least or most extreme (El-Melegy at al., 2009). Nonetheless, Rusiecki (2012) found that iterated LMedS has a tendency to beat the SA-LMedS.

RESULTS AND DISCUSSION

Table 3, 4 and 5 demonstrate the correlations between execution aftereffects of robustified nonlinear autoregressive and nonlinear autoregressive moving normal of the artificial neural system time arrangement models on Malaysian Aggregate, Sand and Roof Materials value files information, respectively.

Table 3
Comparison of the best results of ordinary and modified backpropagation algorithms on Malaysian Aggregate Price Index Data

Malaysian Aggregate Price Index Data							
BP Learning Algorithm	Input Lags	Error Lags	Hidden Nodes		NAR		NARMA
MSE	10	10	20		592.877		253.726
M-estimators (L2)	15	15	25		0.123		0.013
M-estimators (L1)	15	15	25		0.123		0.013
M-estimators (L1-L2)	10	10	20		0.053		0.006
M-estimators (LP)	25	25	40		0.040		0.002
M-estimators (Fair)	15	15	25		0.074		0.006
M-estimators (Huber)	15	15	20		0.006		0.000
M-estimators (Cauchy)	25	25	40		0.094		0.094
M-estimators (Geman-McClaure)	15	15	25		0.072		0.006
M-estimators (Welsch)	15	15	20		0.015		0.000
M-estimators (Tukey)	20	20	35		0.070		0.002
ILMedS	15	15	20		0.053		0.003
BP Learning Algorithm	Input Lags	Error Lags	Hidden Nodes	Swarm Size	Iteration	NAR	NARMA
PSO-LMedS	15	15	40	40	20	0.005	0.005
FFA-LMedS	15	15	20	20	20	0.070	0.002

Table 4
A comparison of the best results of ordinary and modified backpropagation algorithms on Malaysian Sand Price Index Data

Malaysian Sand Price Index Data							
BP Learning Algorithm	Input Lags	Error Lags	Hidden Nodes		NAR		NARMA
MSE	10	10	10		0.004		0.006
M-estimators (L2)	20	20	20		0.120		0.013
M-estimators (L1)	20	20	20		0. 119		0.013
M-estimators (L1-L2)	25	25	35		0.049		0.011
M-estimators (LP)	25	25	35		0.878		0.002
M-estimators (Fair)	10	10	10		0.136		0.017
M-estimators (Huber)	25	25	25		0.235		0.000
M-estimators (Cauchy)	25	25	35		0.152		0.114
M-estimators (Geman-McClaure)	40	40	45		0.005		0.003
M-estimators (Welsch)	25	25	25		0.172		0.000
M-estimators (Tukey)	40	40	45		0.161		0.002
ILMedS	25	25	25		0.053		0.003
BP Learning Algorithm	Input Lags	Error Lags	Hidden Nodes	Swarm Size	Iteration	NAR	NARMA
PSO-LMedS	10	10	40	40	25	0.005	0.002
FFA-LMedS	10	10	20	20	25	0.063	0.000

Table 5
A comparison of the best results of ordinary and modified backpropagation algorithms on Malaysian Roof Materials Price Index Data

Malaysian Roof Materials Price Index Data							
BP Learning Algorithm	Input Lags	Error Lags	Hidden Nodes		NAR		NARMA
MSE	20	20	35		309.435		87.614
M-estimators (L2)	10	10	20		0.113		0.013
M-estimators (L1)	10	10	20		0.143		0.012
M-estimators (L1-L2)	10	10	20		0.088		0.007
M-estimators (LP)	15	15	30		0.878		0.002
M-estimators (Fair)	10	10	10		0.134		0.017
M-estimators (Huber)	15	15	40		0.235		0.000
M-estimators (Cauchy)	15	15	30		0.152		0.094
M-estimators (Geman-McClaure)	20	20	25		0.005		0.003
M-estimators (Welsch)	15	15	40		0.172		0.000
M-estimators (Tukey)	20	20	25		0.161		0.002
ILMedS	15	15	40		0.053		0.003
BP Learning Algorithm	Input Lags	Error Lags	Hidden Nodes	Swarm Size	Iteration	NAR	NARMA
PSO-LMedS	20	20	40	40	35	0.005	0.002
FFA-LMedS	20	20	20	20	35	0.070	0.000

The outcomes depend on the diverse parameter settings blends in both the ANN-NAR and ANN-NARMA models.

CONCLUSION

In this study, nonlinear time arrangement neural system models (NAR and NARMA) were utilised to adapt instability without bounds (Kilicman & Roslan, 2009). As it is difficult to get rid of the vicinity of anomalies in genuine information set, preparing feedforward neural systems by the prevalent backpropagation calculation might create wrong and offbase models on the ground that the first MSE learning calculation is not hearty, and accordingly, effectiveness is lost (Norazian, Shukri, Azam, & Bakri, 2008). In this manner, there is a need to supplant the MSE cost capacity with other strong cost capacities such as M-estimators, ILMedS, PSO-LMedS and FFA-LMedS.

In future work, FFA-LMedS should be investigated for true information which comprises 30% to half distant information. Finally, the proposed calculations for preparing neural systems might be adjusted to different fields of counterfeit consciousness, framework distinguishing proof, design acknowledgment, machine learning, quality control and streamlining and exploratory processing.

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