IJETS@R
(ISSN: 2587-0238)

Cengiz, U., Özdemir, B., Pediz Ö. & Mert Kantar, Y. (2025). Determination of Energy Consumption Factors of Iron and Steel Production Facilities with Statistics Methods, *International Journal of Education Technology and Scientific Researches, 10(30), 12-23.*
DOI: http://dx.doi.org/10.35826/ijetsar.764

Article Type: Research Article

DETERMINATION OF ENERGY CONSUMPTION FACTORS OF IRON AND STEEL PRODUCTION FACILITIES WITH STATISTICAL METHODS

Uğur CENGİZ
General Manager, Bilecik Iron and Steel Industry and Trade Inc., Bilecik, TÜRKİYE, u.cengiz@bilecikdemircelik.com.tr
ORCID: 0000-0001-7874-6820

Beyhan ÖZDEMİR
General Manager, Mavi Prizma, Eskişehir, TÜRKİYE, beyhan@maviprizma.com
ORCID: 0000-0003-2752-6064

Özge PEDİZ
PwC Independent Auditing and CPA Inc, Eskişehir, Türkiye, pedizozge@gmail.com
ORCID: 0009-0007-7505-2306

Yeliz MERT KANTAR
Prof. Dr., Eskişehir Technical University, Eskişehir, TÜRKİYE, ymert@eskisehir.edu.tr
ORCID: 0000-0001-7101-8943

Received: 26.11.2024 *Accepted: 13.02.2025* *Published: 01.03.2025*

ABSTRACT

Iron and steel production plays an important role in both global and national economies and serves as the cornerstone of industrialization. Steel, primarily composed of iron, is central to this industry. In countries like Turkey, where ore resources are limited, steel production heavily relies on scrap metal melted using Electric Arc Furnaces or Induction Furnaces. Since this process requires intensive energy consumption, it is of great importance to accurately measure and manage energy consumption to improve the efficiency of production processes and support sustainability goals. This study aims to determine the main factors affecting energy consumption by examining the energy consumption in induction furnaces at Bilecik Iron and Steel Factory. Using econometric modelling and one-way analysis of variance (ANOVA), the study uses multiple linear regression analysis to estimate a suitable model. The ANOVA results reveal significant differences in energy consumption among induction furnaces. The main determinants identified include casting time, tapping temperature, and billet quantity. Panel data analysis models were also used in this study to analyse the relationship between energy consumption and influencing factors across both time and cross-sectional dimensions (e.g., different furnaces). The findings provide actionable insights into reducing energy consumption and emphasize the importance of the study as a methodological example for similar energy estimation analyses in other steel production facilities. This study not only contributes to the optimization of operational efficiency but also highlights the importance of making inferences using statistical modelling to minimize energy use in industrial processes.
Keywords: Energy consumption, induction furnaces, iron and steel, steel production, regression analysis, panel data analysis, ANOVA.

Corresponded Author: Prof. Dr. Yeliz MERT KANTAR, Eskişehir Technical University, ymert@eskisehir.edu.tr
Ethics Committee Approval: This study does not require ethics committee approval.
Plagiarism/Ethics: This article has been reviewed by at least two referees and has been confirmed to comply with research and publication ethics, containing no plagiarism.

INTRODUCTION

According to the Brussels-based World Steel Association (world steel), 1 billion 808.6 million tons 2,06% of world crude steel production was carried out in Turkey in 2018. Thus, Turkey is for global crude steel 8th and ranks 2nd in Europe. According to the Brussels-based World Steel Association (worldsteel), global crude steel production in 2024 was 1,882.6 million tonnes, a 0.8% decrease from the previous year. Turkey's crude steel production in 2024 increased by 9.4% to 36.9 million tonnes, accounting for approximately 1.96% of the world's total production. This positions Turkey as the 8th largest steel producer globally and the 2nd largest in Europe. The steel industry is among the most energy consuming sectors in the world (Dock et al. 2023). Iron and steel sector, which uses energy intensively, Turkey's share of total energy consumption and its share in industrial consumption of 7.5% are around 22.9% (Kaya, 2019). In the steel industry, energy's share of input costs, it is in the 2nd place after the raw material. Increase in energy demand and costs, our external commitment on energy, competition conditions, environmental factors as in all over the world, it is imperative the effective use of existing energy resources in our country therefore, energy efficiency studies in the industry come to the fore. Therefore, various studies have been published on energy consumption of industrial sectors. For example, Jin et al. (2017) have studied the energy consumption and carbon emission of the integrated steel mill with oxygen blast furnace, Knop (2000) have done comparison of the economics of crude steel production based on fine ore reduction versus shaft furnace reduction. He & Wang (2017) presented a list of energy efficiency technologies and practices applicable to the steel industry, which includes some case studies. Johannes et al. (2021) studied the development of a holistic as well as a temporally and technologically resolved energy system model of an electric steel mill, which serves to evaluate energy efficiency measures and the integration of renewable energy. Considering the literature in this context, both reducing energy consumption and reducing carbon emissions have been the focus of many studies.

Steel production in Turkey is made in two ways, ore and scrap. In this context, there are 7 factories in Turkey that produce steel from scrap. Bilecik Iron and Steel Factory (BISF), which produces ribbed steel by processing scrap, ranks first in this sector in terms of production and turnover.

The literature reveals a significant gap in studies that utilize statistical methods to predict energy consumption in the steel industry. Examples from a small number of literatures is listed as follows: Karthick et al. (2024) presented a machine learning model for predicting energy consumption in the steel industry, which aids in energy management, cost reduction, environmental regulation compliance, informed decision-making for future energy investments. While Holappa (2020) aimed to contribute by creating a forecasting model that predicts energy consumption in the steel industry and this model accurately predicts energy consumption in the steel industry, leading to more sustainable and efficient practices, Al-Shaibani (2023) developed a predictive model for power consumption in the steel industry, integrating linear regression for continuous variable estimation and KNN clustering to classify load types. The study in (Na et al. 2024) examined energy consumption in the iron and steel industry from a theoretical perspective, focusing on the energy consumed during material transformation. The theoretical energy consumption for each of the coking, sintering, pelletising, ironmaking, steelmaking and hot rolling processes is analysed in detail. The results provide an important resource for the development of sustainable practices by revealing the determinants of energy consumption. Kao et al. (2020) developed a hybrid model to overcome the forecasting difficulties arising from the non-linear nature of electricity consumption. This model aims to predict energy consumption more accurately.

In areas other than the steel industry, there are a large number of studies that have been developed and proposed to predict energy consumption. These studies make significant contributions to the literature by providing modelling and forecasting methods to improve energy efficiency in different sectors. For example, Ridwana et al. (2020) emphasized the necessity of energy-efficient building systems to reduce the significant energy consumption in the rapidly growing construction sector. They proposed an artificial neural network-based model with data classification to improve the accuracy of hourly or sub-hourly energy consumption forecasts for four buildings. The proposed model performed better in assessing electricity demand compared to conventional regression models and shows promise for building energy conservation applications. Baba (2021) evaluated three different methods for estimating daily energy consumption in an industrial area. Ngoc-Son Truong et al. (2021) proposed the application of additive artificial neural network (AANN) models to predict residential energy consumption using a dataset collected from a building with a solar PV system. With this approach, the accuracy of energy consumption prediction is improved and AANN models are shown to be an effective tool for energy efficiency analyses, especially in residential buildings.

The purpose of this study; analyse the data produced by the BISF, located in Bilecik, Türkiye, in the short and long term by applying statistical methods and to convert the results obtained in the same factory to benefit by evaluating. It is known that energy consumption in iron and steel factors generally are due to induction furnaces, crucible furnaces, continuous casting and rolling mill annealing furnace. In this project, the induction furnaces, where 79% of energy is approximately consumed in the factory, were selected as pilot zone (Xu and Cang, 2010). Factors causing consumption have been determined and inferences and precautions have been listed regarding the consumption caused by these factors.

METHOD

Research Design

This study adopts a quantitative research approach, utilizing econometric and statistical modelling techniques to analyse energy consumption in induction furnaces at BISF. The research design employs methodologies such as multiple linear regression, panel data analysis, and one-way analysis of variance (ANOVA) to identify key factors influencing energy consumption and provide statistical insights for optimizing energy efficiency.

Panel regression models, specifically the Fixed Effects (FE) and Random Effects (RE) models, are used to examine variations in energy consumption across time-series and cross-sectional dimensions. The Hausman test determines the most appropriate model for the dataset.

Regression analysis establishes the linear relationship between a dependent variable and one or more independent variables, identifying significant factors affecting energy consumption. ANOVA, on the other hand, assesses whether differences in means across multiple groups are statistically significant by decomposing total variance into between-group and within-group components.

Panel regression follows the general equation:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_1 X_{2it} + \cdots . + \beta_k X_{kit} + u_{it}$$

- Y_{it}: The dependent variable of the i-th individual at time t-th

- X_{it}: Independent variable(s).

- β_0: Constant term, β_j: Slope parameter of the jth variable,

- u_{it}: Error term (person and time dependent)

In FE Model, individual effects are included in the model as fixed. In the RE Model, individual effects are randomly distributed and included in the error term. Hausman Test is used to choose between fixed and random effects models.

Data Collection

The data used in this study were collected from operational records of induction furnaces at BISF, covering a specified time period. The dataset includes variables such as energy consumption, casting time, tapping temperature, and billet quantity, all of which are crucial for assessing the factors influencing energy usage. Data were obtained from factory logs, sensor measurements, and production reports.

Due to its structured nature, the dataset was formatted as a panel data model, enabling the analysis of both temporal and cross-sectional variations in energy consumption. Secondary sources, including industry reports and relevant literature, were reviewed to support the research findings.

Data Analysis

BISF plant possesses a substantial dataset encompassing various factors influencing energy consumption. In this study, data on energy consumption (watt), billet types (A furnace: A1, A2; B furnace: B1, B2; C furnace: C1, C2), casting time (minutes), temperature (°C), casting number, sawdust (kg), skal_steel, and scale were collected between 06/03/2020 and 06/05/2020 as part of the TÜBİTAK 2209-B project. The sample size is 1914. To derive meaningful insights, adjustments were made to the dataset during the analysis process.

A unique aspect of the data is that sintering was performed for the first casting of each induction furnace (A1-A2, B1-B2, and C1-C2), requiring additional energy beyond the energy used for melting. Consequently, the total energy consumption was disaggregated into two components: energy used for melting and energy used for sintering. The descriptive statistics for the variables analysed in this study are presented in Table 1.

Table 1. Descriptive Statistics of Variables That Can Affect Energy Consumption In Induction Furnaces.

Variables	N	Minimum	Maximum	Mean	St. Deviation
Energy	1914	432.0	1078.0	654.5	68.91
Billet	1914	16	31.60	27.06	2.14
Casting time	1914	61	1344	151.9	42.10
Temperature	1914	1512	1785	1669	31.29
Casting number	1914	1	60	22.94	14.00
Sawdust	1914	0	22.90	4.48	8.43
Skal_steel	1914	0.0	2.10	0.79	0.42
Scale	1914	0.80	23.20	4.48	7.57

Note: The data used in this study were obtained within the scope of the 2209 B project conducted in collaboration with BISF. The data were collected by BISF, and the analysis process was carried out in coordination with BISF management. All necessary permissions for data usage have been obtained.

Variables to Model Energy Consumption

The following variables represent the semi-finished products and raw materials utilized during the steel production process, each contributing to energy consumption in various ways:

Billet: This semi-finished product is a crucial input in steel production, serving as the starting material for rolling processes.

Temperature: It refers to the temperature of the liquid metal during the iron and steel production process and is usually measured in centigrade (°C).

Casting time: Casting time refers to the time it takes to complete the casting process.

Sawdust: A raw material often used during casting to prevent oxidation or as an insulating layer. Its quantity may influence energy efficiency by affecting heat retention or loss during the process.

Scraps: Another raw material used in the steelmaking process. The composition and quality of skal steel can impact melting efficiency and energy usage, as impurities or variations in composition may require adjustments in furnace operations.

Skal_steel: it is steel that has an oxidized and slag-covered surface formed during production.

Scale: A byproduct and raw material that can be recycled back into the production process. The presence of scale in the raw material mix might influence the energy dynamics of melting and refining processes, as its properties can alter thermal conductivity and energy transfer rates.

These variables collectively represent essential components of the steel production cycle. Understanding their contributions to energy consumption is critical for optimizing production efficiency and minimizing operational costs. By incorporating these factors into the energy consumption model, the study aims to identify key drivers and opportunities for energy optimization in steel manufacturing.

FINDING

Initially, the energy consumption model was estimated using the multiple linear regression analysis method in R programming. All potential variables contributing to energy consumption were included in the model, and the results are summarized in Table 2.

Table 2. The Results of Multiple Linear Regression Analysis

Independent Variables	Coefficients	Std. Error	t	Significant	R^2	F
Constant	314,52076	71,62562	4,391	0,000	0,3471	144,8
Billet	-16,40188	0,65380	-25,087	0,000		
Casting time	0,47040	0,03045	15,450	0,000		
Temperature	0,41861	0,04189	9,994	0,000		
Casting number	0,18374	0,09519	1,930	0,537		
Sawdust	0,31771	0,0706	1,035	0,3009		
Skal_steel	6,64234	4,34978	1,527	0,1269		
Scale	0,21474	0,27617	0,778	0,4369		

Model 1: Energy = 314.520 - 16.401Billet + 0.470Castingtime + 0.418Temperature + 0.183Castingnumber + 0.317Sawdust + 6.642Skal_steel + 0.214 Scale

When the variables in Table 1 are evaluated at a significance level of $\alpha = 0.05$, the variables Castingnumber, Scale, Sawdust, and Skal_steel are found to be statistically insignificant. Consequently, these insignificant variables were excluded from the model. The results of the revised model estimation are presented in Table 2.

Table 3. The Results of Multiple Linear Regression Analysis.

Independent Variables	Coefficients	Std. Error	T	Sig.	R^2	F
Constant	340,83978	70,01264	4,868	0,000	0,3446	348,8
Billet	-15,85670	0,59605	-26,603	0,000		
Castingtime	0,46371	0,03034	15,285	0,000		
Temperature	0,40276	0,04081	9,869	0,000		

Model 2: Energy= 340,839 – 15,856*billet + 0,463*Castingtime + 0,402*Temperature is signification model according to student t and F tests.

Table 3 reveals that Billet, Casting Time, and Temperature are the key variables influencing energy consumption. Specifically, the variable Billet shows a negative correlation with energy consumption, while both Casting Time and Tipping Temperature have a positive effect on energy consumption. According to the R^2 value, Billet, Casting Time, and Temperature together account for 34% of the variability in energy consumption, which is the dependent variable.

In Model 2, holding all other variables constant, a 1-unit increase in Billet results in a decrease of 15.85 units in energy consumption. Conversely, a 1-unit increase in Casting Time leads to an increase of 0.46 units in energy consumption, and a 1-unit increase in Tipping Temperature corresponds to an increase of 0.40 units in energy consumption. Another variable that affects energy consumption may be the type of induction furnaces. Production facility has 3 sets of induction furnaces, A_1- A_2, B_1- B_2 and C_1- C_2. Graph of energy spent with induction furnaces is given in Figure 1. In this context, the effect of induction furnaces difference on energy consumption was investigated by one-way analysis of variance (ANOVA).

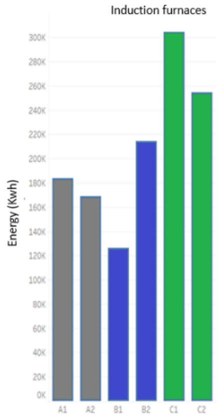

Figure 1. Induction Furnaces and Spent Energy Graph.

In ANOVA model, induction furnaces have been examined in 3 groups as A, B and C to understand whether there is a difference induction furnaces. Descriptive statistics of these furnaces are included in Table 4.

Tablo 4. Descriptive Statistics of Electricity Consumed in Induction Furnaces.

	N	Mean	Std.Deviation	Std.Error	Minimum	Maximum
A	544	648,1384	66,3390	2,8442	431,54	979,24
B	528	645,2878	64,0301	2,7865	474,41	953,30
C	842	664,2964	72,2019	2,4882	433,90	1078,08

Above output indicates that 544 castings were taken from furnace A, with an average energy consumption of 648.13 units. The maximum energy consumption was 979.24 units, while the minimum was 431.54 units. For furnace B, 528 castings were processed, with an average energy consumption of 645.28 units. The maximum energy spent was 953.30 units, and the minimum was 474.41 units. For furnace C, the average energy consumption was 664.3 units, with a maximum of 1078.08 units. Notably, some variation in energy consumption is observed among the furnaces.

<u>Hypothesis</u>

H_0: There is no significant difference between the average energy consumption of the induction furnaces.

H_1: There is a significant difference between the average energy consumption of at least two induction furnaces

Tablo 5. ANOVA Result.

Source of Variation	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	147628,445	2	73814,222	15,788	0,000
Within Groups	8934533,344	1911	4675,318		
Total	9082161,788	1913			

(α = 0,05)

Considering the ANOVA table above, it is seen that $\alpha < 0.000$. In this case, the null hypothesis of H_0 is rejected. In other words, it has been observed that the amount of energy consumed in induction furnaces varies are different, at least one furnace. Tukey test was applied to determine which or which ones make a difference on the energy consumed in furnaces A, B and C. The test result is given in Table 6.

Tablo 6. Tukey Test Results.

Induction furnaces (i)	Induction furnaces (j)	Mean Difference (i-j)	Std. Error	Sig.
A	B	2,8506	4,1772	0,774
	C	-16,1580	3,7612	0,000
B	A	-2,8506	4,1772	0,774
	C	-19,008	3,7957	0,000
C	A	16,1580	3,7612	0,000
	B	19,0086	3,7957	0,000

According to the significance level of α = 0.05, it has been determined that there is no difference between the A and B induction furnaces in the factory that will affect the amount of energy they consume during melting. However, it has been observed that the energy expended by the C induction furnace for melting is different from the A and B furnaces. Instead of combining the data, it may be appropriate to make separate analyses for each quarry.

In Table 7, $F(4, 2431) = 276.23$ and $p < 0.000$, therefore the independent variables (temperature, Castingtime, billet, sawdust) as a whole explain the energy variable significantly. The results of this fixed effect model show that factors such as temperature and casting time play a decisive role in energy consumption, while the 'billet' variable significantly reduces energy use. Although the variable 'sawdust' shows a negative effect, the level of statistical significance is weaker. The presence of large differences between kilns (rho ≈ 92%) supports the use of a fixed effect model.

Table 7. Fixed-Effects Panel Data Model Results

Dependent Variable:	Energy (Fixed Effects)
Number of Observations:	2,438
Group Variable:	Furnaces (3 groups)
R^2:	within = 0.3125 between = 0.4494 overall = 0.3071
F(4, 2431):	276.23
p-value:	0.0000

Coefficient Estimates

Variable	Coefficient	Std. Err.	t	P>|t|	95% Confidence Interval
Temperature	0.6746834	0.1281	5.27	0.000	0.4235, 0.9258
Castingtime	-3.6253	0.2912	-12.45	0.000	-4.1963, -3.0543
Billet	-0.5602	0.0955	-5.86	0.000	-0.7476, -0.3727
Sawdust	-0.0106	0.0060	-1.76	0.078	-0.0225, 0.0012
Cons	11.0251	1.3064	8.44	0.000	8.4629, 13.5870

This analysis can be instructive for decision makers who wish to optimize energy use or improve production efficiency. In particular, close monitoring of casting time and temperature can have important consequences in terms of energy savings.

CONCLUSION and DISCUSSION

Energy consumption caused by the induction furnace has been analysed using statistical methods. Throughout the study, the factors affecting the energy consumed in induction furnaces and the degree of importance of these factors has been researched.

Obtained results can be listed as follows:

- According to the regression model, the "Billet amount" negatively impacts energy consumption, indicating that melting smaller quantities of material reduces energy usage.
- Casting time and temperature are positive contributors to energy consumption, highlighting the significant role process optimization can play in reducing energy costs.
- The R^2 value of the model shows that 34% of the variation in energy consumption can be explained, suggesting that other factors, either outside the process or unmeasured, account for the remaining variability. This implies the need for the inclusion of additional variables to improve the model.
- The ANOVA results show no significant difference between the energy consumption of furnaces A and B, but furnace C exhibits a distinct difference. This suggests that technical variations between furnaces may influence energy efficiency.
- The higher energy consumption in furnace C may require a review of maintenance processes or an analysis of the types of materials used.
- These differences highlight the need for future analyses to model the furnaces individually, considering their specific characteristics.
- No statistically significant difference in energy consumption was observed between furnaces A and B, while furnace C displayed a significant difference according to Tukey test. This suggests that process-based improvements in energy management could be beneficial.
- Potential causes for this difference may include furnace type, material properties, and operational variables. A deeper investigation of these factors is necessary. Such detailed analyses could provide valuable insights for enhancing energy efficiency in similar production facilities.
- These results show that energy consumption is largely determined by variables such as temperature and casting time, as well as the large differences between furnaces (rho ≈ 92%) justify the use of the fixed effect model.
- In future research, efficiency analysis will be further pursued using stochastic frontier methods and data envelopment analysis to optimize energy consumption in steel production facilities (Yenizmez 2025a, Yenilmez 2025b).

SUGGESTIONS

Training programs on energy management and process optimization should be implemented to minimize the impact of operators on variables influencing energy consumption, such as casting time and temperature. Optimizing casting processes can improve energy efficiency; for instance, reducing casting time and maintaining specific temperature ranges for energy-intensive processes would be beneficial. Maintenance schedules for Furnace C should be reassessed due to its higher energy consumption. Technological upgrades may be necessary to address inefficiencies. Energy consumption should be continuously monitored at the furnace level, and efficiency should be assessed through real-time analyses. The integration of energy management systems could enable more effective use of process data.

Future studies should aim to collect data over extended periods and analyse the long-term variables affecting energy consumption.

REFERENCES

Al-shaibani W. T., Babaqi T. & Alsarori A. (2023). Power consumption prediction for the steel industry. *Proceedings of the IISE Annual Conference & Expo 2023*, Electrical Engineering and Systems Science Systems and Control.

Dock, J., Janz, D., Weiss, Kienberger T. & Weiss J. (2021). Time-resolved energy consumption modelling of electric steel production. *Elektrotechnik Und Informationstechnik*,138, 4-5, 274-280.

He, K. & Wang, L. (2017). A review of energy use and energy-efficient technologies for the iron and steel industry. *Renewable & Sustainable Energy Reviews*, 70, 1022-1039.

Jin, P., Jiang, Z, Bao, C., Hao, S. & Zhang, X. (2017). The energy consumption and carbon emission of the integrated steel mill with oxygen blast furnace. *Resources Conservation and Recycling*, 117, 58-65.

Karthick, K., Dharmaprakash, R., & Sathya, S. (2024). Predictive modeling of energy consumption in the steel industry using CatBoost regression: A data-driven approach for sustainable energy management. *International Journal of Robotics and Control Systems, 4*(1), 33-49.

Kao, Y. S., Nawata, K., & Huang, C. Y. (2020). Predicting primary energy consumption using hybrid ARIMA and GA-SVR based on EEMD decomposition. *Mathematics, 8*(10), 1722.

Kaya D. (2019). Demir Çelik Sektöründe Enerji Verimliliği. *Bayburt Üniversitesi Fen Bilim. Dergisi*, 2(2),201-204.

Knop K. (2000). Comparison of the economics of crude steel production based on fine ore reduction versus shaft furnace reduction. *Stahl Eisen*, 120 (11), 57-66.

Na H., Sun, J., Yuan, Y., Qiu, Z., Zhang, L., & Du, T. (2024). Theoretical energy consumption analysis for sustainable practices in the iron and steel industry. *Metals, 14*(5), 563.

Xu C. &Cang D. (2010). A Brief Overview of Low CO2 Emission Technologies for Iron and Steel Making, *J. Iron Steel Res. Int*., c. 17, 1-7.

Ridwana I., Nassif N., & Choi W. (2020). Modeling of Building Energy Consumption by Integrating Regression Analysis and Artificial Neural Network with Data Classification. *Buildings*, 10(11), 198, https://doi.org/10.3390/buildings10110198.

Truong N.S., Ngo N. T. & Pham AD. (2021). Forecasting Time-Series Energy Data in Buildings Using an Additive Artificial Intelligence Model for Improving Energy Efficiency., *Computational Intelligence and Neuroscience*, https://doi.org/10.1155/2021/60285

Yenilmez, İ. (2025a). Performance of imputation techniques: A comprehensive simulation study using the transformer model. *Sigma Journal of Engineering and Natural Sciences – Sigma Mühendislik ve Fen Bilimleri Dergisi*, *43*(1), 199–212.

Yenilmez, İ. (2025b). Efficiency analysis of Turkish container ports: SFA or DEA?. *Verimlilik Dergisi*, 105–118.

Ethics Statement: In this article, the journal's writing guidelines, publication principles, research and publication ethics, and journal ethical rules have been adhered to. The responsibility for any violations that may arise concerning the article lies with the author(s). "This study is a study that does not require ethics committee approval."

Declaration of Author(s)' Contribution Rate: The contribution of the first author is 25%, the second author's contribution is 25%, the third author's contribution is 25%, and the fourth author's contribution is 25%.

CONTRIBUTION RATE	CONTRIBUTORS
Idea or Notion	Beyhan ÖZDEMİR, Özge PEDİZ, Uğur CENGİZ, Yeliz M.Kantar
Literature Review	Yeliz MERT KANTAR, Beyhan ÖZDEMİR
Yöntem	Yeliz MERT KANTAR, Özge PEDİZ
Data Collecting	Uğur CENGİZ, Özge PEDİZ
Data Analysis	Özge PEDİZ, Yeliz MERT KANTAR
Findings	Beyhan ÖZDEMİR, Özge PEDİZ, Uğur CENGİZ
Discussion and Commentary	Uğur CENGİZ, YELİZ MERT KANTAR

Funding: No contribution and/or financial support was received during the writing process of this study.

Data Availability Statement: The data were collected by Bilecik Iron and Steel Factory. The availability of data is under the permission of Bilecik Iron and Steel Factory.

Acknowledgments: This study was supported by TÜBİTAK with 2209-B Industry Oriented. This study was supported by Eskisehir Technical University Scientific Research Projects Commission under grant no 23ADP185.

Conflict of Interest: No conflict of interest has been declared regarding the article.