HİTİT SOSYAL BİLİMLER DERGİSİ
Hitit Journal of Social Sciences
e-ISSN: 2757-7949
Cilt | Volume: 17 • Sayı | Number: 2
Ağustos | August 2024

Forecasting Türkiye's Paper and Paper Products Sector Import Using Artificial Neural Networks

Yapay Sinir Ağları ile Türkiye Kâğıt ve Kâğıt Ürünleri Sektörü İthalat Tahmini

Yunus Emre GÜR
Corresponding Author | Sorumlu Yazar
Dr. | Dr.
Fırat Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, Yönetim Bilişim Sistemleri Bölümü, Elazığ, Türkiye
Fırat University, Faculty of Economics and Administration Sciences, - Department of Management Information Systems, Elazığ, Türkiye
yegur@firat.edu.tr
https://orcid.org/0000-0001-6530-0598

Kamil Abdullah EŞİDİR
Dr. | Dr.
Fırat Kalkınma Ajansı, Elazığ, Türkiye
Fırat Development Agency, Elazığ, Türkiye
abdullahesidir@yahoo.com
https://orcid.org/0000-0002-8106-1758

Makale Bilgisi | Article Information

Makale Türü | Article Type: Araştırma Makalesi | Research Article
Geliş Tarihi | Received: 14.07.2023
Kabul Tarihi | Accepted: 15.05.2024
Yayın Tarihi | Published: 31.08.2024

Atıf | Cite As

Gür, Y.E, &. Eşidir, K.A. (2024). Forecasting Türkiye's Paper and Paper Products Sector Import Using Artificial Neural Networks. *Hitit Sosyal Bilimler Dergisi, 17*(2), 206-224. https://doi.org/10.17218/hititsbd.1327799

Yazar Katkıları: %50-%50
Değerlendirme: Bu makalenin ön incelemesi iki iç hakem (editörler - yayın kurulu üyeleri) içerik incelemesi ise iki dış hakem tarafından çift taraflı kör hakemlik modeliyle incelendi. Benzerlik taraması yapılarak (Turnitin) intihal içermediği teyit edildi.
Etik Beyan: Bu çalışmanın hazırlanma sürecinde bilimsel ve etik ilkelere uyulduğu ve yararlanılan tüm çalışmaların kaynakçada belirtildiği beyan olunur.
Etik Bildirim: husbededitor@hitit.edu.tr https://dergipark.org.tr/tr/pub/hititsbd
Çıkar Çatışması: Çıkar çatışması beyan edilmemiştir.
Finansman: Bu araştırmayı desteklemek için dış fon kullanılmamıştır.

Author Contributions: 50%-50%
Review: Single anonymized - Two Internal (Editorial board members) and Double anonymized - Two External Double-blind Peer Review
It was confirmed that it did not contain plagiarism by similarity scanning (Turnitin).
Ethical Statement: It is declared that scientific and ethical principles have been followed while conducting and writing this study and that all the sources used have been properly cited.
Complaints: husbededitor@hitit.edu.tr - https://dergipark.org.tr/tr/pub/hititsbd
Conflicts of Interest: The author(s) has no conflict of interest to declare.
Grant Support: The author(s) acknowledge that they received no external funding to support this research.

Forecasting Türkiye's Paper and Paper Products Sector Import Using Artificial Neural Networks

Abstract

The paper and paper products sector is a crucial component of the Turkish economy, characterized by significant interactions with various other sectors. Türkiye imports substantial amounts of paper, playing a vital role in the growth and sustainability of this sector. Accurate import forecasting is essential for strategic planning and resource management. This study aims to forecast the imports of the Turkish paper sector for the period from April 2023 to March 2024 using two artificial neural network (ANN) models: Multilayer Perceptron (MLP) and Radial Basis Function (RBF). The dataset, obtained from the Turkish Statistical Institute (TurkStat), covers 219 months of data from 2005 to 2023. The dependent variable is Türkiye's monthly import value of paper and paper products, while the independent variables include the monthly average US Dollar exchange rate, monthly imports of Türkiye, the Manufacturing Industry Production Index, the Paper Production Index, and the monthly exports of paper and paper products from Türkiye. The MLP model forecasts that the monthly imports of paper and paper products will range between 270 to 300 million USD, while the RBF model predicts values between 268 and 321 million USD. These findings underscore the efficacy of ANNs in providing accurate and reliable forecasts. This study addresses a gap in the literature by applying ANN methods to forecast imports in the paper and paper products sector, presenting a novel approach that can assist companies in making better-informed decisions regarding inventory management, production planning, and marketing strategies. By leveraging the advanced computational power and pattern recognition capabilities of ANNs, the study aims to enhance the strategic planning processes in the paper and paper products industry. The traditional methods often used in trade data analysis and forecasting are limited in capturing the complex and non-linear relationships present in economic data. This study's application of ANNs offers a significant advancement by utilizing models that can better handle such complexities. The accuracy of the MLP and RBF models highlights their potential as valuable tools for economic forecasting, providing insights that are crucial for optimizing supply chain operations and improving market responsiveness. The results indicate that companies can achieve better operational performance and increased customer satisfaction by effectively forecasting future import requirements. The originality of this study lies in its methodological approach, utilizing ANN models to forecast import values in a sector where traditional methods have been predominant. This innovative approach not only contributes to the existing body of knowledge but also offers practical applications for businesses within the sector. The detailed analysis of the data, combined with the robust modeling techniques employed, provides a comprehensive framework for understanding the dynamics of paper imports and making strategic decisions based on accurate predictions. In conclusion, the study demonstrates the significant success of artificial neural networks in predicting import values for the Turkish paper and paper products sector. The findings provide valuable information that can aid companies in strategic planning, enhancing their ability to manage inventory, plan production, and develop effective market strategies. The research contributes to the literature by filling a gap with its innovative approach, offering new perspectives and practical applications for improving decision-making processes in the industry.

Keywords: Artificial Neural Networks Models, Multi-Layer Perceptron (MLP), Radial Basis Function (RBF), Paper and Paper Products, Time Series

Yapay Sinir Ağları ile Türkiye Kâğıt ve Kâğıt Ürünleri Sektörü İthalat Tahmini

Öz

Kâğıt ve kâğıt ürünleri sektörü, Türkiye ekonomisinde önemli bir yere sahip olup, diğer sektörlerle etkileşim içerisindedir. Türkiye, büyük miktarlarda kâğıt ithal etmekte ve bu ithalat, sektörün büyümesi ve sürdürülebilirliği açısından hayati öneme sahiptir. Doğru ithalat tahmini, stratejik planlama ve kaynak yönetimi için gereklidir. Bu çalışma, Türkiye kâğıt sektörünün 2023 Nisan - 2024 Mart dönemi ithalatını öngörmeyi amaçlamaktadır. Bu amaçla Multilayer Perceptron (MLP) ve Radial Basis Function (RBF) olmak üzere iki farklı yapay sinir ağı modeli kullanılmıştır. Türkiye İstatistik Kurumu'ndan (TÜİK) elde edilen veri seti, 2005 ile 2023 yılları arasındaki 219 aylık veriyi kapsamaktadır. Modelin bağımlı değişkeni, Türkiye'nin aylık kâğıt ve kâğıt ürünleri ithalat değeri olup, bağımsız değişkenler ise aylık ortalama Amerikan Doları kuru, Türkiye aylık ithalatı, İmalat Sanayi Üretim Endeksi, Kâğıt Üretim Endeksi ve Türkiye aylık kâğıt ve kâğıt ürünleri ihracatıdır. MLP modeli, aylık kâğıt ve kâğıt ürünleri ithalatının 270 ile 300 milyon USD arasında olacağını tahmin ederken, RBF modeli tahmin değerlerini 268 ile 321 milyon USD arasında öngörmektedir. Bu bulgular, yapay sinir ağlarının doğru ve güvenilir tahminler yapma konusunda önemli başarılar sağladığını göstermektedir. Bu çalışma, kâğıt ve kâğıt ürünleri sektöründe ithalatı öngörmek için yapay sinir ağı yöntemlerinin uygulanmasıyla literatürdeki bir boşluğu doldurmakta ve şirketlerin envanter yönetimi, üretim planlaması ve pazarlama stratejileri konusunda daha bilinçli kararlar almasına yardımcı olabilecek yenilikçi bir yaklaşım sunmaktadır. Yapay sinir ağlarının gelişmiş hesaplama gücü ve desen tanıma yeteneklerinden yararlanarak, çalışma, kâğıt ve kâğıt ürünleri endüstrisinde stratejik planlama süreçlerini geliştirmeyi amaçlamaktadır. Geleneksel yöntemler genellikle ticaret verilerinin analizinde ve tahmininde kullanılırken, ekonomik verilerdeki karmaşık ve doğrusal olmayan ilişkileri yakalamakta sınırlı kalmaktadır. Bu çalışmanın yapay sinir ağı uygulamaları, bu tür karmaşıklıkları daha iyi yönetebilen modeller kullanarak önemli bir ilerleme sunmaktadır. MLP ve RBF modellerinin doğruluğu, bunların ekonomik tahminlerde değerli araçlar olma potansiyelini vurgulamaktadır ve tedarik zinciri operasyonlarını optimize etmek ve pazar yanıt verebilirliğini artırmak için kritik bilgiler sağlamaktadır. Sonuçlar, gelecekteki ithalat gereksinimlerini etkili bir şekilde tahmin ederek, şirketlerin operasyonel performanslarını iyileştirebileceğini ve müşteri memnuniyetini artırabileceğini göstermektedir. Bu çalışmanın özgünlüğü, geleneksel yöntemlerin hakim olduğu bir sektörde ithalat değerlerini tahmin etmek için yapay sinir ağı modellerini kullanmasında yatmaktadır. Bu yenilikçi yaklaşım, mevcut bilgi birikimine katkıda bulunmakla kalmayıp, aynı zamanda sektördeki işletmeler için pratik uygulamalar sunmaktadır. Verilerin detaylı analizi ve kullanılan güçlü modelleme teknikleri, kâğıt ithalatının dinamiklerini anlamak ve doğru tahminler yaparak stratejik kararlar almak için kapsamlı bir çerçeve sağlamaktadır. Sonuç olarak, bu çalışma, Türkiye kâğıt ve kâğıt ürünleri sektöründe ithalat değerlerini tahmin etmede yapay sinir ağlarının önemli başarılarını göstermektedir. Bulgular, şirketlerin stratejik planlama yaparken envanter yönetimi, üretim planlaması ve pazarlama stratejileri geliştirme yeteneklerini artırabilecek değerli bilgiler sağlamaktadır. Araştırma, yenilikçi yaklaşımıyla literatürdeki bir boşluğu doldurarak, sektörün karar verme süreçlerini iyileştirmek için yeni perspektifler ve pratik uygulamalar sunmaktadır.

Anahtar Kelimeler: Yapay Sinir Ağları Modelleri, Çok Katmanlı Algılayıcılar, Radyal Tabanlı Fonksiyon, Kâğıt ve Kâğıt Ürünleri, Zaman Serileri

Introduction

The manufacture of paper and paper products includes the conversion into paper of waste paper obtained from cellulose, wood pulp and other major raw materials from annual plants such as various tree species, jute, hemp, cane and other major raw materials by various mechanical and chemical processes. These intermediate products and the recycling of waste paper fall under the medium heavy industry category of the sector. The manufacture of paper and paper products is an important sector for the Turkish economy, both as a source of employment and because of its linkages with other sectors. The forest products and waste paper industries have a strong impact on the sector. In addition, there is a relationship between the inputs of the printing, publishing and packaging sub-sectors and the sector (Karadeniz et al., 2021, p.161).

While the paper and paper products manufacturing sector in Türkiye was self-sufficient until the 1980s, it became dependent on foreign markets with the introduction of imported products. With an expanding production capacity of 3.8 million tonnes, this is the largest production area in the corrugated board sector. Türkiye has the sixth largest production capacity in Europe in this sector and has reached European standards. Since 2013, the sector, which has grown faster than the manufacturing industry, has also made rapid progress in the use of waste paper. Paper and paper products provide important inputs to the industrial, chemical and mining sectors as final product suppliers to the packaging sector. The sector, which accounts for 1.4 per cent of total exports including gold exports, has not been as successful as expected due to production costs. Exports have been disrupted as a result of growing security concerns about countries geographically close to most exporting countries (Iraq, Azerbaijan, Israel and Iran) (Akyüz et al., 2017, p.62).

The Turkish paper sector is underdeveloped in terms of production, despite its growth potential, developing domestic market and demand. There are problems with access to raw materials. The paper sector is very important for the country's economic growth. However, it is low technology intensive. Research and development activities are necessary for the sector to grow and add value. R&D and design activities are very important to reduce production costs and improve product quality. Production costs prevent the sector from being competitive. A significant proportion of inputs and services are imported. Import of pulp is one of the main problems. Waste and scrap are an important part of paper production. The collection of waste paper is not sufficient for the country and paper scraps are imported. Raw materials purchased in foreign currency damage the sector due to upward changes in exchange rates (General Directorate of Industry, 2022).

Foreign trade data for "Pulp, paper and paperboard products" are shown in Table 1. Sectoral foreign trade has increased over the years. In 2000, paper exports reached about USD 2.8 billion. While paper imports amounted to USD 939 million in 2000, they reached USD 3.9 billion in 2022. This means that paper imports have increased 4.2 times in 22 years.

Table 1. Paper and Paper Products Foreign Trade Data (Chapter No: 48)

Years	Paper Exports (Million USD)	Paper Imports (Million USD)	Years	Paper Exports (Million USD)	Paper Imports (Million USD)
2000	174	939	**2012**	1.033	2.883
2001	251	652	**2013**	1.141	3.092
2002	316	855	**2014**	1.204	3.171
2003	386	1.164	**2015**	1.186	2.684
2004	479	1.528	**2016**	1.353	2.685
2005	582	1.767	**2017**	1.520	2.812
2006	625	2.043	**2018**	1.716	2.750
2007	861	2.470	**2019**	1.796	2.514
2008	1.078	2.605	**2020**	1.743	2.404
2009	1.005	2.214	**2021**	2.194	2.720
2010	1.217	2.820	**2022**	2.848	3.960
2011	1.427	3.110			

Source: TURKSTAT, 2023

In the era of globalisation, international trade is becoming increasingly important, and many countries attach great importance to foreign trade in order to achieve their economic growth and development goals. Türkiye has become an important player in the paper and paper products sector due to its geopolitical position and location on strategic trade routes. Accurate and reliable import forecasts in this sector are crucial for companies to make strategic planning and commercial decisions and to manage their resources effectively. The aim of this paper is to forecast imports in the Turkish paper and paper products sector using the Artificial Neural Network (ANN) method. Artificial neural networks are a machine learning technique that mimics the functioning of the human brain and can model complex relationships. Due to its advanced computational power and pattern recognition capabilities, ANN has been successfully used to build forecasting models.

The aim of this study is to forecast imports in the Turkish paper and paper products sector for the period 2023 April-2024 March by applying ANN algorithms. These forecasts can provide valuable information to help companies operating in the sector make decisions on issues such as inventory management, supply chain planning and market strategies. The originality of this study is to forecast imports in the Turkish paper and paper products sector using the ANN method. In the existing literature, traditional methods are often used to analyze and forecast trade data. Therefore, investigating the impact of using ANN on the prediction of paper imports in the sector will fill the gap in the literature and provide a new perspective for companies.

Forecasting imports in the Turkish paper and paper products sector using Artificial Neural Networks (ANN) methods is very important for several reasons. Accurate import forecasting directly affects the inventory management decisions of businesses in the sector, including determining the safety stocks needed to meet demand requirements while minimizing excess inventory costs (Barrow and Kourentzes, 2016). Improving forecasting accuracy is vital for reducing uncertainty in the supply chain, enabling informed decisions and operational optimization (Sanders and Ritzman, 2004). Moreover, precise demand forecasting supports logistics coordination within the distribution network, allowing manufacturers to align production schedules with projected demand, thereby improving operational efficiency and market responsiveness (Kmiecik, 2023). In summary, accurate import forecasting not only helps with inventory management, but also contributes to overall supply chain optimization and effective decision-making processes in the industry.

However, accurate import forecasts using ANN methods can improve the competitiveness and sustainability of the sector. With a clear understanding of future import requirements, companies can streamline their procurement processes, minimize excess inventory and reduce the risk of stock-outs. This not only improves operational performance but also increases customer satisfaction by ensuring on-time product delivery (Kilimci et al., 2019). In conclusion, forecasting imports using ANN methods in the Turkish paper and paper products sector is crucial for increasing operational efficiency, improving decision-making processes, and increasing the competitiveness of the sector. By leveraging advanced forecasting techniques such as ANN, businesses can gain valuable insights into future import trends, optimize supply chain operations, and ultimately achieve long-term success in a dynamic and competitive market environment.

1. Literature Review

MLP (Multi-Layer Perceptron) and RBF (Radial Basis Function) artificial neural networks are two popular and effective artificial intelligence/machine learning algorithms used in many forecasting problems. Both have a wide range of applications and are also used for import forecasting.

MLP is a type of artificial neural network that adjusts weights using a learning algorithm known as backpropagation (Hagan et al., 1997, p.24). RBF networks are a type of neural network whose output is the sum of a set of functions. The centre (or 'basis') of each function is usually one of the input data points, and these basis functions are usually Gaussian functions (Buhmann, 2000, pp.2-3). These techniques are widely used in forecasting studies in economics and finance in general.

Khashei and Bijari (2010) conducted a study to improve time series forecasting using MLP and RBF neural networks. In this study, the authors proposed a hybrid model that combines these two neural network models. Although it is generally possible to use MLP and RBF networks for import forecasting, the accuracy of the forecasts depends on the nature and quality of the data, the training algorithm and a number of other factors. Therefore, a comprehensive model selection and validation process is often required to determine whether these methods are the most appropriate approach for import forecasting (Zhang *et al.*, 1998, p.36).

Which of the MLP and RBF methods performs better depends on the nature of the data and the modelling requirements. For import forecasting, these factors will often depend on the specific situation and data used. In particular, if the data set is large and contains complex relationships, a hybrid model combining MLP and RBF networks may be considered to give better results. For example, Wang *et al.* (2018) proposed the use of such a hybrid model and conducted experiments on various financial time series. Such an approach may also be suitable for import forecasting. Kuan and Liu (1995) used MLP to forecast exchange rates and obtained high accuracy rates.

Kumar and Thenmozhi (2006) compared MLP with the traditional ARIMA model and found that MLP provides more accurate forecasts of stock market indices. In addition, Refenes et al (1994) used MLP to forecast exchange rates and found that the model was effective in capturing the dynamics of exchange rates. Such studies suggest that MLP can be used as a potential tool for forecasting import demand. However, the effectiveness of MLP depends on the data set, the parameters of the model and the training algorithm. MLP can be particularly sensitive to overfitting, a situation where the model learns the training data very well but fails to generalise to new data (Prechelt, 1998, p.61). Therefore, the use of MLP often requires careful parameter selection and a proper validation process. As a result, MLP can often be an effective tool for forecasting complex and non-linear time series, and this may be the case for import demand forecasting. However, which model gives the best results depends on the data, the model parameters and other factors. Therefore, a comprehensive model selection and validation process is often required.

RBF neural networks can be a powerful tool, especially when the output is a complex function of input factors. This can be particularly useful in economic and financial forecasting. Mai et al (2014) presented an easy-to-implement hourly electrical load forecasting model for large commercial office buildings based on a radial basis function neural network (RBFNN), using outdoor weather data and historical load data as inputs, without tedious trial-and-error parameterisation procedures. Data from a real building under different weather conditions are used to evaluate the performance of the model, and promising results are obtained showing that the proposed method can accurately predict the evolving hourly electricity load of the building. Such an approach can also be applied to import demand forecasting. Importantly, RBF neural networks can be a potential tool for this type of problem due to their ability to model complex and non-linear relationships for import demand forecasting.

Faraji *et al.* (2020) investigate optimal day-ahead scheduling and operation of prosumers with corrective actions based on very short-term load forecasting. This study compares RBF-ANN and MLP-ANN models for efficient scheduling and operation of prosumer systems, emphasizing, among others, the role of accurate forecasting in renewable energy management. Safa et al. (2021) use MLP and RBF models for gap filling of net ecosystem CO2 exchange data on rain-fed maize. This study demonstrates the application of ANN approaches to fill the missing data and demonstrates the effectiveness of MLP and RBF in environmental data analysis. Towfiqul et al. (2022) focused on forecasting rainfall trends in Dhaka, Bangladesh using MLP and RBF models. This study evaluates the performance of these ANN models in predicting rainfall patterns and provides insight into their effectiveness in environmental forecasting applications. Momeneh and Nourani (2022) focus on predicting groundwater level fluctuations using a hybrid of AI models and multi-discrete wavelet transforms. The study highlights the robustness and efficiency of RBF models due to their simple architecture and tolerance to noisy data, emphasizing their suitability for groundwater forecasting. These references collectively illustrate the various applications of MLP and RBF algorithms in forecasting studies in various fields, demonstrate their effectiveness in handling complex forecasting tasks, and contribute to advances in predictive modeling techniques.

Artificial Neural Networks (ANNs) have received considerable attention in import and export forecasting due to their ability to handle complex patterns and non-linear relationships in data. Several studies have highlighted the effectiveness of ANNs in forecasting different economic indicators such as stock prices, exchange rates and trade volumes. Egrioglu and Bas (2023) introduced a new deep neural network, the Deep Dendritic Neural Network, which demonstrates the potential of advanced neural network architectures for forecasting tasks. This shows that there is a continuous effort in the research community to improve the predictive capabilities of ANNs. Cecati *et al.* (2015) highlighted the popularity of ANNs in short-term electric power system forecasting, underlining their importance in ensuring efficient and reliable operations. This application demonstrates the versatility of ANNs in performing various forecasting tasks beyond traditional economic indicators. Dumor and Yao (2019) discussed the successful application of ANNs in forecasting trade volumes and demonstrated the adaptability of these models in capturing the complexity of trade relationships. This highlights the potential of ANNs in import and export forecasting by leveraging their ability to model non-linear models. Furthermore, Muhamad *et al.* (2021) compared the performance of fuzzy time series and ANNs in forecasting natural rubber exports, showing that different approaches may be appropriate for specific forecasting tasks. This highlights the importance of choosing the most appropriate forecasting method based on the characteristics of the data.

Overall, the literature review shows that there is a growing body of research supporting the use of ANNs in import and export forecasting. From stock prices to trade volumes, ANNs have demonstrated their effectiveness in capturing complex relationships and patterns, making them a valuable tool in the field of economic forecasting.

2. Research Methodology

A number of factors influence the demand for imports of paper and paper products. These factors may vary from one country to another and from one period to another. By analysing some publications and academic studies in the literature for the model set-up, we have identified the factors that may affect import demand and listed them as follows:

•Economic situation: In general, the economic situation of a country affects the import demand for paper and paper products. This is measured by factors such as economic growth, income levels and unemployment rates. For example, as a country's economy grows, consumption generally increases, which can increase the demand for paper and paper products imports (Crespo and Fontoura, 2007, p.411).

•Industrial production: Anderton (1999), analysing the relationship between innovation, product quality, variety and trade performance, examined the impact of industrial production on imports in Germany and the United Kingdom. In particular, he found that imports of paper and paper products may increase if domestic production fails to meet demand. This may be an important factor influencing the demand for imports of paper and paper products.

- *Consumption trends:* Consumer preferences and trends also influence import demand for paper and paper products. For example, demand for higher quality or a particular brand may increase the demand for imports (Lancaster, 1966, p.133).
- *Prices:* The price of paper and paper products also affects the demand for imports. In general, when prices fall, demand rises and vice versa (Goldberg and Knetter, 1996, p.3).
- *Policies:* Grossman and Helpman (1995) focus on how trade policies can affect international trade and imports in particular. In particular, the authors note that policies that encourage or discourage imports can directly affect the demand for imports. This may be an important factor affecting imports of paper and paper products.

Sectoral import forecasts are very important for economic planning and decision making. In this study, the relevant literature was reviewed and analysed to determine the factors affecting import demand in the paper and paper products sector. Once the factors were identified, the necessary data were collected for the analysis. In econometric analysis, data for the dependent and independent variables collected from the right data sources and prepared according to the model significantly affect the consistency of the estimates (Gujarati, 2003, p.636). This study uses official data. The analysis uses data provided by the Turkish Statistical Institute (TurkStat). The dataset covers a period of 219 months (18 years) from January 2005 to March 2023. There are a total of 219 records for each variable: 5 independent variables and 1 dependent variable. The dependent variable of the model is Türkiye's monthly import value of paper and paper products. The independent variables are: monthly average US dollar exchange rate, monthly imports of Türkiye, manufacturing production index, paper production index, monthly export value of paper and paper products of Türkiye.

Artificial Neural Network (ANN) models were developed for two different models (MLP and RBF) for monthly forecasting of paper and paper products imports. The architecture of the neural network models was designed and the number of layers, neurons and activation functions were determined. To train the model, a randomly selected part of the dataset was chosen as the training dataset and the other part as the test dataset. The sum of squares function was used to minimise the error function. The prediction results are compared with the actual import data to determine the accuracy of the model. In the next step, the forecasting process for Türkiye's monthly imports of paper and paper products was started. For each independent variable, the values of the independent variables were estimated for the period between April 2023 and March 2024 by using different and appropriate ARIMA models from time series analysis techniques. SPSS 25 software was used for the forecasting process. Through this software, Türkiye's import values of paper and paper products for the period from April 2023 to March 2024 were estimated by taking into account the independent variable estimation data.

2.1. Multi-Layer Perceptron Neural Networks

A Multilayer Perceptron (MLP) model is a type of artificial neural network consisting of multiple layers of interconnected nodes or neurons used to predict the value of a dependent variable in a multivariate dataset (Pala and Camurcu, 2016; Kurniawan et al., 2020). The architecture of an MLP is typically used for supervised learning and consists of an input layer, one or more hidden layers and an output layer. The nodes in each layer sum the weighted inputs from each node in the previous layer, add a bias to this sum, and pass the result through an activation function (Kurniawan et al., 2020).

Each node of an MLP essentially functions as a perceptron, hence the MLP is often referred to as a "perceptron". Unlike single-layer perceptrons, which are simple linear classifiers, MLPs can solve nonlinear problems because they contain one or more nonlinear hidden layers.

The prediction process is a feedforward process that proceeds from the input to the output of the network. In this study, the hyperbolic tangent activation function is used in the hidden layer and the output layer. The mathematical formula of the activation function is shown in Equation (1).

$$a = \tanh(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}} \tag{1}$$

The weighted sum $z^{[l]}$ for each hidden layer node is formulated as shown in Equation (2):

$$z^{[l]} = W^{[l]}a^{[l-1]} + b^{[l]} \tag{2}$$

where, $W^{[l]}$ and $b^{[l]}$ represent the weight matrix and bias vector in layer l, respectively, and $a^{[l-1]}$ represents the activations (or inputs for the input layer) in the previous layer. The activation $a^{[l]}$ for each $z^{[l]}$ is calculated as shown in Equation (3):

$$a^{[l]} = \tanh\,(z^{[l]}) \tag{3}$$

However, a similar process is applied in the output layer, but here the calculated activations are the final predictions of the model. The weighted sum calculation of the output layer is formulated as in Equation (4):

$$z^{[L]} = W^{[L]}a^{[L-1]} + b^{[L]} \tag{4}$$

where, L stands for the output layer. The activation function of the output layer is shown in Equation (5):

$$a^{[L]} = \tanh\,(z^{[L]}) \tag{5}$$

These activations are the model's predictions for the multivariate dependent variables. During the training of the model, the difference (error) between the predictions and the actual values is used to update the weights of the network using the backpropagation algorithm. This allows the model to iteratively improve its performance.

2.2. Radial Basis Function Neural Networks

Radial Basis Function (RBF) Neural Networks are a special type of artificial neural network used especially in problems such as function approximation, classification and time series forecasting. RBF neural networks use radial basis functions to model the relationship between inputs and outputs (Shin, 1994; Sekeroğlu and Tuncal, 2021). These networks usually consist of three layers: an input layer, a hidden layer and an output layer.

The input layer contains a node for each independent variable in the data set. Each node has a radial basis function, which is calculated based on the distance between the input vector and the center of the node. The most commonly used radial basis function is the Gaussian function. The output layer produces the final output by summing the outputs from each node in the hidden layer and performing a weighted sum (Shin, 1994).

The basic idea of RBF neural networks is to calculate the "distance" of the input vector from the center of each hidden layer node and use these distances to generate outputs. For each node i in the hidden layer, the distance d between the input vector x and the center c_i of the node is calculated using a distance measure (usually Euclidean distance) and the radial basis function RBF is applied. This process is shown in Equation (6).

$$d_i = \sqrt{\sum_j \left(x_j - c_{ij}\right)^2} \tag{6}$$

where, x_j is the j-th element of the input vector and c_{ij} is the j-th element of the center of the i-th hidden node. This distance is then applied to the RBF as shown in Equation (7):

$$RBF(d_i) = e^{-(\epsilon d_i)^2} \tag{7}$$

where, ϵ is a parameter that controls the width of the radial basis function.

The output layer collects activations from all nodes in the hidden layer and performs a weighted summation to produce the final output as shown in Equation (8):

$$y_k = \sum_i w_{ik} RBF(d_i) \tag{8}$$

RBF neural networks are particularly effective at modeling data distributions concentrated around specific points in space. These networks can generate complex boundaries and are often a suitable option for small to medium-sized data sets. The centers and weights in the hidden layer are usually determined by an optimization process

3. Application and Analysis Results

Table 2 presents a selection from the dataset of variables used in this study, showcasing the key metrics that form the basis of our analysis. The dataset includes various time series data points for each variable, illustrating their fluctuations over the study period. By examining these variables, we gain insights into the trends and patterns that influence the import values of paper and paper products in Türkiye. This detailed view is essential for understanding the dynamics at play and for constructing accurate predictive models. The comprehensive dataset covers crucial factors such as the monthly average US Dollar exchange rate, monthly imports and exports, the Manufacturing Industry Production Index, and the Paper Production Index, among others.

Table 2. Part of the dataset of variables used in the study

Periods	Monthly Average US Dollar Rate	Türkiye Imports (USD)	Manufacturing Industry Production Index (2015=100)	Paper Production Index (2015=100)	Paper Exports (USD)	Paper Imports (USD)
2005-1	1,3565	7.219.679.862	59,8	49,3	38.543.074	123.117.690
2005-2	1,3165	8.323.736.797	56,8	46,2	42.496.145	141.639.789
2005-3	1,3113	10.196.352.932	56,4	43,4	48.958.921	159.723.247
2005-4	1,3600	9.595.500.303	57,1	43,4	48.788.415	152.322.488
2005-5	1,3716	9.811.620.456	57,6	44,7	47.324.332	155.592.831
2005-6	1,3612	9.947.498.949	57,6	44,1	52.900.000	157.326.713
...	...	...	...	...	...	...
...	...	...	...	...	...	...
...	...	...	...	...	...	...
2022-10	18,5981	27.497.799.701	146,4	140,1	228.756.285	253.752.877
2022-11	18,6244	28.297.921.962	144,9	137,5	240.685.738	255.542.629
2022-12	18,6705	30.749.482.171	147,5	130,1	244.730.913	296.296.140
2023-1	18,7914	31.842.537.023	150,8	129,8	211.216.260	276.023.272
2023-2	18,8572	28.899.809.811	141,1	127,9	192.793.709	237.362.699
2023-3	19,0035	30.317.789.375	149,7	130,1	238.474.411	285.550.529

Table 3 shows the process summary of the Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) models. Both models used 153 training and 66 test datasets. The percentages were 69.9% for the training set and 30.1% for the test set.

Table 3. Summary of the Artificial Neural Network Model Developed

	Number of Datasets	Percent
Training	153	% 69,9
Test	66	% 30,1
Total	219	% 100

Table 4 shows the details of the designed MLP model. Table 4 shows the details of the input layer, hidden layer and output layer. The input layer contains the independent variables of the model. There are six independent variables in the input layer. In the MLP model, information is processed between hidden layers and learning takes place. Two hidden layers are used. The number of units in the first hidden layer is 8 and the number of units in the second hidden layer is 6. Hyperbolic Tangent (tanh) is used as the hidden layer activation function. Sum of Error Squares was used as the error function. Hyperbolic Tangent was preferred as the hidden layer activation function.

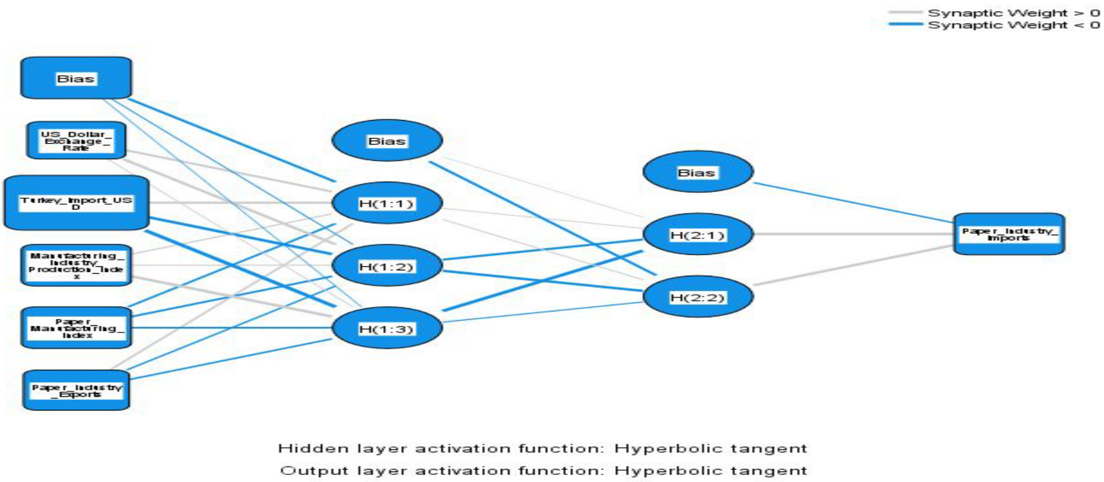
Table 4. Structure of the Designed MLP Model

Input Layer	**Independent Variables**	Monthly Average Dollar Rate Türkiye Imports Manufacturing Industry Production Index (2015=100) Paper Production Index (2015=100) Paper Exports	
	Number of Variables		5
	Rescaling	Normalize	
Hidden Layer	**Number of Hidden Layer**		2
	Number of Units in Hidden Layer[a]		8
	Number of Units in the Hidden Layer[a]		6
	Activation Function	Hyperbolic Tangent	
Output Layer	**Dependent Variable**		1
	Number of Output Layer Units		1
	Rescaling Method	Normalize	
	Activation Function	Hyperbolic Tangent	
	Error Function	Sum of Squares of Error	

a. Except for the bias uni

Figure 1 shows the architecture and layers of the designed MLP model. The input layer receives the input data to the model and passes it to the hidden layers. Each hidden layer uses activation functions to process the input data and learn different attributes. More hidden layers allow the model to learn more complex relationships. The output layer produces the final prediction results. The activation function used in this layer is used to calculate the output values. The hyperbolic tangent function is used as the output layer activation function. Bias units are extra units added to the hidden units in each layer and represent an additional parameter that affects the learning process of the model.

Figure 1. Architecture and Layers of the Designed MLP Model



Each layer in the MLP model has weights and bias values. These values are optimised during the learning process of the model to ensure the best fit to the input data. However, Figure 2 shows the architecture and layers of the designed RBF model. Due to its structure, the RBF model can contain at most one hidden layer. The RBF model is a machine learning method that gives successful results in many applications. The hidden layer contains radial basis functions that are characteristic of the RBF model. This layer transforms the input data into a series of basis functions. Each RBF has a central point and a domain. These functions measure the distances between the input data and the centres and calculate their outputs.

Figure 2. Architecture and Layers of the Designed RBF Model

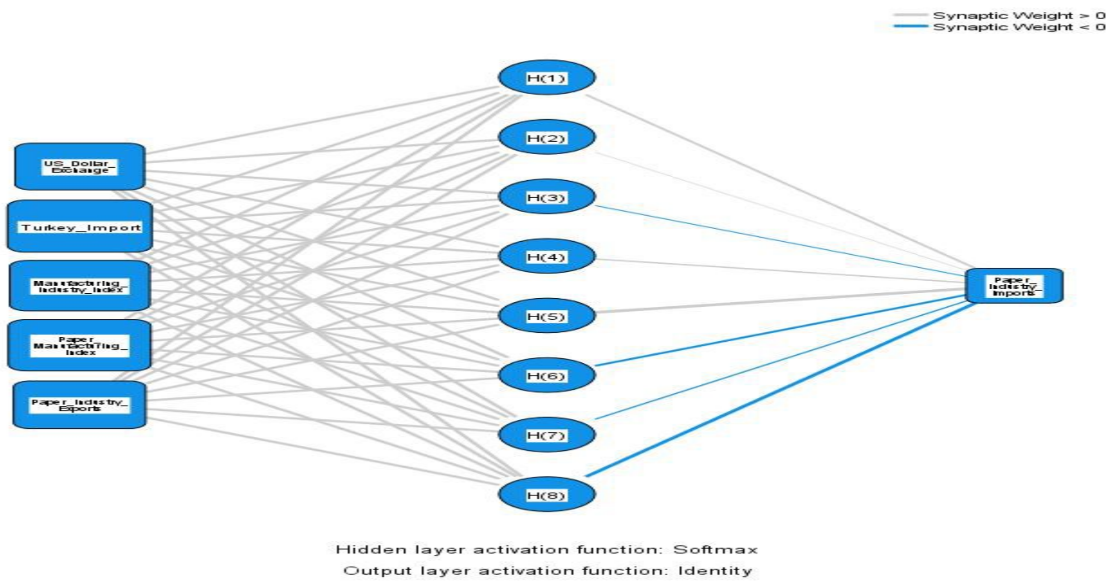


Table 5 shows the performance measures of the ANN model in the training and testing phases. Performance measures are metrics used to evaluate the success of the model in the training and testing phases. Lower error values indicate that the model provides a better fit and the predictions are closer to the actual values.

Table 5. Model Summaries

Statistical Errors		**MLP**	**RBF**
Training Phase	Error Sum of Squares	1,982	22,008
	Relative Error	0,26	0,29
Test Phase	Error Sum of Squares	0,895	8,615
	Relative Error	0,218	0,21

In the training and testing phase, the Sum of Error Squares is a statistic used to measure the performance of a prediction model. Here, the difference between actual values and predicted values is measured. A lower value of the Sum of Squares indicates that the model predicts the training and test data better. The SES measures how close the model's predictions are to the true values, but it is not the only metric used to determine how well a model can generalise (i.e. how well it will perform on new data). Other measures include Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and R^2.

The sum of squared errors of the MLP model is 1.982 in the training phase and 0.895 in the testing phase. The relative error value in the MLP model was 0.26 in the training phase and 0.218 in the test phase. In the RBF model, the sum of error squares value is 22.008 in the training phase and 8.615 in the test phase. In the RBF model, the relative error value was

0.29 in the training phase and 0.21 in the test phase. In both models, there is a decrease in both error values. The models were successful in both training and testing phases. Low error values indicate that the predictions of the models are accurate and consistent.

Table 6 shows the contribution of each variable to the performance of the ANN models by presenting the ranking and normalized importance of the independent variables in the model. The measures show the impact of each independent variable on the model. The monthly import value of Türkiye has the highest importance in both models. The US dollar exchange rate is the least important independent variable in both models.

Table 6. Importance of Independent Variables

	MLP Model		RBF Model	
Independent Variables	**Importance**	**Normalized Importance**	**Importance**	**Normalized Importance**
US Dollar Exchange Rate	0,053	%16	0,188	%84,3
Monthly Türkiye Imports	0,332	%100	0,223	%100
Manufacturing Industry Production Index	0,236	%71,1	0,200	%89,7
Paper Production Index	0,236	%71,2	0,197	%88,4
Paper Exports	0,143	%43	0,192	%86,2

Statistical errors of ANN models are shown in Table 7. These statistics present the metrics used to evaluate the performance of the ANN model. The closer the absolute value of the correlation coefficient is to 1, the stronger the relationship between the estimates and the actual values. In other words, the closer a model's correlation coefficient is to 1, the better the model's performance (Zhang, 2003, p.160). However, the Regression value expresses the percentage of the total variance in the dependent variable explained by the independent variables. The regression value ranges from 0 to 1, where 1 denotes a perfect fit where the independent variables fully explain the variance of the dependent variable. On the other hand, 0 indicates that the independent variables of the model have no effect on the dependent variable. Therefore, in evaluating the performance of the ANN model, the higher the regression value, the better the performance of the model (Riedmiller ve Braun, 1993, p.87). Also, the MAPE value represents the percentage of errors, so values are usually expressed as percentages. A MAPE value of 0 indicates that a model can make excellent predictions (that is, no prediction errors). Larger MAPE values indicate larger estimation errors (Hyndman ve Koehler, 2006, p.680). In addition, prediction models with MAPE error values less than 10% are considered as "high accuracy" prediction models (Looney, 1996, p.212; Siami Irdemosa ve Dindarloo, 2015, p.78; Esidir et al., 2022, p.70). When Table 7 is examined, the Correlation, Regression and MAPE values show that the models make estimations consistent with the real values. In both models, the MAPE error value is less than 10% and is around 8%.

Table 7. Statistical Errors of ANN Models

	MLP Model	**RBF Model**
Correlation	0,87	0,86
Regression	0,756	0,74
MSE	139.323.941.138.250	29.989.048.501.615
MAPE	0,081	0,082
Number of Datasets	219	219

The next step was to forecast the future of the paper and paper products sector. The values of the independent variables for the months of April 2023 and March 2024 were estimated using various ARIMA models from time series analysis models. The ARIMA (0,1,1)(0,0,0) model was used for the monthly average US dollar exchange rate forecasting process and the ARIMA (0,1,1)(1,0,0) model was used for the monthly imports of Türkiye. ARIMA (0,1,0)(1,0,1) model is used for manufacturing production index (2015=100), ARIMA (0,1,1)(1,0,1) model is used for paper production index (2015=100) and ARIMA (0,1,1)(0,0,1) model is used for exports of paper and paper products. Table 8 shows the statistical errors of the independent variables.

In the ARIMA model, the values in the time series are modelled over past values and the forecasting process is performed for future periods. Any series to be analysed can be analysed with SPSS software, whether it is stationary or not, whether it contains seasonal elements or not. By using the Expert Modeler in SPSS software, the data set relating to the independent variables of our research was made stationary.

Table 8. Statistical Errors of Independent Variables

Statistical Errors	Average Dollar Rate	Monthly Türkiye Imports	Manufacturing Industry Production Index	Paper Production Index	Paper and Paper Products Exports
R^2	0,999	0,893	0,996	0,992	0,937
RMSE	0,148	1.588.060.821	1,666	2,893	12.478.803
MAPE	2,096	7	1,335	2,335	7,325
MaxAPE	8,053	44,592	5,786	12,762	69,729
Normalize BIC	-3,577	42,569	1,441	2,322	33,148

MAPE expresses estimation errors as a percentage and is meaningful in its own right. For this reason, it is more widely accepted in analytical studies than other methods. Forecasting models with MAPE error values below 10% are considered as "high accuracy" forecasting models (Eşidir et al., 2022, p.274). As can be seen in Table 8, the MAPE value is less than 10% for all independent variables. Again, the R^2 values are very close to 1.

Table 9 shows the results of Türkiye's monthly import forecasts for paper and paper products. According to the forecasts for the coming periods, monthly imports of paper and paper products are expected to be around 270 to 302 million USD according to the MLP model. In the RBF model, the forecast values vary between USD 268 and 321 million.

Table 9. Monthly Import Value Estimation Results

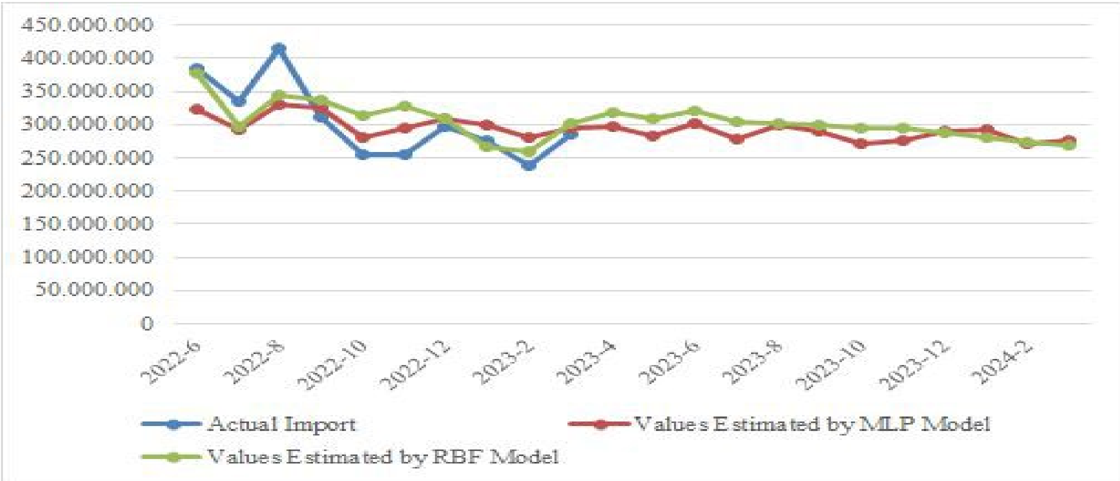
Period	Actual Imports	Values Estimated with MLP Model	Values Estimated with RBF Model
2022-6	384.259.006	323.532.397	377.033.153
2022-7	335.310.724	293.241.595	297.682.613
2022-8	414.749.437	329.627.053	344.247.891
2022-9	311.043.012	325.732.824	337.325.878
2022-10	253.752.877	281.065.726	312.626.293
2022-11	255.542.629	295.258.388	328.148.645
2022-12	296.296.140	308.128.421	308.663.676
2023-1	276.023.272	300.050.239	266.899.531
2023-2	237.362.699	280.989.481	259.851.385
2023-3	285.550.529	294.479.929	301.188.127
2023-4		296.352.956	317.585.109
2023-5		284.195.436	308.193.055
2023-6		301.747.562	321.415.662
2023-7		278.757.714	304.899.298
2023-8		299.590.862	301.872.659
2023-9		290.869.349	298.821.632
2023-10		270.561.579	295.704.948
2023-11		275.352.263	295.119.682

Table 9. Monthly Import Value Estimation Results (cont'd)

2023-12	290.436.325	288.172.648
2024-1	293.193.865	280.170.037
2024-2	270.136.404	274.724.557
2024-3	275.170.679	268.196.968

Figure 3 shows the results of the monthly import forecast in graphical form. According to the analysis, monthly imports of paper and paper products are estimated to be around USD 300 million. The graphical representation of the forecast results shows more clearly the change and trend in the forecast over time.

Figure 3. Monthly Import Forecast Results for Paper and Paper Products



Conclusion and Evaluation

The paper sector is used in the forest products industry and the recovered paper sector in the production process and in many sectors, especially in the printing, publishing and packaging sectors, as an input to the product. While the recovery rate of paper in Europe is around 70-75%, the rate in T ürkiye is 40-45%. In Türkiye, paper imports have also increased rapidly in line with the rapid growth in paper consumption since 2002. About half of the paper consumption is imported. The main problem of the paper sector is that the country is completely dependent on foreign sources for cellulose/pulp, which is the main raw material of the paper sector. High energy prices and the cost of financing investments also have a negative impact on the development of the sector.

The prediction results were obtained by considering the data used and the performance of the model. In the MLP model, hyperbolic tangent is used as the activation function in the hidden and output layers. In the MLP model, the first hidden layer contains 8 units and the second hidden layer contains 6 units. The RBF model contains a single hidden layer due to its structure and the hidden layer of the RBF model contains 7 units. The MAPE error value in the MLP model is 08.1% and the MAPE error value in the RFB model is 08.2% and the values are quite low.

Based on the results of the analysis, it is important to present some theoretical conclusions, implications and policy recommendations for the development of the sector. Artificial neural networks have shown significant success in predicting import values of paper and paper products. This demonstrates the capacity of neural networks to make accurate and reliable predictions when working with complex economic data sets. The analysis shows that Türkiye's monthly import values are affected by independent variables such as the dollar exchange rate, Türkiye's total imports, manufacturing industry production index, paper production index and paper export values. The importance of each of these variables in the model plays a critical role in understanding sectoral dynamics. Import forecasts obtained using artificial neural networks provide valuable information for economic planning and policy-making processes. These forecasts are an important source for understanding the future needs of the sector and developing appropriate strategies.

However, given the fact that the paper and paper products sector is a major importer, investments should be made in localization strategies for raw material procurement. Incentives and R&D support can be offered to source pulp and paper raw materials locally. On the other hand, high energy costs negatively affect the competitiveness of the sector. Policies promoting energy efficiency and the use of renewable energy sources can help reduce costs and increase sustainability. The results of the analysis show that paper exports have a significant impact on imports. Therefore, policies to increase the export capacity of the sector (e.g. export credits, tax reductions) should be developed. In addition, waste paper recycling can reduce imports by reducing the need for raw materials. Incentives and awareness campaigns to increase recycling rates are important.

Türkiye's strategic location offers a significant advantage for the paper and paper products sector. This advantage should be exploited by facilitating international cooperation and access to new markets. Moreover, foreign trade policies should be adjusted to support exports and make imports more efficient. Environmental sustainability is becoming increasingly important for the paper and paper products sector. Therefore, environmentally sound production techniques should be encouraged and waste management and recycling activities should be supported.

The results of the study showed that MLP and RBF models are effective tools that can be used in import forecasting of the sector. There are numerous studies in the literature that have successfully used artificial neural networks in various economic and financial forecasts. The findings of this study are in line with the results of studies such as Khashei and Bijari (2010), Wang et al. (2018) and Kumar and Thenmozhi (2006). These studies have shown that artificial neural networks can provide more accurate results in time series forecasting than traditional models. In particular, forecasting imports in the paper and paper products sector can be an important tool for inventory management, production planning and the development of market strategies.

Although there are studies in the literature showing the effectiveness of ANN in economic and financial forecasting, this study fills an important gap by focusing specifically on import forecasting in the paper and paper products sector. This specialization aims to obtain more accurate and applicable forecasts by taking into account the specific needs and dynamics of the sector.

This study has made significant contributions in terms of sectoral focus, model comparison and practical applications. By focusing on a specific sector such as the paper and paper products sector, the development and application of modeling techniques appropriate to the specific needs of this field has been realized. On the other hand, the comparison of two different ANN models, namely MLP and RBF, has demonstrated their effectiveness and suitability for import forecasting in the paper and paper products sector. Moreover, the obtained forecasts provide practical applications that can help firms in the sector to make more informed decisions in areas such as inventory management, production planning and marketing strategies.

However, the scope of the data set and exogenous factors constitute the limitations of this study. The data set of the study covers a specific time period. Future economic fluctuations or sectoral changes may affect the forecasting success of the model. The study has considered certain independent variables, but other potential exogenous factors that have an impact on the sector may have been overlooked.

In future studies, the robustness of the model can be tested using larger data sets that include different time periods and economic conditions. In addition to artificial neural networks, other machine learning algorithms such as decision trees, support vector machines and deep learning techniques can also be tested in sectoral forecasts. In addition, exogenous factors such as macroeconomic indicators, global supply chain changes and policy changes that may have an impact on the sector can also be taken into account in the development of the model. Furthermore, comparing the findings of this study with studies conducted in similar sectors or in other countries can provide deeper insights into the universal applicability and effectiveness of the model.

In summary, the results of import forecasting for paper and paper products will help companies in the sector to make informed decisions in areas such as inventory management, production planning and marketing strategies. Sectoral import forecasts are useful for companies operating in the sector to increase their competitiveness and take a more effective place in the international market. The results of the study can be used in the economic planning and policy-making processes of the sector and can help to accurately estimate import volumes and values.

References

Akyüz, K. C., Yildirim, İ., Akyüz, İ., & Tugay, T. (2017). Investigation of Financial Performance of Companies in the Sector of Paper and Paper Products Operating in Borsa İstanbul, 4. Uluslarrası Mobilya ve Dekorasyon Kongresi, 2017. Retrieved from: https://avesis.ktu.edu.tr/yayin/0c6abce5-71ac-4340-aee6-97b57f8a3299/investigation-of-financial-performance-of-companies-in-the-sector-of-paper-and-paper-products-operating-in-borsa-istanbul

Anderton, B. (1999). Innovation, product quality, variety, and trade performance: an empirical analysis of Germany and the UK. *Oxford Economic Papers, 51*(1), 152-167. https://doi.org/10.1093/oep/51.1.152

Barrow, D. K. & Kourentzes, N. (2016). Distributions of forecasting errors of forecast combinations: implications for inventory management. *International Journal of Production Economics,* 177, 24-33. https://doi.org/10.1016/j.ijpe.2016.03.017

Buhmann, M. D. (2000). Radial basis functions. *Acta numerica,* 9, 1-38. https://doi.org/10.1017/S0962492900000015

Central Bank of the Republic of Türkiye Electronic Data Distribution System (CBRT-EVDS), https://evds2.tcmb.gov.tr/index.php?/evds/serieMarket Access Date: 27.06.2023.

Crespo, N., & Fontoura, M. P. (2007). Determinant factors of FDI spillovers–what do we really know?. *World development, 35*(3), 410-425. https://doi.org/10.1016/j.worlddev.2006.04.001

Dumor, K., & Yao, L. (2019). Estimating china's trade with its partner countries within the belt and road initiative using neural network analysis. *Sustainability, 11*(5), 1449. https://doi.org/10.3390/su11051449

Egrioğlu, E., & Bas, E. (2023). A new deep neural network for forecasting: deep dendritic artificial neural network. https://doi.org/10.21203/rs.3.rs-2913556/v1

Eşidir, K. A. , Gür, Y. E. , Yoğunlu, V. & Çubuk, M. (2022). Forecasting of Monthly Zero km Car Sales in Turkey with Artificial Neural Networks (ANN) and ARIMA Models. *Pamukkale University Journal of Business Research, 9*(2) , 260-277. https://doi.org/10.47097/piar.1132101

Faraji, J., Ketabi, A., Hashemi-Dezaki, H., Shafie-khah, M., & Catalão, J. P. (2020). Optimal day-ahead scheduling and operation of the prosumer by considering corrective actions based on very short-term load forecasting. IEEE Access, 8, 83561-83582. https://doi.org/10.1109/access.2020.2991482

General Directorate of Industry, (2022). Paper Sector Report 2021, T.C. Ministry of Industry and Technology, pp. 7-23.

Goldberg, P. K., & Knetter, M. M. (1996). Goods prices and exchange rates: What have we learned?, *Journal of Economic literature, 35*(3),1-42. https://doi.org/10.3386/w5862

Grossman, G. M., & Helpman, E. (1995). Trade wars and trade talks. *Journal of political Economy, 103*(4), 675-708. https://doi.org/10.1086/261999

Gujarati, D. N. (2003). Basic Econometrics, McGraw Hill, Newyork

Hagan, M. T., Demuth, H. B., & Beale, M. (1997). Neural network design. PWS Publishing Co.

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. International journal of forecasting, 22(4), 679-688. https://doi.org/10.1016/j.ijforecast.2006.03.001

Karadeniz, E., Iskenderoglu, Ö., & Cemile, Ö. (2021). Scale-Based Analysis of the Financial Performance of the Paper and Paper Products Manufacturing Sector: A Study on the Sector Balance Sheets of the Central Bank of the Republic of Turkey. *Journal of Bartın Faculty of Forestry, 23*(1), 160-171. https://doi.org/10.24011/barofd.891992

Khashei, M., & Bijari, M. (2010). An artificial neural network (p, d, q) model for timeseries forecasting. *Expert Systems with Applications, 37*(1), 479-489. https://doi.org/10.1016/j.eswa.2009.05.044

Kilimci, Z. H., Akyuz, A. O., Akyokuş, S., Uysal, M., Bülbül, B. A., & Ekmis, M. A. (2019). An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. *Complexity,* 1-15. https://doi.org/10.1155/2019/9067367

Kmiecik, M. (2023). Supporting of manufacturer's demand plans as an element of logistics coordination in the distribution network. *Production Engineering Archives, 29*(1), 69-82. https://doi.org/10.30657/pea.2023.29.9

Kuan, C. M., & Liu, T. (1995). Forecasting exchange rates using feedforward and recurrent neural networks. *Journal of Applied Econometrics, 10*(4), 347-364. https://doi.org/10.1002/jae.3950100403

Kumar, R.R., Thenmozhi, M. (2006). Forecasting Stock Index Movement: A Comparison of Support Vector Machines and Random Forest. 9th Capital Markets Conference, Indian Institute of Capital Markets Paper. http://dx.doi.org/10.2139/ssrn.876544

Kurniawan, I., Silaban, L. S., & Munandar, D. (2020). Implementation of convolutional neural network and multilayer perceptron in predicting air temperature in padang. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi), 4*(6). https://doi.org/10.29207/resti.v4i6.2456

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy, 74*(2), 132-157. https://doi.org/10.1086/259131

Looney, C. G. (1996). Advances in feedforward neural networks: demystifying knowledge acquiring black boxes. IEEE Transactions on Knowledge and Data Engineering, *8*(2), 211-226. https://doi.org/10.1109/69.494162

Mai, W., Chung, C. Y., Wu, T., & Wong, W. C. (2014, July). Electric load forecasting for large office building based on radial basis function neural network. In 2014 IEEE PES General Meeting| Conference & Exposition (pp. 1-5). IEEE. 1 https://doi.org/0.1109/PESGM.2014.6939378

Momeneh, S. & Nourani, V. (2022). Forecasting of groundwater level fluctuations using a hybrid of multi-discrete wavelet transforms with artificial intelligence models. *Hydrology Research, 53*(6), 914-944. https://doi.org/10.2166/nh.2022.035

Muhamad, S., Sofean, S. H., Moktar, B., & Shahidan, W. N. W. (2021). Fuzzy time series and artificial neural network: forecasting exportation of natural rubber in malaysia. *Journal of Computing Research and Innovation, 6*(1), 22-30. https://doi.org/10.24191/jcrinn.v6i1.170

Pala, T. & Camurcu, A. Y. (2016). Design of decision support system in the metastatic colorectal cancer data set and its application. *Balkan Journal of Electrical and Computer Engineering, 4*(1). https://doi.org/10.17694/bajece.23930

Prechelt, L. (1998). Early Stopping - But When? In G. Orr and K.-R. Müller (Eds.), Neural Networks: Tricks of the Trade. Springer. https://doi.org/10.1007/978-3-642-35289-8

Refenes, A. P., Zapranis, A., & Francis, G. (1994). Stock performance modeling using neural networks: a comparative study with regression models. *Neural Networks, 7*(2), 375-388. https://doi.org/10.1016/0893-6080(94)90030-2

Riedmiller, M., & Braun, H. (1993). A direct adaptive method for faster backpropagation learning: the RPROP algorithm. In IEEE International Conference on Neural Networks (pp. 586-591). IEEE. https://doi.org/10.1109/ICNN.1993.298623

Safa, B., Arkebauer, T. J., Zhu, Q., Suyker, A., & Irmak, S. (2021). Gap filling of net ecosystem co₂ exchange (nee) above rain-fed maize using artificial neural networks (anns). *Journal of Software Engineering and Applications, 14*(05), 150-171. https://doi.org/10.4236/jsea.2021.145010

Sanders, N. R. & Ritzman, L. P. (2004). Using warehouse workforce flexibility to offset forecast errors. *Journal of Business Logistics, 25*(2), 251-269. https://doi.org/10.1002/j.2158-1592.2004.tb00189.x

Sekeroglu, B. and Tuncal, K. (2021). Prediction of cancer incidence rates for the european continent using machine learning models. *Health Informatics Journal, 27*(1), 146045822098387. https://doi.org/10.1177/1460458220983878

Shin, Y. C. (1994). Radial basis function neural network for approximation and estimation of nonlinear stochastic dynamic systems. *IEEE Transactions on Neural Networks, 5*(4), 594-603. https://doi.org/10.1109/72.298229

Siami-Irdemoosa, E., & Dindarloo, S. R. (2015). Prediction of fuel consumption of mining dump trucks: A neural networks approach. *Applied Energy,* 151, 77-84. https://doi.org/10.1016/j.apenergy.2015.04.064

Towfiqul, A. R. M., Pal, S. C., Chakrabortty, R., Mallick, J., Sarkar, S. K., Fattah, M. A., … & Rahman, M. S. (2022). Multilayer perception and radial basis function models for predicting trends of rainfall in asian megacity Dhaka,Bangladesh.. https://doi.org/10.21203/rs.3.rs-1720286/v1

Turkish Statistical Institute (TurkStat), (2023). Retrieved from: www.tuik.gov.tr. Access Date: 05.06.2023

Wang, Y., Ni, X. S., & Stone, B. (2018). A two-stage hybrid model by using artificial neural networks as feature construction algorithms. https://doi.org/10.48550/arXiv.1812.02546

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50, 159-175. https://doi.org/10.1016/S0925-2312(01)00702-0

Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks:: The state of the art. *International Journal of Forecasting, 14*(1), 35-62. https://doi.org/10.1016/S0169-2070(97)00044-7