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CHOICE OF METHODS AND DATA IN USING ARTIFICIAL NEURAL NETWORK ARCHITECTURE UNDER NORMALIZED AND STANDARDIZED DATA ANALYSIS OF INWARD FDI TO INDIA FROM OTHER BRICS NATIONS

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Abstract
The choice of method in predicting the causation between dependent and independent variables has always been challenging for researchers. Methods' importance, ease, and robustness have eluded the community for a long. In this paper, we try to examine the use of Artificial Neural network (ANN) architecture as an alternative to the standard linear association processes and check whether the ANN architecture yields good results in the first place and what type of ANN architecture to use. Two architectures, namely Radial Bias Function (RBF) and Multi-layer Perceptron's (MLP) have been used under two different data structures, i.e., Standardized and Normalized. The results of the study show that the MLP with a standardized data set provides better results than the other methods, besides showing that the GDP of India is affected by the inflow of FDI from China and Russia and not so much from Brazil and South Africa.

Key Words: Artificial Neural Network, BRICS, India, FDI, Radial Bias Function, Multi-layer Perceptron, Standardized data, and Normalized data

1. Introduction

The BRICS countries, namely Brazil, Russia, India, China, and South Africa are recognized as the most advanced and fast-growing countries among the emerging economies. In the earlier 2000 study, Andreff (2016) showed an increase in inward and outward FDI from post-communist and fast-growing developing countries. BRICS countries are among the ten largest countries in the world, both by land mass and population. The stirring facts about the BRICS group are that these countries have large markets that cater to about eighty percent of their population domestically. This has helped them reap the benefits of strong growth impetus over a few decades and will ensure the same in the future too. This strong presence of the domestic market has helped these countries to tide over their financial crisis better than the developed nations. Their success as an emerging economy has provided an interesting business model for the rest of the world as the other striving nations can recreate them.

India, a Lower Middle-Income nation, had a notable annual GDP growth of 6.81% in 2018, according to Veni (2020). China, one of the BRICS nations with an upper middle-income status, came in second (6.57%). The remaining BRICS nations have surpluses in their current accounts, as opposed to India, Brazil, and South Africa, which have deficits. In contrast to the rest of the world, where the inflation rate is just about 2%, it is above 4% in South Africa and India. Both densely populated China and India have high labour force participation rates. Among the BRICS nations, South Africa (28.18%) and Brazil (12.07) have the highest unemployment rates in 2019. In terms of the value of imports and exports of goods and services, China continued to lead the BRICS. Only in 2018 did the other BRICS economies, with the exception of India, receive more than half of their GDP from the tertiary sector. With contributions to GDP of more than 60%, South Africa and Brazil held the top two spots. A sizeable portion of the industrial sector has been given by China (40.6%) and the Russian Federation (32.15%). China was the only nation to contribute 29.41% of GDP in the manufacturing sector in 2018. compared to the other BRICS nations. With a 14.6% GDP contribution from the agricultural sector, India is the only nation that contributes higher. According to research estimates, China has experienced the greatest growth in FDI inflow among the BRICS countries over the study period. During the study period, the values of the coefficients (growth rates) were recorded in ascending order by Brazil, India, the Russian Federation, and South Africa. However, when it comes to the FDI outflow from BRICS over the study period, Brazil and the Russian Federation have had the largest growth rates. Brazil. According to predictions, China held onto the second and third spots, while South Africa remained in fourth place for each year from 2019 to 2023. India continued to have the lowest ranking since it primarily prioritized attracting FDIs and encouraging domestic investment. If other factors remain constant over the course of the time, the regression coefficient values will be sufficient to forecast the entrance and outflow of FDIs.

Against this backdrop, the study investigates the applications of the Artificial Neural network (ANN) technique as a substitute to the standard linear relationship processes, and in this regard, two types of process, namely Radial Bias Function (RBF) and Multi-layer Perceptron's (MLP) are applied on the database of inward FDI to India from other BRICS countries.

The rest of the paper is organized as follows. The next section briefly review the available related literature followed by a theoretical discussion on the raised issue. The methods and data are described in details before interpreting the research findings and corresponding discussions. The final section concludes the paper.

2. Review of Literature

FDI inflows of BRICS economies have been a subject of great interest in international trade and development, which has made a large number of studies in this area available for scrutiny. Most of these studies have focused on finding the impact of FDI on host country economies depending on the size and structure of the FDI flows.

In his research, Apergis (2009), demonstrated that there is a substantial long-term connection between outward FDI and inward FDI. When the sample was divided into developed and developing economies, a two-way causality was identified. It was established that outward FDI is the most critical factor in improving an economy's growth prospects by attracting FDI initiatives that can generate high momentum growth for the economy. In their study, Rizvi and Nishat (2009) found that FDI does not create employment opportunities and should be supported by other policies to generate employment. The impulse response calculation reveals that, on average, in the three nations, the growth elasticity of employment is relatively low, necessitating the highest priority for employment-enhancing policies.

Bhaumik et al. (2010) observed that the world has seen a new globalization era through outward FDI from the emerging market. High levels of family control and institutional ownership are found as alternatives to the domestic institutions of the host nation. This has fostered different strategic decisions, which has helped in getting support from firms in the West for these processes. Nistor (2015) demonstrates how the volume and composition of FDI flows affect the host nation. Analyzing growth in the FDI of the BRICS economies showed that large annual inflow of stocks during the period of 2004-08 have has resulted in the emergence of these economies at a rapid rate of their growth. The FDI of the BRICS economies has a high positive impact on their growth. Andreff (2016) expounds on a thorough comparative analysis of outward foreign direct investment (OFDI) techniques used by multinational corporations (MNCs) with parent headquarters located in the BRIC countries. The literature on examining MNCs' investment plans from each BRIC countries has already been expanding at an exponential rate over the past ten years. However, overall comparison analyses are still in their infancy.

Sultana et al. (2019), in their study, found that FDI partially influences the macroeconomic parameters such as foreign exchange reserves, exchange rate and imports of India. Since FDI support the foreign exchange reserve, which in turn creates a chain of growth for the economy, such as stabilization of the Indian Rupee, and higher HDI, to name a few, the FDI supports the GDP to a large extent. In a sector level study on India, Venkataraman and Venkatesan (2019) observed significant impacts of FDI on foreign exchange rate. According to Bhattarai and Negi (2020), FDI significantly contributes to rising sales, profits, wages, as well as employment among Indian enterprises. The enhanced technology and ability in management techniques that come with FDI play a part in such a favorable impact. Empirical evidence has been discovered that FDI has favorable effects on the success and expansion of Indian businesses. The study was conducted by the authors using Dynamic optimization and production functions, Regression models, and pseudo-panel data.

The studies referred to in the earlier section highlight extensive use of the linear equation to determine the causation. The approaches to these studies have largely been in the models of a predictive regression equation. This has a shortcoming. In the first place, it replaces the character of the data by assuming that the high-frequency data are not stationary and hence cannot be fit for the distribution test. Therefore, all these data are put to a stationary test to satisfy the quintessential characteristic line. However, a common word of wisdom could be to understand the relation between these economic data in a business-as-usual model. In the second place, they are assigned to Gaussian processes leaving little scope for training the data beyond normality. Hence an alternative approach could be to use the "Artificial Neural Network" (ANN) framework to train data towards a more natural way of understanding a model that could show the results of linkages and biases. Studies have shown that these methods have yielded better results in predicting the outcome under both a trained and non-trained environment. The different methods of soft computing methodologies which are used, ANN techniques are more prominent, which can train and understand the past trend of activities rationally. An artificial neural network (ANN) is a network made up of many interconnected processing units or neurons. The parallel operations of the ANN structures demonstrate parallel distribution systems. The ANN system may be trained using the accumulated knowledge of specific problems and learns from examples. Unknown instances of the issue that make up the training data can be solved using an ANN that has been appropriately trained.

The ANN has been successfully used in problems of classification, optimization, image processing, data comparison and pattern reorganization (Goswami, 2012; Chada et al., 2019). The area where the ANN has been used include computer science, engineering, management of trade and commerce, financial management, and economic planning, just to name a few. During their survey of literature on applications of ANN, Hill, Marquez, O'Connor and Remus (1994) show that it has been successfully used to forecast the time series data, and its effectiveness is better than the regression-based tools and yielded better results which help in effective decision making. Studies by Tkez and Hu (1999) and Gonzaleg (2000) showed that the use of ANN-based architecture has been able to predict superior results than other methods in macroeconomic parameters such as GDP and output processes in Canada. Defit and Sap (2001) contrasted association rule-based economic forecasting with neural network forecasting using financial market data. Their results demonstrated that the ANN-based association rules enhanced the system's capacity to produce economic forecasts. Several other studies like Atsalakis et al. (2008), Chattopadhyay et al. (2012) and Haider and Hanif (2012) found ANN-based trained architecture to be superior and of good association for relation-based studies. It is observed in this process that the studies there had been no research on the comparative methods in ANN architecture in showing the fit of the relationship processes.

3. Theoretical Discussion

The Artificial Neural Network (ANN) is an interconnection of elements to enable parallel distributing processes. Examples train Ann from the past learned data or problems. It can be trained under a supervised or unsupervised method. In a supervised method, it occurs in the presence of a supervisor akin to a teacher who helps train the data based on past input-output relations. Such supervised training reduces the change of bias and helps in reaching the desired goals easily. Under the unsupervised process, there is no assumption of a supervisor and the network learns by itself by organizing the input-output problems. (Rao and Rao 1995) shows that ANN as a method has been able to make a mark in the field of data forecasting, pattern recognition, image processing and many such related fields of economics, basic sciences, economics and management. According to Haykin (1994), ANNs have a general model that can be found as input, output, as well as intermediate layers. Processing neurons sometimes referred to as hidden neurons, are the calculation layers that are hidden. Prior to actually sending the information to the output layer, these neurons assist in calculation. All of the input neurons can be found to be connected to the d neurons, which carry what are known as input-hidden layer weights. There is h1 number of neurons in the first layer, h2 number of neurons in the second layer, and n number of neurons in the output layer of a multilayer feed-forward network with m numbers of input layers. The configuration could be reduced to 1-m-n, in which 1 number of neurons are in the input layer, m number of neurons are in the hidden layer (in this example, one), and n number of neurons are in the output layer (Rajasekaran and Pai, 2003).

4. Methods and Data

The study is directed to understand the relation of the Inward Foreign Direct Investment (IFDI) of the BRICS economies in relation to the Gross Domestic Product of India (at base prices of 2010-11). The hypothetical apostle used here is to show that the GDP of India has been directly influenced by the IFDI of the BRICS economies (not taking India into consideration) and thus shows a strong trade alliance other than the diplomatic alliance. The data has been sourced for the GDP of India from the RBI official website, and the IFDI data has been adopted from the World Bank database. The data has not been normalized or made stationary so that the effect of the training on ANN is visible as it is.

This paper uses a normative process where two different ANN architectures are taken: Multilayer Perceptron (MLP) and Radial Basis Function (RBF). A feed-forward artificial neural network with layers of nodes-input layers, hidden layers, as well as output layers - is known as a multilayer perceptron, as was previously explained. Backpropagation is a method of supervised learning that MLP employs for its training process. MLP differs from a linear perception due to its numerous layers as well as non-linear activation. Data that cannot be separated linearly could nevertheless be distinguished. A radial basis function (RBF), on the other hand, is a real value function. Therefore, the value only relies on the separation between both the input as well as a fixed point, such as the origin:

$$y(x) = \hat{y}(\|x\|) \qquad (1)$$

or some other fixed-point C (Called center) so that:

$$y(x) = \hat{y}(\|x-c\|) \qquad (2)$$

Therefore, any function which satisfy $y(x) = \hat{y}(\|x\|)$ is a radial function.

A RBF is therefore an ANN that uses radial basis function as activation function. The output networks are a linear combination of radial function of inputs and neuron parameters.

Network Architecture of RBF has three layers: an input layer, a hidden layer with a nonlinear RBF activation function and a linear output layer. The input layer can be moderated as a vector or real number $x \in R^n$. The output of the network is then a scalar function of the input vector, $y: R^n \rightarrow R$ and is given by:

$$y(x) = \sum_{i=1}^{n} \alpha_i \, p(\|x-c_i\|) \qquad (3)$$

Where n is the number of hidden layers, C_i is the center vector for neuron i and α_i is the weight of neuron i in the linear output neuron. The RBF is taken to be Gaussian.

In this study, the focus is to understand the difference that can be drawn between MLP and RBF 'Normalized' and 'Standardized' data set. Rescaling the values into a [0, 1] scale is what normalization entails typically. Data are often rescaled during standardization so that the mean is 0, as well as the standard deviation, is 1 (unit variance). Normalization helps in transforming all the data to a similar scale and reduces the biases arising from the scale variation. On the other hand, standardization is the modification of characteristics by mean subtraction and standard deviation division. This helps in getting over the distribution issues in data. Hence, it is for the sake of argument; that it is hypothesized that standardized data would feature a better ANN output analysis. The key of this paper lies in analyzing a similar data set for obtaining better predictive and causative results by using both MLP and RBF in a normalized and standardized format.
Tkez and Hu (1999), Chattopadhyay et al. (2012), Veni (2020) and Sultana et al. (2019) showed that in microeconomic environment association studies of GDP with FDI does predict tenable results and help in understanding the pattern of relationships that exists between inter economic studies. Hence, the study uses GDP and inward FDI data of the BRICS economic forum collected from the Global Economic Prospects of World Bank (2020) for necessary evaluation as prescribed. The data set reflects the GDP growth (in Base Price of 2010-11) and the IFDI of the various countries in consideration of year-on-year change. The data set is in Indian Rupees (INR).

5. Findings and Discussions

For the purpose of the study, we use both supervised and unsupervised learning in MLP and RBF ANN architecture. The results and the discussions follow. The data set for the following was set to training as given in Table 1.

Table 1. Training and Testing Data

Description	GDPI	IFDIB	IFDIR	IFDIC	IFDISC
Training	100	100	100	100	100
Testing	44	44	44	44	44
Total	144	144	144	144	144

Source: Computed by authors using World Bank (2020) Data
Note: twelve-month data over 12 years are taken to raise 144 points of data, of which 70 percent was trained and 3 percent was tested. GDPI=Gross domestic product of India (at Base price of 2010-11), IFDIB= Inward FDI from Brazil, IFDIR= Inward FDI from Russia, IFDIC= Inward FDI from China and IFDISC= Inward FDI from South Africa. All the data is in INR.

The input and output parameters for the present problem are as follows. The Input parameters are IFDIB, IFDIR, IFDIC and IFDIS; and the Output parameter is GDPI. The Karl Pearson Correlation was calculated between the parameters to understand the degree of relationship of the association present in the data using standard statistical software. The result of the correlation is presented in Table 2.

Table 2. Karl Pearson Correlation Coefficients of the parameters under study

Parameters	GDPI	IFDIB	IFDIR	IFDIC	IFDISC
GDPI	1	0.131	0.025	0.063	0.044
IFDIB		1	0.626	0.744	0.733
IFDIR			1	0.875	0.901
IFDIC				1	0.965
IFDISC					1

Source: Computed by authors using World Bank (2020) Data
Note: All the values are significant at 5% level.

The coefficient correlation parameters show a significantly large association between the GDPI and IFDIB, IFDIR and IFDIC. This also indicates a large correlation between the inflow of FDI to India between the countries such as Brazil, China and Russia. This shall provide a backdrop to understanding the relation of the ANN-based study with Normalized and Standardized data under different learning mechanisms, which were discussed earlier. It can be noted that with a high degree of association, the use of the linear causation model's choice also improves in such cases.

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The ANN-based assessment of the relationship between the GDPI and the other variables which have been taken as covariates, is given in Table 3.

Table 3. ANN Based on assessment of the influence of IFDI of BRICS nations on the GDP of India

Method applied	**N**	**Training (in %)**	**Testing (in %)**	**Valid (in %)**	**Number of Hidden layers**	**Sum of Squared Error in training**	**Relative Error in prediction in training**
MLP (Standardized)	144	66.7	33.3	100	1	48.38	1.08
MLP (Normalized)	144	70.8	29.2	100	1	50.99	1.01
RBF (Standardized)	144	67.4	32.6	100	1	43.70	0.910
RBF (Normalized)	144	69.4	30.6	100	1	49.48	1.00

Source: Computed by authors using World Bank (2020) Data

The results of the ANN-MLP and RBF are encouraging for the study. As we know, RBF is a simpler model for ANN than MLP. It is observed from the table that the sum of the squared error in training is less than 50 percent which is relatively small. Besides, all the models have a relative error of prediction close to 99 percent. In this, we observe that the best prediction level is about 99.91 percent in the case of RBF standardized and the highest is 98.92 percent in the case of MLP Standardized. It means that we can predict the output in a range from 98 percent to 99.91 percent. It is also observable that normalized specification has a more stable prediction in both techniques, whereas there is a swing in the values of the standardized technique. The figures below show the neural network diagrams of all the techniques separately.

It is evident from the network diagram that the MLP (Standardized version of ANN) shows better results than that of the RBL (Standardized). The bias is less and the relationships are well established in the case of MLP. It is observed that all the IFDI parenting in the countries in the study have a major influence on the GDPI. Hence, in the case of the selection of standardized data, it is advisable that MLP with standardized data is taken as it yields superior results. The figure for Normalized MLP and RBF also indicates that the MLP yields better predictive relation. This is based on the observation that despite having a low level of Bias in the prediction process, the network works to show the relationship between the covariates and the dependent factor, thereby reducing the chances of the wrong prediction.
It was observed that in the robust method of ANN, namely standardized MLP, China and Russia impacted the GDP of India, whereas South Africa and Brazil have a relatively low effect. Besides the error or unknown Bias such as economic distance, the quality of bilateral relations could be causing this, which can only be conjectured. It would be in line where other factors are affecting bilateral trade that may be included in future studies. Since this study was focused on showing the ability of ANN-based architecture as an alternative and powerful tool for prediction, it limits itself to that segment only without recourse to other issues which can be dealt with in the use of ANN. This paper also helps in understanding the superiority of one technique over the different ANN processes under various data structure alternatives.

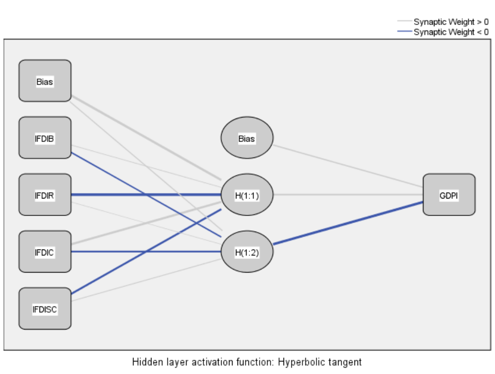

Fig. 1(a). Standardized MLP
Source: Computed and presented by authors using World Bank (2020) Data

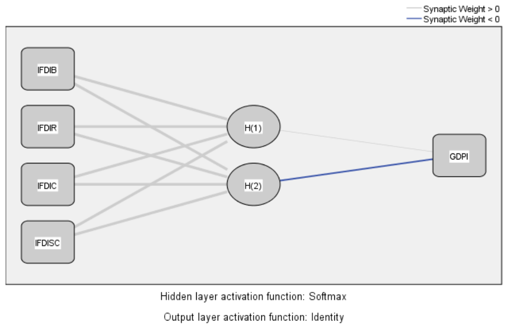

Fig. 1(b). Standardized RBF
Source: Computed and presented by authors using World Bank (2020) Data

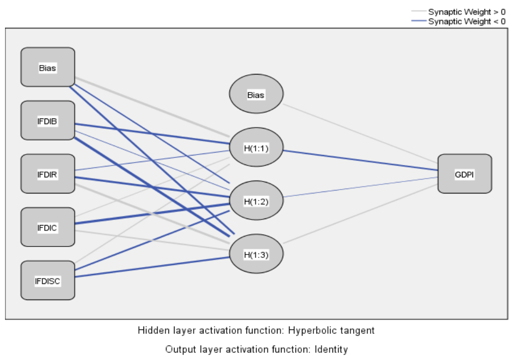

Fig. 2(a). Normalized ANN Network for MLP
Source: Computed and presented by authors using World Bank (2020) Data

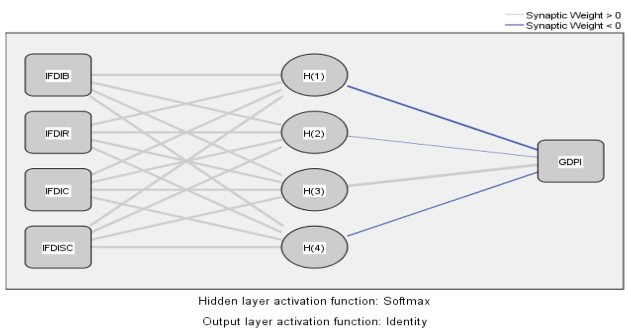

Fig. 2(b). Normalized ANN Network for RBF
Source: Computed and presented by authors using World Bank (2020) Data

6. Conclusion

This investigation has been carried out to find out the relationship between the GDP of India at Base price of 2010-11 with the inflow of FDI from the other BRICS economies. It shows that the GDP of India is highly affected by FDI from China and Russia. The others did not have high influences. This paper observes that ANN-MLP with standardized data predicts and generates better results than other data sets such as normalized MLP and RBF processes.

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