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Predicting Stock Indices Trends using Neuro-fuzzy Systems in COVID-19

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Abstract:
Predicting the ebb and flow of stock markets is a complex and challenging exercise owing to the disruptive and uncertain behavior of stock prices. The COVID-19 pandemic is an example of an event that, had a drastic impact on global stock markets, due to business activities and trading being severely affected. It is important, therefore, to be able to predict how stock markets behave in a crisis period. We find that stock markets obtain the worst returns in countries where there are higher reported positive cases of coronavirus. This study employs adaptive neuro-fuzzy inference systems (ANFIS), comprising of a controller and the stock market process, to predict the behavior of selected stock indices. After training ANFIS and evaluating the resultant data, we estimate statistical errors and found that 100 training epochs provide marginally better results. To test the accuracy of our results, we used hit rate success and report that the neuro-fuzzy system predicts stock market trends with an average accuracy of 65.84%, an improvement over earlier techniques reported in the literature. Finally, we compute the rate of return using a buy-and-hold strategy and a neuro-fuzzy system, and identify that market indices outperform by employing the proposed method.

Keywords: Stock market index, COVID-19, Neuro-fuzzy, forecasting.

JEL Classification: C53, E17, G11, G12.

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1. Introduction

Stock markets are sensitive and volatility can be caused by global or local events can affect stock market trading activities. Over the past two decades, we have observed the impact of various crises - the Asian financial crisis, dotcom bubble, global financial crisis - that have adversely influenced stock markets. Given that on the eve of the financial crisis, the decrease in stock prices was significantly associated with a decline in real economic output (Atsalakis, et al., 2016), it is essential to more accurately predict how stock prices may behave in the future.

The coronavirus (COVID-19) pandemic started in early 2020 and has affected millions of people across the globe. As of September 2020, approximately thirty-five million people were infected, with over a million succumbing to COVID-19. The total number of countries that has been drastically impacted in this manner is, at the time of this study, approximately 215. Owing to this crisis, business activities have halted, which eventually affects both economic and stock market activities. As every crisis negatively influences the stock markets, the behavior of the market is based on uncertainty, ambiguity, and a high frequency of data. Hybrid intelligence networks provide different options for the unconventional management of complex issues. These networks have been extensively employed in numerous functions. Bahrammirzaee (2010) used artificial neural networks (ANNs) along with other methods, such as neuro-fuzzy systems that integrate the human-like cognitive form of fuzzy sets. The benefit of this network is to act as a general approximator for performing the strengths of translating power. Guillaume and Charnomordic (2011) incorporated a fuzzy-logic inference system (FIS) with an ANN by combining it with derivative-free optimization methods, which provide appropriate results for neuro-fuzzy controllers utilized for the prediction of stock markets. Similarly, Rajab and Sharma (2019) suggested a proficient and interpretable neuro-fuzzy system to forecast stock prices by applying various technical parameters that emphasize accuracy trade-offs. Their simulation findings show that a neuro-fuzzy system provides a better balance between accuracy and interpretability.

To estimate impacts on stock markets, an ANFIS technique is generally used (Makridou et al., 2013; Guillaume and Charnomordic, 2011), as it measures the complex trends of stock markets appropriately under stipulated procedures. Atsalakis and Valavanis (2009) argued that various models provide better results in a stable state of economic conditions and the absence of complex behavior of stock markets (Belke and Gokus, 2011), but they are unable to make predictions in a crisis period. This study applies a neuro-fuzzy system to forecast how the stock indices behave during the pandemic period. We choose our sample based on the highest and lowest deaths as of August 2020 and consider 19 stock indices to predict their behavior using a neuro-fuzzy system. We report that stock markets obtain lower returns in countries where the reported cases of COVID-19 are higher. This study uses the ANFIS technique based on the controller and stock market process. To estimate the accuracy of the results, we compute the mean square error (MSE), mean absolute error (MAE), hit rate success, and RoR using the B&H strategy and trading simulations. We report that 100 training epochs marginally estimate better results. We also find that a neuro-fuzzy system, on average, predicts the trends of stock indices with an average accuracy of 65.84%. Furthermore, we report that market indices outperform using a neuro-fuzzy system over the B&H strategy.

2. Literature Review

Predicting stock market trends is important from the viewpoint of investors, as it helps to explore growth opportunities, determine investment potential and identify risk-return patterns. Generally, the purpose of investment in the stock market is to earn profits. However, the forecasting behavior of the stock market provides a cushion for investors to decide whether they invest in stock or withdraw their funds. The forecasting behavior of the stock market assists investors in identifying the possible risks that could affect various geographical destinations, and subsequently diversifying their asset portfolio.

Previous studies (Apostolakis et al., 2021; Mahmud and Meesad, 2016; Atsalakis and Valavanis, 2009) have used various techniques to examine the movement of stock markets and predict their behaviors. Atsalakis and Valavanis (2009) used a neuro-fuzzy adaptive control system to estimate trends of stock prices. They considered the data of both the Athens and New York Stock Exchanges to trade and assess the ANFIS and reported that this technique has been executed well in trading simulations and its results are better than the buy-and-hold strategy. In contrast, they employed thirteen other computing techniques to predict the accuracy of stock market trends and found that ANIFS is a supervisory approach. Lin et al. (2002) argued that the neuro-fuzzy system had originally evolved to model large datasets in a manner stimulated by human minds. It recreates the biological nervous system for analyzing the data. The objective of artificial intelligence is to simulate the decision-making competence and capabilities of human minds (Kumar et al., 2012). A neuro-fuzzy system is a consolidation of neural networks and fuzzy logic. Hence, this technique is applied to predict the behavior of stock markets, economic policy, pattern recognition, and medicines.

Trinkle (2006) applied ANFIS and neural networks to estimate the abnormal returns of three public firms. He compared the results of ANFIS and neural network techniques with the ARMA model and reported that both techniques are superior in terms of their predictive ability. Abbasi and Abouec (2008) examined the pattern of stock prices using ANFIS and found that the behavior of stock prices could be determined with a low level of errors. Yunos, Shamsuddin and Sallehuddin (2008) proposed a hybrid neuro-fuzzy with ANFIS to forecast the daily trend of the stock market, and their findings suggest that ANFIS has more predictive ability than artificial neural networks (ANN). In another study, Boyacioglu and Avci (2010) investigated the pattern of the Istanbul Stock Exchange by employing ANFIS. They accounted for six macroeconomic factors and three indices as inputs. They found that ANFIS predicted monthly returns with an accuracy of 98.3%. Mahmud and Meesad (2016) used ANFIS to forecast stock price movements of four top stocks listed on the Dhaka stock exchange. They compared their findings with other traditional methods and reported that neural networks provide superior results in terms of predicting stock market behavior.

Earlier studies have widely documented that neuro-fuzzy is a superior method to examine the predictability of stock market returns. Esfahanipour and Aghamiri (2010) employed four different models to examine thirty Taiwanese stocks and found the superiority of the neuro-fuzzy system in measuring future stock returns. Atsalakis and Valavanis (2009) employed different soft computing techniques (e.g., regression model, GARCH-M, neural networks, radial basis function (RBF) network, multilayer perceptron (MLP), and neuro-fuzzy) to contrast results and reported that among others, the neuro-fuzzy system shows the highest hit rate percentage and proved itself as a superior method. Likewise, Kumar et al. (2012) examined the stocks listed on the Bombay stock exchange and reported that the ANFIS technique has the ability to forecast stock returns 10-15 days in advance.

Ly (2021) used ANFIS to predict the number of COVID-19 cases in the UK by considering artificial neural networks and fuzzy logic structures to train the model. They evaluated different dynamics of ANFIS and proved it to be a real-time series prediction model. Moreover, they suggested that data relating to Spain and Italy can intensify the predictive power of COVID-19 cases in the UK.

In a recent study, Apostolakis et al. (2021) argue that a worldwide contagious effect in terms of economic parameters enhances volatility in financing markets. They document that during the COVID-19 pandemic, a higher level of volatility is spread by mid-cap firms to large-cap firms. In light of the superiority of ANFIS, the aim of this study is to predict the behavior of selected stock indices during COVID-19. Though the behavior of stock markets varied on the eve of the crisis, ANFIS on average accurately predicts how stock markets respond and provides an opportunity for investors to take appropriate measures to avoid losses.

3. The Model

Researchers have widely documented that most financial analysts, stockbrokers, and individual investors rely on historical information to predict the behavior of stock markets because the occurrence of an event is adjusted by an increase or decrease in stock prices. The stock market comprises many firms; therefore, the occurrence of an event can subsequently influence the stock market index. This study uses stock market indices as inputs (predictors) to develop a predicting schema that measures the fundamental principle of stock market movement, which eventually forecasts a trend of the stock market index for the next day. To examine the behavior of stock indices, this study follows the methodology of ANFIS. Earlier studies (Rajab and Sharma, 2019; Atsalakis and Valavanis, 2009; Abraham et al., 2005; Jang et al., 1997) document that ANFIS is a better technique, as it can capture the movements of stock markets. We divide the process of a neuro-fuzzy system into training and evaluation phases.

A diagram of the neuro-fuzzy system during the training and application–evaluation phases is shown in Figs. 1a and 1b (Atsalakis and Valavanis, 2009).

Figure 1a: Control system during the training phase.

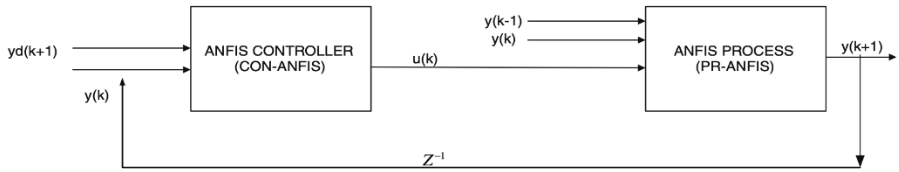
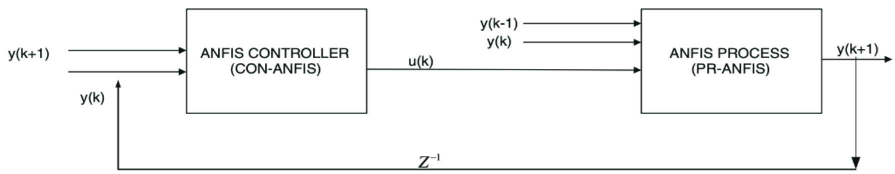


Figure 1b: Control system during the application-evaluation



The controller (CON-ANFIS) regulates the framework of the stock market process (PR-ANFIS) and subsequently predicts the trend of stock indices (i.e., next day). The process and controller can be managed by a neuro-fuzzy system that is applied to both phases and expressed as:

$$y(k+1) = f\big(y(k), u(k)\big) \tag{1}$$

$$u(k) = g \tag{2}$$

where $y(k+1)$ and $y(k)$ refer to the stock market index at time $k+1$ and k, respectively, and $u(k)$ is the control signal at time k. The issue of control is to determine the mapping $\varphi(\cdot)$ for the controller, which identifies certain anticipated performance through the overall system.

3.1. Controller – Training Phase

The controller (CON-ANFIS) is trained on the inverse learning method, also as general learning. However, an offline system is applied to construct the converse dynamics of the process in the learning phase. In terms of the application phase, the neuro-fuzzy system is applied in order to create control actions to model the process of the market index. Both phases may operate concurrently, which suggests that this technique adjusts well with classical adaptive control structures. The general form of equation (1) can be written as (Kumaran, Ravi, & Mugilan, 2013):

$$y(k+n) = F(y(k), U) \tag{3}$$

where n refers to the order of the process. F denotes multiple composite functions, and U is the control actions from k to $k+n-1$. This equation shows that in control input u, time moves from k to $k+n-1$ in precisely n time phases. Considering the inverse dynamics process of a market index, U becomes a specific function of $y(k)$ and $y(k+n)$:

$$U = G\big(y(k), y(k+n)\big) \tag{4}$$

where the existence of exceptional input classifications U quantified through mapping G can be obtained from stock market index $y(k)$ to $y(k+n)$ in n time phases. In this system, an inverse mapping G must be obtained. To estimate the inverse mapping G, the ANFIS method is a Sugeno first-order model with $2n$ inputs and n outputs per broad training datasets $[y(k)^T, y(k+n)^T; U^T]$. where $y(k+1)$ refers to the output of the stock market index, which is a function of earlier stock market index $y(k)$, and the input $u(k)$. Thereafter, the ANFIS controller reproduces the inverse dynamics of mapping G. Based on $y(k)$ and the predicted stock market index $y_d(k+n)$, the ANFIS controller produces a projected $\hat{U}$:

$$\hat{U} = \hat{G}\big(y(k), y_d(k+n)\big) \tag{5}$$

Subsequently, by computing n phases, this method will take $y(k)$ close to the anticipated $y_d(k+n)$ as the representative of $\hat{G}$, which is accurately the same as the inverse mapping G. If $\hat{G} \neq G$, then $y(k)$ are far from $y_d(k+n)$. To circumvent this issue, an additional dataset may be employed to improve the process, where $\hat{G}$ will become closer to G, indicating the precision of the training process. In the application phase, the predicted $y_d(k+n)$ is not accessible beforehand. To measure $y_d(k+n)$ as the next day's trend, this study uses the rate of change of the three-day moving average of the stock market index.

To train the controller, this study uses the dataset $[y(k), y(k+1); u(k)]$. where $y(k)$ and $y(k+1)$ indicate the change in the stock market index at time k and $k+1$, respectively. $u(k)$ is always positive and measured as $u(k) = \sqrt{\big(y(k) - y(k+1)\big)^2}$.

3.2. Stock Market Process – Training Phase

In this process, the current index of the stock market is used to predict the variation in the next day's index. Using the present inputs and prior outputs of the model, the changes in the actual stock market index are obtained from the controller:

$$y(k+1) = f\big(y(k), y(k-1), u(k)\big) \tag{6}$$

This study presumes that the underlying forces of the process of the market index are unknown. The training phase is emphasized on a first-order ANFIS that estimates $[y(k-1), y(k), u(k)]$ the change in the predicted stock market index at $y(k+1)$. The PR-ANFIS model is a Sugeno first-order technique with *3n* inputs and one output. This method employs a hybrid learning algorithm that clubs the back-propagation gradient descent and the least square method, in order to produce a fuzzy intrusion network where membership functions are regulated as per the inputs and output trading dataset.

3.3. Measuring stock indices on the eve of COVID-19

This study forecasts the stock indices on the eve of COVID-19 that can adversely influence the stock markets on the one hand and the entire economy on the other. The trend of stock indices is represented by the rate of change, indicating a parameter of market momentum. Rate of change (RoC) is a central measure that moves above and below zero. This indicator gauges the percentage change in the index over a certain period and is measured as:

$$RoC_{(x)} = \frac{I_{(x,t)} - I_{(x,t-n)}}{I_{(x,t)}} \tag{7}$$

Where $I_{(x,t)}$ shows the closing market index of country x at time t, which indicates that the percentage change in the market index can be positive or negative.

3.4. Estimation by Statistical Performance Measures

To examine the accuracy of the results, statistical errors assess the sum of the difference between actual and forecasted indices. Atsalakis et al. (2016) used MAE and MSE to measure the accuracy of these estimations as:

$$MSE = \frac{1}{N} \sum_{t=1}^{N} e_t^2 \qquad (8)$$

$$MAE = \frac{1}{N} \sum_{t=1}^{N} e_t \vee \qquad (9)$$

3.5. Hit Rate Success – Trend Evaluation

In general, stock indices are affected by market reactions. During the trading session, if the market index increases in the following session, investors will participate to acquire more shares to dispose of them tomorrow. For instance, if there is a probability of a lower closing market index in the next day, investors will sell or hold their stocks. The pattern of the stock index is significantly based on trend forecasting and is calculated as follows:

$$Hitrate = \frac{h}{n} \qquad (10)$$

Where h is the number of accurate estimations of the trend of stock indices and n is the number of tests (60 sessions in the analysis).

4. Sample and Data

This study used the daily data between the date of the first reported case of coronavirus in the country and 31st August 2020. We selected 19 countries to forecast the behavior of stock indices. To examine the effect of coronavirus on the stock indices, we split our sample into the highest and lowest deaths. Table 1 exhibits the position of the highest deaths of COVID-19 as of 31 August 2020, stock market indices, analysis period, and training data.

Table 1: The first reported case of COVID-19, total death, indices, analysis period, and training data

Country	Deaths	Index	The day when the first case of COVID was confirmed	Period	Training data (daily prices)
USA	5,997,163	S&P 500	20/1/2020	21/11/2019–31/8/2020	196
Brazil	3,862,311	Bovespa	26/2/2020	26/12/2019–31/8/2020	171
India	3,621,245	BSE Sensex 30	30/1/2020	26/11/2019–31/8/2020	192
Russia	995,319	MOEX	21/2/2020	16/12/2019–31/8/2020	175
Peru	647,166	SPBLPGPT	6/3/2020	2/1/2020–31/8/2020	168
South Africa	625,056	JTOPI	5/3/2020	3/1/2020–31/8/2020	166
Colombia	607,938	COLCAP	6/3/2020	2/1/2020–31/8/2020	161
Mexico	595,841	IPC	28/2/2020	24/12/2019–31/8/2020	173
Spain	439,286	IBEX 35	31/1/2020	25/11/2019–31/8/2020	195
Chile	409,974	IPSA	8/3/2020	6/1/2020–31/8/2020	166
Argentina	401,226	MERVAL	3/3/2020	2/1/2020–31/8/2020	160
UK	334,467	FTSE 100	29/1/2020	25/11/2019–28/8/2020	193
France	277,943	CAC 40	24/1/2020	20/11/2019–31/8/2020	198
Canada	127,940	TSX	27/1/2020	25/11/2019–31/8/2020	193
China	89,895	Shanghai composite	31/12/2019	27/09/2019–31/8/2020	224
Sweden	85,958	OMX Stockholm 30	4/2/2020	2/12/2019–31/8/2020	185
Japan	67,865	Nikkei 225	24/1/2020	25/11/2019–31/8/2020	186
Australia	25,746	ASX	25/1/2020	22/11/2019–31/8/2020	195
Hong Kong	4,802	Hang Seng	23/1/2020	22/11/2019–31/8/2020	191

5. Results

5.1. Summary statistics

Table 2 shows the summary statistics of selected stock indices based on daily training data reported in Table 1. Among the sample countries, on average, the Colombian stock index (COLCAP) performed worst (-0.194%), followed by the Chilean stock index – IPSA (-0.157%) and FTSE-100 (-0.112%). The results show that on average, the Russian stock index (MOEX) obtained the highest return of 0.135%, followed by the Argentinian stock index – MERVAL (0.082%) and Shanghai composite (0.066%). When we divide our sample into the highest and lowest COVID-19 cases to examine their returns and volatility, we find that stock indices obtained the lowest returns (-0.047%), where the cases of COVID-19 were higher, and they have higher volatility of returns. Similarly, the position of returns and volatility is better in those stock indices where the reported cases of coronavirus are lower. The median returns of the majority of stock indices are positive, which indicates the positive returns of stock indices over the sample period. When we analyze the standard deviation, the results report that Brazilian and Argentinian stock indices are more volatile than other sample indices. Likewise, the returns of all stock indices are negatively skewed except MOEX, Nikkei 225, and ASX.

Table 2: Summary Statistics of Selected Stock Indices

	Mean	Median	Min.	Max.	Std. Dev.	Skewness	Kurtosis
S&P 500	0.061%	0.271%	-12.765%	8.968%	2.372%	-0.851	7.913
Bovespa	-0.098%	-0.019%	-15.993%	13.022%	3.331%	-1.232	7.584
BSE Sensex 30	-0.029%	0.104%	-14.102%	8.595%	2.247%	-1.540	10.678
MOEX	0.135%	-0.005%	-8.884%	8.835%	1.990%	0.039	3.999
SPBLPGPT	-0.063%	0.078%	-11.009%	4.064%	1.753%	-1.859	9.856
JTOPI	-0.004%	0.122%	-10.450%	7.907%	2.251%	-0.875	4.858
COLCAP	-0.194%	0.024%	-13.281%	12.470%	2.677%	-0.843	11.210
IPC	-0.105%	-0.137%	-6.638%	4.744%	1.698%	-0.471	1.875
IBEX 35	-0.142%	-0.052%	-15.151%	7.528%	2.273%	-1.690	11.039
IPSA	-0.157%	0.271%	-12.765%	8.968%	2.525%	-0.850	7.913
MERVAL	0.082%	0.175%	-15.629%	9.773%	3.783%	-0.702	3.099
Highest COVID cases	*-0.047%*	*0.076%*	*-12.242%*	*8.625%*	*2.445%*	*-0.986*	*7.275*
FTSE 100	-0.112%	0.067%	-11.512%	8.667%	2.003%	-1.042	7.522
CAC 40	-0.083%	0.044%	-13.098%	8.056%	2.184%	-1.346	8.100
TSX	-0.016%	0.141%	-13.176%	11.294%	2.350%	-1.273	12.488
Shanghai composite	0.066%	0.125%	-8.039%	5.554%	1.308%	-1.178	8.310
OMX Stockholm 30	0.019%	0.080%	-11.173%	6.849%	1.994%	-1.072	5.748
Nikkei 225	-0.004%	-0.061%	-6.274%	7.731%	1.791%	0.262	3.567
ASX	0.050%	0.039%	-9.157%	11.881%	2.039%	0.550	8.229
Hang Seng	-0.029%	0.024%	-5.720%	4.925%	1.597%	-0.412	1.667
Lowest COVID cases	*-0.014%*	*0.057%*	*-9.769%*	*8.120%*	*1.908%*	*-0.689*	*6.954*

5.2. A Neuro-fuzzy System

The purpose of this study is to predict the stock indices because stock markets act as a barometer representing the position of the bench of stocks and providing a direction for existing and potential investors whether they should or should not invest. We used the ongoing coronavirus pandemic as a crisis period to forecast the behavior of stock indices. The datasets formulated for both controller $[y(k), y(k+1); u(k)]$ and process $[y(k-1), y(k), u(k); y(k-1)]$. where $y(k)$ = the difference of closing stock index between k and $k-1, u(k) = \sqrt{\left(y(k) - y(k+1)\right)^2}$ and $y(k+1)$ = a 3-day moving average is used in the evaluation phase as the closing stock index for the next day is not available.

This study uses MATLAB to estimate the result of the controller model in the training phase. The formation of the control model is similar for all stock indices selected for analysis due to the mix of the same number of membership functions. $y(k)$ and $y(k+1)$ are two inputs along with three membership functions (3^2=9) that produce a single output $u(k)$; this shows the variation in the stock market index and is used as input in the process model. The membership functions assist in transforming inputs to linguistic groups. After the training, membership functions will also change. The selected stock indices are sensitive on the eve of COVID-19. In the case of a small change in the next-day stock index, volatility is also lower, as reflected by $u(k)$, which represents the lower sensitivity of the stock market index.

Employing the ANFIS, the data were trained to forecast the next day's stock market return in the process model comprising three inputs $y(k)$, $y(k+1)$, and $u(k)$. where $u(k)$ is extracted from the controller model. Three inputs generate $y_d(k+1)$, which shows the next day change in the stock index. Similar to the controller model, three membership functions are used (3^3=27). The process model has a higher number of rules due to a greater number of inputs relative to the controller model. Upon the completion of training data, ANFIS generates forecasted values for the next-day market return, which determines the behavior of stock markets on the eve of COVID-19.

5.3. Estimation by Statistical Performance Measures

Table 3 exhibits the estimation of MSE (Panel A) and MAE (Panel B) using 100 and 300 training epochs. The results report that the estimation of MSE and MAE for 100 training epochs is somewhat better in terms of overall performance. The estimation of errors indicates the accuracy of the prediction, but they cannot predict the movement of stock indices. As such, investors' decisions rely on the increase or decrease in the stock index. To estimate the accuracy of the results, we employ the hit rate success and rate of return (RoR) on the market index.

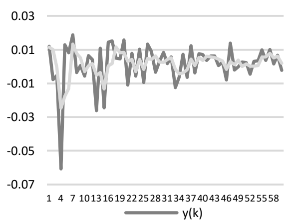
Table 3: Empirical estimation of MSE, MAE, and hit rate performance of selected stock indices

Index	Panel A: MSE (%)		Panel B: MAE (%)		Panel C: Hit rate (%)	
	Training epochs		Training epochs		Training epochs	
	100	300	100	300	100	300
S&P 500	0.00010	0.00010	0.00685	0.00681	66.63	67.60
Bovespa	0.00013	0.00012	0.00958	0.00961	57.31	55.11
BSE Sensex 30	0.00007	0.00007	0.00654	0.00650	64.13	66.70
MOEX	0.00012	0.00013	0.00850	0.00871	67.24	68.12
SPBLPGPT	0.00007	0.00007	0.00611	0.00613	68.56	69.43
JTOPI	0.00010	0.00009	0.00806	0.00861	74.21	73.22
COLCAP	0.00009	0.00009	0.00677	0.00663	67.31	67.11
IPC	0.00009	0.00008	0.00688	0.00673	61.43	62.43
IBEX 35	0.00017	0.00016	0.01053	0.01089	65.74	64.11
IPSA	0.00014	0.00015	0.00913	0.00926	63.35	62.75
MERVAL	0.00054	0.00057	0.01672	0.01764	62.44	62.98
FTSE 100	0.00013	0.00012	0.00801	0.00862	64.78	65.66
CAC 40	0.00014	0.00014	0.00834	0.00884	65.32	65.01
TSX	0.00006	0.00006	0.00576	0.00569	66.25	67.17
Shanghai composite	0.00016	0.00017	0.00968	0.00947	67.33	66.87
OMX Stockholm 30	0.00001	0.00001	0.00754	0.00781	66.88	66.11
Nikkei 225	0.00011	0.00010	0.00843	0.00802	70.24	68.98
ASX	0.00009	0.00011	0.00835	0.00807	66.39	65.93
Hang Seng	0.00011	0.00011	0.00813	0.00837	65.35	64.98
Sample average	0.00013	0.00013	0.00777	0.00813	65.84	65.80

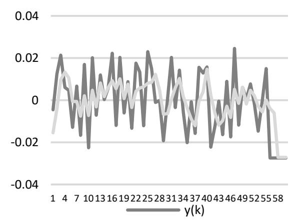
5.4. Hit Rate Success

Table 2 (Panel C) presents the forecasting accuracy per number of epochs for the selected stock indices. Using 100 and 300 training epochs, the forecasting accuracy falls between 55.11% and 74.21%. On average, the hit rate performance is 65.84% and 65.80% for 100 and 300 training epochs, respectively. This evidence suggests that the neuro-fuzzy system, on average, predicts accurately 65.84% of stock market index movements. Atsalakis and Valavanis (2009) compared the results of different techniques used to estimate the hit rate reported by earlier studies and documented that neuro-fuzzy predictions of stock market activities had an accuracy of 68.33%, which is higher than other methods. Fig. 2 illustrates the position of actual and predicted stock index change of the selected indices.

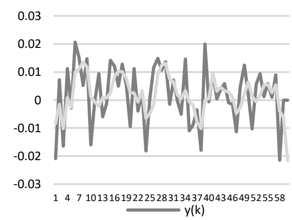
Fig. 2: Actual and predicted stock index change



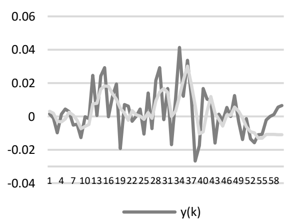
S&P 500 (USA)



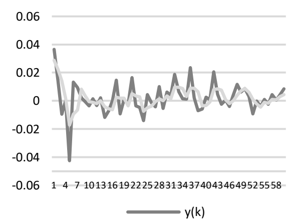
Bovespa (Brazil)



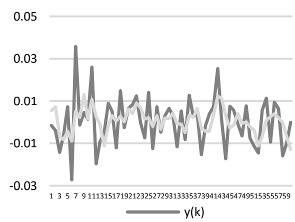
BSE Sensesx 30 (India)



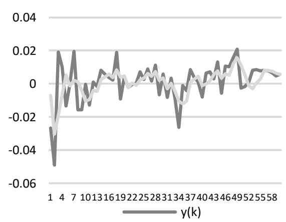
MOEX (Russia)



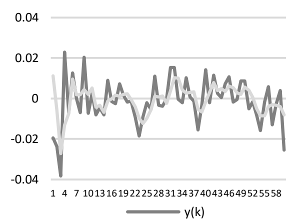
SPBLPGPT (Peru)



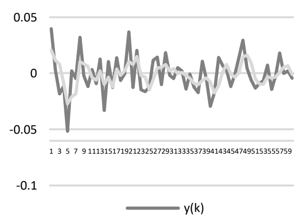
JTOPI (South Africa)



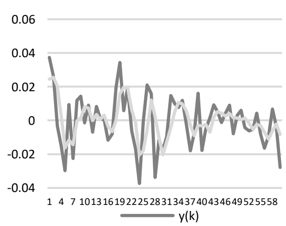
COLCAP (Colombia)



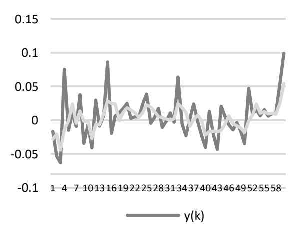
IPC (Mexico)



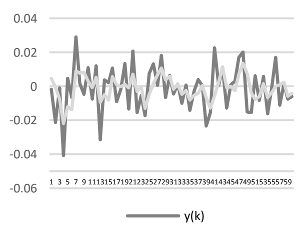
IBEX 35 (Spain)



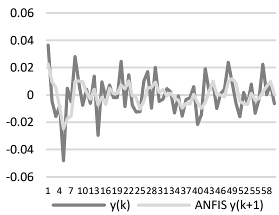
IPSA (Chile)



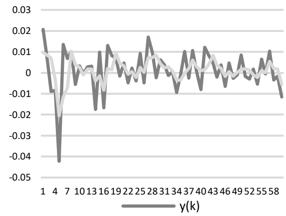
MERVAL (Argentina)



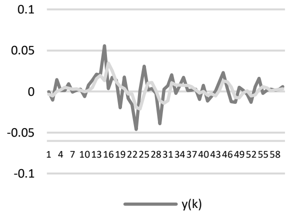
FTSE 100 (UK)



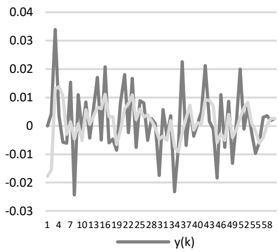
CAC 40 (France)



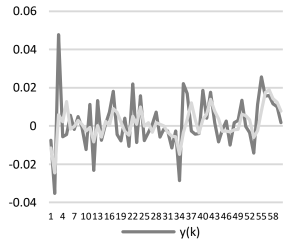
TSX (Canada)



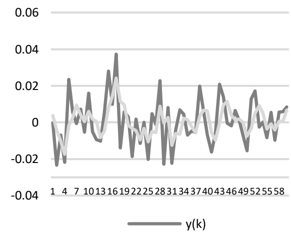
Shanghai Composite (China)



OMX S30 (Sweden)



Nikkei 225 (Japan)



Hang Seng (Hong Kong)

5.5. Comparing RoR of stock indices

This section compares the rate of return using the buy-and-hold (B&H) strategy and a neuro-fuzzy system. B&H refers to the participation in investment based on the market index and holds it until the end of the simulation horizon for the portion of the coronavirus period studied here. The RoR is computed as:

$$ROR = \frac{netgain \in stockindex}{initialinvestment} \tag{11}$$

A neuro-fuzzy system envisages that an investor increases participation in the stock market when there is a forecast showing an upward trend for the next day and reduces participation if the market is predicting a downward trend. While participating in the stock market, an investor may take a short or long position; however, in this study, we assume that an investor takes a long position. We suppose that an investor has $10,000 to participate in the stock market and measure the RoR of the trading simulation and RoR of the B&H strategy. Table 4 compares the RoR using both methods. The results show that RoR employing the neuro-fuzzy system outperforms the B&H strategy. During the early coronavirus outbreak, all stock indices outperformed, which illustrates that investors who intend to participate in stock markets/stocks may use a neuro-fuzzy system to predict the stock markets and earn abnormal returns. We further argue that prediction using the proposed method is more accurate without considering the volatility of the stock market.

It is important to note that investors may yield positive returns by investing in risk-free government securities when the forecast of stock indices is trending downward. In this regard, a comparison can be made by calculating returns on investment. We can argue that on the eve of loss when predicting an upward trend as a downward trend is not the same, similar to the loss when measuring a downward trend as an upward trend. In the case of the Spanish stock index (IBEX-35), the overall returns of the market are negative, whereas in the case of the FTSE-100, we suppose that if an investor distributes assets to risk-free government bonds, it may yield some positive returns. In addition, the accurate prediction of the trend of the stock index does not identify the intensity of the movement of the stock index. This suggests that income from precision estimation and losses from improper prediction may be different. On a practical note, investment policies are clubbed with more complex trading measures along with hedging strategies to overcome the volatility of the investment.

Table 4: Comparison of the RoR between a neuro-fuzzy system and the B&H strategy

Index	B&H strategy	RoR
S&P 500	14.45	18.21
Bovespa	12.12	21.68
BSE Sensex 30	14.19	23.15
MOEX	19.48	27.61
SPBLPGPT	19.22	22.67
JTOPI	10.05	18.31
COLCAP	14.92	26.31
IPC	-1.66	18.31
IBEX 35	-5.93	19.67
IPSA	3.28	21.14
MERVAL	15.83	31.62
FTSE 100	-3.29	18.98
CAC 40	1.81	14.53
TSX	8.70	11.05
Shanghai composite	19.04	24.37
OMX Stockholm 30	7.09	7.68
Nikkei 225	5.58	8.90
ASX	-0.01	10.55
Hang Seng	9.65	14.45

6. Conclusion

This study uses a neuro-fuzzy adaptive control system to predict the trend of the next day's stock indices in the early COVID-19 period. A neuro-fuzzy system can predict the patterns of stock markets. This technique is based on the ANN adaptive capacity, which is based on fuzzy logic qualitative estimation. A neuro-fuzzy system conducts training and evaluation phases, which refine the output of the system.

This study employs nineteen stock indices to predict their behavior on the eve of the coronavirus. To assess the prediction results, we estimate MSE, MAE, hit rate success, and the RoR of the B&H strategy and trading simulations. Based on the historical information and the suggested controller, this technique precisely predicts the patterns of stock indices. This technique outperforms in the context of trading simulations, which shows that the rate of returns is higher relative to the B&H strategy. This evidence illustrates that the proposed technique provides robust and accurate predictions of stock market trends during a crisis period.

In summary, we may infer that a neuro-fuzzy-based controller is appropriate to predict stock indices during a crisis period where investors can earn positive returns. For future research, it is proposed that researchers consider macroeconomic factors using ANFIS that can influence the prediction of stock markets during the crisis period.

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