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# RANKING THE FINANCIAL INEFFICIENCY FACTORS OF COMPANIES WITH THE COMBINED APPROACH OF DATA ENVELOPMENT ANALYSIS AND NEURAL NETWORK

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**Abstract:** The purpose of this article is to identify and rank the factors of financial inefficiency of companies. For this, a combined approach and two techniques of Data Envelopment Analysis (DEA) and Artificial Neural Network (ANN) are used. The work is done in two stages. In the first stage, we use the data envelopment analysis model and evaluate the efficiency of the companies. In the second stage, the efficiency score obtained for the companies is used and neural network methods are used to determine the factors of financial inefficiency in the companies admitted to the stock exchange. The results of the research show that the proposed approach identifies and prioritizes the factors of financial inefficiency of companies listed on the Tehran Stock Exchange.

**Keywords:** financial inefficiency factors; ranking; data envelopment analysis; neural network.

**JEL Codes:** G20, C6, M2.

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## 1. Introduction

Measuring and evaluating performance has been of interest to humans since the distant past. The purpose of performance evaluation is to improve, improve and improve performance. Nowadays, due to the growing importance of organizations in society, the evaluation of the performance of organizations and managers has received a lot of attention, and various indicators are proposed as a measure of the performance of managers in organizations (Huang, 2015). Productivity, efficiency, effectiveness are examples of these evaluation criteria. Performance evaluation is not limited to the evaluation of individuals, but any system or organization can be evaluated based on its goals and its success rate in achieving goals can be measured (Fare et al, 2013). Different methods are used to measure the efficiency of units. In general, there are two groups of major methods for measuring efficiency. These two groups are parametric methods and non-parametric methods (Asmare, and Begashaw, 2018). Data envelopment analysis is a non-parametric method based on mathematical programming to evaluate the efficiency of decision-making units that have multiple inputs and multiple outputs. In 1957, Farrell measured the efficiency of the production unit by using a method similar to the efficiency measurement in engineering topics. The case that Farrell considered for measuring efficiency included an input and an output. Charnes, Cooper and Rhodes developed Farrell's view and presented a model called data envelopment analysis. Data envelopment analysis is used as a suitable tool to estimate the efficiency of companies that use production technologies with multiple inputs and multiple outputs (Kohl et al., 2019). An artificial neural network is adapted from the working of a real neural network. The nerve that plays the role of transmitting information and messages in the body is one of the neurons. The neuron or node is the smallest unit of information processing that forms the basis of the functioning of neural networks (Chen et al., 2020). Each neuron receives inputs and after processing them, produces an output signal. Therefore, each neuron in the network acts as an information processing and distribution center and has its own input and output (Thakur and Konde, 2021). Data envelopment analysis and neural network as two efficient tools are usually used in financial issues for different stages. Data envelopment analysis was usually used to calculate the efficiency of companies and neural network in order to predict and classify in the field of risk, financial helplessness, bankruptcy, profit management, etc. in different studies (Kuah et al., 2010; Dharwal and Kaur, 2016). In this research, with a new approach, we combine data envelopment analysis and neural network in such a way that we first evaluate the financial efficiency of companies in the stock exchange. In the following, according to the results of the efficiency evaluation and the neural network, the financial inefficiency factors of the companies will be determined. In fact, the main problem of the research is stated as follows:

How can the factors of financial inefficiency of the companies be determined by combining mathematical techniques?

## 2. Literature review

### 2.1. Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a method to evaluate the efficiency of decision-making units (DMU) with multiple inputs and multiple outputs. CCR and BCC models are basic models in data coverage analysis (Banker et al, 1986). Many models have been presented in data envelopment analysis to evaluate efficiency (Emrouznejad et al., 2022). Some of these models are used for ranking according to the efficiency score. (For example Hosseinzadeh Lotfi et al., 2013; Moeini et al., 2015; Labijak-Kowalska and Kadziński, 2021; Yazdi et al., 2023). Some of these models are used to select suppliers (for example Vörösmarty and Dobos, 2020; Fotova Čiković et al., 2022; Fathi et al., 2022; Karimi et al., 2022). Some models have also been presented to evaluate the efficiency according to the type of structure of DMUs (for example Kao; 2014; Karimi et al., 2016; Wojcik et al., 2017; Ebrahimi et al., 2021; Zhu, 2022). Some other researchers extended data envelopment analysis models with imprecise data (for example, Peykani et al., 2022; Montazeri, 2020; Banker, 2021; Peykani et al., 2020;). According to the stated cases, DEA is an efficient tool for efficiency evaluation, which is always of interest to researchers.

### 2.2. Neural Network

Artificial Neural Network (ANN) is inspired by the network of neurons in the human brain and tries to develop information processing. In fact, instead of dictating something to the computer, the neural network helps to teach the computer itself to react appropriately to events. Each neuron in this network is a processing element and solves different problems along with other processing elements (Abdolrasol et al., 2021). In recent years, ANN has been used in various sciences. One of the main applications of this method is forecasting (Wu, and Feng, 2018). For example, De Oliveira et al., (2013) and Chhajer et al., (2022) discussed stock price forecasting using ANN. Omar et al., (2017) used ANN to predict fraudulent financial reporting. Also, Dikshit et al., (2021) discussed the forecast of drought in the 21st century with these methods. Faieq and Mijwil (2022) used to predict heart diseases. In the research presented by Abdelkareem et al., (2022) they used a neural network in hydrogen production. Dhillon and Verma (2020) reviewed the application of neural network in object detection. As stated, ANN has been used as an efficient tool for prediction in various sciences.

### 2.3. Data Envelopment Analysis and Neural Network

In recent years, a lot of research has been done by combining neural network and data envelopment analysis. Wu et al., (2006) evaluated the branch efficiency of a large Canadian bank by combining a DEA-neural network. In this regard, Mostafa (2009) calculated the efficiency of Tap Bank Arab with this tool. With the combination of Emrouznejad and Shale (2009). They obtained the efficiency of large-scale datasets by combining DEA-neural network. Also, Kwon and Lee (2015), Yuan et al. (2020), Zhu et al., (2021), Namakin et al., (2021), Moslemi et al., (2021), Zhong et al., (2021), Yang et al., (2022) all evaluated the efficiency by combining DEA-neural network. Nazari-Shirkouhi et al., (2023) selected suppliers in pharmaceutical companies by combining the Z-number data envelopment analysis (Z-DEA) model and artificial neural network (ANN). Fathi et al., (2023) predicted financial distress using the frontier data envelopment analysis (WPF-DEA) model and artificial neural network. Kashanifar et al., (2022) solved the problem of binary classification by combining Data Envelopment Analysis (DEA) and Radial Basis Function Network (RBFN). In the research presented by Tabatabai and Tabatabai (2024), they increased the safety of road transportation by combining data envelopment analysis and machine learning.

### 2.4. Study gap

By studying the research conducted for the use of data envelopment analysis and neural network in the stock exchange, it was found that in the previous research, more was discussed about efficiency evaluation topics and regarding the determination of inefficiency factors that are the reasons influencing the inefficiency of decision-making units. No research has been done. The importance of this issue for decision-makers in the stock market is so important that it is always questioned and there is a study gap in this field. In fact, determining the main inefficiency factors of companies is the main goal of this research, and in order to achieve this goal, this research provides an optimal model for determining and ranking the inefficiency factors in companies admitted to the Tehran Stock Exchange. The used model is a combination of two data envelopment analysis techniques and a neural network.

## 3. Methodology and empirical data

This research is descriptive with an applied nature and cross-sectional in terms of time. In this research, the library method will be used to collect data, so it can be classified as field research. The statistical population of this research is the companies active in the Tehran Stock Exchange. Information about active companies is collected from stock exchange sites. Financial efficiency evaluation indicators are suggested by reading and searching in authoritative books and articles, and some of them are considered by academic experts and the stock exchange, and the rest of the indicators are removed. After collecting information and data, data analysis is done. The statistical population of this research is the companies admitted to the Tehran Stock Exchange in the period of 2016 to 2020. The purpose of this research is to identify and rank inefficiency factors in companies. For this, many studies have been done and finally, according to the studies of the articles, a checklist of criteria affecting financial efficiency for companies was collected. In the following, with field studies and obtaining opinions from experts in the field of Tehran Stock Exchange, several years of researcher's records in the field of finance and stock exchange, the evaluation criteria of financial inefficiency were finalized and localized, which numbered 6 variables as performance indicators for measuring the financial inefficiency of companies in Tehran Stock Exchange was selected. These variables are listed in Table (1) below:

**Table 1 Definition of research variables and related references**

| | **Variable** | **Definition** | **Reference** |
|---|---|---|---|
| 1 | Financial facilities | It is equal to the number of facilities received by the company from banks and financial institutions. | Muchiri et al., 2017; Farid and Ghadakforoushan, 2018. |
| 2 | Financial expenses | This cost is equal to the interest on bank installments, tax crimes and company's financial advice. | experts |
| 3 | Operating profit | The remaining profit after calculating all operating costs. | Jayathilaka, 2020; Azizi and Mohammadi, 2023. |
| 4 | Capital | Any type of financial assets or the value of financial assets such as cash in bank accounts, as well as factories, machines and equipment that companies have for production. | Jackson and Fethi , 2000; Rosales-Córdova, and Carmona-Benítez, 2023. |
| 5 | Current liabilities | Current debt to debt that is due in one year or less. | Al Karim and Alam, 2013; NGUYEN et al., 2021. |
| 6 | Dividend imputation | It is the amount of profit that is divided into each share in the studied year from the company's profit. | experts |

Source: author's view

It is worth mentioning that the variables financial expenses and Dividend imputation have been added to the above variables according to the opinion of industry experts.

The rest of the variables are given according to the previous research and the opinion of experts in this field.

The steps of this research are as follows.

1- Identifying the primary variables of efficiency evaluation using the study of research literature.
2- Finalizing performance evaluation variables and separating them into two input and output categories through interviews with experts.
3- Using the data coverage analysis model to evaluate the efficiency of companies admitted to the Tehran Stock Exchange.
4- Separation of efficient and non-efficient companies related to companies admitted to the Tehran Stock Exchange.
5- Using the neural network model with the input matrix of performance evaluation indicators of inefficient companies and the output matrix of their efficiency.
6- Sensitivity analysis of the neural network model with the least squared error with the title of the optimal model in order to determine the inefficiency factors of the companies admitted to the Tehran Stock Exchange.

### 3.1. Efficiency evaluation model

Suppose we have n DMUs that produce s output by consuming m inputs. Also, we denote the i-th input and the r-th output of $DMU_j$ with the symbols $x_{ij}$ and $y_{rj}$, respectively. Charnes et al. (1978) presented the following input-axis CCR envelope model to evaluate the efficiency of $DMU_o$:

$$
\begin{aligned}
&Min\ \theta \\
&s.t. \\
&\quad \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \qquad i = 1, \dots, m \\
&\quad \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \qquad r = 1, \dots, s \\
&\quad \lambda_j \geq 0 \qquad j = 1, \dots, n
\end{aligned}
\tag{1}
$$

where $\lambda j$ is a structural variable and is used to construct a non-negative combination of observed DMUs. If $\theta^*=1$ (optimal answer of model 1), $DMU_o$ is efficient, otherwise, it is called inefficient.

We call model (1) above radial models. In fact, inputs decrease or increase along a radius. This model may fail to identify some combined inefficiencies. To solve this problem, non-radial models were introduced in data envelopment analysis. One of the most famous non-radial models is the Russell measures model, which is as follows (Pastor et al., 1999):

$$
\begin{aligned}
& R(x_o, y_o) = \min \frac{\frac{1}{m}\sum_{i=1}^{m} \theta_i}{\frac{1}{s}\sum_{r=1}^{s} \phi_r} \\
& s.t. \\
& \quad \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_i x_{io} \qquad i = 1, \dots, m \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} \ge \phi_r y_{ro} \qquad r = 1, \dots, \\
& \quad 0 \le \theta_i \le 1 \qquad i = 1, \dots, m \\
& \quad \phi_r \ge 1 \qquad r = 1, \dots, s \\
& \quad \lambda_j \ge 0 \qquad j = 1, \dots, n
\end{aligned}
\tag{2}
$$

In this model, the reduction ratio of each of the input components and the increase ratio of each of the output components are simultaneously considered in the efficiency calculation. In fact, it is a non-oriented model. In fact, the numerator and denominator of the fraction of the objective function can be interpreted as the average input inefficiency and the average output inefficiency, respectively. The optimal value of the objective function is $0 < R(x_o,\ y_o) \le 1$, and if this value is equal to 1, the unit under evaluation is efficient, otherwise, $DMU_o$ is inefficient. Model (2) is a fractional model, but different versions of it can be used which are linear programming, one of these efficient models is as follows (Shen et al. 2019):

$$
\begin{aligned}
& R_{input}(x_o, y_o) = \min \frac{1}{m}\sum_{i=1}^{m} \theta_i \\
& s.t. \\
& \quad \sum_{j=1}^{n} \lambda_j x_{ij} = \theta_i x_{io} \qquad i = 1, \dots, m \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro} \qquad r = 1, \dots, s \\
& \quad 0 \le \theta_i \le 1 \qquad i = 1, \dots, m \\
& \quad s_r^+ \ge 0 \qquad r = 1, \dots, s \\
& \quad \lambda_j \ge 0 \qquad j = 1, \dots, n
\end{aligned}
\tag{3}
$$

Model (3) is a linear version of model (2), which only includes the average inefficiencies of the inputs in the objective function. Also, for the optimal solution of model (3) we have: $0 < R_{input}(x_o,\ y_o) \le 1$. Also, $DMU_o$ is effective if $R_{input}(x_o, y_o) = 1$, otherwise it will be ineffective.

## 4. Empirical results

In this study, data analysis was done in two stages. In the first stage, the available models were used in data envelopment analysis and we evaluated the efficiency of the decision-making units in the statistical research population. In the next step, using the output of the first step, which is the efficiency score of inefficient decision-making units, and the methods available in the neural network, and with the help of sensitivity analysis, the inefficiency factors were determined and ranked in the studied statistical population.

### 4.1. Evaluating efficiency using data envelopment analysis models

At this stage, the efficiency of the decision-making units in the studied statistical population was evaluated. In fact, data coverage analysis models were used and an efficiency score was obtained to evaluate the companies. The studied companies include 19 companies between 2016 and 2020. Having said that, we had a number of 95 companies, which were evaluated using the technique of data envelopment analysis. In order to evaluate and measure the efficiency of the companies under investigation according to the data coverage analysis model, it was necessary to choose appropriate criteria to be included in the model, so that an accurate measurement of the efficiency of the companies can be done. Here, 6 variables were selected for measurement. which are as follows:

- Financial facilities;
- Financial expenses;
- Operating profit;
- Capital;
- Current liabilities;
- Dividend imputation.

Due to the fact that in the first stage of this research, the technique of data envelopment analysis was used to measure the efficiency and ranking of the studied companies, so we needed to determine the inputs and outputs in order to use this model. One of the principles of data coverage analysis is determining inputs and outputs according to cost and profit. In simpler terms, any index whose reduction is intended by the decision-maker or manager is called an input index, and any index whose increase is intended by the decision-maker or manager (according to the decision made for the decision-making unit) is called an output index. According to the above research variables, these two categories are as follows:

Input variables: Financial facilities ($I_1$), Financial expenses ($I_2$), Current liabilities ($I_3$).

Output variables: operating profit ($O_1$), capital ($O_2$), Dividend imputation ($O_3$).

In order to extract the primary data related to the variables of the present research, the technology management site of the Tehran Stock Exchange was used. In order to prepare the data and measure the variables of the research using the primary data, Excel software was used. The descriptive statistics related to the input, intermediate and output indicators are given in table (2) below.

**Table 2 Descriptive statistics related to input and output variables**

| | $I_1$ | $I_2$ | $I_3$ | $O_1$ | $O_2$ | $O_3$ |
|---|---|---|---|---|---|---|
| **Average** | 1413.911 | 51152.73 | 726130.6 | 238841.2 | 736843.6 | 0.85161 |
| **Middle** | 0 | 31955 | 534687 | 181577 | 516990 | 0.882999 |
| **Minimum** | 0 | 1754 | 141405 | -131506 | 122716 | 0.007619 |
| **Maximum** | 46776 | 268634.5 | 4268695 | 1042164 | 4025589 | 0.96416 |
| **standard deviation** | 5593.699 | 51927.65 | 662847.8 | 199687.1 | 759705.7 | 0.113294 |
| **Number of observations** | 95 | 95 | 95 | 95 | 95 | 95 |

Source: author's view

After collecting information, data analysis is done. In this section, we will use the objective of calculating efficiency using the data envelopment analysis model for the studied companies using the data envelopment analysis method. For this, we will calculate the value of $R_{input}(x_o, y_o)$ $(O = 1, \ldots, n)$ for companies from model (3). Lingo software is used to implement the linear programming model (3). The results of running model (3) are given in table (3) below.

**Table 3 $\mathbf{R_{input}(x_o, y_o)}$efficiency score obtained using model (3) for companies**

| | **Efficiency score in 2016** | **Efficiency score in 2017** | **Efficiency score in 2018** | **Efficiency score in 2019** | **Efficiency score in 2020** |
|---|---|---|---|---|---|
| **1** | 0.78 | 0.25 | 0.48 | 0.38 | 0.27 |
| **2** | 1 | 0.58 | 0.74 | 0.44 | 0.25 |
| **3** | 0.91 | 0.42 | 0.57 | 0.69 | 0.58 |
| **4** | 0.63 | 0.31 | 1 | 0.53 | 0.42 |
| **5** | 0.91 | 0.19 | 0.51 | 0.60 | 0.31 |
| **6** | 0.55 | 0.32 | 0.47 | 0.57 | 0.19 |
| **7** | 1 | 1 | 0.55 | 0.38 | 0.32 |
| **8** | 0.71 | 0.37 | 0.45 | 0.46 | 1 |
| **9** | 1 | 0.35 | 0.35 | 0.51 | 0.37 |
| **10** | 0.56 | 0.22 | 0.49 | 0.70 | 0.35 |
| **11** | 1 | 0.30 | 0.51 | 0.36 | 0.22 |
| **12** | 0.47 | 1 | 1 | 0.36 | 0.30 |
| **13** | 1 | 0.49 | 1 | 0.55 | 1 |
| **14** | 0.56 | 1 | 1 | 0.29 | 0.49 |
| **15** | 0.83 | 0.30 | 0.55 | 1 | 1 |
| **16** | 0.78 | 0.49 | 0.86 | 0.56 | 0.30 |
| **17** | 0.50 | 1 | 1 | 0.91 | 0.49 |

| | | | | | |
|---|---|---|---|---|---|
| **18** | 1 | 0.42 | 0.57 | 1 | 1 |
| **19** | 0.52 | 0.31 | 1 | 0.37 | 0.42 |

Source: author's view

$R_{input}(x_o, y_o)$ efficiency score can be a criterion for ranking companies. So that any company that has a higher efficiency score is in a better position. In Table (3), out of 95 years of the investigated company, 22 years were found to be efficient and 73 years were ineffective. The input and output variables of the year of inefficient companies were considered as the input matrix for artificial neural networks, and the efficiency values of each year of the inefficient company were considered as the output matrix of artificial neural networks, which were further determined by the neural network models of the causes of financial inefficiency of these companies. It is identified according to the investigated variables.

### 4.2. Using neural network models to rank the financial inefficiency factors of companies

In the first stage, relevant data was prepared from the efficiency of the companies and the output of the data coverage analysis model, and the data matrix was formed. In order to determine the best input pattern to the network, various factors may be effective in the phenomenon, so in this research, according to the factors influencing the performance of branches, 6 neurons were introduced as the input layer of the network, which are:
-Financial facilities ($X_1$);
- Financial expenses ($X_2$);
- Operating profit ($X_3$);
- Capital ($X_4$) ;
- Current liabilities ($X_5$);
- Dividend imputation($X_6$).
The output neuron is the efficiency of each year of inefficient companies. The input matrix is 6*73 and the output matrix is 1*73. To decide when to stop the training, the data was randomly divided into three sets, 70% of the desired data was allocated for network training, 15% for network validation, and the remaining 15% for network testing.
In this part, the normalized data resulting from the efficiency of the companies and the output of the data envelopment analysis model by multi-layer perceptron artificial neural networks (MLP) and with momentum training algorithms, descending and Lorenberg-Marquardt with sigmoid transfer function and Hyperbolic was trained and tested with a secret and with different neurons, and after applying different patterns and training the network, the best pattern was selected among the

patterns. The selection criterion is the network that has received the best training, has the lowest mean squared error (MSE) and has provided acceptable results. Of course, in choosing the network, we must also pay attention to the phenomenon of over-processing, because the network will not have an acceptable generalization in the tests where the error is very close to zero.

At first, the data matrix, by multi-layered perceptron neural network with the value of epochs = 1000, with hyperbolic and sigmoid tangent transfer functions and with the momentum training law, which is used to determine the most appropriate momentum value of different neural network models, in which the momentum value (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9) were considered and also tested and trained with descending and Lorenberg-Marquardt linearizers, the results of this analysis are given below. First, we select the best structure in the multi-layer perceptron, the values obtained for which are given in the table (4) below.

**Table 4 Trial and error test to choose the best structure for multilayer perceptron**

| Structure | Network type | Transfer function | Education Law | Momentum rate | Test | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | MSE | confidence level | MAE | R |
| R1 | | TAN | | 0/1 | 0/05898064 | 0/94101936 | 0/21611646 | 0/02770837 |
| R2 | | TAN | | 0/2 | 0/05339212 | 0/94660788 | 0/20369696 | 0/19266709 |
| R3 | | TAN | | 0/3 | 0/05864217 | 0/94135783 | 0/21089419 | 0/07013188 |
| R4 | | TAN | | 0/4 | 0/05864778 | 0/94135222 | 0/2134036 | 0/04783467 |
| R5 | | TAN | Momentum | 0/5 | 0/05653542 | 0/94346458 | 0/20888978 | 0/05557381 |
| R6 | | TAN | | 0/6 | 0/05975778 | 0/94024222 | 0/21723459 | 0/0412824 |
| R7 | | TAN | | 0/7 | 0/05509063 | 0/94490937 | 0/20519971 | 0/10768065 |
| R8 | | TAN | | 0/8 | 0/0540692 | 0/9459308 | 0/20579165 | 0/19603594 |
| R9 | MLP | TAN | | 0/9 | 0/05436917 | 0/94563083 | 0/20635183 | 0/18307582 |
| R10 | | TAN | Gradient descent | | 0/05426152 | 0/94573848 | 0/19898907 | 0/05865082 |
| R11 | | TAN | Levenberg–Marquardt | | 0/05983225 | 0/94016775 | 0/21588254 | 0/21769425 |
| R12 | | SIG | | 0/1 | 0/10763498 | 0/89236502 | 0/29621821 | 0/24621184 |
| R13 | | SIG | | 0/2 | 0/10521763 | 0/89478237 | 0/29291932 | 0/23773248 |
| R14 | | SIG | | 0/3 | 0/06908685 | 0/93091315 | 0/23443458 | 0/12560953 |
| R15 | | SIG | Momentum | 0/4 | 0/05671338 | 0/94328662 | 0/21195275 | 0/28790024 |
| R16 | | SIG | | 0/5 | 0/05529169 | 0/94470831 | 0/20862339 | 0/28568791 |
| R17 | | SIG | | 0/6 | 0/05556568 | 0/94443432 | 0/20953205 | 0/30927478 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| R18 | | SIG | | 0/7 | 0/05252572 | 0/94747428 | 0/20220129 | 0/30936113 |
| R19 | | SIG | | 0/8 | 0/05013746 | 0/94986254 | 0/19551225 | 0/31657281 |
| R20 | | SIG | | 0/9 | 0/0512896 | 0/9487104 | 0/19799749 | 0/28144703 |
| R21 | | SIG | Gradient descent | | 0/05554756 | 0/94445244 | 0/20694829 | 0/11225767 |
| R22 | | SIG | Levenberg–Marquardt | | 0/05579077 | 0/94420923 | 0/20716094 | 0/12361321 |

Source: author's view

The best structure for the neural network is when the square root of the error, that is, its MSE, is the lowest value or its confidence level is the highest value, which according to the above table, this structure corresponds to R19 with a sigmoid transfer function with a momentum training law of 0.8 and with an MSE value =0.05013746 and with a confidence level of 0.949 and also with a correlation coefficient of R=0.316 and the average absolute value of the error MAE=0.195. Figure (1) mean square of training error and evaluation error and Figure (2) comparison of actual output and predicted values by multilayer perceptron neural network with hyperbolic tangent transfer function and with momentum learning law of 0.1 to 0.9 along with table of mean square of error and the correlation coefficient is given.
Figure (1) The mean squared error (MSE) for the training data is presented in terms of the number of repetitions. In order to determine the optimal number of repetitions, MSE was determined for the evaluation data. As it can be seen from Figure (1), the amount of network error for the evaluation data has a downward trend with the increase in the number of repetitions and finally reaches a constant value which indicates the effect of the number of repetitions on the learning ability of the network. Also, this figure shows that the desired error has reached a reasonable level and this network is able to correctly identify the relationship between the input and output parameters.

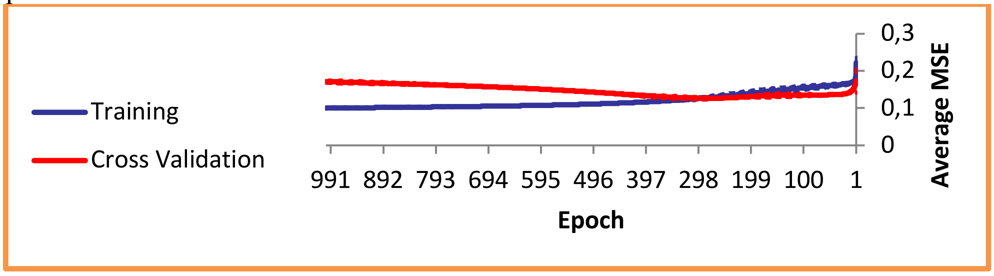


**Figure 1 Mean squared training error and evaluation error with multilayer perceptron and momentum**
Source: author's view

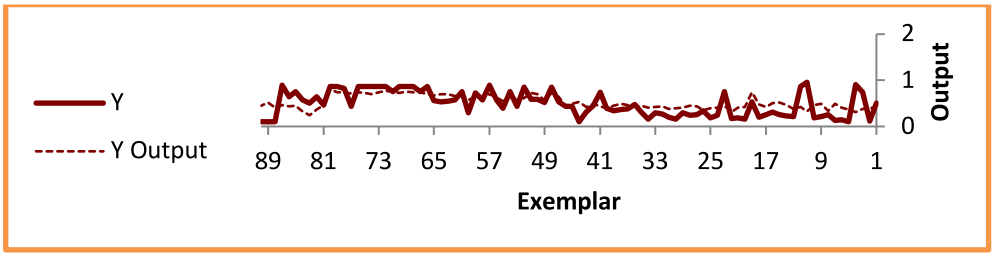


**Figure 2 Comparison of the actual output of the network with the output predicted by multilayer perceptron**

Source: author's view

As mentioned, R19 multilayer perceptron neural network with sigmoid transfer function with 0.8 momentum training law is selected as the most optimal artificial neural network to determine and rank financial inefficiency factors of companies. Now, in order to determine and rank the inefficiency factors, we will analyze the sensitivity of the selected neural network. Sensitivity analysis is actually a method in which the amount of change in the outputs is analyzed by making changes in the inputs. Sensitivity analysis shows which input will have the greatest impact on the output. In the following, with this point of view, we will analyze the sensitivity of the R19 multilayer perceptron neural network with the sigmoid transfer function. So that we can rank the factors of financial inefficiency of companies according to their results. Table (5) below shows the results of this sensitivity analysis in order to rank the factors of financial inefficiency of companies.

**Table 5 Sensitivity analysis in order to rank the factors of financial inefficiency of companies**

| Input variable name | Input variable symbol | Amount of sensitivity analysis | Impact rating |
|---|---|---|---|
| Financial expenses | $X_2$ | 0/02592 | **1** |
| Capital | $X_4$ | 0/01860 | **2** |
| Current liabilities | $X_5$ | 0/01729 | **3** |
| Financial facilities | $X_1$ | 0/01672 | **4** |
| Dividend imputation | $X_6$ | 0/01340 | **5** |
| Operating profit | $X_3$ | 0/00975 | **6** |

Source: author's view

According to the results of Table (5), the financial expenses, capital and total current liabilities have obtained the highest score in the sensitivity analysis with the sensitivity analysis values of 0.02592, 0.0186 and 0.01729, respectively, and according to these results, the above variables have the highest impact on inefficiency. Finance of the studied companies. On the other hand, Dividend imputation and operating profit have obtained the lowest score in sensitivity analysis with sensitivity analysis values of 0.01340 and 0.00975, respectively, and according to these results, the mentioned variables have the least impact on the financial inefficiency of the studied companies.

### 4.3. Discussion

The subject of this research is to identify and rank the financial inefficiency factors of cement, plaster and lime industry companies during the years 2016 to 2020. In this study, the combined method of data envelopment analysis with neural network, which is one of the common methods of evaluating efficiency in different fields for production and service units, has been used to rank the financial inefficiency factors of cement, plaster and lime industry companies in Iran. The process is done in two steps. In the first stage, the data coverage analysis model was used and the performance of 95 companies (19 companies over 5 years) in the cement, plaster and lime industry was evaluated using 6 criteria.

The results of the evaluation of the efficiency for the years of the companies showed that out of 95 years of the company, 22 years of the company were found to be efficient and 73 years of the company were found to be ineffective. Next, in order to identify the factors of financial inefficiency, 22 years of efficient company were removed. After removing the years of efficient companies, the information of 73 years of non-performing companies was considered as the input of the second stage. In the second stage, information of 73 years of inefficient companies was used and the ranking of financial inefficiency factors in cement, plaster and lime industry companies was done using neural network methods. A multilayer perceptron (MLP) neural network was used for this purpose. The aim was to find the best structure for choosing the most optimal network for ranking inefficiency factors in cement, plaster and lime industry companies. The best network structure should be the one with the least square root of the error, that is, MSE, or with the highest level of confidence. The results of the neural network investigation indicate the superiority of the R19 multilayer perceptron neural network with a sigmoid transfer function with a momentum training law of 0.8 compared to other investigated models and as the most optimal network for ranking inefficiency factors in cement and plaster industry companies. And lime is selected. Next, sensitivity analysis was used for the neural network to rank the inefficiency factors. Sensitivity analysis is actually a method in which the amount of change in the outputs is analyzed by making changes in the inputs. This problem indicates which input will have the greatest impact on the output. In the following, with this point of view, we will analyze the sensitivity of the R19 multilayer perceptron neural network with the sigmoid transfer function with the momentum training law of 0.8. In order to be able to rank inefficiency factors in cement, plaster and lime industry companies according to its results. From the results obtained by the multi-layer perceptron neural network model, financial cost, capital and total current liabilities had the highest impact on the inefficiency of cement, plaster and lime industry companies.

Existing methods in this field, such as the research of Muslimi et al., (2021), Zhong et al., (2021), and Yang et al., (2022), have all used the combination of data envelopment analysis and neural network to evaluate efficiency. Some research such as Kashanifar et al. (2022) used a combination of these two techniques for binary classification. But in the present research, we prioritized the factors of financial inefficiency of companies from the combination of data envelopment analysis and neural network.

## 5. Conclusions

In order to plan and control their organization, the managers of organizations and departments need to measure and evaluate the performance of the subordinate units of their organization so that they can compare the units and be aware of the weaknesses and strengths of the units and provide the necessary suggestions to increase the performance of the units. In this article, the factors of financial inefficiency of companies were identified and determined using mathematical techniques. In this study, to determine the factors of financial inefficiency of companies, the scientific method of data envelopment analysis with neural network, which is one of the common methods of evaluating efficiency in different fields for production and service units, has been used. The work was done in such a way that efficient and inefficient companies were identified from the method of data envelopment analysis, and then the factors of financial inefficiency were ranked using the neural network technique. Data envelopment analysis and neural network techniques are both well-known techniques used for performance evaluation. However, in this article, the combination of these two techniques was used to rank the inefficiency factors of companies.

The obtained results show that in the studied industry, financial cost and current liabilities are the two main factors of inefficiency of companies. One of the problems that exist in this area is the failure to collect claims from the operational activities of the companies on time, because of this, the companies are unable to pay their current expenses and their operational process faces problems. On the other hand, tax

problems (related to the financial cost of companies) are another case that exists in this area and causes companies to not be able to use public services due to upstream laws. Another thing that causes inefficiency in this area is not using the company's facilities to generate profit. This industry has a low Net Asset Value (NAV), so capital is one of the inefficiency factors of the studied industry. All these cases show that the obtained results are consistent with the reality of the companies, and the managers of the companies as well as the upstream decision makers of the industry should pay special attention to improving these inefficiency factors in order to be efficient.
According to the obtained results, companies can be informed about their efficiency status in the studied industry. Also, in order to improve their efficiency, they can use companies that have a higher efficiency score as a model. On the other hand, if companies want to improve their performance, they should consider the variables that have a higher priority in the ranking, because they cause companies to improve faster. Finally, it is suggested that the companies in this field pay special attention to the inefficiency factors presented in this article for macro-functional policy making.
To implement the model presented in this article, the data related to cement, plaster and lime industry companies in Iran were used, and the identified financial inefficiency factors were related to this industry. However if the study subject changes, inefficiency factors may change, and this limitation is related to the study subject, but the research process and the use of the combined model of data envelopment analysis and neural network will not have implementation limitations.
According to the approach used in the present study, it is suggested that in future studies, researchers use other decision-making techniques to evaluate the efficiency of companies or use other models of data envelopment analysis, such as the efficiency model, instead of the data envelopment analysis technique. Use cross for evaluation. It is also possible to use other neural network methods instead of multi-layer perceptron method, and any of these can be considered by researchers in future research.

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## Author Contributions

NFM and BK conceived the study and were responsible for the design and development of the data analysis. BK and SS were responsible for data collection and analysis and also for data interpretation. NFM and SS were responsible for the literature review section.

## Disclosure Statement

The authors have not any competing financial, professional, or personal interests from other parties.

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