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Research Article

Comparison of estimation methods in univariate estimation: The Turkish cement industry case

Tek değişkenli tahminde tahmin yöntemlerinin karşılaştırılması: Türkiye çimento endüstrisi örneği

Selim Tüzüntürk[1]

Fatma Sert Eteman[2]

[1] Associate Professor, Bursa Uludağ University, Bursa, Türkiye, selimtuzunturk@uludag.edu.tr

ORCID: 0000-0002-8987-2280

[2] Assistant Professor, Munzur University, Tunceli, Türkiye, fatmasert@munzur.edu.tr

ORCID: 0000-0002-7372-4224

Corresponding Author:

Selim Tüzüntürk,

Bursa Uludağ University, Bursa, Türkiye,

selimtuzunturk@uludag.edu.tr

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Abstract

This study aims to develop a method for forecasting cement production in the Turkish cement manufacturing industry and to draw conclusions about future production development by applying it. The data used in this study is the total monthly cement production of the Turkish cement industry. The data consists of 93 months, from January 2017 to September 2024. Artificial neural network modelling procedures were applied to the model, and forecasting was performed using deep learning tools. The estimation's performance was quite good, and it was concluded that the network could be generalised. The results showed that the model developed can forecast monthly production, with threshold values and weights obtained from the trained network. Monthly cement forecasts were issued through December 2026. The success of modelling univariate time series data with ANNs was validated by comparing it with Winters' and SARIMA methods using MAPE statistics. The most suitable forecasting method was found to be ANNs, and the findings were discussed.

Keywords: Cement Production, Artificial Neural Networks, Winters' Model, ARIMA, Forecasting

Jel Codes: C45, C53, E23

Öz

Bu çalışma, Türk çimento imalat sanayinde çimento üretimini tahmin etmek için bir yöntem bulmayı ve bu yöntemle çimento üretimini tahmin ederek gelecekteki üretim gelişimi hakkında bazı sonuçlar çıkarmayı amaçlamaktadır. Bu çalışmada kullanılan veri, Türk çimento sanayinin toplam aylık çimento üretimidir. Veriler, Ocak 2017'den Eylül 2024'e kadar 93 ayı kapsamaktadır. Oluşturulan modele yapay sinir ağı modelleme prosedürleri uygulanmış ve derin öğrenme araçları yardımıyla tahmin yapılmıştır. Tahminlerin performansı oldukça iyi olup, ağın genelleştirilebilir olduğu sonucuna varılmıştır. Sonuçlar, eğitilen ağdan elde edilen eşik değerleri ve ağırlıklar kullanılarak geliştirilen model ile aylık üretimlerin tahmin edilebileceğini göstermiştir. Aylık çimento tahminleri Aralık 2026'ya kadar yapılmıştır. Tek değişkenli zaman serisi verilerinin YSA'lar ile modellenmesinin başarısı, MAPE istatistikleri kullanılarak Winters ve SARIMA yöntemleri ile karşılaştırılarak doğrulanmıştır. En uygun tahmin yönteminin YSA olduğu bulunmuş ve bulgular tartışılmıştır.

Anahtar Kelimeler: Çimento Üretimi, Yapay Sinir Ağları, Winters Modeli, ARIMA, Tahmin

JEL Kodları: C45, C53, E23

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Introduction

Cement was defined in the Longman dictionary as a grey powder made from lime and clay. It becomes hard when mixed with water, allowed to dry, and used in buildings. The primary use of cement is to produce concrete (Supino, Malandrino, Testa and Sica, 2016). It is a key ingredient in concrete, a mixture of cement, water, aggregates, and a few ingredients called admixtures (Cembureau, 2016). Cement has various economic properties. The cement industry is capital-intensive, energy-consuming, and vital for sustaining nations' infrastructure (Selim and Salem, 2010). Economies of scale are essential in production (Norman, 1979; McBride, 1981). Given high investment costs, the market is oligopolistic, with few producers in each consumption region (d'Aspremont, Encaoua, and Ponssard, 2000; Walton, 2009). In addition to being difficult to substitute for as a building material, the price elasticity of cement demand is low because of its small share in construction costs (Kulaksızoğlu, 2004). The demand for cement is considered price-inelastic due to the lack of apparent substitutes (Selim and Salem, 2010). Cement is a heavy product but light in price. Its transportation costs are high relative to the product's unit value. For this reason, most of the cement is sold near the production facilities and meets local consumption. Most of the production is locally consumed. A good chunk of the cement produced is exported (Selim and Salem, 2010). Exported cement is transported long distances by land or sea (Imbabi, Carrigan and McKenna, 2012).

While the number of cement facilities in developed countries is generally decreasing, it is increasing in developing countries (Supino et al., 2016). Efforts to protect the environment in developed countries – especially in Europe – have led to the relocation of cement production plants to countries with weaker environmental regulations (Selim and Salem 2010). The world's cement industry is a significant source of carbon emissions (Supino et al., 2016). This industry is a heavy polluter (Rodrigues and Joekes, 2011). The issue of pollution is beyond the scope of this study. However, there is a broad literature, and studies by Poudyal and Adhikari (2021) and Bekun, Alola, Gyamfi, Kwakwa, and Uzuner (2023) are recent examples. The European cement industry is trying to minimise its carbon footprint by taking precautions through regulations. Beyond these regulations, innovative efforts in cement production are also underway worldwide. Carbon emissions are being reduced using cheaper materials.

Developed countries have steady levels of cement demand. In contrast, developing countries need the cement industry more (Fışkın and Cerit, 2019). Developing countries have more infrastructure, buildings, and construction needs. In countries like China and India (and undoubtedly many others), parts of the population lack adequate housing or basic services, such as electricity and treated water (Rodrigues and Joekes, 2011). From Türkiye's domestic demand perspective, much cement is produced in Türkiye. Türkiye is focused on construction, so the demand for cement increases, especially during election periods. During election periods, municipalities and public institutions begin construction, which increases demand for cement. Again, after significant earthquakes (for example, the 17 August 1999 Gölcük earthquake, which caused 17,480 deaths, or the 6 February 2023 Kahramanmaraş earthquake, which caused 45,784 deaths), cement demand in Türkiye increased. Consequently, cement is vital for meeting basic human needs for water and air when constructing new buildings and rebuilding structures.

Cement and concrete have been used to build durable structures for quite some time (Cembureau, 2023). A house, a school, a hospital, a road, a highway, a bridge, a tunnel, a wind farm, a hydroelectric dam, a port, energy transport and distribution, a wastewater collection pipe, a shopping mall, a skyscraper, and many other types of constructions are made up of cement products. In addition, cement is a vital building material in renovating old buildings and urban transformation in countries located in high-risk earthquake zones, such as Türkiye, to take precautions against earthquakes. Cement is the second most consumed product in the world after water (Imbabi et al., 2012; Schlorke, Tu, Stec, Mallagray and Kaleem, 2020). The world consumes over 4 billion tons of cement annually (Schlorke et al., 2020). Cement production increases with high urbanisation to meet the ever-increasing demand worldwide. In 1900, the total world production of cement was about 10 million tons; in 1998, it was 1.6 billion tons (Aitcin, 2000). The European Cement Association (Cembureau) reported in 2023 that global cement production in 2022 totalled 4.1 billion tons. The same report states that China is the leading producer in this sector, accounting for 51.6% of the total output. Cement production amounts of the world's five leading cement producers in different years are shown in Table 1 below.

Table 1: Productions of the Top Five Cement Producers of the World (Million Tons)

Country	2001	2005	2010	2015	2016	2017	2018	2019	2020	2021	2022
1. China	661.0	1,079.6	1,881.9	2,350.0	2,403.0	2,316.3	2,176.7	2,300.0	2,376.9	2,362.8	2,118.0
2. India	102.9	146.8	220.0	270.0	289.3	285.0	327.7	320.0	290.0	351.6	387.6
3. USA	88.9	99.4	65.2	83.4	84.7	86.1	87.8	88.6	89.3	93.0	93.0
4. Türkiye	35.9	42.8	62.7	71.4	75.4	80.6	72.5	57.0	72.3	78.9	73.7
5. Brazil	39.4	39.2	59.1	72.0	57.6	54.0	53.5	53.4	61.1	65.9	63.6

Source: Cembureau 2023 activity report.

Table 1 shows that the world ranking in cement production has not changed over the years. The ranking is: First China, second India, third USA, fourth Türkiye, and fifth Brazil.

However, 2023 statistics show Vietnam is among the top 5 largest producers. Cement production statistics for 2023 showed that China is again seen on the top of the list with 2,100 million tons of output, India is again seen in second place with 410 million tons of production, Vietnam is in third place with 110 million tons of output, USA is in fourth place with 91 million tons of production, and Türkiye is in the fifth place with 79 million tons of output (World Population Review, 2023).

Türkiye is among the top five producers in the world and also meets a significant part of the cement demand of the European Union (EU) countries. Cembureau's 2023 and 2024 cement trade reports show that Türkiye met 43.7% of the EU's cement and clinker needs in 2022, 35.8% in 2023, and 41.7% through June 2024. According to these statistics, analysing Türkiye's cement production in relation to the EU's resource needs is essential. It is critical to meet both external and domestic demands. In this regard, the forecasting of its future development is interesting. The city's development significantly increases infrastructure and cement consumption (Aitcin, 2000). Due to the demand created by population growth and urbanisation, and the commercial importance of managing the needs related to this demand, forecasting future cement production is worth analysing. Some organisations, such as the World Economic Council for Sustainable Development (WSCD), have also attempted to forecast global cement production using future scenarios. Besides, these attempts to forecast production trends at the country's level are also worth analysing.

Besides its importance in infrastructure and building construction, cement is an indispensable industrial product for economic development (Uwasu, Hara and Yabar, 2014). Bildirici's (2019) study on China and the USA, and Bildirici's (2020) study on China, India, Brazil, Türkiye, and the USA, are among the studies that examine the relationship between growth and cement production. The cement industry has a sizeable economic impact due to its long and diverse supply chain. The cement sector contributes to the economy through its total production, measured by production growth (tons) and monetary value (money). Value is also added to growth with the creation of tax payments. In addition, it contributes to job opportunities (an increase in employment). Briefly, the cement industry has a multiplier effect on the economy and jobs. The construction of infrastructure, buildings, and other structures generates cash flow and new job opportunities for the economy. Money passed hand to hand spreads throughout the economy, and employment increases as new job opportunities arise. The cement industry contributes 5.4% to global gross domestic product (GDP) and 7.7% to global employment (Schlorke et al., 2020). The number of cement sector employees in 2022 was 50,980 in Cembureau and 34,975 in the EU-27 (Cembureau, 2023). In 2023, Türk Cement had 56 integrated plants, 21 grinding stations, and 12189 employees (Türk Cement, 2024). Production is closely associated with economic activities. Thus, cement production is predicted to continue to grow globally in the coming decades as world economic growth is expected (Uwasu et al., 2014). The above essential contributions of the cement industry to the economy also suggest that forecasting future production in the Turkish cement manufacturing industry is worth analysing.

In the framework outlined above, the problem is forecasting future production in the Turkish cement manufacturing industry. This study examines forecasting future Turkish cement production. How much will cement production be in Türkiye in the future? An answer to the research question is sought. Although cement production is expected to increase with future demand, the most appropriate model for production estimation will be determined by the study.

When the forecasting literature on cement is examined, a wide variety of topics emerge. For instance; forecasting cement price index (Kamaruddin, Ghani and Ramli, 2012), forecasting cement prices (Ilbeigi, Ashuri and Joukar, 2017), forecasting cement stock prices (Abbasi, Khan and Hanif, 2017), forecasting electricity consumption in the cement sector (Mendes, Costa, Silva, Coelho, VERA-Tudela and Pinto, 2023), forecasting the amount of future carbon emissions resulting from cement production (Cheng, Reiner, Yang, Cui, Meng, Shan and Guan, 2023), cement sales forecasting (Juliana, Lubis and Lubis, 2023), and cement demand forecasting (Xu, Gong and Yan, 2023; Yazdanbakhsh, 2025). On the other hand, the limited number of studies (Padhan, 2012; Tüzemen and Yıldız, 2018; Contreras-Reyes and Idrovo-Aguirre, 2020; Polat, Kervancı and Özceylan, 2024) in the literature on cement production forecasting indicates that new studies should be conducted in this field, and this gap should be filled. In two of these rare studies, Padhan (2012) and Tüzemen and Yıldız (2018) sought to identify the best model for forecasting cement production in a country. In one of them, Contreras-Reyes and Idrovo-Aguirre (2020) presented a new forecast approach. And in one of them, Polat, Kervancı, and Özceylan (2014) found a best-fit model for a factory's production forecast. Padhan (2012) examined the forecasting performance of competing models for cement production in India using monthly data from April 1993 to March 2011. Among the ARIMA and SARIMA models, SARIMA performed better, with the lowest MAPE. Tüzemen and Yıldız (2018) forecasted cement production in Türkiye for the 2000-2016 period using three smoothing methods. Researchers determined that the best model was a period-doubling moving average, depending on the accuracy measures. Contreras-Reyes and Idrovo-Aguirre (2020) used Chilean cement production data from 1991 to 2015 to address the problem of backcasting and forecasting for non-stationary data. Polat, Kervancı and Özceylan (2014) used five years of production data from a cement factory in the southeastern Anatolia region of Türkiye. The researcher found that the support vector regression model performed best across the accuracy measures.

Within the framework of the above discussions, this study aims to develop a method for forecasting cement production in the Turkish cement manufacturing industry and to draw conclusions about future production development by applying this method. Due to the data on cement's seasonality and trend significance, the three most common methods adopted are ANN, Winters', and SARIMA. Although ANN has come to the fore in discussions in the forecasting literature, in this study, the validity of the ANN method estimations has also been validated by comparing the MAPE values of alternative methods (Winters' and SARIMA methods), as is usually done in such analysis. In addition, this article aims to contribute to the forecasting literature by applying ANN modelling procedures using deep learning tools within the scope of learning behaviour and by explaining the patterns of the cement production variable. Within this framework, a sample of 93 monthly observations of Turkish cement production data, in tons, was used. ANN procedures were applied using the Deep Learning Toolbox in MATLAB. The actual data period and estimated values were compared, and then future values of the quantities were forecasted for the sample data. Then, the results were evaluated.

The rest of the paper is organised as follows: ANN and Deep Learning were explained theoretically in the next section. ANN's research results were presented afterwards. Then, the forecasting results and the ANN model validation were presented. The final section covers the conclusions.

Methods

The uncertainty of the future has motivated scientists to develop various methods to predict future values. As a result of this curiosity, scientists have found multiple methods to predict future numbers. These methods are generally divided into three parts: judgmental estimation, univariate estimation, and multivariate estimation (Chatfield, 2000). Judgmental estimation includes intuitive judgment, opinions, and subjective probability estimates. On the other hand, univariate and multivariate estimation methods include scientific approaches that follow sequential steps and procedures. While univariate estimation methods are based on a single variable's present and past values, multivariate estimation methods are based on the values of more than one variable (one dependent or more independent).

A well-known forecasting method is the univariate Box-Jenkins analysis, also known as the autoregressive integrated moving average (ARIMA) analysis (Pankratz, 1983). Univariate estimation methods are generally divided into two categories: stationary and non-stationary methods. While autoregressive (AR), moving averages (MA), and autoregressive moving averages (ARMA) models are used for stationary univariate series, ARIMA models are used for non-stationary univariate series. To predict future observation values of a variable, first determine the time series model that best represents the variable's behaviour among the available models, and then estimate future values using that model. In this analysis, the Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are used to select the model.

Multivariate estimation methods are based on functional relationships represented by $y = f(x)$ and describe the relationship between dependent and independent variables (predictors), which are modelled using multivariate regression. The multivariate linear regression model is crucial for examining relationships among variables and for forecasting (Aljandali, 2017). In these models, causal relationships are studied, and future values of the dependent variable are predicted from the independent variable values, called causal factors.

On the other hand, Artificial Neural Networks (ANNs) are methods used to solve various problems in pattern recognition, prediction/forecasting, optimisation, associative memory, and control (Jain, Mao and Mohiuddin, 1996). When Artificial Neural Networks (ANNs) are used to predict future values, the most crucial feature of the ANN method is that it learns the behaviour or pattern of the variable from past observations (Singh and Challa, 2016). The successful application of both linear and nonlinear models is another significant contribution of ANNs (Walczak and Cerpa, 2001). The two standout features of ANN modelling are learning behaviour and the ability to capture the correct pattern in the related variable. On the other hand, univariate time series models such as AR, MA, ARMA, and ARIMA are not suitable for predicting nonlinear patterns, especially in sales, demand, and production data. Instead of these, researchers prefer to adopt artificial intelligence techniques such as ANN and Adaptive Neuro Fuzzy Inference System (ANFIS), which is a kind of ANN (Singh and Challa, 2016). Several distinguishing features of ANNs, such as (i) opposed to traditional model-based methods, ANNs are data-driven self-adaptive methods in that there are few a priori assumptions about models for problems under study, (ii) ANNs can generalise, (iii) ANNs are universal functional approximators, and (iv) ANNs are nonlinear, make them valuable and attractive (Zhang, Patuwo and Hu, 1998).

ANNs

ANN is a method that simulates the cognitive learning process of the human brain. The brain learns from experience (Anderson and McNeill, 1992). The brain comprises a network of neurons (Drew and Monson, 2000). In this learning mechanism, cells called neurons have essential functions. Neurons help to remember, think, and apply previous experiences to every action (Anderson and McNeill, 1992). Neural networks (NNs) comprise basic units analogous to neurons (Abdi, 1994). An ANN consists of a set of processing elements, also known as neurons, which are interconnected, and it can be described as a directed graph in which each neuron i performs a nonlinear transfer function f_i of the following form (Yao, 1999):

$$y_i = f_i\left(\sum_{j=1}^{n} w_{ij}x_j - \theta_i\right) \qquad (1)$$

Where y_i is the output of the neuron i, x_j is the jth input to the neuron, and w_{ij} is the connection weight between neurons i and j. θ_i is the threshold (or bias) of the neuron.

Inspired by biological NNs, ANNs are massively parallel computing systems with many simple processors and interconnections (Jain et al., 1996). Neurons, interconnections, and learning algorithms comprise the structure of an ANN. The procedure used to perform the learning process is called a learning algorithm (Haykin, 2008). The operation of an ANN involves two processes: learning and recall (Uhrig 1995). There are three main learning paradigms: supervised, unsupervised, and hybrid (Jain et al., 1996). Supervised learning is based on a direct comparison between the actual output of an ANN and the desired correct output, formulated as the minimisation of an error function between the actual production and the desired output (Yao, 1999). The network is provided with correct outputs for every input pattern, and weights are determined to produce answers as close as possible to the known correct answers (Jain et al., 1996). Unsupervised learning is based on correlations among input data, and no information about the correct output is available for learning (Yao, 1999). In unsupervised learning, the network is not provided with accurate production. Hybrid learning combines supervised and unsupervised learning: some weights are learned through supervised learning, while others through unsupervised learning (Jain et al., 1996).

The way neurons are interconnected is called an artificial neural network's topology, architecture, or graph (Krenker, Bester and Kos, 2011). Topology can occur in two different forms depending on the direction of information flow. It can be classified into feedforward and feedback networks (Jain et al., 1996). Feedforward networks are single-layer perceptrons, multilayer perceptrons, and radial basis function nets. As in Kohonen's SOM, Hopfield's, and ART's models, feedback networks are competitive. Multilayer feedforward networks are the most popular and widely used network paradigm in many applications, including forecasting (Zhang et al., 1998). Graphical representation of a multilayer perceptron ANN as follows (Drew and Monson, 2000) in Figure 1:

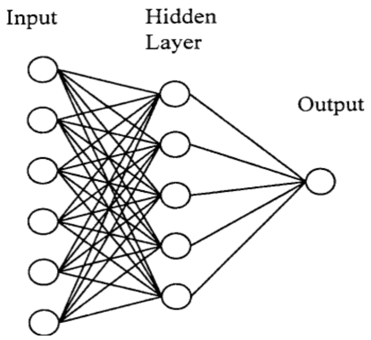

Figure 1: Multilayer Perceptron ANN

In Figure 1, a multilayer perceptron network consists of an input layer, a hidden layer, and an output layer. The process here is as follows: The observation values of the input variables are transferred to the neurons in the intermediate layer via the neurons in the input layer, processed, and the result is sent to the output layer.

Deep learning

Deep learning, a subfield of machine learning (Deng and Yu, 2014), is also known as multilayer neural networks (Goodfellow, Bengio and Courville, 2016). The "deep" in deep learning refers to multiple layers in neural networks (Khajah, Lindsey and Mozer, 2016). The layers formed by connecting many neurons in the network enable the solution of complex problems such as image and video recognition, natural language processing, speech recognition, autonomous vehicles, recommendation systems, and many others. As problem complexity increases, the number and/or size of network layers also increase. Layers can represent deep, complex, and abstract information within the data. Layers also represent different stages of the data processing pipeline, and each stage performs specialised operations to understand more complex, abstract data patterns. However, as the number and the size of layers increase, the required computer power also increases. The deep learning algorithm requires large amounts of data for pattern recognition and significant computational power.

Many methods can be used in deep learning. Therefore, many deep learning techniques are used for different purposes in the literature. Some of those are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), Gated Recurrent Units (GRUs), Deep Reinforcement Learning (RL), Self-Organising Maps (SOMs), and Autoencoders. Anwar, Majid, Qayyum, Awais, Alnowami and Khan (2018) stated that Convolutional Neural Networks (CNNs) are used in image processing problems. Yao, Zweig, Hwang, Shi and Yu (2013) and Kumar, Raju and Sathish (2004) stated that Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and Gated Recurrent Units (GRUs) are used to process sequential data, such as time series and text data. Zhai, Zhang, Chen and He (2018) explained that autoencoders are used in anomaly detection and data compression applications. Li, Yang, Lİ, Qu, Lyu and Li (2022) mentioned that deep Reinforcement Learning (RL) is used to make tactical decisions in games and robotics. Isa, Kalliman, and Lee (2009) explained that Self-Organising Maps (SOMs) group similar data points by projecting the dataset onto a low-dimensional map for data exploration and clustering. Deep learning is a powerful tool for forecasting across various domains, including finance (Kamalov, Smail and Gurrib, 2020), weather (Ren, Li, Ren, Song, Xu, Deng and Wang, 2021), demand prediction (Bedi and Toshnival, 2019), and more. Among deep learning methods, Ghaderi, Sanandaji, and Gahderi (2017) explained that RNNs are the most widely used for prediction. RNNs enable long-term predictions from complex datasets. The RNN method is unnecessary in the current study, as successful predictions are achieved by increasing the number of hidden-layer neurons. RNNs are generally preferred for more complex datasets, such as text processing, due to their difficulty in training, high computational requirements, and large data requirements.

MATLAB's deep learning toolbox

Matrix Laboratory (MATLAB) is a programming and numeric computing platform developed by MathWorks. The program is widely used by statisticians, programmers, mathematicians, and engineers to analyse data, develop algorithms, and create mathematical models. The Deep Learning Toolbox included in the program provides a valuable framework for designing and implementing deep neural networks for both advanced and intermediate users. Program users can implement various Deep Learning methods, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs), to perform classification and regression on time series, images, and text data using the Deep Learning Toolbox's built-in functions or by creating their own tasks. The Deep Network Designer app also allows users to graphically design, analyse graphically, and train networks.

The program is used for complex problems and less complex problems. These problems do not require multiple hidden layers. Therefore, multilayer networks with a single hidden layer are known as Shallow Networks. The current study uses embedded functions to design shallow neural networks in the Deep Learning Toolbox.

Results

Materials and data

MATLAB R2021a and Microsoft Excel were used in the study. Excel was used to process and prepare data for analysis and to visualise the results obtained, and the application was carried out in the Matrix Laboratory (MATLAB) environment. The functions in the Deep Learning Toolbox for MATLAB were used in the analysis.

The study used monthly data on cement production in tons obtained from the Turkish Cement Manufacturers Association's official website (https://www.turkcimento.org). The production data consists of 93 observations spanning the period from January 2017 to September 2024. 85% of this data was used for training the network, and 15% for testing the complete network. Before the data were introduced to the network, they were standardised to the range (-1, +1), and the reverse standardisation was applied before using the network's forecast data.

Model

In the forecasting model developed within the scope of this study, dummy variables were used as independent variables, along with lagged production data. Cement production amount depends on demand. Cement demand, on the other hand, varies seasonally due to the nature of the construction industry. For this reason, temporal dummy variables are included in the model to enable the network to learn seasonal demand changes. Although it is known that demand for cement depends on factors such as population, energy costs, and macroeconomic variables, these variables were not included in the model, as the current study was not aimed at determining a theoretical relationship. The aim of the study is not to choose the variables affecting cement production, but to propose a model that allows estimating future production levels. The dummy variables used in the ANN method can also capture the effects of macro variables not included in the model on the dependent variable. Therefore, macro variables were not included in the model. In addition, the fact that the future values of the dummy variables used in the model do not need to be estimated to predict cement production will provide convenience and consistency in the estimations. While actual data can be used to estimate t+1 when macro variables are included in the model, it is necessary to estimate the future values of the independent variables for t+2 and beyond. This is because it is impossible to predict t+2 without knowing the t+1 values of macro variables, such as interest rates. In this case, production quantities will be estimated based on the estimates, and the resulting production data will introduce a high degree of bias into the prediction. The model created in this context is as follows:

$$C_t = f(C_{t-1}, C_{t-2}, M_{it}, Y_{it}) \quad (2)$$

Here, C_t is the cement production amount in t month ($t = 1,2,3, \dots ,93$), C_{t-1} is the cement production amount in $t-1$ month ($t = 1,2,3, \dots ,93$), C_{t-2} is the cement production amount in $t-2$ month ($t = 1,2,3, \dots ,93$), M_{it} is the dummy variable for month i at time t ($i = 1,2,3, \dots ,12$) and Y_{it} is the dummy variable for year i at time t ($i = 1,2,3, \dots ,8$). The use of dummy variables is as follows in Table 2:

Table 2: Dummy Variables' Coding

Dummy Variable	**Coding Rule (0/1)**
Month Dummies	$M_i = 1$ *if the prediction belongs to January*, 0 *otherwise* ; … *up to December*
Year Dummies	$Y_i = 1$ *if the prediction belongs to* 2017, 0 *otherwise* ; … *up to* 2024

According to the model created, Cement production amounts are a function of the first and second-lagged C_{t-1} and C_{t-2} cement production amounts, the relevant month, and the appropriate year. M_i variables for the month of production are dummy variables. The model has 12 dummy month variables, one for each month. When the production data were plotted, it was observed that the data lacked a trend, so a trend variable was not added to the model. However, it has been observed that the production average varies from year to year. Therefore, eight dummy year variables have been added to the model, one for each year covered by the production data. The dummy-variable trap, which should be considered in the classical modelling method, does not apply to the ANN method.

Network architecture

The network created consists of 3 layers. These are the input, hidden, and output layers, respectively. In the input layer, the model includes several independent variables. These cells transfer the observation values of the independent variables to the hidden-layer cells. Since a total of 22 input variables, including 12 dummy variables used for months and eight dummy variables used for years, are used in the application, in addition to production data with one lag and two lags, there are 22 neurons in the input layer of the created network.

On the other hand, 23 neurons were used in the hidden layer. Determining the optimal number of hidden-layer neurons is a difficult task for network designers. Numerous methods for determining the optimal number of neurons have been proposed in the literature (Vujicic et al., 2016). These studies indicate that the number of neurons in the hidden layer should be fewer or greater than that in the input layer (Syaharuddin, Fatmawati, and Suprajitno, 2022). We decided to try different numbers of neurons in the hidden layer and see the result. For this purpose, networks with 15-30 neurons in the hidden layer have been trained 5 times, and the best result is chosen based on MSE values.

In the network's output layer, there is a single neuron that provides estimates of cement production. The network design in this context is shown in Figure 2.

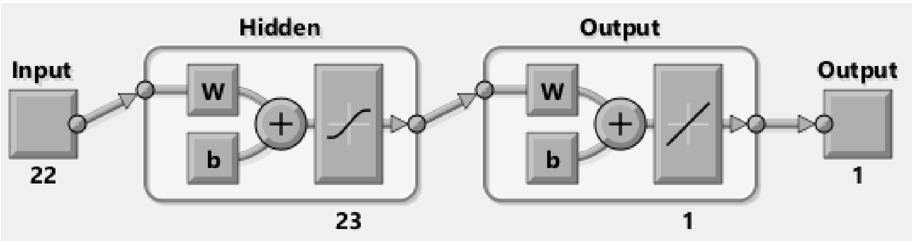

Figure 2: Network Design

In the designed neural network, the standard weighted summation was applied as the aggregation function for all neurons. For the hidden layer, the Hyperbolic Tangent Sigmoid transfer function (tansig) was utilised, defined as

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \qquad (3)$$

which maps input values to the range [-1, 1] and introduces nonlinearity into the model (Haykin, 1999; Hagan et al., 2014). This nonlinearity allows the network to capture complex input–output relationships. For the output layer, a linear transfer function (purelin) was used, as it is particularly suitable for regression problems requiring continuous-valued outputs (Demuth et al., 2008). The combination of a nonlinear hidden layer and a linear output layer is a commonly employed architecture in function approximation and prediction tasks (Hornik, Stinchcombe and White, 1989).

The network has 24 thresholds (bias): 23 for neurons in the hidden layer and one for neurons in the output layer. There is a weight matrix of 22x23 in which the data transferred from the 22 neurons in the input layer to each of the 23 neurons in the hidden layer are multiplied, and a weight matrix of 23x1 size, in which the values transferred from the neurons in the hidden layer to the neuron in the output layer are multiplied. These thresholds and weights were determined during training.

Network training

Network training in ANNs involves determining the network's weight and threshold values to minimise prediction error. Although many training algorithms for this have been developed in the literature, the Bayes Regularisation Backpropagation Algorithm (trainbr) is used in the current study. In this algorithm, the network's weights and threshold values are updated using Levenberg-Marquardt optimisation to improve prediction performance. Mean Squared Error (MSE) was used to measure forecast performance. In this algorithm, training stops when adaptive weight minimisation with regularisation is reached. Therefore, unlike other backpropagation algorithms, in this learning algorithm, the data set is divided into two, as training and testing, instead of three, as training-validation-testing.

The test data set is reserved by not being introduced to the network during training. The network is run by introducing test data to the completed network. The performance value obtained on the test data is essential for the network designer to determine whether the network has memorised the training data and can generalise. In practice, 85% of the data is randomly allocated for training the network and 15% for testing the completed network. The performance of estimates obtained from data assigned to training and testing should be similar.

Estimation results

The weight and threshold values were fixed in the network after training, and cement production data were estimated using these values. The performance of the obtained estimations is measured with low error and high correlation. The Mean Absolute Error (MAE) for the estimates was 449,000. The correlation coefficient between the forecast and the observed value was 0.897. To demonstrate that the trained network does not memorise the training data and can generalise, the performance of predictions made on randomly split training and test data should be examined. It is expected that the performance results of the estimations obtained with test data not used during training, but introduced to the network after training is completed, will be close to those obtained with the data used during training. For this reason, the performance of the estimations obtained from the data used in the training and testing stages was evaluated using MAE and correlation coefficients. The MAE values were 504,756 for the training dataset and 298,714 for the test dataset. The estimation errors calculated during the network test show better performance than during training, indicating that the network generalises and does not memorise the training data set. In addition, the correlations between the estimations obtained with the training and test data and the actual observation values are given in Figure 3:

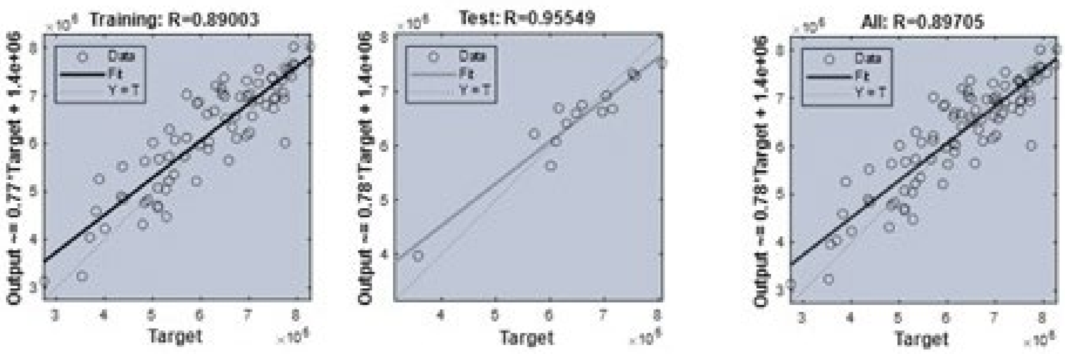

Figure 3: Correlation Coefficients Between Estimates and Observation Values

The high correlation (0.89) between the training data and the neural network's estimated values in Figure 3 indicates that the model has learned the patterns and relationships in the training data very well. This suggests that the model is successfully minimising the difference between its forecasts and the actual values. On the other hand, the high correlation between test data and a neural network's estimated values in Figure 3 is a strong indicator that the model has generalised well. In conclusion, the model has successfully learned the underlying patterns from the training data and can accurately forecast outcomes for new future data.

If the network converges to the systematic structure in the data, the estimation errors should follow a normal distribution. The normality test results are presented in Table 3.

Table 3: Kolmogorov-Smirnov (KS) Normality Test Results for Standardised Errors.

KS	p-Value
0.087	0.092

When the Kolmogorov-Smirnov (KS) normal distribution test result is examined, the null hypothesis cannot be rejected because the p-value is greater than the alpha, which is 0.05. Therefore, the standardised errors have a normal distribution. The estimation results obtained with the designed network, and the actual values are as in Figure 4:

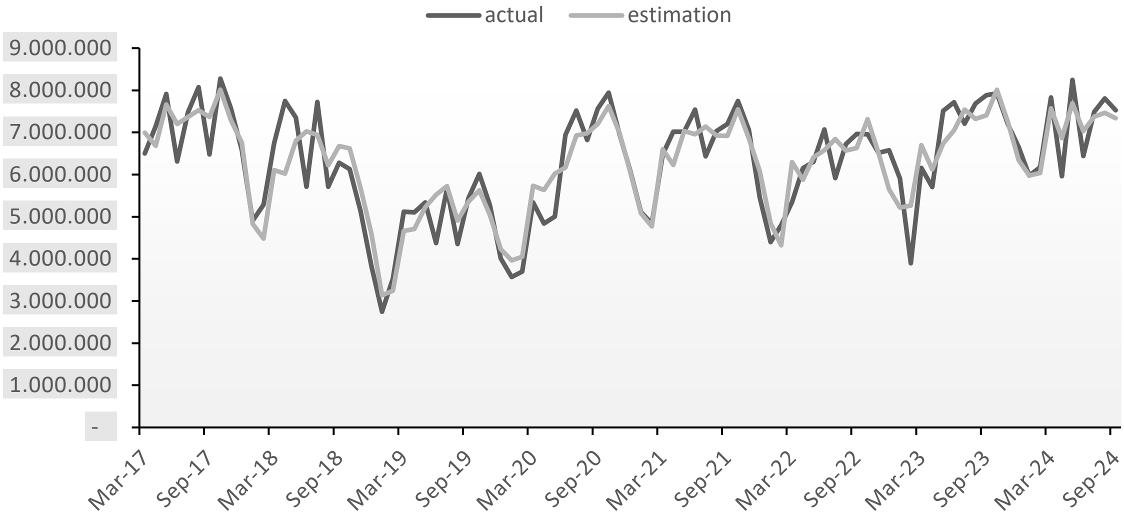

Figure 4: Actual and Estimated Values

The figure shows that the estimated values follow the same pattern as the actual values do. The fact that the estimated and actual values follow a similar pattern is a good sign that the model has learned patterns from the data.

Forecasting results

A forecast of cement production (tons) for the next 27 months, from October 2024 to December 2026, was prepared. The forecasted values obtained are given in Figure 5 below:

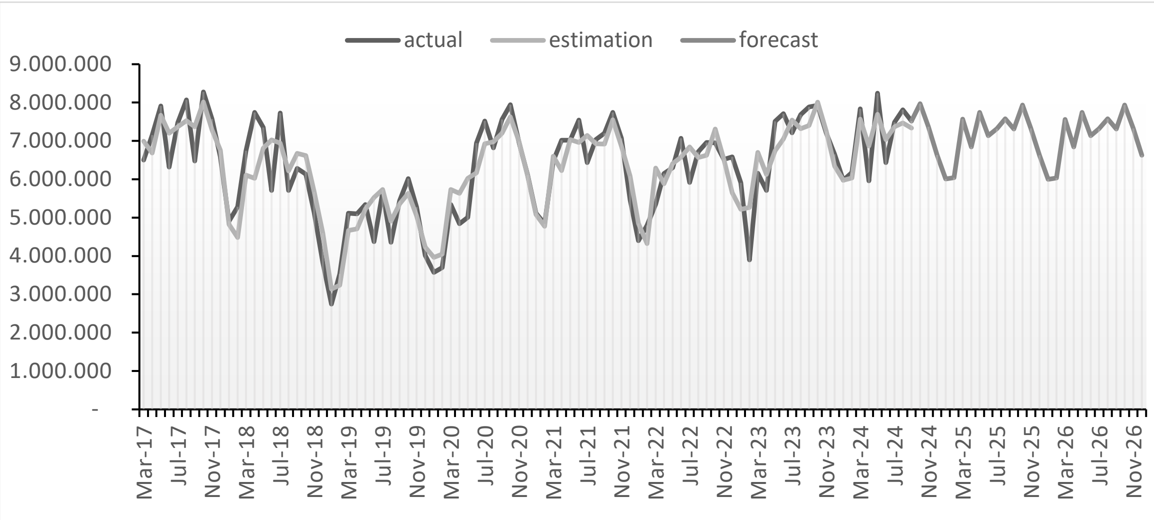

Figure 5: Forecasting of Cement Production Quantities

When Figure 5 is examined, it is seen that the time path graph of the forecasted period shows movements and behaviour patterns similar to those in the past period.

Validation of the best-fit forecasting model

In the forecasting literature, MAPE statistics of alternative models are usually compared with each other to validate the best-fit forecasting model (Liu, Chen, Yang, Hung and Tsai, 2008; Padhan, 2012; Fradinata, Sirivongpaisal, Suthummanon and Suntiamorntut, 2014; Fışkın and Cerit, 2019; Çuhadar, 2020; Han, Sönmez, Avcı and Aladağ, 2022; Yüksel, 2023). In this study, the MAPE statistics of the ANN, Winters', and SARIMA models were used in this comparison.

Winters' triple exponential smoothing

The three components, level, trend, and seasonal, are involved in the multiplicative and additive seasonality models of the triple exponential smoothing model types of Winters'. Table 4 shows the Winters' models.

Table 4: Multiplicative and Additive Models of Winters'

Multiplicative Seasonality Model	Additive Seasonality Model
$L_t = \alpha(Y_t/S_{t-p}) + (1-\alpha)(L_{t-1} + T_{t-1})$ $T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$ $S_t = \delta(Y_t/L_t) + (1-\delta)S_{t-p}$	$L_t = \alpha(Y_t - S_{t-p}) + (1-\alpha)(L_{t-1} + T_{t-1})$ $T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$ $S_t = \delta(Y_t - L_t) + (1-\delta)S_{t-p}$

Here, Y_t is the data value at time t, and p is the seasonal period. L_t is the level at time t, T_t is the trend at time t, and S_t is the seasonal component at time t. α is the weight for the level, γ is the weight for the trend, and δ is the weight for the seasonal component. These three smoothing constants range between 0 and 1. The parameters α, γ, and δ can be chosen to minimise MAPE (Makridakis, Wheelwright and Hyndman, 1997).

The fitted values are estimated for the multiplicative model with $\widehat{Y}_t = (L_{t-1} + T_{t-1})S_{t-p}$ and the additive model with $\widehat{Y}_t = L_{t-1} + T_{t-1} + S_{t-p}$. The seasonal period ($p$) is taken as 12 for the monthly data (Akgül, 2003). The smoothing constants (weights) were determined by selecting the model that best fits among the alternatives according to mean squared deviation (MSD), mean absolute deviation MAD, and MAPE statistics. For additive and multiplicative estimations, the following weights were used: level = 0.2, trend = 0.2, and seasonal = 0.2. All Winters' model estimations were performed in MINITAB 17. Table 5 shows the accuracy comparisons of Winters' models.

Table 5: Accuracy Comparisons of Winters' Models

Alternative Forecasting Models	**MAPE (%)**	**MAD**	**MSD**
Winters' Multiplicative Seasonal	11.699	691287	77175500
Winters' Additive Seasonal	11.237	657452	67384500

In Table 5, two models compete. Here, the accuracy measures (MAPE, MAD, and MSD) are compared, and the smallest values indicate a better model. Because the three accuracy measures for the additive seasonal model are lower than those for the multiplicative model, the additive model outperforms the multiplicative model. According to these measures, Winters' additive model fits the data better.

SARIMA

The ARIMA (p, d, q) model's basic processes include the autoregressive, integrated, and moving-average processes (Yaffee and McGee, 2000). p is the order of the autoregressive (AR) process, q is the moving average (MA) order (Brockwell and Davis, 2002), and d is the order of integration (I). Before running ARIMA models, unit root tests should first be performed. Unit root tests were conducted in EViews 12. Table 6 shows the results of the ADF and PP (Phillips-Perron) unit root tests.

Table 6: ADF and PP Unit Root Tests' Results

			t Statistic	p-value
ADF	Intercept	Level	-3.3485	0.0174
		1st Difference	-8.2772	0.0000
	Trend + Intercept	Level	-3.3212	0.0737
		1st Difference	-8.2118	0.0000
	None	Level	-0.0154	0.6732
		1st Difference	-8.2960	0.0000
PP	Intercept	Level	-3.4017	0.0152
		1st Difference	-8.7719	0.0000
	Trend + Intercept	Level	-3.3762	0.0654
		1st Difference	-8.8483	0.0000
	None	Level	0.2943	0.7675
		1st Difference	-8.7814	0.0000

Table 6 shows the results of the ADF and PP tests for three different situations: (i) a model that only includes an intercept, (ii) a model that only includes a trend and an intercept and (iii) a model that includes neither. Moreover, as shown in Figure 6, these three situations are tested at both the level and the first difference. All test results for all three situations ((i) intercept, (ii) trend and intercept, and (iii) none) show that the null hypothesis is not rejected at the level (p-value ≥ α=0.01), which means that the data has a unit root (or non-stationary). However, when the first difference of the data is taken, the null hypothesis is rejected (p-value < α=0.01), which means that the data are stationary. Then, ARIMA or its extension, the seasonal autoregressive integrated moving average (SARIMA), is employed. The ARIMA notation can be extended to handle seasonal components in the form ARIMA (p, d, q) (P, D, Q)s (Makridakis et al., 1997). Here, (p, d, q) is the non-seasonal part of the model, and (P, D, Q)s is the seasonal part of the model. Two basic approaches are used to determine SARIMA parameters. In the first approach, autocorrelation and partial autocorrelation functions are examined, and the model with the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) is selected for model evaluation. In the second approach, parameter optimisation is performed automatically. The program uses all possible parameter combinations and automatically selects the model with the lowest AIC and BIC criteria values. Since the existing data on cement production exhibit seasonality, the SARIMA model was considered meaningful, and the model shown in Table 8 was ultimately selected among the alternative models. SARIMA model estimations were performed in MINITAB 17. Table 7 below shows the SARIMA model estimation results.

Table 7: SARIMA (1, 0, 0) $(0, 1, 1)_{12}$ Model Estimation Results

	Coefficients	t Statistic	p-value
AR (1)	0.6465	7.59	0.0000
SMA (1)	0.7883	8.27	0.0000
Original Series	93		
After differencing	81		
Sum Square (SS)	50908872209724		
Mean Square (MS)	644416103921		

Here, the difference equals one (D=1), and the seasonality is twelve (S=12). Because the constant term is not significant, it was omitted from the equation. The p-values show that all the coefficients are statistically significant (p-value < α=0.05). MAPE was calculated as 10.905 using EXCEL.

Comparisons of the Candidate Forecast Models

The estimated values and residuals were obtained with MINITAB for the SARIMA and Winters' models, and the MAPE values were calculated. Then, the MAPE statistics were computed using EXCEL for all alternative models. Table 8 shows these statistics.

Table 8: Accuracy Comparisons of Forecasting Models

Alternative Forecasting Models	MAPE (%)
ANN	7.680
SARIMA (1,0,0) $(0,1,1)_{12}$	10.905
Winters Additive Seasonal	11.237

According to the MAPE values in Table 8, the lowest value is 7.680, indicating that the ANN model is the most suitable.

Conclusions

This study, which seeks to answer the question of how and by which method future cement production in Türkiye can be estimated, has concluded that the appropriate method is the ANN method. The success of modelling univariate time series data with ANNs was validated by comparing it with Winters' and SARIMA methods using MAPE statistics. The most suitable forecasting method was found to be ANNs. This result is similar to other studies, such as İslamoğlu (2016), Yücesan (2018), Sönmez and Zengin (2019), and Yurtsever (2022), which found that ANNs provide better results than other methods. The ANN model's performance was quite good, and it was concluded that the network could generalise. The results showed that monthly production can be forecast for future, unknown values using the model developed with threshold values and weights obtained from the trained network. Thus, the research question "How much cement will be produced in Türkiye in the future?" can be answered. The answer was obtained from 27-month forecasts generated by the ANN model. The expectation that production would increase in response to anticipated future demand proved accurate. The forecast average over the 27 months was 71.4 million tons. This value is higher than the average of 93 months of actual data (62.3 million tons). An examination of the actual data, which includes 12-month averages for the last three years, reveals that the 27-month forecast average is again higher than all of them. In fact, production values are gradually increasing. Indeed, the twelve-month average between October 2021 and September 2022 is 61.6 million tons, the twelve-month average between October 2022 and September 2023 is 66.4 million tons, the twelve-month average between October 2023 and September 2024 is 71.02 million tons, and the forecasted 27-month average is 71.4 million tons.

Another aim of the study is to draw inferences from the findings. According to forecasts, Türkiye's average cement production will continue to increase over the next 27 months. There is a growing demand for cement across the country for various reasons, including the need for new buildings, rebuilding old structures, and urban transformation, given its location in an earthquake zone.

Türkiye also needs the cement sector to support the economy regarding growth, trade, and employment. Cement production for Türkiye, a developing country, will continue in the future. On the other hand, Türkiye currently has excess capacity in the cement sector. Cement capacity utilisation rates, which averaged 60% between 2010 and 2017, dropped to 50% between 2018 and 2022. This problem can only be solved in the long term by increasing domestic consumption. Turkey is a country located in an earthquake zone and suffers significant loss of life in earthquakes. Therefore, new earthquake-resistant buildings must be built, and old ones must be renovated. The cement demand generated by urban renewal projects could stimulate domestic consumption. The short-term solution to this problem is cement exports. The most effective method for exporting is sea transportation. Sea transportation has already been implemented in recent years. However, this demonstrates the need to further expand sea export opportunities to distant markets. Meanwhile, capacity expansion should be limited, and investments to improve energy efficiency and reduce the carbon footprint should be encouraged. Indeed, low-carbon production will become essential in the coming years, particularly for continued exports to developed countries. Domestic consumption can only continue to increase within a growth path that ensures price stability, and this requires, first and foremost, the successful fight against inflation. Turkey has long been a significant cement producer, ranking among the top five global producers. Turkish cement producers use a considerable portion of their output to meet domestic demand, while the remainder serves foreign markets. Thus, they contribute to both the domestic and international economy. In particular, Turkish cement producers meet the significant demands of European Union member countries. In terms of foreign demand, Türkiye, which has met 43.7 percent of the EU's cement and clinker needs in 2022, 35.8 percent of its needs in 2023, and 41.7 percent as of June 2024 in the last two and a half years, seems to continue its production activities at a level that will meet the needs of EU countries in the future, according to the predicted values. In addition, it can be said that Türkiye can meet the cement demand of the EU and other foreign countries, as well as the cement needs of Turkish contracting companies to be used in ongoing and expanding contracting activities in countries such as Iraq, Saudi Arabia, Yemen, Jordan, Iran, Tunisia, United Arab Emirates, and Kuwait, with the forecasted values. The contribution of forecasted cement production to future growth and job opportunities will be undeniable.

The policies to be implemented are matters of preference or priority. It is indeed a choice to restrict or not limit cement production for environmental reasons. The forecast of continued increases in production values in the coming period necessitates reshaping current production policies with a green-growth perspective to reduce the sector's environmental impact. The promotion of energy-efficiency-focused technologies, the expansion of the use of alternative fuels and raw materials, and the adoption of low-carbon production strategies will both strengthen compliance with national greenhouse gas reduction targets and increase the sector's contribution to sustainable development.

The research conducted has some limitations and future directions. The existing network did not reflect economic factors (macroeconomic variables, external demand determinants, and financial crises) or natural disasters (such as earthquakes and floods). Because the effect of any variable excluded from the model on cement production is captured by the dummy variables included in the model, the ANN method can capture these effects. In future studies, if the aim is to examine the effects of these factors on production, multivariate regression models can be used instead of the ANN method. Although environmental pollution and the health hazards associated with cement production are outside the scope of the study, in-depth research should be conducted on these issues in Türkiye, which is among the top 5 largest producers in the world. But estimating cement production values is crucial for calculating carbon emissions. Cement production value estimates can serve as a valuable input for carbon footprint calculations. They can serve as a reference for future studies on this topic. Additionally, cement transportation is another vital issue. Issues related to transportation costs and their relation to foreign trade may lead to interesting research in the future.

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