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AN ARTIFICIAL NEURAL NETWORK BASED METHOD FOR COMPANY VALUATION

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ABSTRACT

Purpose - Company value is a crucial issue for everyone operating in financial markets. Both firm managers and investors should calculate the value of a firm, and there are many methods available to do so. Calculating valuation methods is challenging due to the multiple parameters and stages that are involved. Due to these reasons, it's possible for managers, owners, investors, and other stakeholders to estimate a company's value inaccurately or with difficulty. The main objective of this essay is to demonstrate how to evaluate a company's value using the NARX model as an alternative to other models.
Methodology – It is estimated that the firm value using an artificial neural network nonlinear external input autoregressive network model for 50 companies operating in the consumer products and industrial products and services sectors in the Euro Stoxx 50 index. The dataset covers the period from 2000 to 2021, and 20 financial ratios were included as input to the model, with FCFF as the output.
Findings- The NARX model with a 20-6-6-1 or 20-10-10-1 network structure provided the best value for both R and MSE at two-time delays. However, the 20-12-12-1 network structure of the NARX model with a time delay of three has a lower error rate after training and the best R value. The model's prediction success rate is 90.82% using the 20-12-12-1 network structure with a time delay of three.
Conclusion- As a result, this model can be used by investors and business managers to value a company. By using this method, businesses may gain access to more precise and unbiased appraisals that can guide resource allocation and strategic decision-making. By including macroeconomic factors that have an impact on the sector and employing a longer time frame, the study could be improved.

Keywords: Company value, company valuation, cash flow to firm, artificial neural networks, nonlinear external input autoregressive network
JEL Codes: C45, C80, G12

1. INTRODUCTION

Valuation is a crucial and complex topic in finance, as the main objective of companies is to maximize company value. Similarly, stakeholders want the companies value and share value to be maximized. Understanding the methods of company valuation is a crucial qualification in the field of corporate finance. The process of valuing a firm and its business units helps to discover sources of economic value generation and destruction inside the organization, which is significant not just in acquisitions and mergers. (Fernandez, 2002).

Bonds, stocks, and other financial instruments are among the assets that businesses buy and sell to obtain money that is more than their cost of capital. Companies create value in this way (Jordan et al., 2012).

Valuation is also an essential requirement for shareholders. Investors should assess the value of a stock before purchasing it to avoid paying more than its value and to determine an investment strategy by identifying undervalued or overvalued assets.

Value evaluation now goes beyond portfolio management and investing. Every step of a company's life cycle requires value. Finding additional funding is crucial for small, privately held enterprises who are thinking about expanding. Depending on their projected worth for the business, investors will contribute varying amounts of capital. The prices at which businesses are presented to the market in an initial public offering (IPO) when they mature and elect to go public are determined by their valuations. Perceptions of their impact on value will then influence decisions on where to invest, how much to borrow, and how much to return to the owners. (Damodaran, 2011).

Numerous valuation models exist, but there are only two types of valuation: intrinsic and relative. The cash flows you anticipate an asset will produce throughout its lifetime and your level of confidence in those cash flows will determine the intrinsic value of the asset. Assets with strong, consistent cash flows ought to be more valuable than those with low, erratic cash flows. In relative valuation, the market prices of comparable assets are used to determine the worth of an item. So, in order to decide how much to spend for a home, you would consider recent sales of comparable homes in the area. Comparing a stock's valuation to those of other equities in a comparable industry is known as a "peer group". (Damodaran, 2011).

Many methods are used to determine a company's value, including balance sheet-based, relative valuation, and cash flow discounting-based methods. Before starting the valuation, it is necessary to determine what reflects the value of a company. In its simplest form, the value of the company is determined by the cash flow that the company will create over time and the risk-adjusted discount rate.

If we examine the concept of valuation more deeply, we can identify the factors that determine the value of a company, known as value drivers. These include growth in revenues, operating profit margin, investment efficiency level, and cost of capital.

In this study, for determination of company value, the Artificial Neural Networks (ANN) Nonlinear External Input Autoregressive Network Model (NARX) will be used. The Nonlinear Autoregressive Network with exogenous inputs (NARX) is a type of Artificial Neural Network (ANN) architecture that can be used to model complex nonlinear systems, including those with external inputs. (Chen et. al., 1990)

In the NARX model, the network forecasts the following output in the time series using past inputs, past outputs, and any external inputs as inputs. This enables the model to capture the system's nonlinear dynamics while taking into consideration how outside influences may affect the system.

A NARX model's architecture usually consists of two key parts: a set of neurons that take in input from the outside world and a feedback loop that links the network's output to its input. The feedback loop allows the network to learn from its own predictions and correct any errors in its output, while the external input neurons enable the network to take into account any additional information that may be relevant to the system being modelled. (Narendra & Parthasarathy, 1990)

NARX models are commonly used in time series prediction, control systems, and signal processing applications, where it is often necessary to model complex, nonlinear systems that exhibit dynamic behavior. They are a powerful instrument for simulating and forecasting complex systems, and they have been effectively used in a variety of disciplines, including engineering, economics, and finance.

The ability of a NARX model to capture the nonlinear dynamics of the financial system, which can be challenging to model using conventional linear models, is one potential benefit of using a NARX model to forecast company value. The NARX model has the potential to offer more accurate and reliable predictions than simpler models because it considers both past inputs and past outputs as well as any external inputs that might influence the company's value.

The NARX model also has the benefit of being adaptable over time to shifting market circumstances. The model can adapt its parameters in reaction to changes in the underlying system because it takes feedback from its own predictions into account. This is particularly crucial in volatile or rapidly changing markets.

This article's main goal is to use the NARX model to calculate a company's value. Calculating valuation methods can be challenging due to the multiple parameters and stages that are involved. Due to these factors, it's possible for managers, owners, investors, and other stakeholders to estimate a company's value inaccurately or with difficulty. The NARX model will be used to evaluate the company's value in this study, and the variables will be chosen by taking into account the aforementioned value drivers and the benefits listed above. With this method, managers, shareholders, or investors can more correctly estimate the company's value without having to rely on intricate valuation models and minimize risk.

2. LITERATURE REVIEW

Komo, Chang, and Ko (1994) employed two neural network models to predict the stock market. Specifically, they applied these models to the Dow Jones Industrial Index and achieved an 80% success rate in their predictions. Rather, A.M. (2011) used an ANN to predict stock prices. He utilized data from 02-01-2007 until 22-03-2010 for several companies, including TCS, BHEL, Wipro, Axis Bank, Maruti, and Tata Steel. He found that utilizing artificial neural network methods helped to minimize prediction errors.

Wilimowska and Krzytoszek (2013) stated in their introduction that FCFF is considered the company value method in their study and is estimated with artificial neural network, as it is considered the most valid method that reflects the true value of the company. However, FCFF calculation is complex and requires a lot of data, which is why there are few studies in the literature taking it into account. In their study, Wilimowska and Krzysztoszek focused on estimating company value with ANN and presented value drivers that should be considered in the process of company valuation. They used 12 factors as input and 2 factors, namely FCFF and net assets, as output. The estimated company value with the determined value drivers was found to be close to the real value.

Adebiyi et al. (2014) conducted a study to estimate share prices using the ANN method. Adewumi and Ayo compared the forecasting performance of ARIMA and ANN models using published stock data from the New York Stock Exchange. They found that both models achieved good forecast performance, but the ANN model outperformed the ARIMA model.

Patel and Yalamalle (2014) aimed to use artificial neural network techniques to predict the stock price of companies listed under the LIX15 index of the National Stock Exchange (NSE). Their results showed satisfactory output with a median normalized error of 0.05995, median correct direction percentage of 51.06, and median standard deviation of 6.39825.

Persio and Honchar (2016) presented an Artificial Neural Network (ANN) approach to predict stock market indices and considered the S&P500 historical time series. They showed that neural networks are able to predict financial time series.

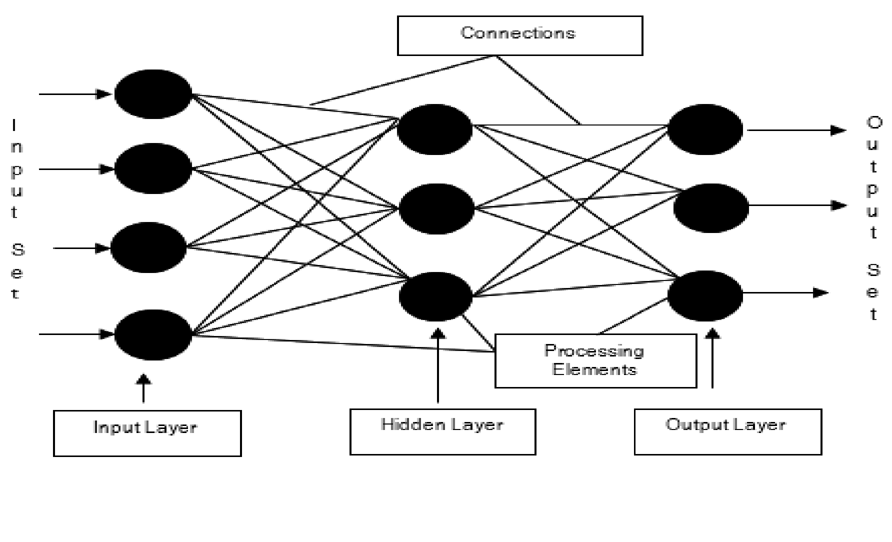
Many conventional and contemporary methodologies are employed to determine company value when we look at the pertinent literature. Husain et al.'s (2020) goal was to empirically demonstrate the modeling of the company's value based on the profitability ratio connected with dividend policy in different manufacturing industries and sub-sectors of automotive components listed in the Indonesia Stock Exchange (BEI) from 2014–2018. (Husain et al., 2020). The research used a Price-to-Book worth (PBV) method to calculate the company's worth. The Profitability Ratio and Dividend Policy did not appear to have a major impact on the Company's Value, nevertheless.

3. DATA AND METHODOLOGY

3.1. Artificial Neural Networks (Ann) Nonlinear External Input Autoregressive Network Model (Narx)

Artificial neural networks (ANNs) are made up of individual neurons organized and linked in a certain fashion determined by their design, just like biological role models. When data is supplied to the network during the learning process, special training algorithms attempt to make the network conform to the goal data by altering the weights of the connections between neurons. (Samarasighe, 2006). Figure 1 shows the architecture of an artificial neural network.

Figure 1: Artificial Neural Network Architecture



Artificial neurons come together to form an artificial neural network, and this formation is not random. Neurons are generally organized into three layers and run in parallel in each layer to create the network. These layers are as follows:

Input layer: Processing elements in this layer receive information from the outside world and transfer it to hidden layers. In some networks, there is no computing done at the input layer.

Hidden layers: The information from the input layer is processed and sent to the output layer through hidden layers. Multiple hidden layers can exist in a network.

An artificial neural network's output layer has processing components that analyze the data from the hidden layer and produce the output the network is supposed to produce for the input set given from the input layer. The finished product is then released to the public. (Oztemel, 2020).

In summary, the structure of a NARX network is typically represented in the form of "input-hidden-output" units, where the input and output units are connected to the hidden units. The input layer takes in the time series data, and the output layer produces the predicted output. The hidden layer(s) are where the non-linear relationships are modelled.

A wide range of nonlinear problems may be represented using artificial neural networks (ANNs), which are flexible computer architectures. ANNs have a significant advantage over other forms of nonlinear models since they are universal approximators and can precisely estimate a broad variety of functions. Their power comes from the simultaneous processing of information from the data. (Zhang, 2003).

Recurrent neural networks (RNNs) with a particular feature known as nonlinear autoregressive networks with exogenous input (NARX) employ a global feedback loop between the output and input layers. They are thus particularly well suited for modeling nonlinear systems. As a standard tool for time series analysis, the linear autoregressive model with exogenous input (ARX) and neural networks can be used to create NARX (Wunsch et al., 2018). The autoregressive with exogenous inputs (ARX) model in time series analysis serves as the foundation for the artificial neural network (ANN) known as NARX. It has been shown that NARX works well for modeling nonlinear systems. (Menezes & Barreto, 2008)

The NARX model is defined by the following equations 1: (Lin et al., 1998)

$$y(t) = f(y(t-1), y(t-2), ..., y(t-n), u(t-1), u(t-2), ..., u(t-m)) \quad (1)$$

where $y(t)$ is the output at time t, f is a nonlinear function, $y(t-1), y(t-2), ..., y(t-n)$ are the previous output values, and $u(t-1), u(t-2), ..., u(t-m)$ are the external inputs.

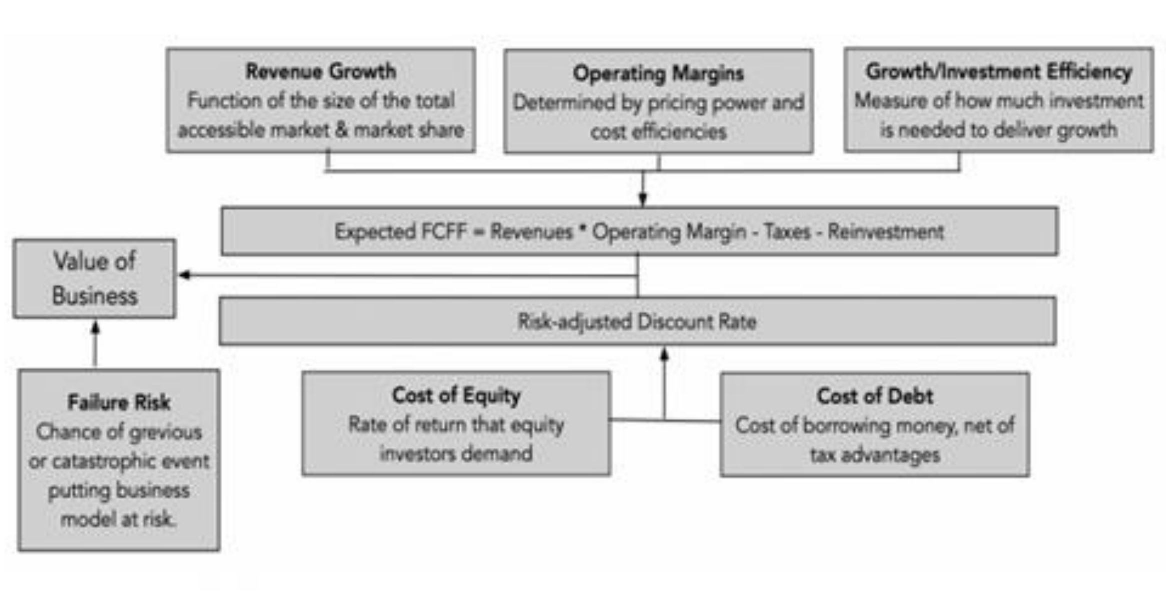
The capacity of a NARX model to capture the nonlinear dynamics of the financial system, which can be challenging to represent using conventional linear models, is one possible benefit of employing a NARX model to estimate business value. By taking into account both past inputs and past outputs, as well as any external inputs that may affect the company's value, the NARX model can potentially provide more accurate and reliable predictions than simpler models.

Another advantage of the NARX model is its ability to adapt to changing market conditions over time. Because the model incorporates feedback from its own predictions, it can adjust its parameters in response to changes in the underlying system, which can be especially important in volatile or rapidly changing markets.

3.2. Variables

The study examined companies in the Euro Stoxx 50 index, which is a stock index comprising the 50 largest companies operating in various sectors within the European Union. Company value estimation will be made using the Artificial Neural Networks NARX method. The inputs to be used in the method have been selected based on the value drivers shown in Figure 2. Twenty inputs have been determined that will help us estimate the value of the company. The output variable to be used to check the validity of the model is the free cash flow of the company.

Figure 2: The Drivers of Value



Note: Cornell, B. and Damodaran, A., Valuing ESG: Doing Good or Sounding Good? (March 20, 2020). NYU Stern School of Business

In this study, Free cash flow to the firm (FCFF) will be considered as output. The FCFF is an important and generally accepted scientific method in determining the true value of the company because the cash flows to be generated in the future depend on factors such as the company's organizational structure, human resources, brand value, goodwill, and intellectual capital (Ozturk, 2009).

The free cash flow to firm is the cash available to all of the company's stakeholders (including debt and equity holders) after all operating expenses, taxes, and capital expenditures have been paid. The FCFF is calculated as follows (Damodaran, 2011a):

FCFF= EBIT * (1-tax rate) + Depreciation and Amortization - Capital Expenditures - Change in Net Working Capital (2)

Where EBIT is earnings before interest and taxes, tax rate is corporate tax rate, depreciation and amortization are non-cash expenses, capital expenditures are the amount of money invested in long-term assets, change in net working capital is the change in the difference between current assets and current liabilities over a period of time.

The model's inputs and outputs are shown in Table 1.

Table 1. Inputs and Outputs of the Model

OUTPUT	INPUT				
Free Cash Flow to Firm	Sales Growth	ROA	Total Assets	Profit margin	Leverage Ratio
	Net Income	ROE	Total Liabilities	Cash Ratio	WACC
	EBIT	ROC	Gross Margin	Current Ratio	Cost of Equity
	EBITDA Margin	ROIC	Sustainable Growth Rate	Quick Ratio	Cost of Debt

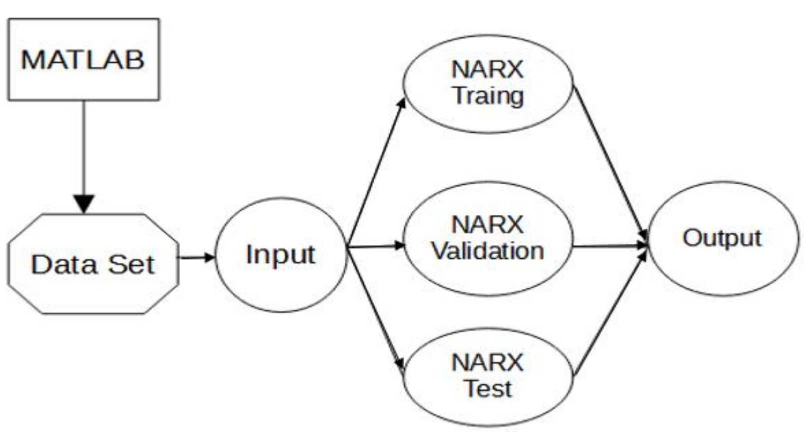
Sales growth, which is the increase in sales and services revenues produced by an organization after deducting sales returns, allowances, discounts, and sales-based taxes, is one of the variables used to assess the firm value. The cost of items sold, general expenditures, taxes, and interest are subtracted from sales to produce net income, on the other hand. Ebitda margin, which is the portion of total sales income that a business keeps after paying the direct costs related to producing the goods and services it sells, is another factor. Ebit stands for earnings before interest expenses and income taxes. The return on assets (ROA) ratio measures a company's profitability in relation to its total assets as a percentage. It provides insight into how well management is utilizing its resources to produce profits. Return on equity (ROE), which is also represented as a percentage, is a metric of a company's profitability that shows how much profit a business makes with the money shareholders have contributed. The percentage return an investment delivers for capital contributors is measured by a metric known as return on capital (ROC). It reveals how successfully a business converts capital into profits. Return on invested capital (ROIC) measures how well a business utilizes the equity and debt sources of capital that are used to fund its operations. The initial and ending balances of Total Invested Capital are averaged to determine Average Invested Capital. Total liabilities are the sum of all short-term and long-term obligations recorded on the balance sheet, whereas total assets are the sum of all short-term and long-term assets. Gross margin is the fraction of total sales income that a company retains after all direct costs associated with producing the goods and services it sells have been paid. Maximum rate of growth that a business can maintain without having to raise more equity or debt is known as sustainable growth rate. The profitability of an organization is gauged by its profit margin, which is the ratio of net income to sales stated as a percentage The cash ratio—calculated as cash and cash equivalents divided by current liabilities—measures the company's liquidity by demonstrating its capacity to settle short-term debt with cash. The current ratio, which is determined by dividing current assets by current liabilities, assesses the company's capacity to settle short-term debts with its available resources. The quick ratio, which is computed as cash and equivalents, marketable securities, and accounts receivable divided by current liabilities, demonstrates the company's capacity to settle its short-term debts using its assets that are readily convertible into cash. The leverage ratio gauges a company's capacity to fulfill its commitments. The term "weighted average cost of capital" (WACC) describes the weighted cost of all capital used by the business to finance its assets. The rate of return that investors need to invest in a company's stock is known as the cost of equity. The return a business gives to its creditors and debt holders is known as the cost of debt. The term "free cash flow to the firm" (FCFF), also known as "operating free cash flow" (OFCF), refers to the amount of cash generated by a business's activities that is accessible to all capital sources within the capital structure of the company.

3.3. Model Structure

The research data used in this study consists of annual historical data taken from the Euro Stoxx 50 index. The Euro Stoxx 50 index is a stock market index that tracks the performance of 50 of the largest companies in the Eurozone. The index is chosen because they are designed to provide a broad-based representation of the Eurozone economy, with the goal of tracking the performance of the region's most important and influential companies. The period from 2000 to 2021 and all data were taken from the Bloomberg Database.

For analysis, 20 indicators were chosen, and the entire dataset was split into 70% training, 15% test, and 15% validation datasets, as shown in Figure 2. The program randomly separated the dataset into three parts, with 70% for training, 15% for validation, and 15% for testing, in order to achieve the best result. The MATLAB program and NARX (Nonlinear autoregressive with external input) method were used for the prediction model and all algorithms. The designed ANN model is presented in Figure 3.

Figure 3: Designed ANN Model

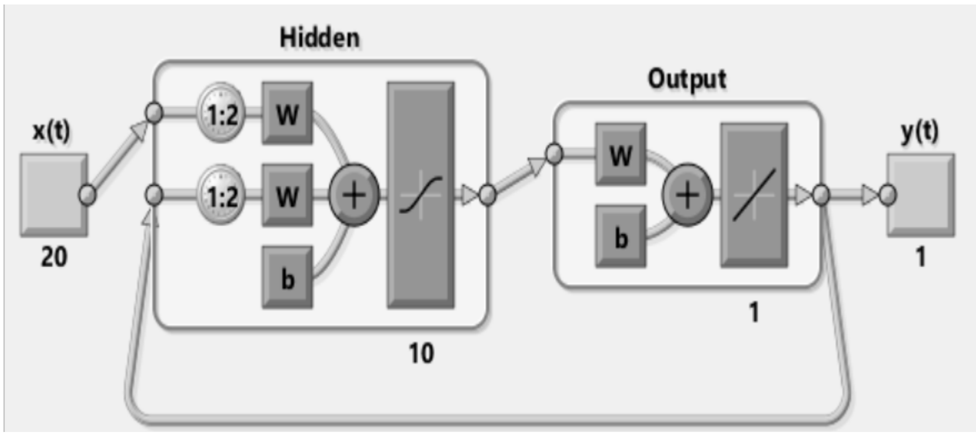


Since the collected data has different values with different scales, it is necessary to adjust and normalize the time series at the beginning of the modelling. The data normalization range is chosen to be [0,1], and the equation for data normalization is given as:

$$z_i = [x_i - \min(x)] / [\max(x) - \min(x)] \tag{3}$$

The NARX structure is depicted in Figure 4. The 1:2 expressions in the hidden layer structure show how many days ago the value was given as the input parameter. This value varies according to the application and data type. In this study, a comparison was made using different ANN layer numbers and delay values.

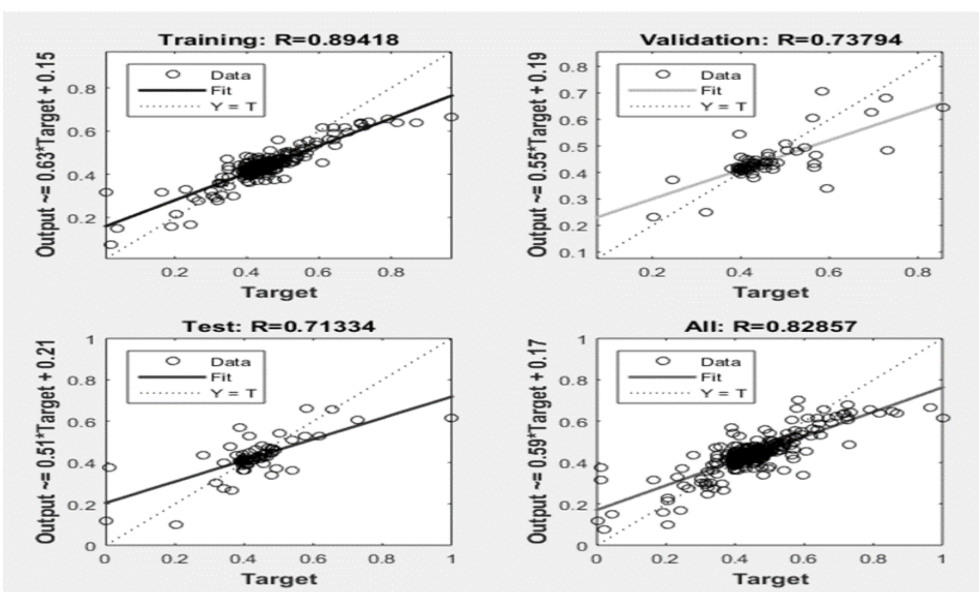
Figure 4: NARX Network Structure



5. EXPERIMENTAL RESULTS

The performance analysis of the ANN model, which has 20 inputs and 1 output, is presented in Table 2. Different hidden layer numbers were tested to reduce the error and achieve best R value, and the results are shown for training, validation, and testing. The main evaluation criterion is for the test data, while validation and training are used to train the model. The best values for both the correlation coefficient (R) and mean squared error (MSE) with 2-time delays were obtained with a 20-6-6-1 or 20-10-10-1 network structure. The R curves for the 20-6-6-1 structure with two hidden layers and six neurons in each layer are presented in Figure 4. The 20-6-6-1 NARX network has 20 input units, 6 hidden units in the first hidden layer, 6 hidden units in the second hidden layer, and 1 output unit. This means that the network takes in a 20-dimensional input time series, processes it through two hidden layers of 6 neurons each, and produces a single output prediction.

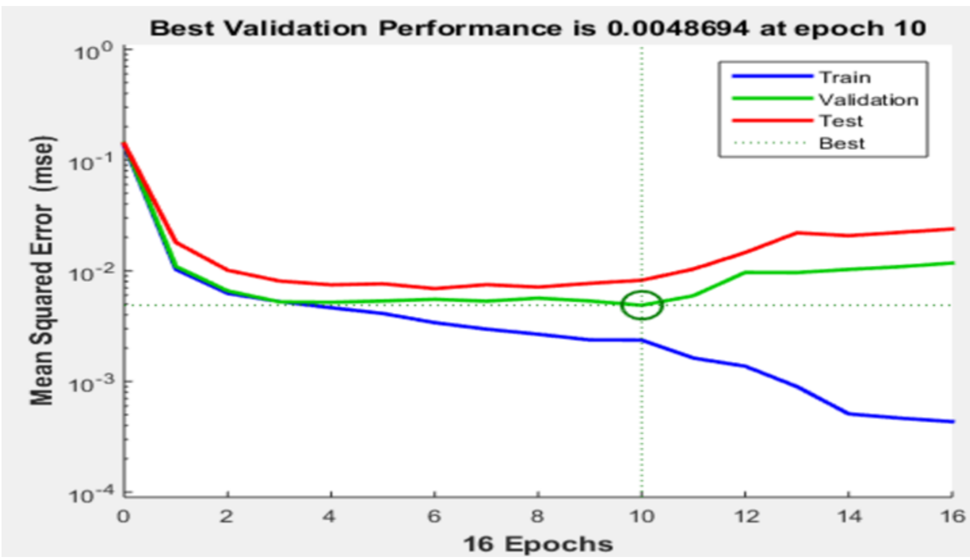
Figure 5: Evaluation of ANN performance with R



The NARX neural network model was created, and the success of training, validation, and test sets was evaluated using regression analysis. The correlation coefficient (R) measures the correlation between outcomes and goals, with a value of 1 indicating a close relationship, and 0 indicating a random relationship. As seen in Figure 5, the values between outputs and targets are very close to 1. The general correlation coefficient of the dataset was 0.82857.

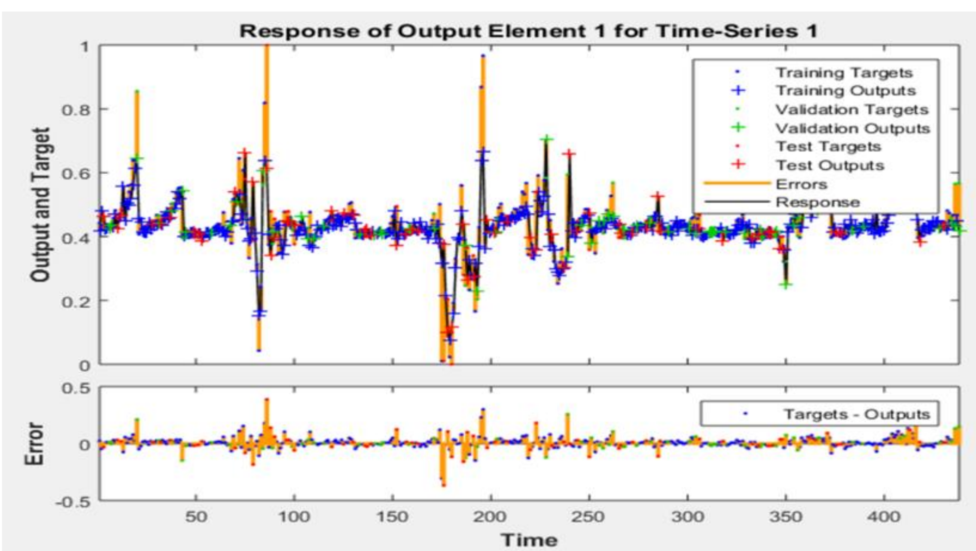
Figure 6 shows the output graph that displays the training structure of the NARX neural network at the end of 16 iterations. The figure indicates the states of the 16 iterations of the training process with respect to the periods. It is observed that the target function reaches the minimum lower point in 16 iterations with a value of 0.0048694. However, starting from the 10th iteration of the 16-iteration training, the validation of the network performance began to deteriorate.

Figure 6: Performance Chart



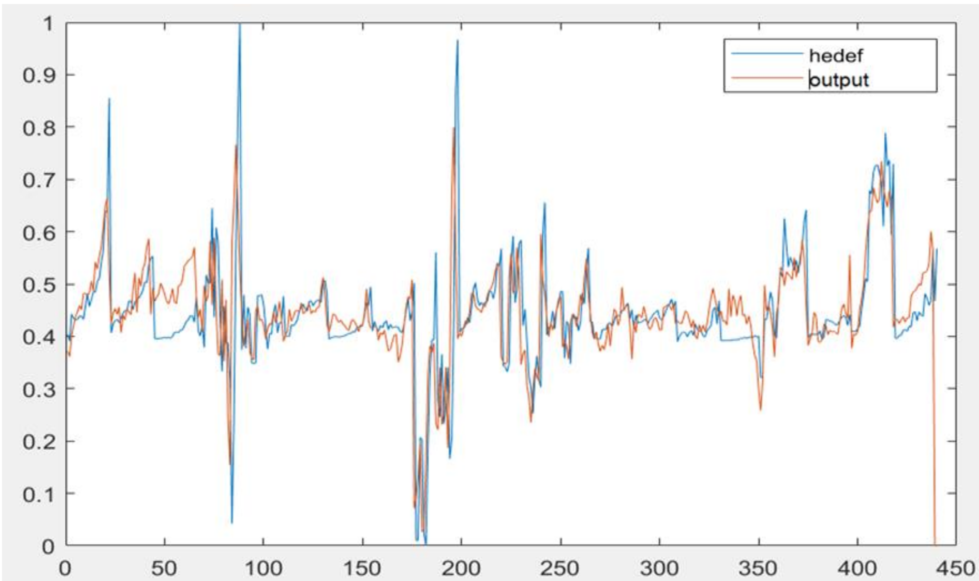
ANN Regression performance graph is shown in Figure 7. The Response Plot chart displays the time variable on the horizontal axis and the Target variable on the vertical axis. The Neural Network responses are synchronized with the calculated system responses.

Figure 7: ANN Regression Performance Chart



In Figure 8, a graph comparing the estimated values with the model and the actual values is presented. Table 2 contains the necessary data for the interpretation of the graph. The table 2 shows the results of different time delays with different layer numbers in 2. According to the analysis results, the best value for both R and MSE at 2-time delays was obtained with a 20-6-6-1 or a 20-10-10-1 network structure. The best value for both R and MSE at 3-time delays was obtained with a 20-12-12-1 network. Overall, it is seen that the 20-12-12-1 network structure with 3-time delays is the best model as a result of the training. It has a minimum mean square error of 0.0017 and a prediction success rate of 90.82%.

Figure 8: Actual and Estimated Values After the Training Phase



The results of different time delays with different layer numbers are presented in Table 2. At the table, time delay refers to the number of time steps used in the input data. For example, a time delay of 20-6-1 means that the input data includes 20-time steps, with 6 inputs and 1 output. Data Structure refers to the structure of the input data. For example, 20-6-1 means that there are 20-time steps, 6 inputs, and 1 output.

R value refers to the correlation coefficient, which measures the strength and direction of the relationship between the predicted values and the actual values. R formula is shown in Equation 4:

$$R= \frac{\sum_{i=1}^{n}(x_j-x)\,(y_j-y)}{\sqrt{\sum_{i=1}^{n}(x_j-x)^2}\sqrt{(y_j-y)^2}} \tag{4}$$

MSE value refers to the mean squared error, which measures the average squared difference between the predicted values and the actual values. The MSE formula is shown in Equation 5, and the:

$e_j=y_t-\hat{y}_t$
y_j= The value realized in period j,
$\hat{y}_j$= The predictive value calculated for period j,
n= the estimated number of periods,
e_j= To show the prediction error in the j period.

$$MSE=\frac{1}{n}\sum_{j=1}^{n} e_j^2 \tag{5}$$

The table 2 is divided into three sections for each time delay: Training, Validation, and Test. The Validation and Test parts show the model's performance on new data that it has never seen before, while the Training section displays the model's performance on the data used to train it.

Table 2: Performance Results

Time Delay	Data Structure	20-6-1		20-10-1		20-6-6-1		20-10-10-1		20-12-12-1	
		R	MSE	R	MSE	R	MSE	R	MSE	R	MSE
2	Training	0.8337	0.0037	0.8062	0.0035	0.8941	0.0024	0.9003	0.0022	0.8939	0.0021
	Validation	0.7273	0.0058	0.5659	0.0129	0.7379	0.0049	0.6205	0.0085	0.7843	0.0048
	Test	0.5599	0.0100	0.8131	0.0040	0.7133	0.0082	0.5792	0.0047	0.5706	0.0081
3	Training	0.8273	0.0040	0.8562	0.0065	0.7921	0.0046	0.8582	0.0064	0.9082	0.0017
	Validation	0.7143	0.0071	0.7408	0.0082	0.6885	0.0093	0.5524	0.0110	0.6822	0.0091
	Test	0.7645	0.0052	0.6430	0.0065	0.8356	0.0039	0.5986	0.0097	0.5021	0.0204

5. CONCLUSION

In order to maximize value, companies and investors must understand the notion of company value. Every stage of a company's life cycle, such as setting the stock price in initial public offerings, figuring out the cost of borrowing, and mergers and acquisitions, depends on valuation. Investors must also use the company's value to establish their investment strategy, enabling them to pay for shares based on their value. However, determining company value is challenging, and numerous methods are used to calculate it. This study uses the FCFF as an output. It is one of the most important and widely accepted methods for reflecting a company's real value.

In this study, the NARX-ANN method and the FCFF methodology were used to calculate the real value of the company. The NARX-ANN method combines financial data and takes into account non-linear correlations. So that the value of the company is determined more precisely and comprehensively.

The results of the study show how well the FCFF model captures the intrinsic value of the company. All important points, such as free cash flows, cost of capital, and growth potential, are taken into account in the FCFF calculation. And the valuation process has been significantly improved using the NARX-ANN methodology because it captures the dynamic nature of financial data and allows for non-linear relationships.

The strength of the study is that it works with FCFF valuation, which takes into account many important factors such as industry dynamics and company-specific variables, and the ability to capture the impact of these variables on the company's value using the NARX-ANN methodology. Especially in dynamic and uncertain market conditions, this comprehensive approach reduces reliance on simple assumptions and provides a more robust valuation framework. In addition, the NARX-ANN model learns and adapts to changing market conditions faster, which strengthens its forecasting ability.

The study aims to estimate the value of a company using the ANN Narx method with financial variables that have been selected based on the value drivers. The model includes 20 financial variables as input and FCFF as output, and the study was conducted with 50 companies in the Euro Stoxx 50 index. The Narx neural network estimates the FCFF output value with input values, and the trained artificial neural network realizes the estimation of the company value. As a result, the best value for both R and MSE at 2-time delays in the NARX model was obtained with the 20-6-6-1 or 20-10-10-1 network structure. On the other hand, as we are looking for the structure that performs best with our model and the training results show, the 20-12-12-1 network structure of the NARX model with a 3-time delay is the best, has a lower error rate resulting from training, and has the best R value.

Table 2 shows the performance of a NARX model with a time delay of 20-12-12-1 on a training, validation, and test dataset. The R and MSE values for each dataset are provided. The R values indicate a positive correlation between the predicted and actual values, while the MSE values indicate the degree of error between the predicted and actual values.

The results suggest that the NARX model performs well on the training dataset, with R values of 0.8939 and 0.9082 and MSE values of 0.0021 and 0.0017 for time delays 2 and 3, respectively. This suggests that the model is able to accurately capture the patterns in the training data. The model's overall prediction accuracy with a 20-12-12-1 network structure and a 3-time delay is 90.82%.

As a result, the NARX-ANN method combined with the FCFF valuation approach provides an all-encompassing framework for company valuation. This method takes into account all the factors and non-linear connections that affect the company's value and accommodates external influences, thus providing a more precise and comprehensive assessment of a company's intrinsic value. The model is a useful tool for investors, analysts, and decision-makers seeking a strong and forward-looking company valuation approach as financial markets continue to evolve and become more complex. By including macroeconomic factors that have an impact on the sector and employing a longer time frame, the study could be extended.

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