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A Hybrid Statistical Approach for Stock Market Forecasting Based on Artificial Neural Network and ARIMA Time Series Models

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***Abstract*— The time series analysis and forecasting is an essential tool which can be widely applied for identifying the meaningful characteristics for making future ad-judgements; especially making decisions in finance under the numerous type of economic policies and reforms have been regarding as the one of the biggest challenge in the modern economy today.**

High volatile fluctuations in instability patterns are common phenomena in the Colombo Stock Exchange (CSE), Sri Lanka since after the introduced open economy policies in 1978. As a subset of the literature, very few studies have been focused on CSE to find out the new forecasting approaches for forecasting stock price indices under the high volatility. As a result, main purpose of this study is to take an attempt to understand the behavioral patterns as well as seek to develop a new hybrid forecasting approach based on ARIMA-ANN for estimating price indices in CSE.

The model selection criterion results in Akaike information criterion and Schwarz criterion suggested that, ARIMA (4, 1, 3) and ARIMA (1, 1, 1) traditional approaches are suitable for predicting ASPI and SL20 price indices respectively. However, model accuracy testing results of the mean absolute percentage error (MAPE) and Mean absolute deviation (MAD), suggested that new proposed ARIMA-ANN hybrid approach is the most suitable for forecasting price indices under the high volatility than traditional time series forecasting methodologies.

Keywords—ARIMA, ANN, ARIMA-ANN, CSE and Volatility

I. INTRODUCTION

The time series analysis and forecasting is an essential tool which has been widely applied for identifying the meaningful characteristics for making future ad judgements; especially decisions in economic and finance should be taken for predicting and forecasting future patterns under the numerous type of policies as well as mathematical and economic assumptions or between both with computing assumptions.

The stock market is a place where aggregation both buyers and sellers in a single platform for offering shares to the general public to raise their capital needed for restructuring, expansion for new operations. During the past two decades, stock market has been advanced as main forms of investment in numerous organizations as well as individuals for arranging huge investments funds. As a result, many companies have been listed in stocks markets around the world and investing huge amount from their capitals regularly.

Generally, it is common phenomena that, when the company is running well, the price of their stocks going up and make profit for their investors and vice versa. The miscellaneous types of financial and economic factors have been causing directly on the price of the stocks move up and down with high volatility fluctuations [1]. They are; interest rates, economic outlook, inflation, deflation, changers in national economic policies, economic and political stocks and etc. So, makings decision in equity markets have been regarding as the one of the biggest challenge in the modern economy; especially, analyzing and forecasting unstable data patterns in developing stock markets with limited sample observations under the numerous economic policies and reforms.

As a result, the financial data analyzing has become more complex under the modern market practices today. As a result, numerous types of methods and methodologies can be found in the literature for forecasting data patterns under the high volatility fluctuations. Based on their behaviors, all these methodologies can be split into two categories namely parametric and non-parametric [2]. The parametric approaches basically develop based on stationary stochastic process under the limited number of parameters. However, non-parametric approaches detailed estimate the covariance without considering any structural view. Due to the well balanced statistical assumptions as well as well- knowns Box-Jenkins methodology, an autoregressive moving average (ARMA) and it's generalization models of autoregressive integrated moving average (ARIMA) have been playing significant role in the literature today [1, 3].

However, most of these approaches are more suitable and appropriated only just for empirical data studies under the

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normality, linearity and stationary assumptions [4]. For example, some forecasting models are great at short-term predictions, but cannot capture the seasonality or variability with very limited number of sample observations; especially to predict stock price trends for highly non-linear and non-stationary random time sequences with noise data [1].

As a result of these complications regards to the traditional time series approaches, neural network computing model with new hybrid methodology was proposed by McCulloch and Pitts to handle incomplete, noise and uncertain data in multidisciplinary systems. Because of the flexible nonlinear modeling capability, this novel concept was popular and has been successfully applied to various systems such as financial, economic, military, geological and agricultural systems for signal processing, pattern recognition, classification, time series forecasting and etc.; especially, artificial neural network (ANN) based hybrid methodologies are more suitable for forecasting stock market predictions than others under the non-linear high volatility [4].

A. *Problem Definition: Colombo Stock Exchange (CSE)*

The Colombo Stock Exchange (CSE) is one of the most modernized stock exchange in South Asia providing a fully automated trading platform for their locals as well as foreign customers. As of 22 April 2015, the CSE has 297 listed companies representing 20 business sectors have been offering variety of investment options on local and foreign investors with a combined market capitalization over RS. 3014.49 Bn (US $23.19Bn), which corresponds to approximately 1/3 of the Gross Domestic Product of the country [1].

Currently, two price indices are mainly manipulating in CSE. They are; All Share Price Index (ASPI) and S&P Sri Lanka 20 Price Index (S&P SL20). The ASPI is market capitalization weighted index, which measures the movement towards share prices of all listed companies. Theoretically, the weights are defined based on the number of ordinary shares listed in the market. Therefore, price movements of larger companies to have a greater impact on the index than others[5,6].

Both theoretical and empirical studies, which have done based on stock market around the world suggested that combining linear and nonlinear methods can be effective and efficient way to improve model accuracies than single models. So, this study mainly takes an attempt to understand the trends and behavioural patterns in the CSE and seek to develop a new hybrid methodology based on ARIMA and ANN for estimating share price indices in long-term investments in Colombo Stock Exchange (CSE), Sri Lanka [7].

The rest of the paper is organized as follows. The traditional forecasting approaches with new ANN methodology review in section II. The new proposed combination methodology explains in Section III. The Section IV and Section V explains about experimental results and ends up with concluding remarks and future work respectively.

II. METHODOLOGY

As a subset of the literature, very few studies have been focused on CSE to find the high volatility forecasting's. So, the main purpose of this study is to propose suitable hybrid approach based on Artificial Neural Network (ANN) and ARIMA in stock market predictions in CSE. The methodology of the study can be describes as follows. In the first phase, stock market forecasting's and predictions is doing under the ARIMA and ANN approaches separately. Next, the new proposed combined approach of Artificial Neural Network and ARIMA (ANN-ARIMA) is applied. Finally, three different test accuracy techniques will apply to find the suitable model for forecasting in CSE, Sri Lanka after ended the civil war in north part of the country in 2009.

A. *The Artificial Neural Network (ANN) approach for time series modeling*

The ANN algorithms are universal and highly approximates that have been widely used in the field of engineering, cognitive science and finance today for pattern recognition, classifications and time series forecasting's; especially in finance, include index construction, portfolio selection, identification as well as verification of economic models, economic forecasting, risk rating and etc [9,10]. Because of the less sensitivity for error term assumptions, high tolerate noises, robustness and heavy tails, ANN algorithms are more suitable for mapping non-linear data patterns than others.

The main objective of this study is to provide an overview of a stepwise methodology to design a neural network for forecasting stock market price indices under the high volatility [11]. To achieve the objectives, backpropagation neural network (BPN) is briefly discussed under eight-steps as follows [12,13].

Step 1: Variable Selection

Step 2: Data collection

Step 3: Data preprocessing

Step 4: Training, testing and validations

Step 5: Define Network paradigms

(Hidden layers, Hidden neurons, Output neurons)

Step 6: Evaluation

Step 7: Training (Number of iterations and learning rate)

Step 8: Implementation

Basically, BPN learning algorithm consists of a collection of inputs and processing units such as neurons and nodes connected with three layers namely input layer, output layer and hidden layer [14]. So, ANN learning algorithm is an interconnected group of nodes with connected to the vast network of neurons in a brain. Each circular node and arrow represents an artificial neuron and connection from the output of one neuron to the input of another neuron respectively.

The proposed network architectural model in the current study consists of single hidden layer fully connected feedforward network include single input layer, hidden layer and output layer as follows in Figure [15] .

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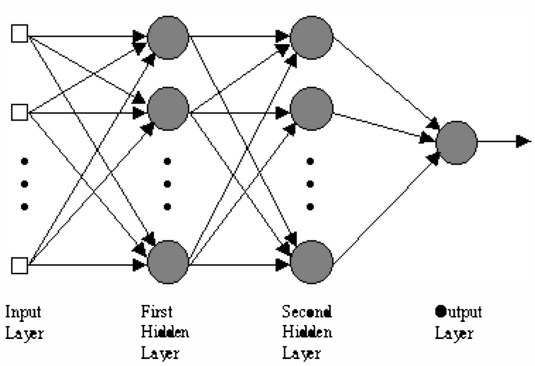

Figure 1: Neural Network Model

The equation (1) explains the mathematical relationship between the inputs (y_{t-1}, $y_{t-2}, \ldots, y_{t-p}$) and the outputs (y_t) as follows [16, 17].

$$y_t = \propto_0 + \sum_{j=1}^{q} \propto_j \; g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij}\, y_{t-i}\right) + \varepsilon_t \quad (1)$$

Where;

$i = 0,1,2,\ldots,p \; and \; j = 1,2,\ldots,q$ and $\propto_j$ and β_{ij} represent the model parameters often called the connected weights and p and q represent the number of input nodes and number of hidden nodes respectively. Furthermore, the logistic function $g(t)$ which is widely used as the hidden layer transfer function is given as follows [14, 15 and 16].

$$g(t) = \frac{1}{1+e^{-t}} \quad (2)$$

Based on equation (1) and equation (2), the ANN model in fact performs a non-linear function for mapping past observations (y_{t-1}, $y_{t-2}, \ldots, y_{t-p}$) to future values (y_t) can be defined as[16];

$$y_t = f\left(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, \omega\right) + \varepsilon_t \quad (3)$$

Where; ω indicates a vector of all parameters and f is a function determined by the network structure and connected weights. Based on these assumptions, neural network can be equivalent as a nonlinear autoregressive model.

B. Autoregressive integrated moving average (ARIMA)

In time series analysis, a non-seasonal autoregressive integrated moving average (ARIMA) has been widely applied for forecasting future movements of non-stationary data patterns; especially, Random-walk and random-trend models, autoregressive and exponential smoothing models are special cases of ARIMA models. Basically, an ARIMA generalization of an Autoregressive moving average model (ARMA) consists under the three parts. They are; the auto regressive parameter (p), the number of non-seasonal differences needed for stationarity (d) and the number of lagged forecast errors in the prediction equation in moving average model (q) [17, 18].

The linear combination of auto regressive process of order p ($AR(p)$) and the moving average model of order q ($MA(q)$) with for the autoregressive integrated moving average can be written as follows [20].

$$X_t = c + \sum_{i=1}^{p} \varphi_i \, X_{t-i} + \varepsilon_t \quad (4)$$

Where;

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$

Where μ is the mean of the series, $\theta_1, \theta_2, \ldots, \theta_p$ and $\varphi_1, \varphi_2, \ldots, \varphi_p$ are model parameters, c is a constant and white noise independent and identical parameter $\varepsilon_t \sim WN(0, \sigma^2)$. Considering both $AR(p)$ and $MA(q)$ properties, $ARMA(p.q)$ can be written as follows [21].

$$\left(1 - \sum_{i=1}^{p} \alpha_i L^i\right) X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \quad (5)$$

Where, L is the lag operator of the model. The ARMA methodology can be mainly generalized in to two ARIMA methodologies. If the series is non-stationary, then;

$$Y_t = (1 - L)^d X_t \quad (6)$$

While the series is wide-sense stationary, then [17, 19 and 20];

$$\left(1 - \sum_{i=1}^{p} \alpha_i L^i\right) Y_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \quad (7)$$

The Box-Jenkins parameter optimization methodology and minimum values of Akaike information criterion (AIC), Schwarz criterion (SBIC) and Hannan–Quinn information criterion (HQIC) methods mainly used to select the best model as described under figure 1.

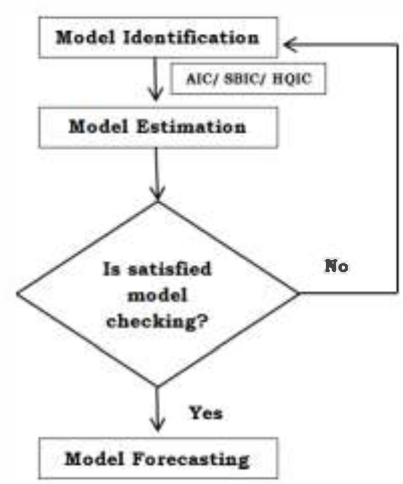

Figure 2: The Stages for building ARIMA [1]

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C. The Hybrid (ANN-ARIMA) Methodology for forecasting

In the past two decades, ANN and ARIMA (ANN-ARIMA) techniques widely applied to achieve high accuracy forecasting's in linear and non-linear domains respectively; especially to forecast financial data onto the different type of economic and financial conditions [21, 22]. However, some of these methodologies are not fully suitable under the high volatility. As a result, combined methodologies under the linear autocorrelation structure and non-linear weighted average component have created high accuracy forecasting and analyzing economic data outliers and multi-collinearity than single model approaches [23, 24 and 25].

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

Where; L_t and N_t denotes the linear and non-linear component and $\propto$ and β respectively. This new proposes hybrid methodology can be described under the two phases based on their linear and non-linear behaviors. In the first phase, traditional ARIMA approach is mainly used to analyze the linear part of problem. Based on the residual analysis results, in the second stage, neural network model based approach applied to capture the nonlinearity.

As an initial step, ARIMA model apply to find the linear component. Let we assume that, the residual from the linear model will contain only the non-linear relationships. The residuals of the linear component can be defined as follows.

$$e_t = Y_t - \widehat{L_t} \tag{9}$$

Where, e_t denotes the residual of linear model at time t and $\widehat{L_t}$ presents the forecasting value for the estimated ARIMA at time t. According to the results, if we can find any non-linear significant pattern in the residuals, it indicates the limitations of ARIMA. If we ca see any non-linear significant pattern in residuals, as a next step, ANN modeling approach can be applying to discover the non-linear relationships [26, 27 and 28].

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

Where n represent the input nodes and f is the non-linear function which determined based on ANN approach. However, if the non-linear model is not an appropriate, it means that, the error term ε_t is not necessarily random [28].

$$\widehat{y_t} = \widehat{L_t} + \widehat{N_t} \tag{11}$$

D. Model Accuracy Testing

Model accuracy testing is a significant way for identifying the suitable model for forecasting accuracy results. Numerous methods have been carried out in the literature to accomplish this goal. In this study, Mean absolute deviation (MAD), mean absolute percentage error (MAPE), mean absolute error (MSE) and root mean square error (RMSE) were mainly proposed. The formula of MAPE, MAD and MSE are defined as follows [1, 3]:

$$\varepsilon_{MAPE} = \frac{1}{M}\sum_{j=1}^{M}\frac{|X_A - X_P|}{X_A} \tag{12}$$

$$\varepsilon_{MAD} = \frac{1}{M}\sum_{j=1}^{M}|X_A - X_P| \tag{13}$$

$$\varepsilon_{RMSE} = \sqrt{\frac{1}{M}\sum_{j=1}^{M}(X_A - X_P)^2} \tag{14}$$

Where; X_A and X_P represent the actual value and predicted value of price at t time respectively. Moreover, the Table I represents the scale of judgment of forecast accuracy regarding to Error (MAPE) and clearly indicated that, minimum values of MAPE make more accuracy for forecasting future predictions.

TABLE I
MODEL ACCURACY TESTING

MAPE	Judgment of Forecast Accuracy
<10%	Highly Accurate
11% to 20%	Good Forecast
21% to 50%	Reasonable Forecast
>51%	Inaccurate Forecast

Note: ARIMA Model Accuracy Testing Results

III. EMPIRICAL RESULTS

CASE STUDY: COLOMBO STOCK EXCHANGE

The study was carried out on the basis of secondary data, which were obtained from Colombo Stock Exchange official database, Central Bank of Sri Lanka Financial reports, different types of background readings, other relevant sources and etc. Two principal price indices namely ASPI and SL 20 daily trading data from September 2010 to December 2013 were extracted and tabulated for calculations. New ANN-ARIMA Hybrid methodology was mainly applied for identifying the market validations with the combination of volatility, randomness and expected rate of market return in CSE .

A. Stationary/Non Stationary Model Checking

TABLE II

ADF AND PP TEST RESULTS

Price Index	Significant Result		Price Index	Significant Result	
	Level Data			Level Data	
	ADF	PP		ADF	PP
ASPI	0.5945	0.5225	ASPI	0.0000	0.0000
SL 20	0.3923	0.4212	SL 20	0.0000	0.0000

Note: All the tests assume asymptotic normality.

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As an initial step, stationary and non-stationary conditions were measured using two Unit root approaches namely Augmented Dickey-Fuller test statistic (ADF) and Phillips-Perron test statistic (PP). The Table 2 results suggested that, first difference level data significantly stationary under the 0.05 level of significance. As a result, ARIMA is more significant and applicable for predicting future results. As a next step, minimum values of Akaike info criterion (AIC), Schwarz criterion (SC) and Hannan-Quinn criterion (HQC) selection criteria were used to select more appropriate model between ARIMA(0,1,0) to ARIMA(5,1,5). The Table III and Table IV result suggests that, ARIMA (4, 1, 3) (AIC (10.7948), SC (10.8359), and HQC (10.81066)) and ARIMA (1, 1, 1) (AIC (8.7634), SC (8.7848), and HQC(8.7719)) models are most suitable for predicting future patterns of ASPI and SL20 respectively.

As a next step, proposed ANN-ARIMA hybrid methodology applied to forecast non-linear composite in the price indices based on MATLAB training algorithms. The proposed model is a three layer back forward network which includes one input layer, one hidden layer and one output layer respectively. To find best accuracy model, hidden layer with 2, 3, 4,5 , 10 and 15 neurals with one output layer used. The out of sample error results suggested that 2 neurals with one hidden layer is more accurate than others.

TABLE III

The model selection criterion for ARIMA: ASPI Price Index

p/q	0	1	2	3	4	5
		10.82742	10.82917	10.83151	10.83101	10.83322
		10.83326	10.84084	10.84902	10.85436	10.86241
0		10.82966	10.83365	10.83823	10.83998	10.84443
	10.82431	10.82673	10.81358	10.81603	10.81811	10.82018
	10.83016	10.83841	10.83112	10.83941	10.84734	10.85524
1	10.82656	10.83122	10.82032	10.82501	10.82934	10.83365
	10.82554	10.82731	10.81726	10.81895	10.82028	10.82244
	10.83724	10.84486	10.84066	10.8482	10.85538	10.86339
2	10.83004	10.83405	10.82625	10.83019	10.83376	10.83817
	10.82749	10.81357	10.80122	10.80921	10.80441	10.80894
	10.84506	10.837	10.8305	10.84435	10.8454	10.85579
3	10.83424	10.82257	10.81247	10.82271	10.82015	10.82694
	10.82768	10.81446	10.80045	10.79489	10.79857	10.80105
	10.85112	10.84376	10.83562	10.83592	10.84547	10.85381
4	10.83668	10.82572	10.81396	10.81066	10.81659	10.82132
	10.82938	10.81679	10.81832	10.80394	10.79067	10.79029
	10.85872	10.85199	10.85939	10.85088	10.84348	10.84896
5	10.84065	10.83032	10.8341	10.82198	10.81096	10.81283

Note : Yellow colour boxes indicates the significant results under 0.05 levels of significance.

TABLE IV

The model selection criterion for ARIMA: SL20 Price Index

p/q	0	1	2	3	4	5
		8.79018	8.783721	8.78306	8.786307	8.791017
		8.800821	8.805003	8.814984	8.828873	8.844223
0		8.794408	8.792177	8.795744	8.80322	8.812157
	8.777119	8.76348	8.765709	8.771054	8.785042	8.790869
	8.787782	8.784806	8.797698	8.813706	8.838357	8.854847
1	8.781356	8.771954	8.77842	8.788003	8.806228	8.816292
	8.774097	8.765378	8.770819	8.775435	8.78104	8.753488
	8.795466	8.797432	8.813557	8.828858	8.845148	8.828281
2	8.78259	8.778117	8.787803	8.796666	8.806518	8.783212
	8.778468	8.773102	8.767316	8.782936	8.779684	8.743755
	8.810587	8.815928	8.820848	8.847175	8.854629	8.829406
3	8.791234	8.790124	8.788592	8.808468	8.809471	8.777797
	8.786007	8.780969	8.78566	8.770886	8.746986	8.76766
	8.828921	8.834611	8.850031	8.845985	8.832813	8.864215
4	8.803065	8.802291	8.811247	8.800738	8.781102	8.80604
	8.791898	8.786026	8.761235	8.747777	8.753296	8.758224
	8.84565	8.850528	8.836488	8.83378	8.850049	8.865728
5	8.813267	8.811668	8.791151	8.781966	8.791759	8.800961

Note : Yellow colour boxes indicates the significant results under 0.05 levels of significance.

Finally, as a comparison mode the selected ARIMA models, ANN methodology and proposed ARIMA-ANN hybrid method were used to assess the out-of-sample forecasting performance for the horizon of one week ahead (testing sample). The corresponding results are summarized in Table V as below (figure 2).

TABLE V
The model accuracy for coming Week

ASPI	**Model Accuracy**	**Forecasting Models**		
		ARIMA	**ANN**	**ARIMA-ANN**
	MAPE (%)	1.0449	0.6534	0.3524
	MAE	62.7512	36.9834	21.2208
	RMSE	72.7560	54.8763	30.2510
SL20	**MAPE (%)**	0.8691	0.6754	0.4254
	MAE	28.8660	19.8767	14.1000
	RMSE	36.4308	24.8786	15.8930

*denotes the model with the minimum error values

According to the error analysis results, new proposed ARIMA-ANN is highly accurate (less than 10%) with lowest MAPE error values. Moreover, MAPE accuracy testing results suggested that our proposed algorithm (ASPI_ARIMA-ANN:

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0.3524, SL20_ARIMA-ANN: 0.4254) is more significant than traditional ARIMA methods (ASPI_ARIMA (4, 1, 3): 1.0449; SL20_ARIMA (1, 1, 1) : 0.8691) for forecasting short time predictions.

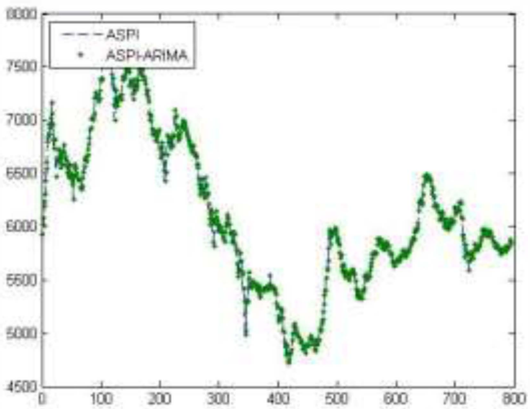

Figure 3: ASPI forecasting plot

IV. CONCLUSION

The miscellaneous types of investing practices can be seen in the modern world today; especially, saving money in the commercial banks, investing capitals for buying gold or lands are significant. Because of the economic crisis in 2008, inflation rates as well as interesting rates in fix deposits in many countries have been flowing badly with negative fluctuations. As a result, investing in stock market is the easiest and fastest way for building a healthy financial future in capital markets around the world today.

The prices of the stocks mainly depend on the financial stability of the company, turn over value, share volume and other variety of other financial and economic factors. So, find the suitable forecasting method to predict long and short term stock market predictions is a big challenge today; especially developing markets with chaotic and nonlinear behaviors have been created it more complicated.

As a result, this study mainly focused attempted to identifying the suitable hybrid forecasting approach based on ANN with traditional ARIMA approach under the high volatility. Two different model selection criterion results of minimum values of Akaike information criterion and Schwarz criterion suggested that, ARIMA (4, 1, 3) and ARIMA (1, 1, 1) are most suitable for predicting short term patterns of ASPI and SL20 price indices respectively between September 2010 to December 2013. Furthermore, model accuracy testing results of the mean absolute percentage error (MAPE) and (MAPE[ARIMA (4, 1, 3)] > MAPE [ANN] , MAPE [ARIMA (1, 1, 1)]> MAPE [ANN]), suggested that new proposed hybrid model is more significant and gives best solution for predicting future predictions under the high volatility fluctuations than traditional forecasting approaches.

Finally, we strongly believed that, current study makes significant contribution to policy makers as well as government to open up new direction to develop the CSE investments in Sri Lanka.

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