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Abstract	An Artificial Neural Network (ANN) algorithms have been widely used in machine learning for pattern recognition, classifications and time series forecasting today; especially in financial applications with nonlinear and nonparametric modeling's. The objective of this study is an attempt to develop a new hybrid forecasting approach based on back propagation neural network (BPN) and Geometric Brownian Motion (GBM) to handle random walk data patterns under the high volatility. The proposed methodology is successfully implemented in the Colombo Stock Exchange (CSE) Sri Lanka, the daily demands of the All Share Price Index (ASPI) price index from April 2009 to March 2017. The performances of the model are evaluated based on the best two forecast horizons of 75% and 85% training samples. According to the empirical results, 85% training samples have given highly accurate in their testing process. Furthermore, the results confirmed that the proposed hybrid methodology always gives the best performances under the high volatility forecasting compared to the separate traditional time series models.

Keywords (separated by '-')	Back propagation neural network - Geometric Brownian motion - Autoregressive integrated moving average - Colombo stock exchange - Hybrid forecasting approach

A Novel Hybrid Back Propagation Neural Network Approach for Time Series Forecasting Under the Volatility

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Abstract. An Artificial Neural Network (ANN) algorithms have been widely used in machine learning for pattern recognition, classifications and time series forecasting today; especially in financial applications with nonlinear and non-parametric modeling's. The objective of this study is an attempt to develop a new hybrid forecasting approach based on back propagation neural network (BPN) and Geometric Brownian Motion (GBM) to handle random walk data patterns under the high volatility. The proposed methodology is successfully implemented in the Colombo Stock Exchange (CSE) Sri Lanka, the daily demands of the All Share Price Index (ASPI) price index from April 2009 to March 2017. The performances of the model are evaluated based on the best two forecast horizons of 75% and 85% training samples. According to the empirical results, 85% training samples have given highly accurate in their testing process. Furthermore, the results confirmed that the proposed hybrid methodology always gives the best performances under the high volatility forecasting compared to the separate traditional time series models. AQ1

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1 Introduction

Capital Investment in the stock market is the easiest and fastest way of building a healthy financial foundation for future life. In the past few decades, stock markets have become more institutionalized to invest large investment funds to the general public [1]. As a result, financial managers around the world have been spent their time to simulate the stock prices purposively in order to make them in profitable investments. AQ2 However, making decisions in equity markets still have been regarding as one of the biggest challenge in the modern economy, because of the numerous type of economic booms, policies and reforms.

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As a real world practice, two common approaches have been widely using in financial theories and practices to predict stock prices. They are as technical analysis tools and fundamental analysis methods [2]. The technical theories believe that the past patterns of the price behaviors repeat itself tends to recur in the future again. Furthermore, the fundamental analysis is a method of evaluating a security and assesses, by examining related economic, financial, and other qualitative and quantitative factors. However, the modern financial indices have been exhibiting unpredictable random walk path and estimate the near predictions are hard and impossible to outperform without taking any additional risk with the traditional time series approaches which are developed based on the normality, linearity and stationary conditions [3].

During the last few decades, miscellaneous types of new methodologies have been developed under different scenarios. Some of which are only applicable in theoretical aspects. However, most of these new approaches are combined both traditional as well as modern network approaches such as Artificial Neural Network (ANN), fuzzy logic and exhibited both continuous and discrete dynamic behaviors [4].

The Combining of both traditional linear (Autoregressive integrated moving average (ARIMA), Support Vector Machine algorithm (SVM), exponential smoothing model) and modified nonlinear approaches, building combined forecasting mechanisms have emerged new way in the finance since 2000. Various types of methodologies have been proposed in the literature. For instance, Zhang et al. (2003) introduced a novel hybrid methodology based on ARIMA and ANN models [4]. Theoretically, Zhang et al. methodology can be explained under the linear and nonlinear domains. They assumed that the ARIMA model fitting contains only the linear component and their residuals contain just only the nonlinear behavioral patterns [5].

As a result of these complications regards to the traditional time series approaches, the main purpose of this study is to take an attempt to develop Artificial Neural Network (ANN) and Geometric Brownian Motion (GBM) based new hybrid forecasting approach to handle incomplete, noise and uncertain data estimating in multidisciplinary systems. Because of the less sensitivity for error term assumptions, high tolerate noises, robustness and heavy tails, multilayer perceptron with Back propagation ANN algorithms are more suitable for mapping non-linear data patterns than traditional time series mechanisms. The new proposed network architecture mainly consists of input, hidden and one output layers. Furthermore, as the hidden and output layers by using the hyperbolic tangent sigmoid nonlinear transfer function and linear transfer functions, the proposed methodology designed for one-step-ahead forecast. Indeed, the ARIMA model is used as a comparison mode. The proposed methodology is successfully implemented for forecasting price indices in the Colombo Stock Exchange (CSE), Sri Lanka.

The rest of the paper is set out as follows. The estimated new ANN methodology is described in Sect. 2. The Sect. 3 presents the experimental findings and ends up with concluding remarks with Sect. 4.

2 Methodology

Time series forecasting is a dynamic research area that has been drawing considerable attention for solving the miscellaneous type of applications in the real world today. The proposed methodology of this study mainly consists of three major parts to forecasting stock market indices under the different scenarios. They are; Geometric Brownian motion (GBM) approach, artificial neural network and GBM based new hybrid approach and model comparison study based on traditional time series methods.

2.1 The Geometric Brownian Motion

The Geometric Brownian motion approach is one of the significant methodology which has been widely using in finance for making proper decisions under the random walk behavioural patterns.

The daily stock market price index S_t is said to be a stochastic process represents the most closed up-to-date valuation of index until trading commences again on the next trading day [4]. Let we assume that, the stock market price index S_t has a Geometric Brownian Motional behavior's and represents as a stochastic differential equation as Eq. (1) [5].

$$dS_t = \mu S_t \delta t + \sigma S_t dW_t \tag{1}$$

Where, the $\mathbf{W_t}$ is a Winner process with $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ constants. Where; the mean of the distribution of percentage drift $\boldsymbol{\mu}$ and the volatility or sample standard deviation are given by Eqs. (2) and (3) respectively [6];

$$\mu = \bar{S} = \frac{1}{M}\sum\nolimits_{t=1}^{M} S_t \tag{2}$$

$$\sigma = r = \sqrt{\frac{1}{(M-1)\delta t}\sum\nolimits_{t=1}^{M}\left(R_t - \bar{R}\right)^2} \tag{3}$$

The S_t and S_{t-1} denotes the asset values of the i^{th} and it's previous day market values respectively. Moreover, if the price on two consecutive days was not available, it would be assumed that the price remained unchanged and hence return is zero. Let's apply the techniques of separation of variable and integrating Eq. (1) with respect to t;

$$\int_0^t \frac{dS_t}{S_t} = \int_0^t \left(\mu\, dt + \sigma dW_t\right) dt \tag{4}$$

Let's we assume that the initial condition of $\mathbf{W}_0$ is 0. Furthermore, the $\frac{\mathbf{dS_t}}{\mathbf{S_t}}$ relates to the $\mathbf{d}(\ln \mathbf{S_t})$ and term $\boldsymbol{S_t}$ is under the Ito process [7].

$$d(\ln S_t) = \frac{dS_t}{S_t} - \frac{1}{2}\sigma^2 dt \tag{5}$$

$$d(\ln S_t) = \mu t + \sigma w_t - \frac{1}{2}\sigma^2 dt \tag{6}$$

The analytical solutions of the Eq. (6) is given by [8];

$$S_t = S_0 \exp\left(\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma w_t\right) \tag{7}$$

The Eq. (7) shows continuous stochastic process of Geometric Brownian motion that can be used for simulated the forecast of stock market indices.

The following algorithm can be used for forecasting data with lage number of sample observations.

```
%Assuming the following parameters
s=0; % Daily asset prices
R= ((s(t)-s(t-1)*100))/s(t-1); % asset returns
M= (0:1: N); % total number of observations
MU=sum (R)/ (M); % drift rate
TS=1% constant time difference between two samples
SIGMA= sqrt([sum(r-MU)^2]/((M-1)*(TS))) ;% volatility rate
T = (0:1: N) *TS; time interval
%Geometric Brownian Morton Approach
WT = sqrt(TS) *[0; cumsum(randn(N,1))]; % approximation to the
Normal distribution
W = (MU - 0.5*SIGMA^2) *T + SIGMA * WT
GBM =  s(0)* exp( W ); assets forecasting
```

2.2 The Novel GBM-ANN Hybrid Method for Forecasting

As a result of high volatility and unstable patterns, the traditional time series forecasting approaches can't achieve successes in both linear and non-linear domains. According to the literature, none of the methodologies still haven't been making sufficient for these circumstances. So, combined methodologies under the linear autocorrelation structure and non-linear weighted average component have created high accuracy forecasting than single model approaches.

The proposed new hybrid methodology composed with two main phases based on their linear and non-linear domains as follows [9].

$$Y_t = L_t + N_t \tag{8}$$

Where; L_t and N_t denote the linear autocorrelation and non-linear component of the time series pattern Y_t respectively. In the initial step, the GBM with Ito' lemma approach approaches is used to forecast the stock market indices under the stationary and non-stationary conditions.

As a next step, the residual of the linear component is evaluate using the Eq. (9).

$$e_t = Y_t - \hat{L}_t \tag{9}$$

Where e_t denotes the residual of the GBM and $\hat{L}_t$ presents the forecasted value of the estimated time series at time t. However, if we can see any non-linear behavioral patterns in residuals, as a next step, the ANN modeling approach is used to discover the non-linear behavioural patterns.

$$e_t = f(e_{t-1}, e_{t-2}, e_{t-3}\ldots, e_{t-n}) + \varepsilon_t \tag{10}$$

$$\hat{y}_t = \hat{L}_t + \hat{N}_t \tag{11}$$

Where n represents the input nodes and f is the non-linear function which determined based on ANN approach. The newly proposed BPNN Algorithm for forecasting non-linear behaviours as follows.

2.3 BPNN Algorithm for Forecasting Non-linear Behaviours

The back propagation neural network (BPNN) algorithm was introduced first time in the 1970s, but it was successfully applied for real world applications in 1986 by David et al. The BPNN algorithm is summarized under five-steps as follows [10].

Step 1: Define Inputs

Consider the forms of error data series. $\varepsilon_t = \{e\}_t$; where $t = 1, 2, \ldots, n$.

Step 2: Define Neural Network paradigms (Hidden layers, Input and Output neurons)

The back propagation algorithm is a method for training the weights in a multilayer feed-forward neural network [11]. As such, it requires a network structure to be defined of one or more layers where one layer is fully connected to the next layer. The general structure of the back propagation neural network can be expressed as Eqs. (12), (13) and (14) [12, 13].

$$net_j = \sum_{i=1}^{m} w_{ij} X_i; \quad j = 1, 2, \ldots, n \tag{12}$$

$$R_j = f_{hidden}\left(net_j\right) = f\left(\sum_{i=1}^{m} w_{ij} x X_i\right) \tag{13}$$

$$Y_k = f_{output}\left(\sum_{j=1}^{n} w_{jk} R_i\right); \quad k = 1, 2, \ldots z \tag{14}$$

Where, X_i, R_j, Y_k and w_{jk} represent the inputs and outputs of the hidden layer, outputs of the network and the connection weights respectively [14, 15].

Step 3: BPNN forecasting

The identified BPNN network is used here to forecast $(n+1)^{th}$ error point. The network is run 1000 iterations [16, 17]. The proposed network architectural model consists of single hidden layer connected feed forward network include single input layer, hidden layer and output layer as follows in Fig. 1.

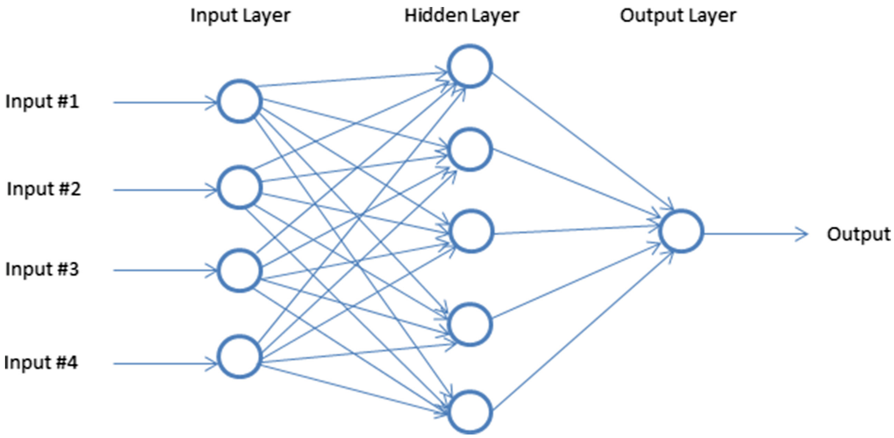

Fig. 1. Typical three layered feed-forward neural network [18, 19]

Step 4: Implementation

The current study, MAE and MAPE are utilized to evaluate the accuracy one-step ahead forecast. The error measures are as follows [20–23].

$$MAE = \left| S_i - \widehat{S}_i \right| \tag{15}$$

$$MAE = \left| \frac{S_i - \widehat{S}_i}{S_i} \right| \tag{16}$$

Where S_i and $\widehat{S}_i$ are the actual value of the original series and predicted value from the proposed hybrid model respectively. The smaller values of these error measures are considered to find the more accurate forecast result among the focused models.

The proposed hybrid model exploits the unique feature of GBM and ANN in determining different patterns. Tues, it creates an additional advantage to model linear and nonlinear patterns separately by using by separate models and then combine the forecasts to improve the overall modeling performances [20].

3 Results and Discussion

3.1 Data Preprocessing

The proposed methodology is evaluated using All Share Price Index (ASPI), Colombo stock exchange, Sri Lanka from April 2009 to March 2017 were extracted and tabulated for our calculations. The data source consisted 1926 observations, first 85% of 1637 daily observations were used during the training (in-sample or training sample) and the remaining 288 (about 15% of the sample) were considered as the out of sample to test the generalization capabilities of proposed models. The visual inspection of the daily ASPI pattern in Fig. 2 indicates that the data observations contain considerable noise with significant non-linear trend with considerable volatility during the sample period of time.

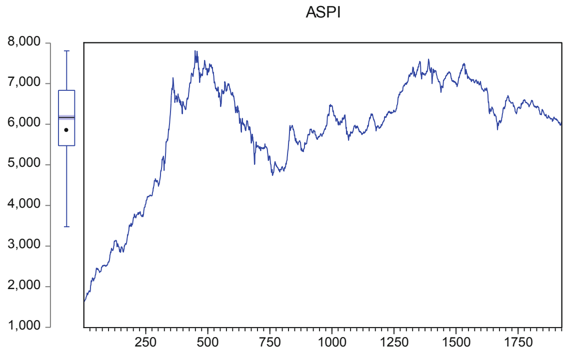

Fig. 2. Time series plot of ASPI

As a next step, unit root test used to test whether the ASPI time series variable existence of stationary of unit root or not. In the current study three different methods namely Augmented Dickey–Fuller test (ADF), Phillips–Perron test (PP) and KPSS test were used (Table 1).

Table 1. Unit root test result_level data

		t-statistic	Prob*.
Augmented Dickey-Fuller test statistic		−29.916	0.0000
Test critical values:	1% level	−3.9646	
	5% level	−3.4130	
	10% level	−3.1285	
Phillips-Perron test statistic		−30.2394	0.0000
Test critical values:	1% level	−3.9646	
	5% level	−3.4130	
	10% level	−3.1285	

(*continued*)

Table 1. (*continued*)

		t-statistic	Prob*.
KPSS test statistic (LM test)		0.13079	0.0000
Asymptotic critical values*	1% level	0.2160	
	5% level	0.1460	
	10% level	0.1190	

According to the ADF and PP results in Table 2, only the first difference data stationary under the 0.05 level of significance. Furthermore, KPSS test results confirmed that, data series is stationary after making the series in their first differences.

3.2 Data Modeling and Forecasting

The current study was carried out based on four different volatility measurements in order to find best volatility model of GBM for forecasting stock price indices in CSE. They are as Simple volatility (SV), Log volatility (LV), High and low volatility (HLV) and High-Low Close volatility (HLCV).

Table 2. GBM forecasting for different volatility methods

Error	SV	LV	HLV	HLCV
MAPE (%)	0.2425	0.1997	0.0889	0.0328*
MAD	17.1055	14.086	6.276	2.332*

The error accuracies of MAPE and MAD results in Table 2 suggested that High-Low Close volatility (HLCV) method has achieved minimum error accuracy comparing other three methods. So, in the next step, HLCV based Geometric Brownian motion with Ito's Lemma approach was used to assess the out-of-sample forecasting performance for the horizon of one month ahead. As a next step, the residual were measured. The behaviours of the residuals presented a non-randomly dispersed around the horizontal axis. So in the next step, suitable BPNN learning algorithm is employed to forecast error demands estimated based on one-step-ahead forecasting's.

In the initial stage, the network settings were fixed with 0.01 learning rate and single hidden layer neuron. Furthermore, to generate the accuracy results, the network was trained 1000 times. The same procedure was repeated step by step up to the number of hidden layer neuron equal 8 with respect to the constant learning rate. The estimated results can be summarized as Table 3.

Table 3. ANNs with different no. of hidden neurons

No. of neurons	ASPI testing (15%)		
	MAE	RMSE	MAPE (%)
1	38.124	56.376	0.54
2	38.973	58.456	0.52
3	37.657	57.879	0.51
4	35.456*	55.354*	0.49*
5	38.146	57.983	0.52
6	38.986	58.892	0.54
7	39.875	58.994	0.56
8	38.765	58.013	0.61

*Denotes the model with the minimum error values

In practice, the minimum error accuracies can be used to identify the best model. According to the results in Table 3, the minimum value of MAE (35.456), RMSE (55.354) and MAPE (0.49) indicated that, the number of four hidden neurons is given best performances than others. Furthermore, to find the best learning rate, the selected numbers of hidden neurons were fixed and the learning rate was increased step by step from 0.01 to 0.08 with 0.01 increments. The results suggested that BPNN (1-4-1) with 0.06 learning rates is employed 1000 times to forecast best one-step-ahead forecasting ASPI price index.

To find more accurate results, best two forecast horizons of 75% and 85% training sample sizes are used and their error measures MAE and MAPE are summarized in Table 4.

Table 4. Forecasting performances

Sample	Model	One-step-ahead forecast	Actual value	Error accuracy testing		
				MAD	MSE	MAPE (%)
75% Training sample	ARIMA	7203.72	***7235.25***	31.53	994.1	0.435
	GBM	7215.67		19.58	383.3	0.270
	ANN-ARIMA	7218.69		16.56	274.2	0.227
	ANN-GBM	7232.54		2.71	7.344	0.037
85% Training sample	ARIMA	7017.05	***7020.8***	3.75	14.06	0.053
	GBM	7021.67		0.87	0.75	0.012
	ANN-ARIMA	7018.506		2.29	5.26	0.038
	ANN-GBM	7020.572		0.22*	0.05*	0.003*

*Denotes the model with the minimum error values

The Table 5 results suggested that, 85% testing sample gives the best performance with minimum MAD, MSE and MAPE (%) with 0.228, 0.051984 and 0.324 respectively. Furthermore, results show that while applying neural networks alone can improve the forecasting accuracy over than single ARIMA. The same scenario can be seen in their separate forecasting's as displayed result in Fig. 3.

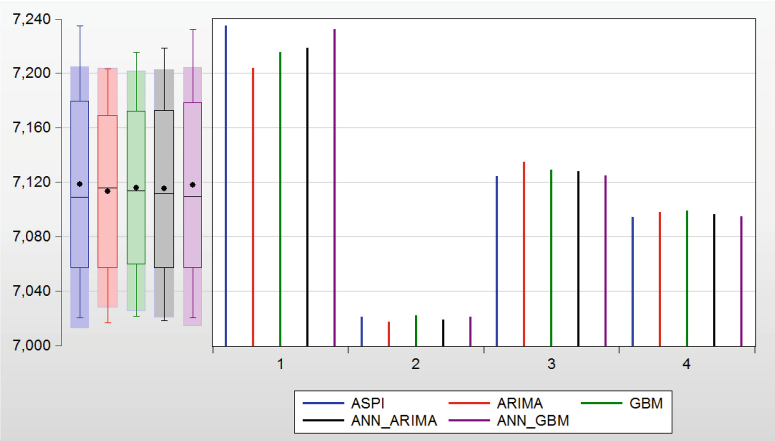

Fig. 3. One-step-ahead forecast forecasting for ASPI

The results concluded that, combining linear and nonlinear models together, the overall forecasting errors can be significantly reduced than separate single models. In ASPI scenario, the proposed ANN-GBM hybrid model always gives the best performances with compared to the single models (Fig. 4).

Table 5. The model accuracy for coming week

Model accuracy	Forecasting accuracy (%)			
	ARIMA	GBM	ARIMA-ANN	ARIMA-GBM
MAD (%)	13.08	9.94	5.39	2.31*
MAE	267.76	161.49	45.71	6.75*
RMSE	16.36	12.70	6.76	2.59*

*Denotes the model with the minimum error values

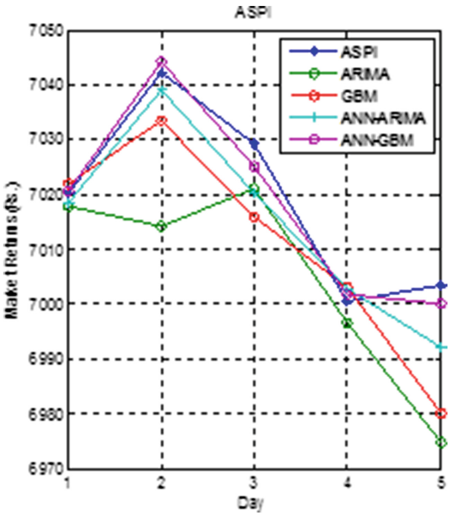

Fig. 4. ASPI forecasting for coming week

4 Conclusion

According to the literature, most of the studies have been using time series forecasting methods as their benchmark. So this is a first time in literature used GBM and ANN based hybrid approach to test the effectiveness of stock market forecasting. The empirical study results suggested that the proposed methodology have given high accurate predictions regarding the one – day head forecasting under the volatility.

As a next step as a comparison mode, the selected ARIMA models, GBM, and proposed ARIMA-ANN/GBM-ANN hybrid method were used to assess the out-of-sample forecasting performance for the horizon of one week ahead (testing sample) and the corresponding results are summarized in Table 4 and Fig. 2. According to the error analysis results, new proposed ARIMA-GBM is highly accurate (less than 10%) with lowest RMSE error residuals.

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Codes and Mat Lab Program for Proposed Hybrid Methodology

The new hybrid methodology is more appropriate to handle incomplete, noise and non-linear random time sequences with limited data samples. The proposed algorithm is as follows.

```
x=input variable; t=target variable; k=new; f=0;
Q = size(x,2);  Q1 = floor(Q*0.95);  Q2 = Q-Q1;
ind = randperm(Q); ind1 = ind(1:Q1); ind2 = ind(Q1+(1:Q2));
x1 = x(:,ind1);
t1 = t(:,ind1);
x2 = x(:,ind2);
t2 = t(:,ind2);
net = feedforwardnet(2);
net=configure(net,x,t);
net=init(net);
net.trainFcn = 'trainlm';  % Levenberg-Marquardt
net.trainParam.epochs = 1000;
net.trainParam.mu = 0.05; %Minimum performance gradient
net.trainParam.mu_dec = 0.1; %Initial mu
net.trainParam.mu_inc = 10; %mu decrease factor

net.trainParam.mu_max = 1e25; %mu increase factor
net.trainParam.show = 25; %Maximum mu
% Choose a Performance Function
net.performFcn = 'mse';  % Mean squared error
net.layers{1}.transferFcn = 'tansig';
net.layers{2}.transferFcn = 'purelin';
% Choose Plot Functions
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotregression', 'plotfit'};
net.trainparam.showWindow=false;
numNN = 1000;
nets = cell(1,numNN);
for i=1:numNN
%disp(['Training ' num2str(i) '/' num2str(numNN)])
nets{i} = train(net,x1,t1);
end
%Eroor Comparison
n=numNN;w1;k1=cell(1,n);
for i=1:n
if w1(i)==min(w1)
    k1{i}=i;
else
    k1{i}=0;
end
```

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During the process of typesetting your chapter, the following queries have arisen. Please check your typeset proof carefully against the queries listed below and mark the necessary changes either directly on the proof/online grid or in the 'Author's response' area provided below

Query Refs.	Details Required	Author's Response
AQ1	This is to inform you that corresponding author has been identified as per the information available in the Copyright form.	
AQ2	Please provide a definition for the significance of [asterisk, bold, italics] in the Tables 1, 2 and 4.	
AQ3	The second occurrence of Table 4 citation and captions are changed to Table 5 and the remaining is renumbered sequentially. Please check and confirm.	