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An Emerging Topic in Finance: Use of Artificial Intelligence in the Field of Finance

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Abstract. This study aims to provide readers with a simple and understandable introduction to the use of artificial intelligence technologies in the field of finance in different areas. In addition, this study also includes literature reviews in each section that includes the most important studies using traditional econometric methods and various artificial intelligence technologies. Even though the use of artificial intelligence technologies in the field of finance is diverse, the areas where it is mostly used in the world in general are credit assessment, bankruptcy prediction, stock market index and stock price prediction, optimal capital structure prediction and exchange rate prediction, which are also sections of this study. In this study, the main financial applications using artificial intelligence technologies are grouped under two main headings. These topics are financial forecasts and detection of financial crises, chaos and uncertainty in financial markets. Many factors are thought to be effective on the optimal capital structure. In this context, more studies need to be conducted in the world that address the capital structures and the factors that are thought to affect these structures in terms of clarifying the concept of optimal capital structure. It is important for both investors and researchers to increase the factors to be examined and also to include companies from different sectors in researches. With the increase in such studies, it will be possible to obtain deeper information and to make more accurate comments concerning financing preferences of companies and also the consequences of these preferences Determining the optimal capital structure is actually extremely difficult as it involves a very complex decision-making process and a large number of interactive decision variables. In such a case, for example, an artificial neural network (ANN) can be developed as an artificial intelligence technology that can analyze and evaluate all financial information that has the possibility of affecting the decision-making process. When analyzing with artificial neural network (ANN), real data regarding different capital structures can be uploaded to the system. Thus, a debt/equity ratio can be determined to make the most accurate decision, and the company value can be maximized after this optimal capital structure decision.

Keywords: Artificial Intelligence, Emerging Topic, Field.

1. INTRODUCTION

It is not difficult to predict that artificial intelligence technology will become increasingly involved in life today. However, we are aware that researchers in the field of social sciences still distance themselves from artificial intelligence. Currently, many researchers around the world choose to use only traditional statistical and econometric methods in their studies. However, today, when we are bombarded with so much data and the number of data to be processed increases every few years, the use of artificial intelligence has become a necessity in some areas.

The field of finance is one of the areas where the use of artificial intelligence is becoming increasingly widespread, accuracy and speed are becoming increasingly important, and there is no room for mistakes. Especially since the 2008 crisis, researchers, policy makers and investors have once again seen how vital financial forecasts are in preventing financial crises and uncertainties.

In these days when the parties are increasingly discussing whether artificial intelligence technology will benefit or harm humanity in the future, one thing we are sure of is the fact that we cannot escape change. If we want to take a greater place as researchers in the world literature and if we want the universities, we work at to climb higher in the world rankings in terms of academic success, we need to benefit from artificial intelligence technologies as soon as possible. As the use of artificial intelligence technology by researchers becomes more widespread, researchers will be able to obtain more successful results in areas where traditional methods cannot produce solutions or are inadequate. Increasing this success will undoubtedly make significant contributions to strengthening the bond between universities and companies in terms of university-industry cooperation.

Detecting financial crises and chaos and uncertainty in financial markets has become increasingly important, especially since the 2008 crisis, and researchers have begun to focus on their studies in this field. In fact, the common purpose of all these studies is to predict a possible crisis that may occur in the future to ensure that effective measures are taken before a crisis occurs, and thus to minimize the effects of a possible crisis.

2. MAIN FINANCIAL APPLICATIONS USING ARTIFICIAL INTELLIGENCE TECHNOLOGIES

It is not a coincidence that artificial neural networks, one of the newly developed non-linear methods, are increasingly used in social sciences such as finance and economics, as in many other fields. Artificial neural networks (ANN), one of the artificial intelligence technologies, predict a number of features most accurately, making this method an increasingly attractive method for researchers and users. First of all, artificial neural networks (ANN), as a data-based linear method, can perform non-linear modeling and analysis without the need for prior knowledge between inputs and outputs. In this sense, they are very general and flexible modeling tools for financial forecasts. Secondly, artificial neural networks (ANNs), as universal functional estimators, can easily

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predict a continuous function with the desired accuracy. Third and finally, artificial neural networks (ANN) can generalize easily. For example, after learning the data presented to them, they can easily make inferences about the invisible, or missing, part of the data, even if the sample contains noisy data. All these unique features make artificial neural networks (ANN) indispensable in solving many prediction problems.

So, what kind of issues are artificial neural networks, one of the leading artificial intelligence technologies and widely accepted for modeling many complex problems and analyses, used in the field of finance? It is an undeniable fact that, especially recently, artificial neural networks are being used more and more widely in financial analysis and decision-making due to their many prominent features. In this context, a wide variety of financial applications can be made with the help of artificial neural networks in the field of corporate finance, and these applications can be reviewed, audited and evaluated. Many researchers believe that many applications in corporate finance can be developed with artificial neural networks (ANN) technology. Hsieh (1993), one of these researchers, listed these applications: financial simulation, investor behavior prediction, financial evaluation, credit approval, stock and asset portfolio management, pricing of public offerings and determination of optimal capital structure. Many researchers have made similar groupings. However, with the increase in company bankruptcies and financial crises since the early 1990s, it has become necessary to add an extra field to these groupings to detect financial crises and the chaos and uncertainties experienced in financial markets.

In this study, the main financial applications using artificial intelligence technologies are grouped under two main headings. These topics are financial forecasts and detection of financial crises and chaos and uncertainty in financial markets. Financial predictions will be examined under five subheadings, and these subheadings are credit evaluation, bankruptcy prediction, stock market index prediction and stock price forecast, optimal capital structure prediction and exchange rate prediction.

2.1. Financial Forecasts

Financial forecasting is one of the areas where artificial intelligence technology has been successfully applied in the field of finance. Financial forecast can be defined as historical financial making predictions about the future situation based on data process. Accurate financial forecasting assists decision makers in making the right decisions and planning for the future. It also provides significant advantages and benefits to decision makers so that people may have a chance to change existing variables in the future to predict the future accurately and may obtain a favorable outcome.

Many banks use this technology to improve their financial and business operations. Especially Expert systems (ES), which are one of the artificial intelligence technologies, are frequently used by banks for this purpose. The use of expert systems in the field of finance is quite diverse. For example, they can be used by banks and other financial institutions to provide them competitive advantage over their competitors. They can also be used in personal financial planning. In this way, banks and financial institutions can use this technology to offer their customers financial products that they will personally like. Financial institutions will also have the opportunity to collect personal information from their customers which will increase the type and number of products they sell.

One of the most used methods for financial analysis is ratio analysis. However, ratio analysis is inadequate in many cases. For example, ratio analysis is too restrictive and rigid, and the referenced results may not be suitable at all times and in every situation. Alternative decision-making methods can also be used to overcome such problems. For example, in their study, Guiterrez and Carmona (1988) implemented fuzzy logic technique to the traditional liquidity analysis with the aim of measuring the liquidity situations of companies. In this way, by actually including the fuzzy logic technique into the analysis and by removing the line between verbal and numerical analysis, the researchers have had the opportunity to model many different types of knowledge and provided convenience to the experts.

The fact that the financial markets are so complex and nonlinear and the relationships between numbers are often beyond the comprehension level of an ordinary human being, has led to more frequent use of the artificial intelligence technologies.

More and more financial advisors are adapting to artificial intelligence technologies. This makes them be able to prevent from time consuming activities and allows them to concentrate on more asset (portfolio) distribution and financial planning. This situation as in every sector brings the question to mind whether artificial intelligence technology will also take consultants' jobs away. However, as in other fields, artificial resources are also used in financial planning and no matter how advanced artificial intelligence technology is, the human factor will always remain important. Only the job descriptions of financial advisors will change.

For example, thanks to artificial intelligence technology, investors will be able to reach more sophisticated and complex information from financial analysts and advisors. They will be able to obtain information in a much shorter time and have more in-depth and multi-dimensional analysis. In this sense, artificial intelligence is not actually a technology that competes with consultants. On the contrary, if efficiently used, it frees up the time the analysts spend on routine work and instead provide them the opportunity to concentrate on their customers. Thus, banks will be able to realize the expectations and the financial targets of customers. The situation is actually a matter of financial advisors and analysts working in the field of financial planning. It will also encourage the analysts to improve themselves and enable them to do simpler tasks, that may cause even people to lose their jobs.

2.1.1. Credit Evaluation

Credit evaluation is the financial study carried out to evaluate creditworthiness or in other words, credit availability of individuals and companies applying for loans. Credit evaluation studies have been carried out since 1950s. Actually, credit evaluation process is perceived as a typical grouping problem and loan applications evaluated in this sense are evaluated under one of these previously defined groups depending on the characteristics that they have. In this sense, until now many different methods were tried for this purpose. Among these methods come linear discriminant analysis, logistic regression and iterative partitioning algorithm (recursive partitioning algorithm) are included (Min and Lee, 2007; Bahramirzaee et al., 2009).

The most important task of a credit analyst is to determine the loans he/she will give to his customers. and to decide on the amount and conditions. Doing this is not that easy because he/she has to have sufficient amount of information about the customer, who requests the loan such as having detailed information about the history and previous and current financial situation of the customer. With the rapid growth in the loan portfolios that the credit industry and financial managers are responsible for, the finance industry has also turned to credit evaluation methods that give more accurate and precise results. In the aftermath of this need and orientation, many new studies based on artificial intelligence methods have been conducted and considerable progress has been made in the credit evaluation practices.

Although it seems like loan approvals of individuals or companies depending on the loan approvals seem like it can be done with ordinary computer equipment and software, these systems cannot not fully imitate the objective qualitative features contained in the human decision mechanism. In addition, majority of information about customers is available to decision makers in a standard format. Artificial Neural Networks (ANN) use customers' financial banking data as input vector and the real decisions regarding the credit analysis are seen as the targeted output vector

The main purpose of this system, which were created by using artificial neural networks (ANN), is to provide loans and decide on credit limits in a way by imitating human expertise in this field. So, the system deals with the diversity of data without having to summarize them again and can complete their transactions in the most practical way.

There are many studies that have been done concerning evaluation by using artificial neural networks (ANN). For example, Jensen (1992), in his study, used credit backpropagation neural network (BPNN). He employed demographic and credit information of people who applied for credit for rating as input data and employed the subjects of payments not made on time, closing the account, paying off the debt under the category of payment history network as output neurons for this purpose. Jensen (1992), in his study, claimed that the success rate of the banks that use artificial neural networks (ANN) reach to 82%, whereas this rate is only 74% for banks that use more traditional and expensive methods. Although Jensen (1992), used only 125 loan applications in his study, this study is important in terms of being one of the first studies in this field.

Not only the researchers but also the companies use artificial intelligence technology to have an idea about their success rates. For example, Lloyds Bowmaker Motor Finance company employed the method of artificial neural networks (ANN) to make decisions financially for credit evaluation. Interestingly, the company, which is quite satisfied with this method, believes that this method achieved 10% more success than other traditional methods (Bahramirzaee, 2010). Since the early 1990s, many banks have started to experience artificial intelligence technologies in their operations of credit evaluation. One of these banks is the Security Pacific bank, who used artificial neural networks (ANN), in its evaluations of commercial loans given in small amounts. The neural network that they use is the multilayer perceptron neural network trained by backpropagation algorithm. Bank managers stated that the results they obtained using this method have been more successful as compared to the results they obtained before and expressed their satisfaction about this method (Goonatilake and Treleavan, 1995).

For example, expert systems (ES), which is one of the artificial intelligence technologies has started to be used to evaluate unusual loan requests. Interestingly, while these requests were previously evaluated manually in real time, a bad evaluation rate of 15% was revealed. However, after it was passed to expert systems (ES), this bad evaluation rate decreased to 4% (Stark, 1996). Many studies in the financial sector which compare expert systems (ES) and traditional methods, indicate that the expert systems (ES) is much more successful as compared to traditional methods in credit evaluation. For example, in one of these studies, Bryant (2001) compared the performance of the expert systems (ES) that he proposed against the real-time performance of five loan officers. He concluded that expert systems (ES) were much more successful in credit evaluation than these five loan officers.

In addition to this, Walker and Hodgkinson (2003) applied the expert systems (ES) method to the credit evaluation problems, and they have achieved much more successful results. Kim, Weistroffer and Redmond (1993) are among the researchers, who compared the performances of the expert systems (ES) not only with the traditional statistical methods but also with other artificial intelligence technologies. In this study, in which many artificial intelligence technologies and traditional methods were used, researchers compared the performances of the backpropagation artificial neural networks (ANN) with other methods to determine their success in bond evaluation. The results of the study reach the conclusion that the accuracy rates are respectively 53% for artificial neural networks (ANN), 43% for logistic analysis, 36% for linear regression and discriminant analysis and 31% for expert systems

Recently, banks and financial institutions also started to show interest in hybrid technologies in addition to the traditional statistical and econometric methods and to various artificial intelligence technologies for credit evaluation. Undoubtedly, the most important reason underlying this interest is the fact that hybrid methods provide much more successful results than artificial intelligence methods on their own Each method has certain advantages as well as disadvantages including artificial intelligence methods. Here, hybrid methods by combining several artificial intelligence technologies together, eliminate or minimize these disadvantages in order to obtain the most successful results in solving financial problems. Thus, it is possible to obtain more accurate results in credit evaluation.

For example, in his study, Rast (1997) combined the methods of artificial neural networks (ANN) with fuzzy logic and obtained a hybrid system. Thus, by improving an existing credit evaluation method, he provided much more successful results in credit evaluation. He used a hybrid system for modeling credit rating processes of small financial institutions. In his study, in which he used fuzzy adaptive network and various support vector machines-based learning paradigms, he conducted credit evaluation analyses. He tested the hybrid systems with real cases based on corporate loan application approval data sets. He has achieved successful results with his models for which he designed for the use by banks.

As a result, the use of hybrid methods, which is obtained by using one by one or by creating various combinations of artificial intelligence technologies, has gradually increased in credit evaluation from the 1980s to the present. Recent studies have shown us that studies and analyses based on hybrid systems give more successful and efficient results by combining the advantages of various methods and by minimizing the disadvantages and the limitations of the other methods.

2.1.2. Bankruptcy Prediction

Bankruptcy prediction has been one of the most studied topics in the finance and accounting literature due to the importance it has had for a long time. Institutional and financial failure occur when the debts of the institutions or companies increase excessively compared to their assets and they cannot pay their debts and also when they suffer chronic and serious losses. Many of the problems associated with predicting corporate bankruptcies are complex and inextricable. There are many reasons that are effective in their collapse, and these reasons are generally closely related to each other. Although there are many reasons for company bankruptcies, the most accepted reasons are poor management, autocratic leadership, market failure to carry out business operations and poor debt management (Altman et al., 1994). All these counted factors may accelerate the collapse of companies.

Bankruptcy prediction models use a wide variety of methods to obtain different results. The most important of these methods are ratio analysis, discriminant analysis, regression analysis, logit regression and weighted average maximum probability estimate.

Beaver (1966) is one of the first researchers, who predicted corporate bankruptcy by using financial ratios. Beaver (1966), who based company size and industry type to his matching, applied paired sample analysis and found significant differences between the rates of companies in bankruptcy and the rates of healthy companies. With these results, Beaver (1966) suggested that he can predict corporate failures and bankruptcies that will occur within the next five years. Although Beaver (1966) put a lot of effort into this study, the success of his work was limited. There are several reasons of it. First, the basic methodology of this approach respectively allows to select a single determinant even from a very large set of financial ratios. However, it is known that many factors can be effective to contribute to company failures. However, it turned out that the classical methods have limited sample sizes in decision making and forecasting. In addition to this, classical methods do not produce successful results when the data set is non-linear in many applications. Also, over time, structural relationships between bankruptcy prediction and the reasons leading to business bankruptcy are changing. For example, in many corporate bankruptcies, changes that occur over time in financial variables which are called unstable structural parameters, is one of the main criticisms brought to this method. The last criticism of this method is that many techniques that are used to predict company bankruptcies are obtained mostly as a result of a quantitative and complex rather than qualitative judgement and is not open to numerical analysis.

Altman (1968) introduced a multiple approach to the univariate analysis method by including variables in corporate bankruptcy prediction simultaneously into the model and thus developed the single analysis method. This is a statistical method, which is included into the scope of multivariate discriminant analysis (MDA). It involves placing previously unclassified observations into an appropriate class based on establishing a classification scheme. Altman (1968) produced his study from the data from appropriate accounting tables on company financial reports. This method is known as Altman's Z-Score.

This model may also not give valid results when deviations from the normality assumption become the rule rather than the exception especially in modeling business bankruptcy predictions. In fact, this means that it may lead to deviations in the significance testing of violations of the assumption of normality and estimated error rates (Altman, 1994).

Considering the complexity of business operations and the effects of external factors, it has been observed that it is not sufficient to explain company failure based on a single model that takes the reasons mentioned above into consideration. Already, if it had been this much simple, ratio analysis or multivariate discriminant analysis (MDA) alone would be sufficient. It is due to this complex nature of bankruptcy prediction that traditional methods of predicting corporate bankruptcies have failed. At this point, artificial neural networks (ANN) method is used as an alternative method. Artificial neural networks (ANN) have become a method used for corporate bankruptcy prediction as an alternative to classical methods and there are several effective reasons for it.

While the validity and effectiveness of classical statistical methods depends on the assumptions such as linearity, normality and the prediction values' being independent of each other, the same not true for artificial neural networks (ANNs). Especially since it is a modeling technique that does not require linearity, it attracts great attention among researchers and financial analysts. Business bankruptcy prediction is also one of the financial subjects that attracts interests of researchers and analysts.

Due to its inductive nature, neural networks have the ability to bypass the steps of drawing a conclusion from the relationships between theory formulation and institutional bankruptcy and the factors affecting them. When this quite complex and non-linear relationship between bankruptcy and the factors affecting it is considered, it is clear that neural networks is a very suitable method for modeling such a complex relationship.

Corporate financial analysts and other researchers generally, today, find themselves trying to cope with large amounts of information. Most of this information is digital data, which is called noisy information. Analysts try to analyze financial decisions by compiling relevant information using graphs and charts and by using various statistical methods in an integrated manner. They also try to make financial decisions by using information obtained from various sources based on various methods in an integrated manner.

Even though financial analysts take into consideration the relationships when making decisions, they may not always be able to combine this different and unequal information, which has the potential to affect their own predictions. Artificial neural networks (ANN) in this sense, in general, can analyze even very large amounts of information without any problems. Additionally, neural networks allow predicting bankruptcy much more effectively even in the case of noise and randomness in the financial data

When it comes to corporate bankruptcy, the first thing that comes to mind is the possibility of bank bankruptcy. Researches on company bankruptcy contribute to the decision making in terms of profitability of financial institutions. The financial status of banks and other institutions also affects all sectors in an economy. If financial authorities could detect problems in advance and can detect the possibility of bankruptcy of a bank or other institution in advance by saving that institution from bankruptcy, they both help that institution and contribute to the economy in general. Artificial neural networks (ANN) solve complex problems in this sense and can be used as a new method in many business applications with its success in bankruptcy prediction.

In the finance literature, there are many studies that have been made for bankruptcy prediction that show that artificial intelligence technologies provide much better results than classical statistical methods Odom and Sharda (1990) are among the first researchers, who conduct research on company bankruptcies, by using artificial intelligence technology. They developed an artificial neural networks (ANN) model with the aim of bankruptcy prediction, and they tested their model by collecting financial data from many companies. They also analyzed by using multiple discriminant analysis (MDA) with the same data set. The results of the research indicate that it is more suitable to use artificial neural networks (ANN) in solving the current problem regarding bankruptcy.

Tam (1991) used backpropagation neural network method for bank bankruptcy prediction and according to the results of the study, this method gives more accurate predictive results as compared to the statistical methods such as K-nearest neighbor, discriminant analysis and factor-logistic. In another study that use similar methods, Tam and Kiang (1992) used the methods of discriminant analysis, logistic regression, K-nearest neighbor and two artificial neural networks (ANN) regarding bank bankruptcy prediction and measured the accuracy performances of all of these methods in prediction. According to their results, while the prediction success of artificial neural networks (ANN) that use training data of previous year is superior as compared to other methods, discriminant analysis method is superior to the artificial neural networks (ANN) that use training data of two years ago. However, they concluded that in validation samples both types of analysis, the method of artificial neural networks (ANN) was superior to other methods.

Coats and Fan (1993) proposed an artificial neural networks (ANN) model as an alternative to the multiple discriminant analysis (MDA) method for the same ratios they used. The findings of the study suggest that the artificial neural network (ANN) that they propose performs much better than the multiple discriminant analysis (MDA) method. Bell (1997), in his study that is about bank failures and bankruptcies, compared the logistic regression and the artificial neural networks (ANN) methods. The research shows that both methods have the same level of success

In the future, as alternative and integrated methods to the artificial neural networks (ANN), other artificial intelligence technology methods, have taken their place in the finance literature. Chief among these methods is genetic algorithm, fuzzy logic (fuzzy sets) and rough sets. As a result of integration of artificial neural networks (ANN) models with other artificial intelligence technology methods, their prediction performances have increased to cases where a single method is used.

2.1.3. Stock Market Index and Stock Price Forecast

Stock exchange is a platform in which shares of stock exchange companies are offered to the public at a predetermined price and through which companies provide financial resources by this mean. Investors who buy stocks of companies either expect to receive dividends at the end of the period or for the company to make a profit or they hope to sell the stock at a higher price in the future. Every day for this purpose, financial transactions worth tens of billions of dollars are carried out.

The most popular stock exchanges in which investors invest the most around the world are New York Stock Exchange (NYSE), NASDAQ, Toronto Stock Exchange, Amsterdam Stock Exchange, London Stock Exchange, Paris Stock Exchange, Philippine Stock Exchange, Singapore Stock Exchange, Kuala Lumpur Stock Exchange, Tokyo Stock Exchange, Hong Kong Stock Exchange, Shanghai Stock Exchange and Bombay Stock Exchange. Index, on the other hand, is a statistical measurement of the market or industry as a whole and companies and provides measurement of the companies or group of companies within a certain period of time. The price indices by which stock prices are determined in a market or market segment are called stock market indices (Vui et al., 2013).

Stock market indices are, by their nature show non-linear and volatile features. In addition, stock market index prediction is difficult basically due to their dynamic, complex, non-parametric and chaotic structure. Moreover, although this is more valid in developing countries almost all stock markets are affected by many complex variables such as political events, company policies, general economic situation, expectations of personal and institutional investors, movements in other stock markets and even investor psychology.

Especially recently, among investors and professional analysts, stock market index prediction and stock price prediction attract a lot of attention. Until now many traditional statistical methods have been used for stock market index prediction. Recently, artificial intelligence technology-based methods that are combinations of various learning algorithms are one of the most commonly used methods by researchers

Especially the ability of the artificial neural networks (ANN) to learn from non-linear data trends and generalize provides great convenience in solving stock market index prediction problems. In addition, artificial neural networks (ANN) can better adapt to the sample data and the relationship between input and output, and thus, better prediction results can be obtained compared to traditional methods.

Two traditional methods used in stock market index prediction from past to present include technical analysis and fundamental analysis. Technical analysis is a numerical time series technique used for stock market forecasting based on historical data using charts as the primary data source. Although analysts make their predictions based on technical analysis which uses daily data, making daily or weekly trend predictions is not as easy as it seems.

Fundamental analysis focuses on the factors affecting supply and demand. According to the fundamental analysis, gathering and interpreting information for stock price prediction in terms of analysis is the most important process. Thus, it is possible to benefit from the time difference that occurs between an event and the players' reactions to this event in a best way. The most important data that are used in fundamental analysis are the economic data obtained from financial reports that are published by companies annually or quarterly and from audit reports and from financial statements such as the balance sheet and income statement. Again, current news about companies is also important for fundamental analysis.

While researchers and analysts develop effective commercial strategies to analyze stock market index values and stock prices and of course to make profit, on the other hand, they aim to develop the least complex prediction models using the least amount of input data needed to make the best prediction (Atsalakis and Valavanis, 2009). Artificial neural network (ANN) is a popular machine learning algorithm that is widely accepted by experts and that is used frequently for prediction purposes for time series and stock market index and stock prices. Kimoto et al. (1990) are the first researchers who developed modular neural network machine learning with the aim of watching the movements of the Tokyo Stock Exchange index and to predict best times for buying and selling stocks. Afterwards, use of artificial neural networks (ANN) in stock analysis has become increasingly widespread.

Wu and Lu (1993), tried to predict the S&P 500 index in their study using by artificial neural networks (ANN). Researchers stated that prediction results they obtained using artificial neural networks (ANN) yielded more accurate results as compared to the prediction results obtained using the Box-Jenkins model. Chen et al. (2003), in their studies where they tried to predict the direction of Taiwan Stock Exchange Index, used probabilistic neural network (PNN) for it. At the same time, they also compared the results of compared the results of the PNN with the results of the Generalized Methods of Moments, Kalman filter and random walk. The findings of the study indicate that the method of PNN gives much more accurate predictions than the Generalized Methods of Moments, Kalman filter and random walk methods.

Altay and Satman (2005), in their study, which aimed to predict the Istanbul Stock Exchange 30 Index (ISE 30) and ISE all indices, compared the prediction performances of artificial neural networks (ANN) with the

Ordinary Least Squares (OLS) regression model. Although the results that they obtained from the daily and weekly data of the artificial neural networks (ANN) did not achieve a superior result than the linear regression model, the study managed to guess the direction correctly.

Guresen et al. (2011) used a total of four methods to predict the NASDAQ index. These are multilayer ANN (Multilayer Perceptron - MLP), Dynamic ANN (Dynamic Architecture for Artificial Neural Network - DAN2), GARCH-MLP and GARCH-DAN2 models. Result of the research shows that MLP gives the most accurate prediction result. In one of the latest studies by Inthachot et. al. (2015), in which they tried to predict the Stock Exchange of Thailand (SET50) by employing the models of Artificial Neural Networks (ANN) and Support Vector Machines (SVM), used 10 identical technical indicators. Although the study reveals that the result obtained with ANN is more successful, both models need to be improved to obtain better results.

2.1.4. Optimal Capital Structure Estimation

The concept of capital structure has become increasingly popular with the increasing influence of globalization. It has become a concept that has been frequently brought to the agenda recently. For this reason, the concept of capital structure is the most discussed and commented concept in the finance literature. Researchers undertook many theoretical and empirical study regarding the capital concept and the factors affecting this concept. Capital structure decisions have vital importance in terms of financing the investments necessary for businesses to continue their activities. At the center of studies in literature are studies conducted to determine whether minimizing the cost of capital and maximizing market value thanks to changes in the capital structure of the business is possible or not.

In increasingly difficult competitive conditions, companies' ability to carry out their financial activities stably and achieve balanced growth depends on their optimal capital structure. When it comes to optimal capital decision, what comes to mind is the extent to which the company will use foreign capital and equity capital, and what effect this will have on the company value. The most important purpose of financial decisions is to maximize the wealth of shareholders. Therefore, in order to achieve this goal, managers should choose the capital structure that they believe will provide the highest firm value. A wrong decision taken in a way that contradicts the optimal capital structure can negatively affect the profitability of the company, which causes the value of shareholders' wealth to decrease.

Determining the optimal capital structure is actually extremely difficult as it involves a very complex decision-making process and a large number of interactive decision variables. In such a case, for example, an artificial neural network (ANN) can be developed as an artificial intelligence technology that can analyze and evaluate all financial information that has the possibility of affecting the decision-making process. When analyzing with artificial neural network (ANN), real data regarding different capital structures can be uploaded to the system. Thus, a debt/equity ratio can be determined to make the most accurate decision, and the company value can be maximized after this optimal capital structure decision.

Many empirical studies on capital structure have been conducted since 1950s. As the turning point of these studies, Modigliani and Miller's (1958) study can be cited. These two researchers were the first researchers to develop and defend a model stating that under certain assumptions firm value is independent of the firm's capital structure. Approach of two researchers has been exposed criticism by some other researchers due to the assumptions it puts forward. The starting points of these criticisms are the assumptions that the capital market for which this theory operates under full competition conditions, that all investors are rational and not considering the tax impact. Subsequently, Modigliani and Miller first included the impact of corporate tax into their model in 1963 and income tax in 1977 and thus, they updated their proposal model under the tax effect.

Many empirical studies on capital structure predate the 1990s. Many researchers such as Taggart (1977), De Angelo and Masulis (1980), Jalil and Harris (1984) and Titman and Wessels (1984), researched the factors that determine the capital structure and made important contributions to the literature by testing these factors with formulas. In this context, while some of the researchers have focused on testing optimal capital structure theories, others investigated the capital structure dynamics of companies.

Harris and Raviv (1991), in their study, in which they aimed to investigate the capital structures theories such as asymmetric information and agency cost, found that leverage ratios of companies operating in the same sector are similar to those outside the sector. Likewise, Allen (1991) examined the factors affecting the capital structure decisions of the 48 companies whose shares are traded in stock exchanges in Australia and their financing decisions. The results of the study show that the profitability of the companies within the scope of the study depends on their debt level. While Rajan and Zingales (1995), in their research on British companies detected a positive relationship between the leverage ratio and the firm size and the ratio of tangible assets, they determined a negative relationship between leverage ratio and the profitability and the growth opportunities.

Chen and Hammes (1997) have examined the shares of some non-financial companies, whose shares are traded in stock exchanges of seven OECD countries in the period between1990 and 1996. Research results shows that while there is a positive relationship between firm size and leverage ratio, there is a negative relationship between firm profitability and leverage ratio. In addition, the research also determined that risky firms use less debt.

Brounen, Jong and Koedjik (2005), in their study, in which they examined the capital structures of companies in the Netherlands, France, England and Germany, found that companies set target debt ratios. In their study based on survey method, they also determined that agency costs were not effective in capital structure selection

Heyman, Deelof and Ooghe (2008), in their study investigating the capital structures of sole proprietorships in Belgium, reached the conclusion that profitable firms with less tangible assets have also low leverage ratios. The results of the study also show that larger companies borrow in greater amounts on a shorter-term basis.

Noulas and Genimakis (2011), in their study, researched the factors affecting the capital structures of 259 non-financial companies, whose stocks are trading in the Athens Stock Exchange, over the period of 1998 and 2006. While research results point out the existence of a positive correlation between leverage ratio and growth rate, tangible assets ratio, a negative correlation was detected between profitability and leverage ratio.

Kouki and Said (2012), in their research, examined capital structure decisions of 244 non-financial companies in France between 1997-2007. Their results indicate a positive correlation between leverage ratio, profitability and growth rate and a negative correlation between firm size, the ratio of tangible assets and leverage ratio.

Cortez and Susanto (2014) examined the factors affecting the capital structures of 21 Japanese manufacturing companies operating in the manufacturing sector. As a result of the research, based on the data between 2001 and 2012, while a positive relationship was detected between leverage and profitability, a negative relationship was obtained between leverage and profitability.

Castro et al. (2016), by examining companies traded in European stock exchanges between 1990-2012 according to their life cycles, determined that the speed of progress to the optimal capital structure varies according to the life cycles of the companies. The findings of the study reveal that profitability, fixed asset ratio, growth opportunities and the size of the firm are the most important factors that determine the capital structure of a company from company start up till maturity. They also found that the speed of progress rates of entry-stage companies to the optimal capital were at the highest level.

Many factors are thought to be effective on the optimal capital structure. In this context, more studies need to be conducted in the world that address the capital structures and the factors that are thought to affect these structures in terms of clarifying the concept of optimal capital structure. It is important for both investors and researchers to increase the factors to be examined and also to include companies from different sectors in researches. With the increase in such studies, it will be possible to obtain deeper information and to make more accurate comments concerning financing preferences of companies and also the consequences of these preferences

2.1.5. Exchange Rate Prediction

"Why is exchange rate forecasting necessary?" question is one of the questions that has puzzled many economists and financial analysts for years. Especially with the collapse of the Bretton Woods system and the transition to a floating exchange rate system, monetary policy authorities have gained the necessary ground to establish monetary policies independently of external imbalances. However, with the collapse of the Bretton Woods system in the early 1970s, the foreign exchange rate market has also started to follow a very volatile course. Especially, in the last thirty years, the exchange rate market has grown as much as never existed, due to the effect of the floating exchange rate regime and the influence of the ongoing liberalization of trade. In fact, from time to time as a consequence of combining effects of other financial crises, the exchange rate market has become so volatile that it led to deep financial crises that broke out in many developing countries. Mexico (1994), some of the Southeast Asian countries (1994), Asia (1997), Russia (1998), Argentina (2002) and Türkiye (1994 ; 2001) can be given as examples to the countries that experienced these financial crises.

In the floating exchange rate regime, the exchange rate is one of the main mechanisms that can affect, monetary policy, real activities and inflation. For example, the monetary policy authorities can analyze the movements of the exchange rate or estimate the future value of the exchange rate to maintain inflation in stable and reasonable levels and to maximize economic activities. Thus, they can also increase their control over monetary policy.

Another reason why the authorities have a say in monetary policy, watch the foreign exchange market closely is that foreign exchange itself is a source of valuable information about the current economic and financial situation. Analysts can provide the most up-to-date and necessary information about the general and financial situation of the economy by analyzing foreign exchange movements accurately and by making accurate predictions about the course of the foreign exchange. In this way, they can create a much more appropriate monetary policy for a price stability for the future and in order to achieve their aims of reducing unemployment.

Exchange rates are of great importance, especially in international trade. When a company or individual purchases goods or services from another country, it is often required to make payment in the other country's currency. Therefore, before making payments, he/she must purchase the other country's currency from the market to conduct his/her business. If a model or models can be found to accurately analyze the movements of the exchange rate market, it will be possible to limit the fluctuation (volatility) in this market by estimating the exchange rates in the best possible way. Moreover, as the effects of alternative economic policies on the exchange rate will be better understood, the results of these policies will be able to be evaluated more accurately (Pillbeam, 1998).

Many econometric and statistical methods have been suggested a to predict the foreign exchange in a reliable manner. Among the traditional statistical estimation methods, Box Jenkins's Auto Regressive Integrated Average Moving Average (ARIMA) method is based on linear models (Box and Jenkins, 1976). However, ARIMA is a general univariate model, and it assumed that the predicted time series are linear and stationary. Linear models have some disadvantages and therefore, alternative methods have been developed in this area. The method of artificial neural networks (ANN), which stands out as a new prediction method, is one of the leading artificial intelligence technologies in this field.

The studies conducted at the beginning of 1990s and 2000s, mostly made by the researchers in developed countries and aimed for the estimation of exchange rates in these countries. With the development of the artificial intelligence technology and as their share of the developing countries in world trade and their weight in financial system has increased, the number of studies on prediction of the currencies of these countries has increased.

Conducting of foreign exchange rate forecasts with methods other than the traditional statistical ones, especially with artificial neural networks, dates back to early 1990s. One of the first studies conducted in this sense belongs to Refenes et.al (1992). In this study, standard backpropagation algorithm method, which was developed by Rumelhart (1986) was used. The research made predictions by taking the exchange rates of the American Dollar (USD) and the German Mark updated hourly between 1988-1989 as data. In this study, while the first 6 months were used as training data, the next 6 months were used as test data. The neural network that was used made correct predictions and obtained 20% of profit from the last 60 trading days of 1989.

Studies on exchange rate prediction using artificial neural network (ANN) started to become widespread in the 1990s. Gan and Ng (1995), estimated the values of Swiss Franc, German Mark and Japanese Yen against the US Dollar by using two ANNs and standard backpropagation algorithm and single and multiple time series. The findings of the study reveal that the ANN models provide more accurate predictions than random walk models.

Francesco and Schiavo (1999), in their study, in which they conducted various experiments with longer data, tried to estimate the values of the leading four European currencies (French Franc, German Mark, Italian Lire and British Pound) against the US Dollar. For this, they benefited from the data between 1973 and1995 and they analyzed and compared chaotic models with neural networks. In their study where they used a two-layer network trained standard backpropagation algorithm, they concluded that neural networks performed better than chaotic models.

Tang and Fishwick (1993), in their study in which covered the period between May 1984 and October 1993, created a neural network using time series data with technical indicators and used six different leading currencies in their studies. As a result of their studies estimating the period between November 1993 and July 1995, in the case in which they used the neural network with technical indicator, a 74% prediction success rate was obtained. However, in the case in which they didn't use, this rate dropped to 50%. The two researchers also found that the artificial neural network (ANN) model they used gave more accurate results in terms of the direction of change of movement and profitability as compared to the traditional ARIMA model. This study also is also important in terms of showing that it is possible to obtain profit with the artificial neural network (ANN) based foreign exchange prediction models even without very extensive data or information.

In the prediction of Indian Rupee-US Dollar exchange rate, Panda and Narasimhan (2007), compared linear autoregressive model, random walk model and artificial neural network (ANN). A weekly forecast was made using daily exchange rate data. They found that the artificial neural network (ANN) predictions yielded more successful results.

Tutal (2011), in his study, by using daily data of USD, EUR, GBP and JPY exchange rates, made future value and direction predictions of foreign exchanges using artificial neural networks (ANN) and support vector machines (SVM) methods. USD, EUR, GBP and JPY exchange rates with ANN and MAE (Mean Absolute Error) and MAPE (Mean Absolute Percent Error) values were compared. It was observed that both generally applied algorithms are internally consistent and successful, and the values were close to each other.

Galeshchuk (2016), in his study, made foreign exchange rate predictions for USD/EUR, JPN/USD, USD/GBP exchange rates by using daily, monthly and quarterly exchange rate data with the method of the artificial neural networks (ANN). As a result of the application, the lowest forecast error among all foreign exchange rates percentage was obtained with daily, monthly and quarterly data, respectively.

Nwosu et al. (2021) compared the British pound and the Nigerian Naira (GNG) for the Covid-19 pandemic period with random forest model, ANN and ARIMA methods. The study has yielded that artificial neural that networks (ANN) method is better for the prediction of GBP-NGN exchange rate.

3. CONCLUSION

In today's complicated business world, for many companies, improving the work of the enterprises and financial planning processes have utmost importance. In this sense, automation, better integration between systems, and more efficient processes are the main keys to the success and therefore, the development of artificial intelligence is growing rapidly (Aydin & Cavdar, 2015)

Recent studies have shown that exchange rates are not independent of past movements. Additionally, researchers obtained results debilitating the view that exchange rates are subject to a so-called random walk and the price movement is random and unpredictable. Accordingly, researchers argue that historical data cannot be ignored in estimating exchange rates, on the contrary, it is the most important factor in the success of the process. Even though, traditional statistical methods are useful in analyzing linear and static and of certain quality of data, the same methods are not very suitable for more chaotic and nonlinear systems

Finally, there are many factors that trigger the emergence of financial crises. These include poorly managed companies, unexpected changes in the business cycle, changes in the tangible or intangible assets of companies and losses resulting from fraud can be shown. These symptoms can often be deliberately hidden, and it is difficult or even impossible to analyze them with traditional econometric and statistical methods. Therefore, recently, many researchers have turned to artificial intelligence systems by adding their experiences and developed various financial crisis prediction models by using this technology

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