

Research Article

MLP and RBF Algorithms in Finance: Predicting and Classifying Stock Prices amidst Economic Policy Uncertainty

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ABSTRACT

In the realm of stock market prediction and classification, the use of machine learning algorithms has gained significant attention. In this study, we explore the application of Multilayer Perceptron (MLP) and Radial Basis Function (RBF) algorithms in predicting and classifying stock prices, specifically amidst economic policy uncertainty. Stock market fluctuations are greatly influenced by economic policies implemented by governments and central banks. These policies can create uncertainty and volatility, which in turn makes accurate predictions and classifications of stock prices more challenging. By leveraging MLP and RBF algorithms, we aim to develop models that can effectively navigate these uncertainties and provide valuable insights to investors and financial analysts. The MLP algorithm, based on artificial neural networks, is able to learn complex patterns and relationships within financial data. The RBF algorithm, on the other hand, utilizes radial basis functions to capture non-linear relationships and identify hidden patterns within the data. By combining these algorithms, we aim to enhance the accuracy of stock price prediction and classification models. The results showed that both MLP and RBF predicted stock prices well for a group of countries using an index reflecting the impact of news on economic policy and expectations, where the MLP algorithm proved its ability to predict time series data. Countries were also classified according to stock price data and uncertainty in economic policy, allowing us to determine the best country to invest in according to the data. The uncertainty surrounding economic policy is what makes stock price forecasting so crucial. Investors must consider the degree of economic policy uncertainty and how it affects asset prices when deciding how to allocate their assets.



1. INTRODUCTION

The monetary, fiscal, regulatory, and trade policies of governments influence how the private sector conducts business. These policies' uncertainties can have a major impact on both the financial market and the real economy. Uncertainty around macroeconomic policies (monetary, regulatory, and fiscal, and more) is referred to as economic policy uncertainty [1] [2]. M. A. Uddin et al.[3] indicated that economic policy uncertainty is the non-zero risk that the current policies governing the economy which set the game's rules for economic agents may change. The fundamental tenet of finance is uncertainty. In an atmosphere of uncertainty, many expensive investment decisions are made. Investors frequently attempt to make wise predictions using the facts at their disposal when they do not have complete knowledge of macro-level variables or stock dividends. The state of the financial markets can shift in a matter of seconds. Investors therefore pay close attention to stock market news. It is crucial for policymakers and market practitioners to comprehend the causes of stock market volatility [4] [5]. There is a wealth of evidence from previous literature that shows how changes in stock values over time are closely related to changes in the structure of risk factors, business cycles, and macroeconomic aggregate fluctuations. This is the main reason why all stock market users across the globe should closely monitor the state of the global economy and adapt their expectations and decisions regarding investments accordingly [6]

Stock markets suffer negative repercussions from abrupt shifts in economic policy uncertainty (EPU), which can be divided into different main routes [7] [3] [1] [8] [3] [9] [10] [11]:

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The first route results from an increase in EPU, which makes business operations unclear and disrupts market momentum. Shocks of uncertainty can prevent macroeconomic growth and private investment. The future cash flows of investors would decrease as a result of this deterioration in the investing climate, which would result in a drop in stock prices. This leads to uncertain economic policy, economic activity, and future cash flows.

The second route results from an increase in uncertainty shocks, which could worsen market expectations. Market volatility will undoubtedly increase as a result of traders selling their equities out of fear that the economy will get worse. Economic policy uncertainty is taken into account when predicting an increase in stock volatility, which makes investors demand a bigger uncertainty premium. Furthermore, psychologically, stock market prices underreact or overreact to positive or bad news generated by policy uncertainty.

Investment and employment are both susceptible to changes due to policy uncertainty. Until uncertainty is resolved, rational investors cut back their investments or cease them completely. As a result, uncertainty can harm investment and economic growth. Other macroeconomic indicators may be impacted by uncertainty regarding government action. Macroeconomic factors including economic growth, employment, foreign direct investment, and international trade all have a direct impact on the price of shares. Changes in EPU are therefore likely to have an impact on stock price. Stock prices are likely to react considerably to changes in the EPU index to the degree that the uncertainty over government interference in the economy and markets affects consumption, production, economic growth, and corporate investments. The stock market is more volatile with increased uncertainty, and as a result, the stock market index falls. On the other side, due to banks having possible lack of confidence in and anxiety about the markets, lending availability may be restricted during times of severe uncertainty. Banks and creditors may regard the economy to be more risky, which will increase the cost of borrowing. This can deter businesses from undertaking prospective investment projects, which will lead to a decrease the stock index prices. Similar to consumers and businesses, when uncertainty about future taxes, spending levels, regulations, healthcare reform, and interest rates is high, expenditure on investment projects and consumption of goods and services tends to be put off. This also demonstrates a negative correlation between investment activity and rising policy uncertainty [12].

Investors have less knowledge about the future course of the economy and the upcoming policies when EPU is high. Due to investors' increased risk aversion and decreased willingness to purchase equities, this may cause market volatility. Investors are aware that EPU can cause a reduction in business profits, more unemployment, and slower economic growth. As a result, when EPU rises, investors are more inclined to sell their equities, which causes stock prices to fall [13]. According to the behavioral finance theory, investors are not always logical and may base their judgments on feelings like fear and greed. Even when there is no compelling reason to sell equities, investors may become more anxious when EPU is high. This can cause stock values to drop precipitously. But when EPU is low, investors can become more greedy and purchase equities, even if there is no real justification for doing so. Stock prices may recover more slowly as a result of this [14]. EPU affects also investor feelings and stock prices, which results in inefficiencies in capital allocation due to financial friction and constraints [14]. Uncertainty in economic policy has recently attracted attention. This is particularly relevant in light of the recent international events, including the global financial crisis 2008, the sovereign debt crisis, Covid-19, and the Russia-Ukraine conflict, as well as the late 2000s global financial crisis. Academics created the EPU index based on newspaper coverage of policy-related economic uncertainty. Since then, a considerable amount of literature has used the EPU variable to explain the asset risk-return connection and has found that investors desire higher returns because of the risk premium associated with economic policy uncertainty [15].

This study aims to predict stock prices in a group of countries in the developed world while including uncertainty in economic policy and classify countries according to this information. This is achieved through optimization algorithms used in machine learning and the neural network methodology of the two types of multilayer perceptron and basic radiation function. The first section includes the introduction and literature, which covered stock price forecasts and economic policy uncertainty. The second section includes the methodology and mathematical design of the algorithms used. The third section includes the data used and their main characteristics, followed by the results of prediction and classification using the algorithms.

2. MOTIVATION

The motivation for this study stems from the increasing need for reliable predictive models that can effectively navigate the complexities of the global financial markets amidst economic policy uncertainty. Traditional methods of stock price prediction and classification often fall short in accurately capturing the intricacies of the market dynamics under volatile economic conditions. The motivation also includes the following points:

- **Global Economic Landscape:** Characterized by unprecedented levels of uncertainty due to fluctuating economic policies, geopolitical tensions, and the global pandemic, leading to significant volatility in financial markets.
- **Importance of Prediction:** Accurate prediction and classification of stock prices are crucial for optimal asset allocation, risk management, and investment decision-making amidst economic policy uncertainty.

- Investment Strategy Challenges: Investors face challenges in determining the best investment strategies to safeguard their portfolios against adverse effects of volatility, involving meticulous analysis of the effects of economic policy uncertainty on various asset classes.
- Need for Advanced Predictive Models: The complexity and dynamism of financial markets necessitate the application of advanced predictive models. MLP and RBF neural networks offer the advantage of modeling non-linear relationships, adapting to changes in data patterns, and providing accurate predictions in volatile environments.
- Research Aims:
 - a- Assess the performance of MLP and RBF algorithms in predicting stock prices in developed countries, using the economic policy uncertainty index as a key indicator.
 - b- Classify countries based on stock price data and economic policy uncertainty, providing a basis for investors to select suitable countries for investment amidst prevailing economic conditions.
 - c- Contribution to Knowledge: By providing a comprehensive analysis of the performance of these algorithms in the context of economic policy uncertainty, this research aims to contribute to the existing body of knowledge on stock price prediction and classification, and aid investors in making informed decisions in a highly uncertain and volatile global economic landscape.
- Limitations of Traditional Mathematical Models: Traditional mathematical models used in finance, such as the Capital Asset Pricing Model (CAPM) or the Black-Scholes model, rely on assumptions that often do not hold in real-world scenarios, especially in times of economic policy uncertainty. These models assume normality of returns, constant volatility, and ignore the impact of external factors such as economic policy changes, all of which have been proven to be unrealistic in the modern, highly volatile financial markets. There is therefore a pressing need for more advanced and flexible mathematical models that can accurately capture the non-linear relationships and adapt to the dynamic nature of financial markets, making the use of MLP and RBF algorithms highly relevant and necessary.
- Need for Robust Classification Models: Classification of countries based on stock price data and economic policy uncertainty is a crucial task for global investors. Traditional mathematical models often struggle with classification tasks as they are primarily designed for prediction. Machine learning algorithms like MLP and RBF, on the other hand, can be designed and optimized for classification purposes, enabling investors to categorize countries into different risk and return profiles, thus aiding in the decision-making process for global asset allocation. This calls for a comprehensive study and application of these advanced mathematical models to classify countries based on stock price data and economic policy uncertainty, ultimately helping investors make better-informed investment decisions.

3. METHODOLOGY AND NEURAL NETWORK ALGORITHM FRAMEWORK

The closely connected set of models with a broad parameter space and adaptable structure that emerged from research on brain function is referred to as neural networks. With time, several new models were created for non-biological uses, although much of the language used in conjunction with them still reflects their origins. The definition presented above, in comparison, places little burden on model assumptions and structure. As a result, a neural network can roughly represent a variety of statistical models without forcing researchers to make assumptions about the relationships between the dependent and independent variables beforehand. Instead, it is during the form of the relationships is decided during the learning process. If the dependent and independent variables have a linear relationship, the neural network's findings should roughly resemble those of the linear regression model. The neural network will automatically approximate the "correct" model structure if a nonlinear relationship is more suitable. The difficulty in understanding a neural network's synaptic weights is a trade-off for this flexibility. Our methodology aims to classify the ability to predict stock prices according to market due to variations in the calculation of the economic policy uncertainty index in each country, and to determine the extent to which the state of uncertainty is able to forecast the returns of shares of a group of financial markets. Because the model's purpose is predictive, and because predictability offers the possibility of categorization in a single model, these algorithms are favored over econometric methods, which may suffer from dimensionality due to the large time series involved. Additionally, data visualization will be employed to document relationship trends. We are additionally attempting to discover which algorithms are better in predicting and classifying the returns of stocks of developed countries—multilayer perceptron (MLP) or radial basis function (RBF).

3.1 Multilayer perceptron (MLP)

One of the neural network architectures that is most frequently utilized in a variety of fields is the multilayer perceptron algorithm. The flexibility and capacity to mimic complex functions of MLP networks are well recognized. They are able to manage non-linear relationships and identify complex data patterns. Due to their capacity to represent complicated financial data, MLPs are frequently employed in stock market forecasting. Backpropagation training enables them to learn from past data and modify their weights to produce predictions that are as accurate as possible [16],[17][37] .

Architecture:

- **Hidden layer:**

Determines the best amount of units for the hidden layer; the network nodes (units) in the hidden layer are invisible. The weighted sum of the inputs determines the function of each hidden unit. The estimate algorithm determines the weight values, and the function is the activation function. Each hidden unit in the second hidden layer of the network (if there is one) is a function of the weighted sum of the hidden units in the first hidden layer. In both levels, the same activation function is applied [18]. One or two hidden layers can be present in a multilayer perceptron. The activation function links the values of the units in the subsequent layer to the weighted sums of the units in the previous layer [19].

- **Hyperbolic tangent:**

$$\gamma(c) = \tanh(c) = \frac{e^c - e^{-c}}{e^c + e^{-c}} \quad (1)$$

Translates real-valued arguments into the range (-1, 1). This is the activation function for all units in the hidden layers. The layer number is determined based on the characteristics of the data.

- **Sigmoid:**

$$\gamma(c) = \frac{1}{1 + e^{-c}} \quad (2)$$

Translates real-valued parameters into the range (0, 1). The estimation algorithm can identify the number of units in each hidden layer automatically.

- **Output layer:**

The target (dependent) variables are present in the output layer. The activation function links the values of the units in the subsequent layer to the weighted sums of the units in the layer before it.

- **Identity:**

$$\gamma(c) = c \quad (3)$$

Accepts parameters with real values and returns them unaltered. This is how the activation function for units operates in the output layer for scale-dependent variables.

- **SoftMax:**

$$\gamma(c_k) = \frac{\exp(c_k)}{\sum \exp(c_j)} \quad (4)$$

where the total of all the components in the input vector is obtained, and $\exp(c_k)$ is the exponential function applied to the element c_k .

The Softmax function is appropriate for multi-class classification issues where we wish to assign a probability to each class as it ensures the outputs are non-negative and sum to 1. The predicted class is then determined to be the one with the highest probability [20], [21].

Hyperbolic tangent and Sigmoid have the same function in output.

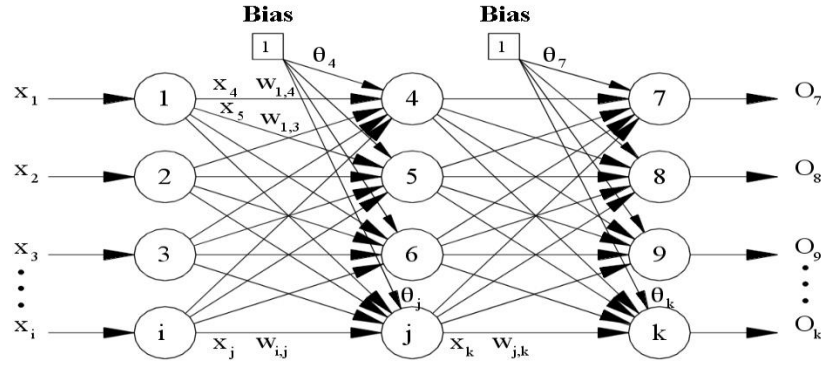


Fig. 1. The structure of a multi-layer perceptron (MLP) neural network.

3. 2 Radial Basis Function (RBF)

RBFs are a form of activation function that is frequently employed in neural networks. These are typically Gaussian functions which calculate the separation between an input vector and its center [22], [23].

$$\phi(x) = \exp(-\gamma\|x - c\|^2) \quad (5)$$

x is the input vector, c is the RBF's center point, $\|x - c\|^2$ is the squared Euclidean distance separating the input vector from the center point, and γ is a parameter that determines the Gaussian curve's width. $\phi(x)$: s the output of the RBF [24], [25].

By applying the Gaussian RBF to the distance between the input vector and the center point, the RBF activation function calculates the output of the RBF neuron. Typically, a metric like Euclidean distance is used to calculate distance. The parameter controls the shape and spread of the RBF as well as the width of the Gaussian curve [26].

Each hidden layer neuron in RBF networks applies an RBF activation function on the separation between the input vector's center point and the input vector. The output of the RBF neuron is then used as the input for the following layer or as the network's final output after passing through an activation function (sigmoid function). The hidden layer uses a radial basis function, which is commonly a Gaussian function, to determine the activity of each neuron inside the layer. Let us use the symbols x for the hidden layer's input, c for the radial basis function's center, and for the width. The hidden layer's j_{th} neuron, designated as h_j , is activated as follows [27]:

$$h_j = \frac{\exp(-\|x - c_j\|^2)}{2\sigma^2} \quad (6)$$

The Euclidean distance between the input x and the center c_j is shown here as $\|x - c_j\|^2$. The hidden layer's output, represented by the letter Z , is the result of combining the outputs of all the neurons in the layer. Let's refer to the biases as b and the weights connecting the hidden layer to the output layer as w . The hidden layer's output is calculated as follows [28]:

$$Z = h_1 \times w_1 + h_2 \times w_1 + \dots + b \quad (7)$$

The value n here refers to the buried layer's total number of neurons.

The specific task determines whether the output layer is activated. The output layer can utilize a softmax activation function to generate probabilities for each class in a classification problem. The output layer of a regression task can provide continuous data using a linear activation function [29].

Let us the letters a , W , and b' to represent the biases, the hidden layer's weights, and the output layer's activation. Calculations for the output layer's activation are as follows:

$$a = W \times Z + b' \quad (8)$$

In this case, W stands for a weights matrix, where each row denotes the weights tying a neuron in the hidden layer to the output layer [30]. The output allows us to determine the most suitable country for investment, in which the uncertainty index achieves accurate predictions on the returns of its financial market shares. We also want to determine how well the index can foretell returns fluctuations.

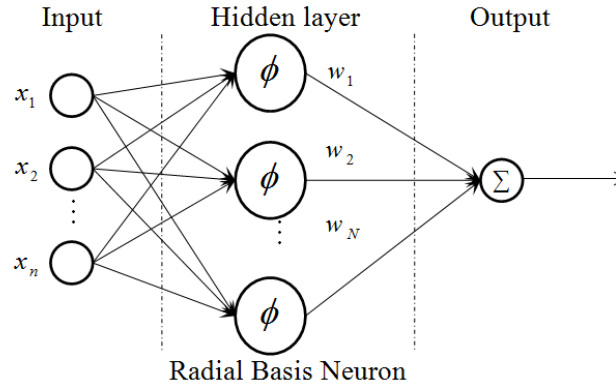


Fig. 2. The structure of a Radial Basis Function (RBF) neural network.

3.3 Optimizations:

A variety of optimization strategies can be applied to train Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks. These include:

Gradient Descent: This fundamental optimization approach modifies the neural network's weights in the direction of the loss function's negative gradient. We will utilize Stochastic Gradient Descent (SGD), one of several gradient descent variations [31], [32]:

$$\text{Update Rule: } \theta = \theta - \alpha \times \nabla J(\theta, x_i, y_i), \quad (9)$$

where (x_i, y_i) is a randomly selected training sample.

Conjugate Gradient: Using an iterative approach to a series of linear conjugate gradient problems, this algorithm determines the minimum of a function [33],[34]:

$$\begin{aligned} \text{Update Rule: } \alpha_k &= (\nabla J(\theta_k))^T \times \nabla J(\theta_k) / (\nabla J(\theta_k))^T \times A \times \nabla J(\theta_k), \\ \theta_{K+1} &= \theta_K + \alpha_K \times \nabla J(\theta_K) - \beta_K \times \nabla J(\theta_{K-1}), \\ \beta_K &= (\nabla J(\theta_{K+1}))^T \times A \times \nabla J(\theta_{K+1}) / (\nabla J(\theta_K))^T \times A \times \nabla J(\theta_K) \end{aligned} \quad (10)$$

Where A is a positive-definite matrix.

3.4 Theoretical difference between MLP and RBF:

Specification:

MLP: A feed forward neural network with an input layer, one or more hidden layers, and an output layer is known as an MLP network. Each layer may include a different number of neurons. Since neurons are totally connected, every neuron in one layer is linked to every neuron in the layer above it.

RBF: networks are frequently employed for pattern recognition or function approximation. They consist of an input layer, a hidden layer with radial basis function neurons, and an output layer. Radial basis functions are used to compute the activations of the hidden layer neurons, which are positioned at certain places in the input space.

Function Approximation:

MLP: Given sufficient hidden units, MLPs may approximate any continuous function to any degree of accuracy, making them universal function approximates.

RBF: Because their receptive fields enable them to concentrate on certain areas of the input space, RBF networks are particularly well-suited for approximating functions with localized patterns.

Learning Algorithm:

MLP: Backpropagation is commonly used to train MLPs, which entails computing gradients and changing weights using methods like gradient descent.

RBF: To establish the center and spread of the radial basis functions, RBF networks can be trained using techniques like clustering (k-means), and then techniques like gradient descent to change the weights.

By determining the degree to which the news content predict stock returns in a group of developed countries' markets (via the EPU index) and the country for which this prediction best succeeds, we hope to test the best algorithm for forecasting and categorization in the financial sector.

3.5 Performance indicators:

The method that produces a convergence between the actual and estimated values is considered to be the best. We utilize two different indicators to measure the best performance. These indicators consist of:

$$E_i = \frac{1}{2} \sum_{i=1}^k (O_i - t_i)^2, \quad (11)$$

where E is Sum of Squares Error (errors are the difference between the variable's real data and the estimated data produced by the neural network, which uses training data to minimize this percentage), O_i is Input data, and t_i is target variable.

$$RAE = \frac{\sum_{i=1}^n |O_i - t_i|}{\sum_{i=1}^n |O_i - \bar{O}_i|}, \quad (12)$$

Where *RAE* is Relative Error for Scale Dependents, where the average value of the dependent variable is used as the predicted value for each time period. We normalize the values in accordance with the following equation to address the issue of the variance in estimated units between the data:

$$\frac{x - \text{mean}}{s}, \quad (13)$$

where S is standard deviation.

4. DATA AND MATERIALS

In this section, the research data and its preliminary analysis are presented. In addition to analyzing the probability distribution and the fundamental relationships that control it, this aids in understanding the dynamics of evolution patterns in the data and the outliers in them. The following table provides a summary of the data we gathered on stock prices and the economic policy uncertainty index for a selection of nations.

TABLE I. MAIN INFORMATION ON RESEARCH VARIABLES

Country	Symbol	Index	Currency	Stock Exchange	Period
United States	US	DOW JONES (DJI)	USD	New York	2000Q1-2023Q6
United Kingdom	UK	FTSE 100 (FTSE)	GBP	London	2000Q1-2023Q6
Canada	CAN	S&PTSX	CAD	Toronto	2000Q1-2023Q6
Russia	RUSS	IMOEX	RUB	Moscow	2000Q1-2023Q6
China	CHIN	HIS	HKD	Hong Kong	2000Q1-2023Q6
Australia	AUS	ASX200	AUD	Sydney	2000Q1-2023Q6
France	FRAN	CAC40	EUR	Bourse de Paris	2000Q1-2023Q6
Germany	GER	DAX30	EUR	Frankfurt	2000Q1-2023Q6
Italy	ITAL	FTMIB	EUR	Milano	2000Q1-2023Q6
Spain	SPAIN	IBEX35	EUR	MADRID	2000Q1-2023Q6
European Union	EU	N100	EUR	EURONEXT	2000Q1-2023Q6
Japan	JAP	NIKKEI225	JPY	TOKYO	2000Q1-2023Q6
Economic Policy Uncertainty	EPU				2000Q1-2023Q6
Stock Index					2000Q1-2023Q6

Using three different underlying components, an index was created to evaluate policy-related economic uncertainty. Quantifying media coverage of policy-related economic uncertainty is the first and most adaptable component. An index of search results from 10 major newspapers from each country makes up the newspaper-based component. In the United States, the Congressional Budget Office (CBO) produces publications that assemble lists of temporary federal tax code provisions, which are the basis for the index's second component. A measure of the degree of uncertainty regarding the direction that the federal tax code will take in the future was established using annual dollar-weighted numbers of provisions of the tax law due to expire during the next ten years. The Survey of Professional Forecasters conducted by the Federal Reserve Bank of Philadelphia serves as the third component of our policy-related uncertainty index. Here, we created indices of uncertainty regarding policy-related macroeconomic variables using the dispersion between individual

forecasters' expectations about future levels of the Consumer Price Index, Federal Expenditures, and State and Local Expenditures. The monthly closing price of the group of indices listed in the table was used to determine stock prices for each nation. The primary data elements were displayed in the preceding table, and the key descriptive and exploratory variables are displayed in the table below:

TABLE II. DESCRIPTIVE STATISTICS FOR VARIABLES

Variables	Observation	Normality J-B	Mean	Standard Deviation	Maximum	Minimum	Skewness	Kurtosis
EPU	3384	13364.***	148.24	99.973	964.14	10.111	2.336	11.54
Stock Index	3384	1043***	10647.81	8637.9	48478.5	144.39	1.192	4.306

Denotes significance of the statistical value at ***1%. at **5%. at *10%.

4.1 EPU (Economic Policy Uncertainty):

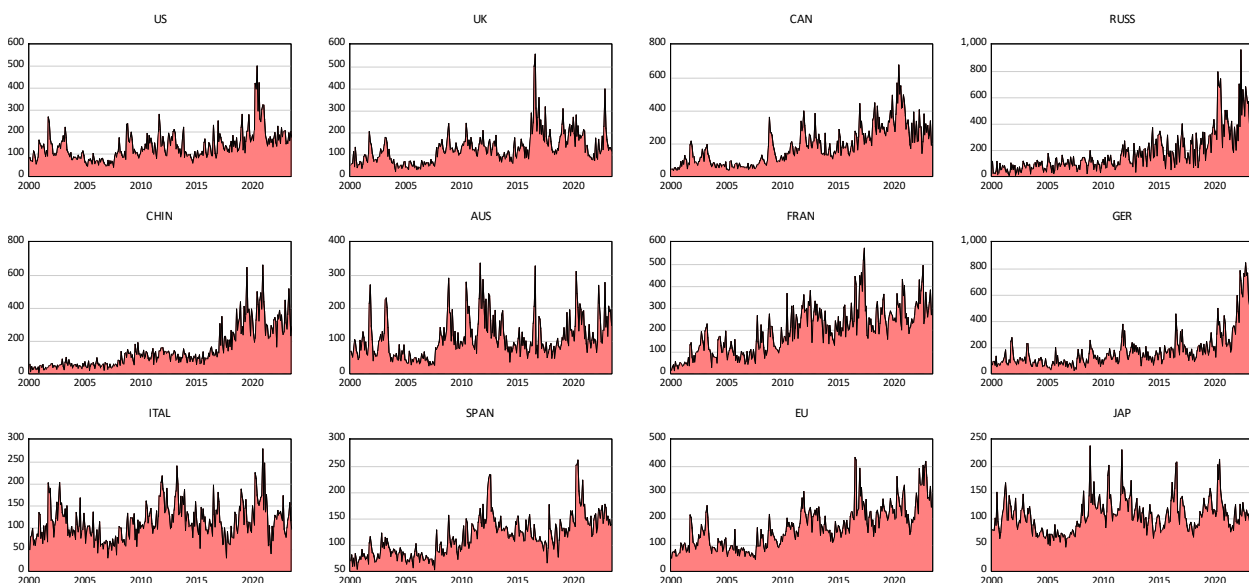
The mean value of EPU is 148.24. This shows that these countries have a high level of uncertainty. The data points appear to be scattered around the mean, according to the standard deviation of 99.97. A higher standard deviation denotes greater unpredictability in the uncertainty of economic policy. With the start of the war in Ukraine, which put doubt on Russian and global economic policy, Russia had the greatest value (964.14) in the fourth month of 2022. The lowest value is (10.11) belongs to China in the eleventh month of 2000, when China had a clear economic strategy and saw rapid economic growth. The skewness value reveals elevations in the index that are higher than the average for all countries, and the kurtosis value shows that the peak of the variable distribution is tapered as a result of the significant swings in the index.

4.2 Stock Index:

As the stock prices of the group of countries changed from 144.39, it is important to note that the high number of standard deviation in stock prices reflects the large dispersion in their values. This was the index of Russia during the 12th month of 2000 and was the result of the debt crisis, manipulation of the financial system, and the collapse of the real estate market with a drop in oil prices. The economy's primary source of income and the Russian government's interference in the market both lowered investor trust. The second month of 2000 saw Italy's stock prices hit their all-time maximum value (48478.5) as a result of the country's robust economic growth, international investment, and supportive governmental policies.

High degrees of skewness and variability can be seen in the EPU and Stock Index. This means that, given the non-normal distribution of the data, there may be considerable volatility and concentrations of values in both the uncertainty of economic policy and stock market performance.

It is evident that rising stock prices occur when economic policy uncertainty is low. The following image serves as an illustration of this:



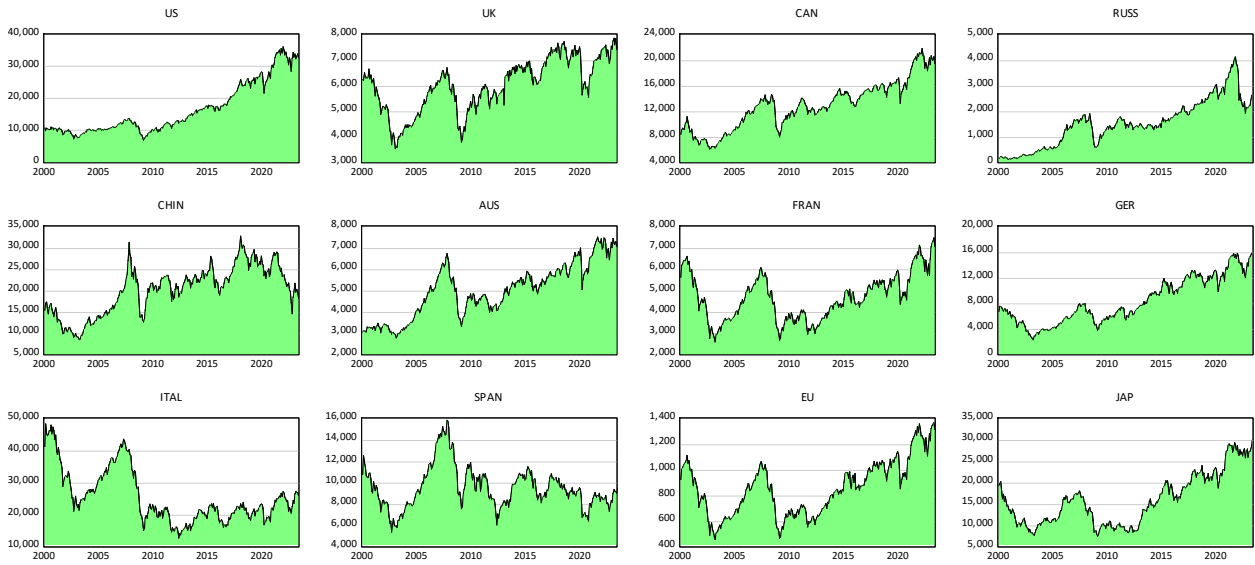


Fig. 3. The development of EPU (red) and stock prices (green) in the group of countries.

Except for Australia, Japan, and Italy, where the levels of uncertainty vary at the category level without trend, we see that the levels of uncertainty in economic policy have a direct relationship with substantial volatility (change at the trend level). This is because these nations' diverse economic systems make them more susceptible to changes in the global economy (crises). Regarding stock prices, we observe that nations that have experienced a positive trend in stock prices (such as the United States, the United Kingdom, China, and Germany) also experience the least amount of uncertainty in terms of economic policy. Positivity in stock price trends may be influenced by economic stability. When the economy is robust and steady, investor confidence is increased, and share prices rise as a result. On the other hand, when the economy experiences swings and instability, stock prices fall. Stock prices are impacted by EPU through a number of channels: First, news about the economy that is related to projections for GDP growth or low unemployment rates, with steady inflation rates driving up stock values. Political news, next the stock price index increases as a result of trade agreements and China. Lower prices are also reflected by political unrest and conflicts, as well as by Russia. Third: Mental health considerations/the “human factor”. Investors may become apprehensive and agitated when bad news about the economy or politics circulates, which lowers demand for stocks and, as a result, lowers their values. On the other hand, as good news spreads, investor confidence and optimism may rise, causing a rise in the demand for equities.

5. EMPIRICAL RESULTS

We utilize the cross-sectional correlation test from [35] to determine how closely swings in uncertainty levels agree between nations and the correlation of patterns in the growth of stock prices between them. To assess for cross sectional correlation, this test is based on common regression analysis and common zero testing. The model's estimation is written as:

$$y_{it} = \beta'_{it}x_{it} + u_{it}, \tag{14}$$

where $i = 1,2,3 \dots, N, t = 1,2,3, \dots, T$ and x_{it} are dimensions of the regression vector, β'_{it} are cross-sectional vectors that correspond to the target parameters to be estimated. It is possible to verify the following hypothesis:

$$H_0: \rho_{ij} = \text{Corr}(u_{it}, u_{jt}) = 0 \text{ for } i \neq j \tag{15}$$

The moment of the residual correlation coefficients for balanced samples is measured as:

$$\hat{\rho}_{ij} = \frac{\sum_{t \in (i,j)}^{T_{kj}} \hat{u}_{i,jt}}{\left(\sum_{t \in (i,j)}^{T_{kj}} \hat{u}_{it}^2\right)^{1/2} \left(\sum_{t \in (i,j)}^{T_{kj}} \hat{u}_{jt}^2\right)^{1/2}}, \quad (16)$$

where $t \in (i, j)$ is used to indicate that we are collecting a subset T_{ij} of the observations i, j that are common to:

$$\tilde{u}_t = \frac{\sum_{t \in (i,j)} \hat{u}_{it}}{T_{ij}}. \quad (17)$$

This assumes that the remaining members of the even subgroups are not zero. The results of this test are shown in the Table:

TABLE III. CROSS SECTIONAL CORRELATION TEST

Variable	Statistics	Probability
EPU	77.122	0.000
Stock Index	76.700	0.000

The results demonstrate that the test statistic probability value is less than a significant level of 5%. As a result, we can rule out the null hypothesis and conclude that stock prices and the variables of economic policy uncertainty are correlated throughout cross sections. Since price changes in one nation (such the mortgage crisis and Russia's war on Ukraine) would be mirrored in prices in other countries, the existence of this association is mostly attributable to the close trade ties between the proposed groups of countries in the sample. The significant levels of uncertainty and price volatility are influenced by news and events from across the world. Additionally, the success of emerging markets and central bank policies may be indicative of shared effects on the group of nations. The neural network's architecture calls for splitting the sample into 20% for testing and 80% for training. To obtain the fewest possible prediction errors, the number of units for each hidden layer and output layer were chosen using gradient descent optimizations. The extensive stochastic volatility in the variables, as shown by the graph, led to the selection of this technique.

The training was conducted online, which allows the weight and distortion to be updated as soon as each sample from the dataset is input. Individual input is fed into the neural network during online training, where error is determined and weight and distortion are adjusted in real-time. This implies that the neural network picks up new information independently from each sample. The following values were used to determine the training options:

Initial learning rate = 0.4, lower boundary of learning rate = 0.001, learning rate reduction in epochs = 10, momentum = 0.9, interval center = 0, and interval offset = ± 5 . We can see the outcomes of the MLP algorithm's stock price predictions for each of the nations in the following table:

TABLE IV. PREDICTION RESULTS USING AN MLP ALGORITHM

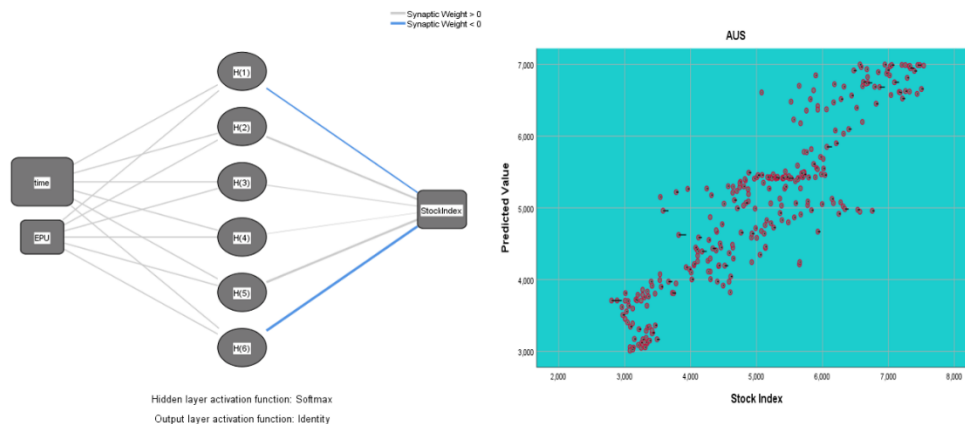
Variable	TRAINING (80%)			TESTING (20%)		
	Relative Error	Sum of Squares Error	Number of Units in Hidden Layer	Relative Error	Sum of Squares Error	Number of Units in Output Layer
AUS	0.08	8.971	11	0.058	1.772	1
CAN	0.1	10.513	3	0.132	4.364	1
CHIN	0.284	32.562	5	0.496	9.896	1
EU	0.248	28.427	3	0.259	6.270	1
FRAN	0.303	34.527	5	0.544	11.478	1
GER	0.097	10.559	1	0.117	2.977	1
ITAL	0.288	31.929	3	0.180	5.257	1
JAP	0.133	15.241	4	0.163	4.309	1
RUSS	0.207	23.602	4	0.135	3.755	1
SPAIN	0.233	24.534	6	0.212	8.710	1
UK	0.181	17.721	3	0.166	6.706	1
US	0.027	2.685	1	0.024	0.986	1
Percent Correct Predictions	92.9%	Activation function	Hyperbolic tangent	96.63%	Activation function	Identity

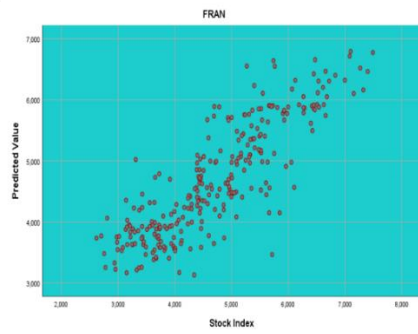
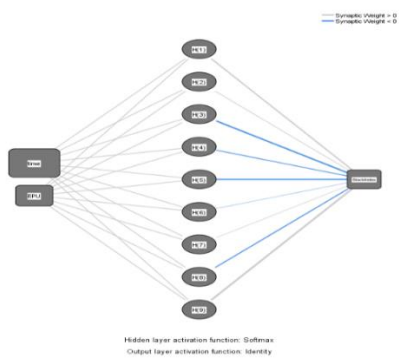
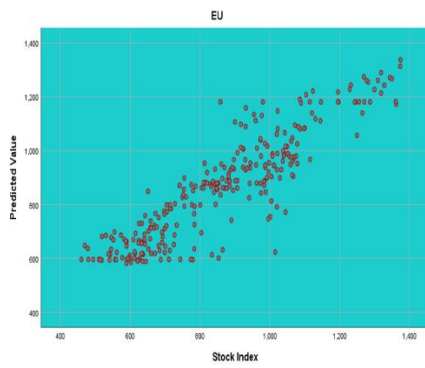
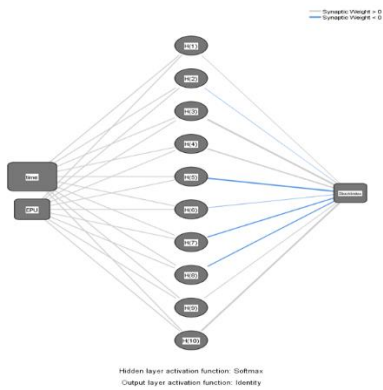
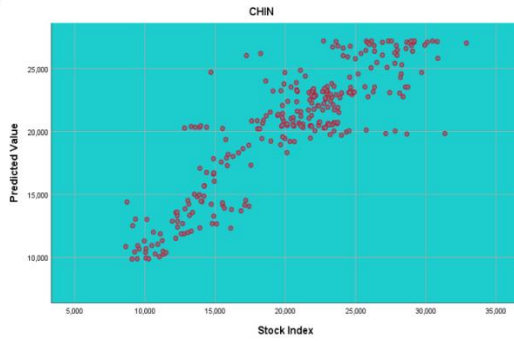
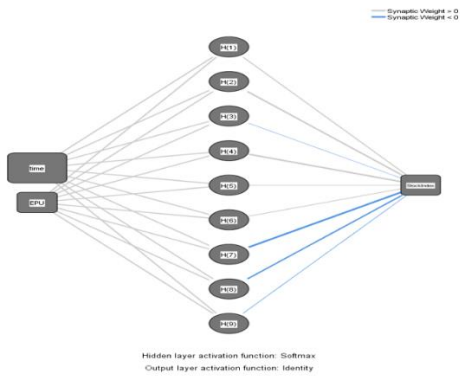
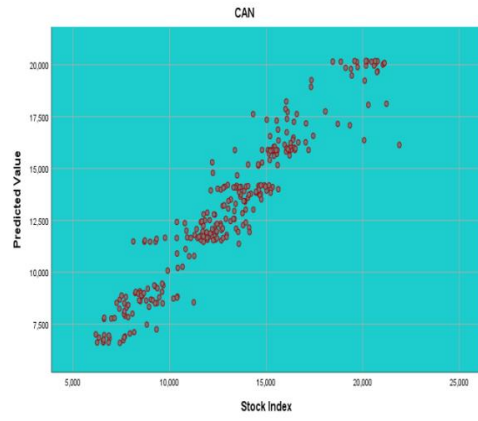
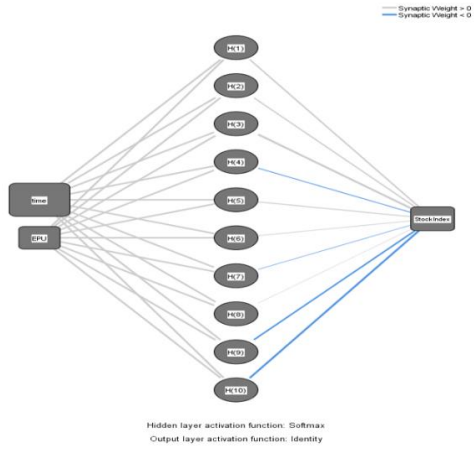
According to the information in the table, the United States demonstrated good performance in prediction based on the relative error, the sum of the squares of the error, as well as the right prediction ratio. The United States has a relative error of 0.024 in the test set and 0.027 in the training set. This indicates that the forecast provided by the model employed was close to the actual values. The United States additionally recorded sum of squares errors of 2.685 in the training set and 0.986 in the test set. This shows that the model was able to make its predictions and was successful. Despite being the lowest performer, France had a lower prediction performance, with relative errors of 0.303 out of 34.527 in the training set and 0.544 out of 11.478 in the test set. However, given the intricacy of the data, the forecast is valid. It should be mentioned that the hyperbolic tangent, which demonstrated a correct prediction rate of 92.9% in the training set, was utilized for the activation function. The test group utilized the Identity activation function, which was 96.63% accurate in its predictions. These findings suggest that the effectiveness of the model and its capacity to predict accurate values can be influenced by the selection of a suitable activation function. Model performance may be impacted by the quantity of units in the hidden layer and the output layer. The number of units in the hidden layer varies in the data shown, with examples including 11, 3, 5, and 6. The intricacy of the data used for each country and the unique forecasting requirements may be contributing causes to this variation. The hidden layer's unit count can have an impact on the model's capacity to recognize patterns in the data and forecast future values. It appears that all nations utilize the same unit for the output layer. This decision may be influenced by the unique requirements of each nation and the type of data.

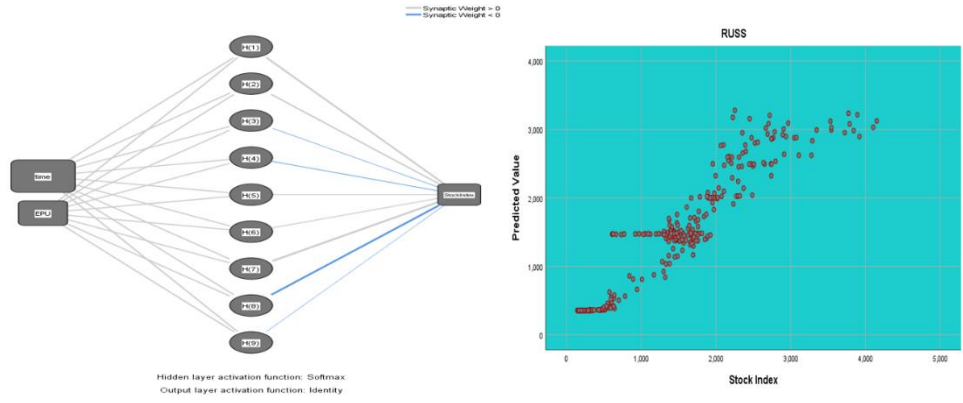
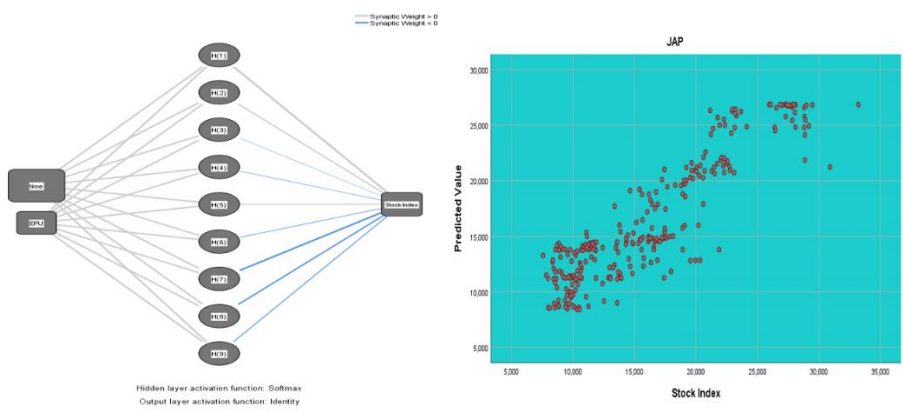
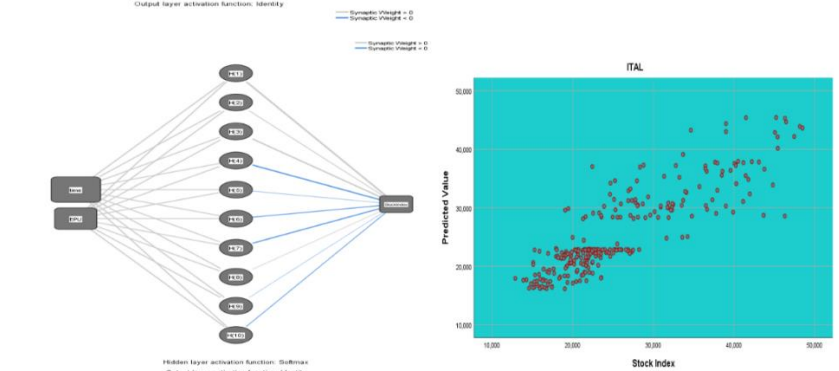
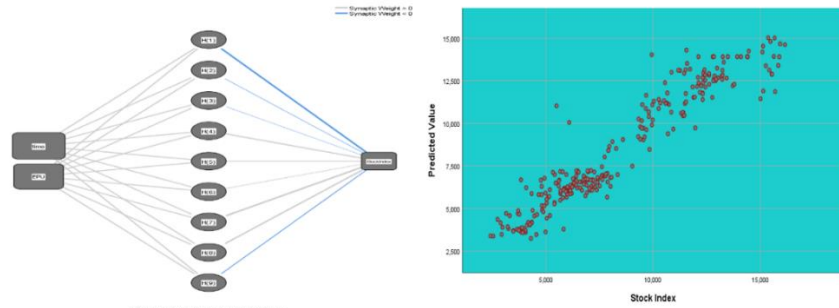
TABLE V. PREDICTION RESULTS USING AN RBF ALGORITHM

Variable	TRAINING (80%)			TESTING (20%)		
Indicators	Relative Error	Sum of Squares Error	Number of Units in Hidden Layer	Relative Error	Sum of Squares Error	Number of Units in Output Layer
AUS	0.169	16.41	6	0.194	8.751	1
CAN	0.074	6.685	10	0.117	5.834	1
CHIN	0.212	21.669	9	0.275	13.94	1
EU	0.186	19.780	10	0.213	5.886	1
FRAN	0.266	24.181	9	0.293	13.978	1
GER	0.102	10.356	9	0.068	1.789	1
ITAL	0.249	23.141	10	0.244	12.35	1
JAP	0.184	18.113	9	0.199	9.184	1
RUSS	0.098	9.284	9	0.156	7.156	1
SPAIN	0.385	38.648	8	0.538	19.93	1
UK	0.304	27.784	10	0.272	14.672	1
US	0.051	5.174	9	0.038	1.558	1
Percent Correct Predictions	90.85%			90.41%		

Spain had the lowest forecast error rate (38.5%) and the United States had the best prediction (5.1%). We also observed that the accuracy rate, which was lower than that of the MLB method, was 90.85% for the training data and 90.41% for the test data. We can thus state that the MLP algorithm is superior at forecasting temporal and multidimensional data. Its ability to learn intricate correlations between variables and forecast future values using past data defines it.







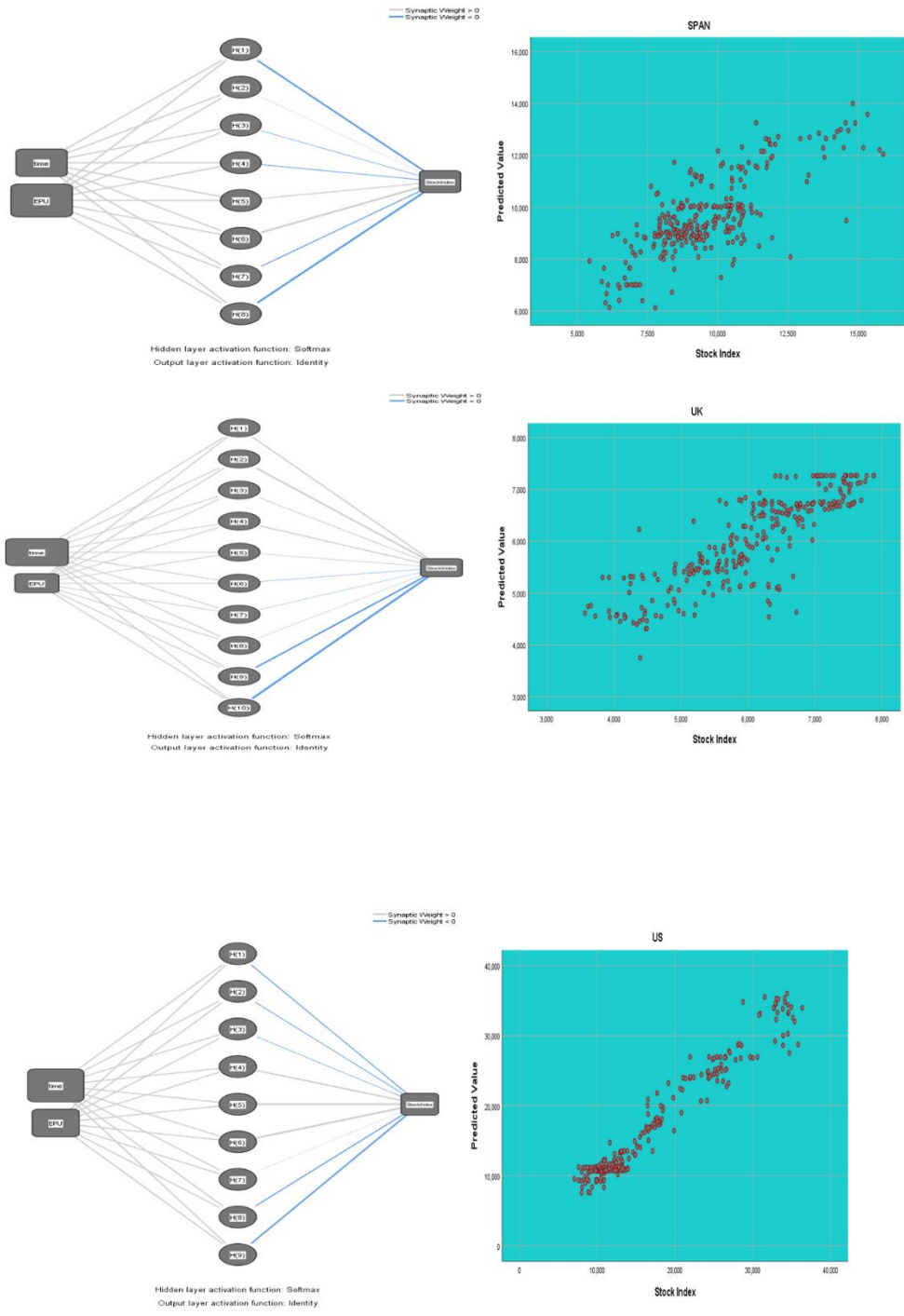


Fig. 4. Estimated and actual points of stock prices (right column) and the number of hidden layers and the output layers in each country (left column)

The figures in the right column show the estimated and actual points of stock prices in each country; the spread of the points is shown linearly, and this indicates the success of the predictions for all countries. The left column indicates the number of hidden layers and the output layers for each country. Blue lines from the hidden layer indicate the output layer for which the weights are negative, indicating that higher levels of uncertainty in economic policy lead to declining stock prices. The asset allocation in the portfolio can be improved using this information. Depending on how each investor expects their financial assets to perform, different percentages of financial assets might be allocated in the portfolio. Assets with higher forecasts may receive a larger allocation, while those with poorer forecasts may receive a smaller proportion. After successfully forecasting stock prices for future periods using the EPU index, this information can be used to classify investment opportunities by country and predict the appropriate investment, based on ROC curve. One significant result of

the neural network model is the ROC (Receiver Operating Characteristic) curve. Given that the binary classification model divides the input into just two categories (like positive and negative), its performance is assessed using this curve. The decision limit (threshold) in the model is adjusted using the ROC curve, which is made up of a collection of points representing various trials. The decision threshold is established based on the model output value (for example, the probability of being categorized as positive). When the decision threshold is modified, the balance between Sensitivity and Error rates in the model also changes:

$$\text{True Positive Rate} = \frac{TP}{TP+FN}, \quad (18)$$

$$\text{False Positive Rate} = \frac{FB}{FB+TN}, \quad (19)$$

The ROC curve plots the detection rate (Sensitivity) and the mistake rate (Specificity) on the vertical axes, respectively. The balance between the detection rate and mistake rate at each point on the curve varies depending on the decision threshold. The performance of the model is improved by the curve's proximity to the graph's upper left corner. The area under the ROC curve, abbreviated as AUC Area, serves as a gauge of model performance. AUC value for Under the Curve goes from 0 to 1, with 1 denoting the model's ideal performance in binary classification. The performance of various binary classification models is compared using the ROC curve and the AUC space in order to determine which model performs the best. The model performs better at differentiating between the two groups the higher the AUC value. In conclusion, the ROC curve and the AUC space help in making classification decisions based on different decision boundaries and offer a valuable evaluation of the effectiveness of a neural network model in binary classification. We obtain based on the model's output:

TABLE VI. AREA UNDER THE CURVE

		Area
Country	AUS	.962
	CAN	.961
	CHIN	.950
	EU	.973
	FRAN	.966
	GER	.959
	ITAL	.965
	JAP	.925
	RUSS	.973
	SPAN	.939
	UK	.955
	US	.942

From the table, we notice that the values for all countries are located at the top left side of the curve, and this indicates excellent predictions for all countries, with the best prediction for the European Union and Russia and the worst performing—for Spain. Therefore, it is also possible to rely on indicators of uncertainty and stock prices when classifying countries by investment opportunity using this model. Thus, this forecasting helps not only to determine the optimal buying and selling times but also their place. The following curves derived from the ROC curve show these results:

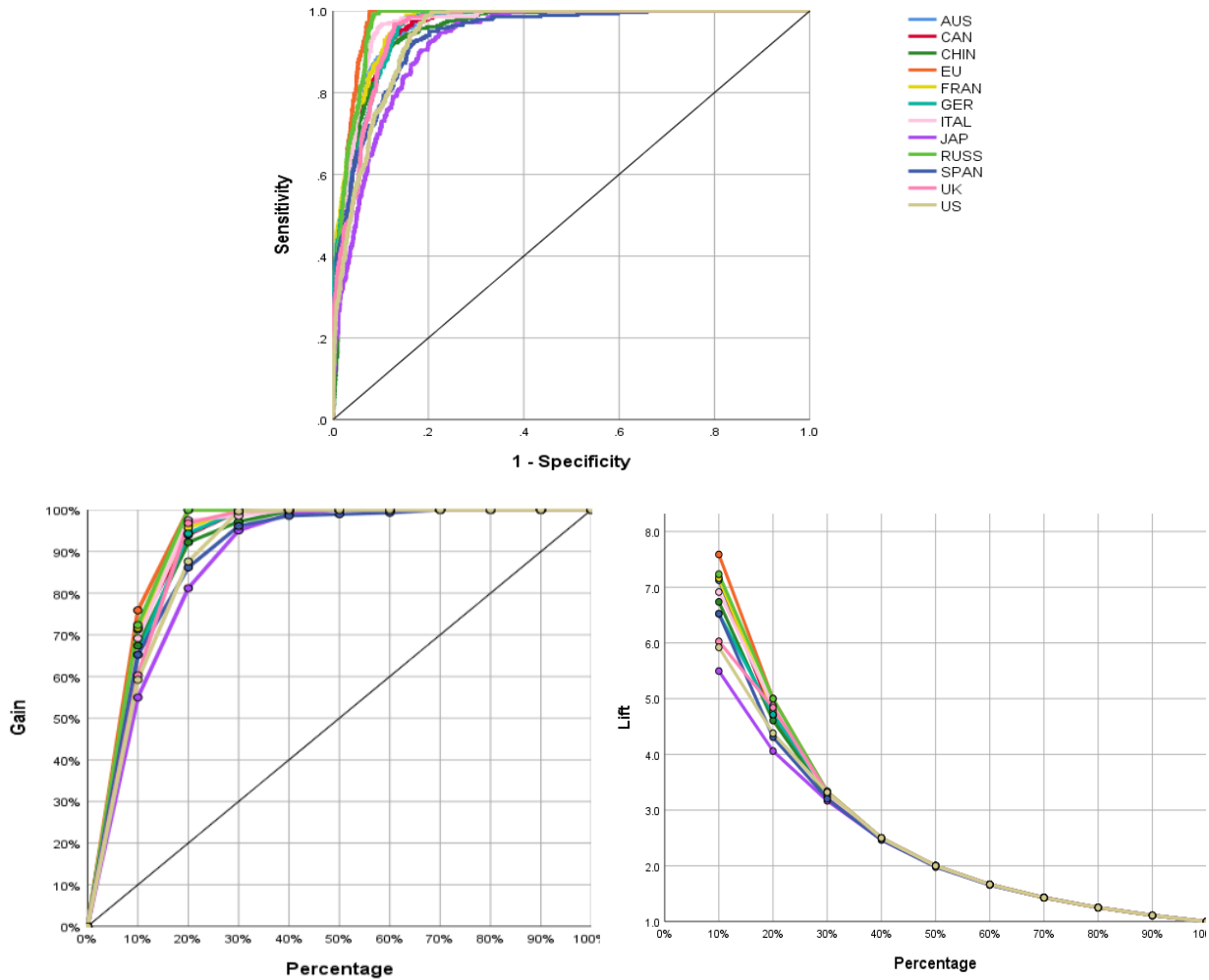


Fig. 5. ROC-GAIN-LIFT Curves.

Both ROC curves indicate the ability of the model to distinguish between positive and negative categories at different decision limits. Since the difference between the detection rate and the error rate is large for all countries, we conclude that the model is better able to discriminate and correctly classify the best country for investment in terms of stock prices and uncertainty in economic policy and time. The lift curve indicates that with increasing training periods, the level of prediction error decreases for all classifications. The following figure shows the relative importance of the variables in the classification:

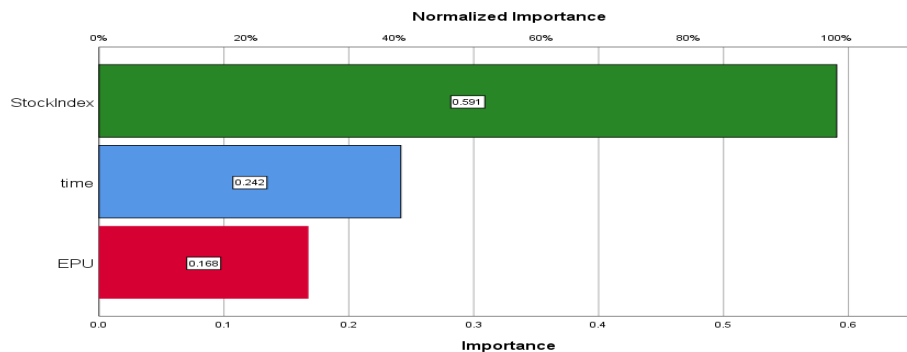


Fig. 6. Relative importance in prediction of research variables.

The figure shows that the best contributor to the correct classification of countries is stock prices with a percentage of 59.1%, the second best is timing (24.2%), and third best is uncertainty in economic policy (16.8%). This reflects the importance of predicting future stock prices to choose the appropriate timing and place for investment.

6. ERROR ANALYSIS:

For the model's predictions to be successful in the long run, the errors must show normal distribution and the stability of the series of residuals for each country, as the fulfillment of these assumptions indicates that the series of errors are not self-correlated and have homogeneity in variance. Thus, with the realization of these assumptions, it can be confirmed that the proposed algorithms succeed both in short-term and long-term predictions. To test normal distribution, we use the Q-Q plot technique, which is a tool used in analyzing statistical data to assess whether the data follows a particular distribution. The tool is used to compare the distribution of the actual data with the normal distribution to validate the assumptions of the statistical model used. A Q-Q plot is plotted by arranging the actual data in ascending order on the horizontal axis and comparing them to the predicted values for a normal distribution on the vertical axis. If the data follows a normal distribution, the graph will be approximately a straight line. If there are differences from this pattern, there may be a shift or modification of the normal distribution:

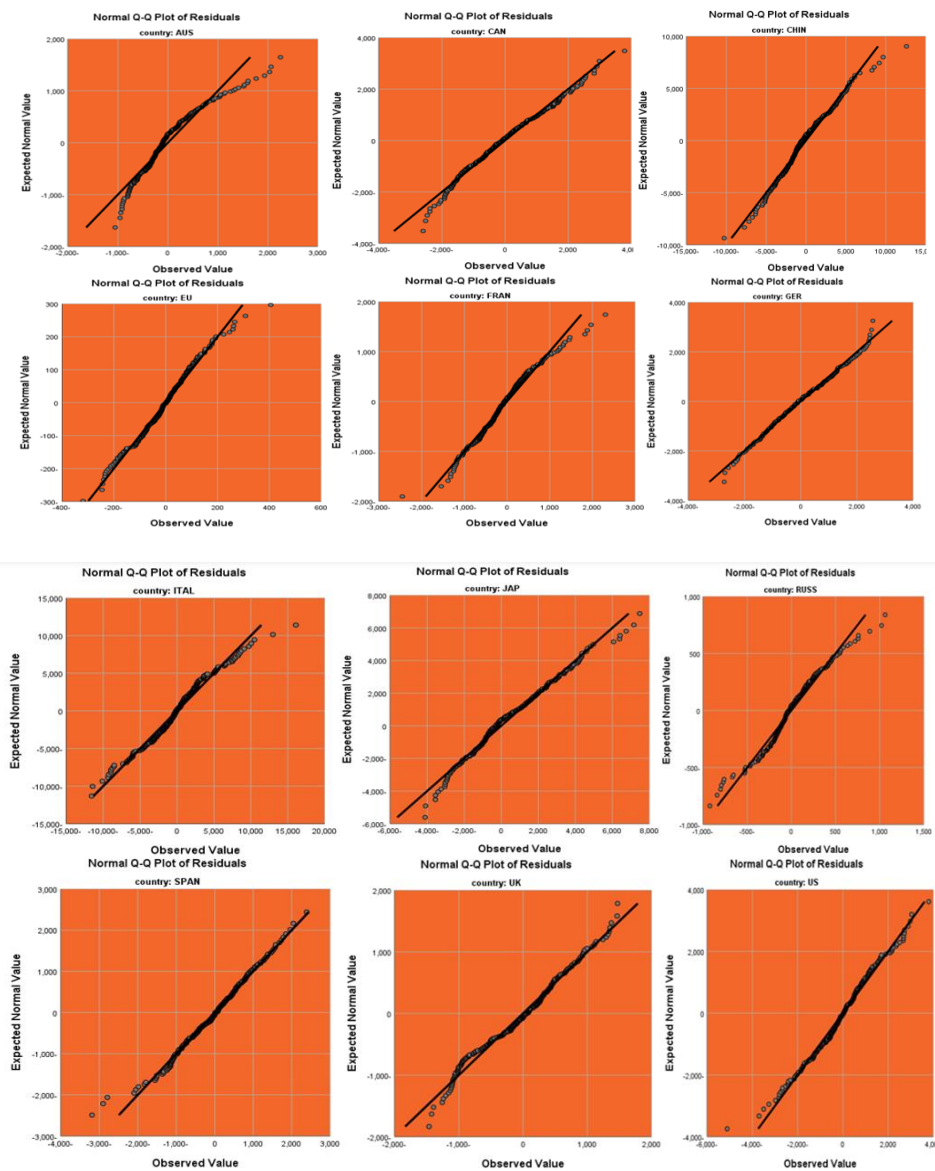


Fig. 7. Q-Q Plot for residuals.

Figure 7 shows that the residual points converge to the normal distribution line in the drawing for all countries, indicating that the prediction errors have a normal distribution. The first assumption is fulfilled. After checking the normal distribution, we use (Im, Pesaran, and Shin) with individual unit root processes to check the stability of the residuals. For each cross section, Im, Pesaran, and Shin first specify a unique ADF regression:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X'_{it} \delta + \varepsilon_{it}. \quad (20)$$

The premise of the null hypothesis is, $H_0: \alpha_i = 0, \text{ for all } i$.

While the alternative hypothesis is given by:

$$H_1: \begin{cases} \alpha_i = 0, & \text{for } i = 1, 2, \dots, N_1 \\ \alpha_i < 0, & \text{for } i = N + 1, N + 2, \dots, N \end{cases}, \quad (21)$$

where i can be rearranged as needed. This can be understood to indicate that a non-zero proportion of the individual processes is stationary. After estimating the separate ADF regressions, the average of the t-statistics for α_i from the individual ADF regressions, $t_{iT_i}(p_i)$:

$$\bar{t}_{NT} = (\sum_{i=1}^N t_{iT_i}(p_i))/N. \quad (22)$$

By applying, we get the following results:

TABLE VII. ERROR STATIONARY TEST

Method	Statistic	Prob.**
Im, Pesaran and Shin W-stat	-7.74284	0.0000

The table shows that the probability value of the test statistic is less than a significant level of 5%. We can therefore reject the null hypothesis and find that the series of residuals is stable in level. With the fulfillment of the two assumptions, we conclude that predictions of stock prices are successful in the long run.

7. CONCLUSIONS:

In this research, two machine learning algorithms with neural network operational mechanisms were proposed to predict stock prices in a group of developed countries. Appropriate units in the hidden layers and outputs, the results showed that both MLB and RBF predicted stock prices for a group of countries well using the economic policy uncertainty index, which reflects the level of impact that world news has on national economic policy and expectations. The MLB algorithm proved its ability to predict chain data. The countries were also ranked according to stock price data and uncertainty in economic policy, thus choosing the best country to invest in, statistically.

Uncertainty surrounding economic policy is what makes stock price forecasting so crucial. Investors must consider the degree of economic policy uncertainty and how it affects asset prices when deciding how to allocate their assets. Investing in a variety of assets, such as stocks, bonds, commodities, and real estate, may be preferred by investors, for instance, in the event of significant economic policy volatility and political unpredictability. This is a form of diversification used to lessen the risks brought on by changes in the market. Additionally, asset allocation decisions based on investors' expectations of how different assets will perform in these circumstances may be impacted by the volatility and uncertainty of economic policy. Investors may choose to increase their exposure to less hazardous assets like bonds or cash assets while decreasing their exposure to these assets.

Data Availability:

The data used in the study are available through the following links:

<https://www.nyse.com/index>

<https://www.londonstockexchange.com/>

<https://www.tsx.com/>

<https://www.moex.com/en>

https://www.hkex.com.hk/?sc_lang=en
<https://www.ssx.sydney/>
<https://www.euronext.com/en/markets/paris>
<https://www.boerse-frankfurt.de/en>
<https://www.euronext.com/en/markets/milan>
<https://www.bolsasymercados.es/bme-exchange/en/Madrid-Stock-Exchange>
<https://www.euronext.com/en>
<https://www.jpx.co.jp/english/>
<https://www.policyuncertainty.com/>

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Conflicts Of Interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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