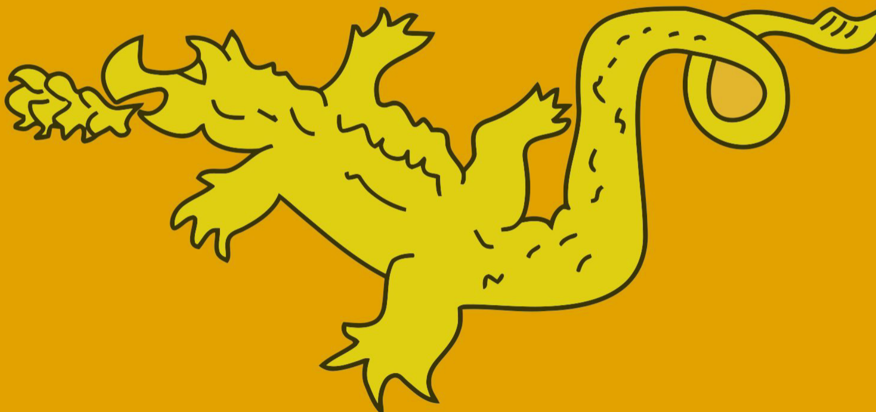

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AN ANECDOTE ABOUT DISINFORMATION FROM ORWELL

In contemporary times marked by the prevalence of digital technologies, the proliferation of disinformation has emerged as a prominent concern on the global agenda. Notably, the phenomenon of disinformation is not confined solely to social media platforms; historically, it has served as a potent tool for propagandistic purposes and as a means of instigating public outrage. Furthermore, beyond its utilization by intelligence agencies, adversaries, or competitors, disinformation encompasses a method employed for shaping and manipulating perceptions, often referred to as social engineering.

Illustratively, insights from George Orwell's War Diaries underscore the pervasive use of disinformation during the Second World War by both Britain and Germany. This involved disseminating misleading information not only to the populations of enemy territories via radio broadcasts and newspapers but also within their own societies. Orwell's diary entries vividly delineate the orchestration of disinformation campaigns in accordance with governmental directives [1]:

"*I have now been in the BBC about 6 months. Shall remain in it if the political changes, I foresee come off, otherwise probably not. Its atmosphere is something halfway between a girls' school and a lunatic asylum, and all we are doing at present is useless, or slightly worse than useless. Our radio strategy is even more hopeless than our military strategy. Nevertheless, one rapidly becomes propaganda-minded and develops a cunning one did not previously have. E.g., I am regularly alleging in my newsletters that the Japanese are plotting to attack Russia. I don't believe this to be so, but the calculation is:*

If the Japanese do attack Russia, we can then say "I told you so". If the Russians attack first, we can, having built up the picture of a Japanese plot beforehand, pretend that it was the Japanese who started it. If no war breaks out at all, we can claim that it is because the Japanese are too frightened of Russia.

All propaganda is lies, even when one is telling the truth. I don't think this matters so long as one knows what one is doing, and why."

Thus, the evolving landscape of the contemporary era, notably the third decade distinguished by the omnipresence of social media platforms, stands as a pivotal epoch in the annals of human history—an era entrenched in an all-encompassing struggle against the proliferation of disinformation. This epoch represents a turning point wherein the convergence of technological advancements and the burgeoning dissemination of information has presented unparalleled challenges.

The battle against disinformation transcends mere technological skirmishes; it embodies a multifaceted war encompassing legislative, societal, and technological fronts. It demands collaborative efforts from governments, technological innovators, media entities, and vigilant citizens alike to fortify the citadels of truth and integrity. The potency of disinformation to manipulate beliefs, sway opinions, and sow discord underscores the urgency for concerted and unwavering action in safeguarding the sanctity of information dissemination. The determination to combat disinformation is not merely a response to contemporary challenges; it symbolizes a resolute commitment to preserving the essence of truth and authenticity in shaping the socio-political landscapes of the future.

December 2022

Prof. Dr. Mustafa Zihni TUNCA
Editor-in-Chief

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Original Paper

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A CASE OF TRAILER SELECTION UNDER FUZZY ENVIRONMENT VIA PIPRECIA EXTENDED AND COCOSO METHODS

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ABSTRACT

The trailer, which is defined as the part behind the chassis in vehicles, is widely used especially in road transportation and allows the simultaneous transfer of large volume product groups. Different types of trailers produced for different needs enable logistics companies and manufacturers to have suitable transportation options for the transfer they need. This study aims to solve a trailer selection problem, which has strategic importance for transportation companies. Thereforen, the criteria that are important in the selection of the trailer are chosen and their weights are calculated via Fuzzy PIPRECIA-Extended. Thereafter, alternatives were evaluated using the Fuzzy CoCoSo method. The results showed that the most essential criterion in the selection of the trailer is found out as "Light structure", and the most appropriate trailer is obtained as the Tırsan.SCL X / 150 - 12/27 Trailer. According to the findings, comprehensive perspectives related to the trailer selection problem is presented. This study will benefit the literature in terms of both application and the integrated methods.

Keywords: *Trailer Selection, Fuzzy PIPRECIA-E, Fuzzy CoCoSo, Multi-Criteria Decision Making.*

1. INTRODUCTION

The trailer is a part of the chassis located behind the chassis of the vehicles. A kingpin is designed with a flange to prevent leakage of the connection points while connecting the trailer to the vehicle. Moreover, there is also a table part where the kingpin can be attached to the tractor part for the trailer to be securely attached to the towing vehicle. Trailers commonly used in road transport allow for the simultaneous transfer of large volumes of product groups. Different types of trailers produced for different needs enable logistics companies and manufacturers to have the transportation options they need. As required by law, each trailer type has its own measurement standards. Consequently, it would be more accurate to choose a different trailer type instead of different sizes of the same trailer in case of having products that will be more disadvantageous to be transported with the trailer type. The carrying capacity and volume of trailers vary depending on the trailer type. These are the trailers and semi-trailers that are most in-demand in the transportation industry. The primary consideration in the sale of these two non-motorized transport vehicles is that they ensure the safety of both people and property. The vehicle's size, mass, system, and detail parts must be carefully reviewed during the production phase. Furthermore, necessary approval documents such as Tip, Martov, Aitm, etc. are some of the essential conditions that should be considered in trailer sales. All these concepts are effective in the selection of the trailer.

This study discusses the trailer selection problem, which is necessary for a company operating in the transportation sector. Five evaluation criteria (Light structure, Solid Chassis, Strong Brake System, Driver's food cabinet (cultural & driver comfort element), After-Sales Support (warranty, service, and spare parts)) are considered to determine the most suitable trailer among the four alternatives. A model proposal is presented by applying relatively new multi-criteria decision-making (MCDM) methods PIPRECIA-E (PIvot Pairwise RElative Criteria Importance Assessment Extended) and CoCoSo (Combined Compromise Solution) methods in an integrated manner under a fuzzy environment. Fuzzy PIPRECIA-E is preferred to calculate the criterion importance levels while Fuzzy CoCoSo is applied for the selection of trailer alternatives.

In the following parts, a literature review is conducted on the methods used in this study. Thereafter, the working principles of the methods are explained in the accompaniment of equations. Then, the trailer selection problem is applied to a transportation company. In the application part, the weights of the criteria that are important in the selection of the trailer are chosen and the most suitable trailer for the company is obtained. Finally, the results are discussed in the conclusion part.

2. LITERATURE REVIEW

The literature review is conducted under two topics. Some of the recent studies that applied Fuzzy PIPRECIA and Fuzzy CoCoSo are given in Tables 1 and 2 respectively. Table 1 depicts studies related to Fuzzy PIPRECIA.

Table 1. Literature Review of Fuzzy PIPRECIA Extended

Authors	Problem	Methods
Dogantas et.al.(2022)	Selection of short-term trailer park amenities employing a fuzzy method	Fuzzy PIPRECIA
Aytekin, A. (2022)	Chosing criteria weights of vehicle tracking system	PIPRECIA-S
Dukic (2022)	Determining factors that have an impact on satisfaction and motivation of employees	PIPRECIA
Arman ve Kundakcı (2022)	Assessing the criteria which are important in the blockchain technology	Fuzzy PIPRECIA
Blagojević et al. (2021)	Analysing the safety of the railway section and passive level crossings	Fuzzy PIPRECIA, Fuzzy FUCOM, and Fuzzy MARCOS
Nedelijkovic et.al. (2021)	Assessing rapeseed varieties in the agriculture	Fuzzy PIPRECIA and Fuzzy MABAC
Blagojević et al. (2020)	Analysing rail traffic safety situation in a total of nine railway sections	Fuzzy PIPRECIA and DEA (Data Envelopment Analysis)
Dalic et al. (2020)	Determination to make a SWOT analysis for logistics performance	SWOT analysis and Fuzzy PIPRECIA
Vesković et al. (2020a)	Selection of the best possible clarification for the business balance of passenger rail operator	Fuzzy PIPRECIA and Fuzzy EDAS
Tomasevic et al. (2020)	Analysis of criteria for the application of high-performance computing	Fuzzy PIPRECIA
Memis et al. (2020)	Analysing road transport risk factors for supply chain management	Fuzzy PIPRECIA
Dobrosavljević et al. (2020)	Evaluation of business process management dimensions for clothing businesses	Fuzzy PIPRECIA and FUCOM
Vesković et al. (2020b)	Evaluation of criteria for selection of reach stackers required for handling facilities within the container terminal operating	Fuzzy PIPRECIA
Stankovic et al. (2020)	Analyzing the road traffic risk	Fuzzy MARCOS and Fuzzy PIPRECIA
Popovic et al. (2019)	Evaluation of underground mining methods	PIPRECIA-E

Jocic et.al. (2020)	Analyzing the quality of e-learning materials using the PIPRECIA method	PIPRECIA
Popovic and Mihajlovic (2018)	Evaluation of projects development of the tourism of the Upper Danube Basin	PIPRECIA-E
Stevic et.al. (2018)	Evaluation of cases for executing IT in a warehouse system	PIPRECIA

To the best of our knowledge, there is no application study in the literature using the extended version of Fuzzy PIPRECIA. For this reason, Table 1 demonstrates the studies that applied Fuzzy PIPRECIA and PIPRECIA-E rather than the fuzzy extended version. As can be seen, Fuzzy PIPRECIA and PIPRECIA-E methods have been applied generally in the logistics sector in recent years. Safety, traffic risk are the main subjects handled via the PIPRECIA method. However, as mentioned before, a selection problem solved with the Extended version of Fuzzy PIPRECIA has not been published in the literature yet. Therefore, using the extended version of Fuzzy PIPRECIA in the selection of the trailer will contribute to the literature. Table 2 depicts the studies implementing the Fuzzy CoCoSo method.

Table 2. Literature Review of Fuzzy CoCoSo

Authors	Problem	Methods
Demir et.al.(2022)	Providing a practical framework for the selection decisions of final measures and policies to be carried out to achieve sustainable urban mobility plans workspace goals	F-FUCOM and F-CoCoSo
Chen et.al. (2022)	Evaluating risks and prioritization of occupational hazards	CoCoSo
Khan and Haleem (2021)	Analysing circular economy methods in terms of emerging economies	CoCoSo
Torkayesh et.al. (2021)	Evaluating the social sustainability performance of G7 countries	CoCoSo
Pamucar et. Al. (2021)	Evaluating circular economy concepts in urban mobility alternatives	Dombi CoCoSo & dDIBR
Deveci et al. (2021)	Evaluation of traffic management systems	CoCoSo and Power Heronian function
Lahane and Kant (2021)	Application in an Indian manufacturing business on the importance of environmentally circular supply chain performance	Pythagorean Fuzzy CoCoSo and Pythagorean Fuzzy AHP
Choudhary and Mishra (2021)	Determining the critical success enablers of industry 4 employing CoCoSo and hybrid fuzzy AHP	CoCoSo and Fuzzy AHP
Cui et.al.(2021)	Identifyinf the essential varriers to the adoption of the Internet of Things in the circular economy in the manufacturing sector	SWARA and CoCoSo
Peng et al. (2021)	Evaluation of intelligent health management	Fuzzy soft decision-making method based on CoCoSo and CRITIC method
Yazdani et al. (2021)	Evaluation of risk factors of outsourcing providers in a chemical company	Fuzzy Failure Mode and Effect Analysis (F-FMEA) and CoCoSo

Alrasheedi et al. (2021)	Evaluation of green growth indicators for sustainable production	CoCoSo and Interval-Valued Intuitionistic Fuzzy Set (IVIFS)
Zavadskas et al. (2021)	Evaluation of the use of buildings according to sustainability criteria.	Fuzzy CoCoSo
Ecer and Pamucar (2020)	Selection of the supplier for a home appliance manufacturer	Fuzzy CoCoSo, Fuzzy BWM Bonferroni and CoCoSo'B
Peng et al. (2020)	Evaluation of financial risks in enterprises	CoCoSo, CRITIC and Q-rung orthopair fuzzy set
Zhang et al. (2020)	The Selection of construction component suppliers for property developers in the residential sector	BWM (Best Worst Method), CoCoSo, Hesitant fuzzy linguistic term set, Interval rough boundaries
Wen et al. (2019)	Selection of third-party logistics (3PL) service suppliers in the financial sector	CoCoSo method and hesitant fuzzy linguistic term set combination

When Table 2 is examined, it is seen that the Fuzzy CoCoSo method is integrated with various methods. As for the field of application, Fuzzy CoCoSo is applied in various fields, unlike PIPRECIA. Supply chain management and finance are the main fields considered in the literature in terms of Fuzzy COCOSO method. Although the Fuzzy CoCoSo method has been utilized with many different methods, no study in the literature integrates it with the PIPRECIA method.

It has been seen in the comprehensive literature review that the studies on trailer selection is limited with the study conducted by Görçün (2019). However, there are additional related studies that handle the selection of production mix of grain trailers (Hoose et al., 2021), material selection for trailer (Francisco et al., 2021; Galos & Sutcliffe, 2019), selection of semi-trailer by considering operational damage (Figlus & Kuczyński, 2018). Consequently, it is obvious that our study will benefit the literature in terms of both the application area and the fact that the methods to be used in an integrated way have not been applied in the literature before.

3. METHODOLOGY

In our study, fuzzy extensions of PIPRECIA-E and CoCoSo methods are used. The reasons to select these methodologies would better to be clarified. Since the PIPRECIA which is relatively novel method has easy evaluation process and has not been applied yet in various fields. Moreover, unlike other MCDM methods based on pairwise comparisons (Analytic Hierarchy Process, Best-Worst Method, etc.), only (n-1) numbers of comparisons are sufficient in PIPRECIA method. CoCoSo method is preferred because of its simple operations and the gap in the literature related to the integration of CoCoSo and PIPRECIA methods.

The application steps and theoretical backgrounds of these methods are shared in the following subsections.

3.1. Fuzzy PIPRECIA-E

Fuzzy PIPRECIA-E is one of the multi-criteria decision-making methods for determining the weights of the criteria. Fuzzy PIPRECIA-E procedure is in Table 3 (Stevic et al., 2018, 7-9).

Table 3. Fuzzy PIPRECIA-E Steps

Step	Equation	Equation Number
Evaluative of decision maker	$\tilde{s}_{jd} = \begin{cases} j \text{ is important than } (j-1) \Rightarrow \tilde{s}_{jd} > \tilde{1} \\ \text{importance of } j = (j-1) \Rightarrow \tilde{s}_{jd} = \tilde{1} \\ (j-1) \text{ is important than } j \Rightarrow \tilde{s}_{jd} < \tilde{1} \end{cases}$	(1)
Integration of opinions	$\tilde{s}_{jl} = \sqrt[D]{(\tilde{s}_{jl1})(\tilde{s}_{jl2})(\tilde{s}_{jl3}) \dots (\tilde{s}_{jlD})}$	(2)
Integration of opinions	$\tilde{s}_{jm} = \sqrt[D]{(\tilde{s}_{jm1})(\tilde{s}_{jm2})(\tilde{s}_{jm3}) \dots (\tilde{s}_{jmD})}$	(3)
Integration of opinions	$\tilde{s}_{ju} = \sqrt[D]{(\tilde{s}_{ju1})(\tilde{s}_{ju2})(\tilde{s}_{ju3}) \dots (\tilde{s}_{juD})}$	(4)
Coefficient	$\tilde{k}_{jl} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \tilde{s}_{ju} \end{cases}$	(5)
Coefficient	$\tilde{k}_{jm} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \tilde{s}_{jm} \end{cases}$	(6)
Coefficient	$\tilde{k}_{ju} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \tilde{s}_{jl} \end{cases}$	(7)
Fuzzy weights	$\tilde{q}_{jl} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \frac{\tilde{q}_{(j-1)l}}{\tilde{k}_{ju}} \end{cases}$	(8)
Fuzzy weights	$\tilde{q}_{jm} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \frac{\tilde{q}_{(j-1)m}}{\tilde{k}_{jm}} \end{cases}$	(9)
Fuzzy weights	$\tilde{q}_{ju} = \begin{cases} j = 1 \Rightarrow 1 \\ j > 1 \Rightarrow 2 - \frac{\tilde{q}_{(j-1)u}}{\tilde{k}_{jl}} \end{cases}$	(10)
Relative weights	$\tilde{w}_{jl} = \frac{\tilde{q}_{jl}}{\sum_{j=1}^{n} \tilde{q}_{ju}}$	(11)
Relative weights	$\tilde{w}_{jm} = \frac{\tilde{q}_{jm}}{\sum_{j=1}^{n} \tilde{q}_{jm}}$	(12)
Relative weights	$\tilde{w}_{ju} = \frac{\tilde{q}_{ju}}{\sum_{j=1}^{n} \tilde{q}_{jl}}$	(13)

Table 3. Fuzzy PIPRECIA-E Steps

Step	Equation	Equation Number
Inverse evaluation	$\tilde{s}'_{jd} = \begin{cases} j \text{ is important than } (j+1) \Rightarrow \tilde{s}'_{jd} > \tilde{1} \\ \text{importance of } j = (j+1) \Rightarrow \tilde{s}'_{jd} = \tilde{1} \\ (j+1) \text{ is important than } j \Rightarrow \tilde{s}'_{jd} < \tilde{1} \end{cases}$	(14)
Integration for inverse evaluation	$\tilde{s}'_{jl} = \sqrt[D]{(\tilde{s}'_{jl1})(\tilde{s}'_{jl2})(\tilde{s}'_{jl3}) \ldots (\tilde{s}'_{jlD})}$	(15)
Integration for inverse evaluation	$\tilde{s}'_{jm} = \sqrt[D]{(\tilde{s}'_{jm1})(\tilde{s}'_{jm2})(\tilde{s}'_{jm3}) \ldots (\tilde{s}'_{jmD})}$	(16)
Integration for inverse evaluation	$\tilde{s}'_{ju} = \sqrt[D]{(\tilde{s}'_{ju1})(\tilde{s}'_{ju2})(\tilde{s}'_{ju3}) \ldots (\tilde{s}'_{juD})}$	(17)
Inverse coefficient	$\tilde{k}'_{jl} = \begin{cases} j = n \Rightarrow 1 \\ j < n \Rightarrow 2 - s'_{ju} \end{cases}$	(18)
Inverse coefficient	$\tilde{k}'_{jm} = \begin{cases} j = n \Rightarrow 1 \\ j < n \Rightarrow 2 - s'_{jm} \end{cases}$	(19)
Inverse coefficient	$\tilde{k}'_{ju} = \begin{cases} j = n \Rightarrow 1 \\ j < n \Rightarrow 2 - s'_{jl} \end{cases}$	(20)
Inverse fuzzy weights	$\tilde{q}'_{jl} = \begin{cases} j = n \Rightarrow 1 \\ j < n \Rightarrow 2 - \dfrac{\tilde{q}'_{(j+1)l}}{\tilde{k}'_{ju}} \end{cases}$	(21)
Inverse fuzzy weights	$\tilde{q}'_{jm} = \begin{cases} j = n \Rightarrow 1 \\ j < n \Rightarrow 2 - \dfrac{\tilde{q}'_{(j+1)m}}{\tilde{k}'_{jm}} \end{cases}$	(22)
Inverse fuzzy weights	$\tilde{q}'_{ju} = \begin{cases} j = n \Rightarrow 1 \\ j < n \Rightarrow 2 - \dfrac{\tilde{q}'_{(j+1)u}}{\tilde{k}'_{jl}} \end{cases}$	(23)
Inverse relative weights	$\widetilde{w}'_{jl} = \dfrac{\tilde{q}'_{jl}}{\sum_{j=1}^{n} \tilde{q}'_{ju}}$	(24)
Inverse relative weights	$\widetilde{w}'_{jm} = \dfrac{\tilde{q}'_{jm}}{\sum_{j=1}^{n} \tilde{q}'_{jm}}$	(25)
Inverse relative weights	$\widetilde{w}'_{ju} = \dfrac{\tilde{q}'_{ju}}{\sum_{j=1}^{n} \tilde{q}'_{jl}}$	(26)
Aggregation of weights	$\widetilde{w}''_{jl} = \dfrac{\widetilde{w}_{jl} + \widetilde{w}'_{jl}}{2}$	(27)

Table 3. Fuzzy PIPRECIA-E Steps

Step	Equation	Equation Number
Aggregation of weights	$\tilde{w}''_{jm} = \frac{\tilde{w}_{jm} + \tilde{w}'_{jm}}{2}$	(28)
Aggregation of weights	$\tilde{w}''_{ju} = \frac{\tilde{w}_{ju} + \tilde{w}'_{ju}}{2}$	(29)

j: *criterion*; $j = 1,2,3,\dots,n$

l: *fuzzy number lower limit*

m: *fuzzy number the most promising value*

u: *fuzzy number upper limit*

d: *decision maker*; $d = 1,2,3,\dots,D$

$\tilde{s}_{jld}$: *relative importance lower limit*

$\tilde{s}_{jmd}$: *relative importance the most promising value*

$\tilde{s}_{jud}$: *relative importance upper limit*

$\tilde{s}_{jl}$: *integrated relative importance lower limit*

$\tilde{s}_{jm}$: *integrated relative imp. the most promising value*

$\tilde{s}_{ju}$: *integrated relative importance upper limit*

$\tilde{k}_{jl}$: *coefficient lower limit*

$\tilde{k}_{jm}$: *coefficient the most promising value*

$\tilde{k}_{ju}$: *coefficient upper limit*

$\tilde{q}_{jl}$: *fuzzy weight lower limit*

$\tilde{q}_{jm}$: *fuzzy weight the most promising value*

$\tilde{q}_{ju}$: *fuzzy weight upper limit value*

$\tilde{w}_{jl}$: *relative weight lower limit*

$\tilde{w}_{jm}$: *relative weight the most promising value*

$\tilde{w}_{ju}$: *relative weight upper limit*

$\tilde{s}'_{jld}$: *inverse relative importance lower limit*

$\tilde{s}'_{jmd}$: *inverse relative imp. most promising value*

$\tilde{s}'_{jud}$: *inverse relative importance upper limit*

$\tilde{s}'_{jl}$: *inverse relative importance lower limit*

$\tilde{s}'_{jm}$: *inverse relative imp. the most promising value*

$\tilde{s}'_{ju}$: *inverse relative importance upper limit*

$\tilde{k}'_{jl}$: *inverse coefficient lower limit*

$\tilde{k}'_{jm}$: *inverse coefficient most promising value*

$\tilde{k}'_{ju}$: *inverse coefficient upper limit*

$\tilde{q}'_{jl}$: *inverse fuzzy weight lower limit*

$\tilde{q}'_{jm}$: *inverse fuzzy weight most promising value*

$\tilde{q}'_{ju}$: *inverse fuzzy weight upper limit*

$\tilde{w}'_{jl}$: *inverse relative weight lower limit*

$\tilde{w}'_{jm}$: *inverse relative weight most promising value*

$\tilde{w}'_{ju}$: *inverse relative weight upper limit*

$\tilde{w}''_{jl}$: *aggregated weight lower limit*

$\tilde{w}''_{jm}$: *aggregated weight the most promising value*

$\tilde{w}''_{ju}$: *aggregated weight upper limit*

3.2. Fuzzy CoCoSo

Fuzzy CoCoSo is the integration of CoCoSo (Yazdani et al., 2019, 2507-2508) and fuzzy calculus structure (Tolga & Turgut, 2018, 55; Stankovic et al., 2020, 3). Table 4 indicates procedure used in Fuzzy CoCoSo.

Table 4. Fuzzy CoCoSo Procedure

Step	Equation	Equation Number
Integration of opinions	$\tilde{x}_{ijl} = \frac{\sum_{d=1}^{D} \tilde{x}_{ijld}}{D}$	(30)
Integration of opinions	$\tilde{x}_{ijm} = \frac{\sum_{d=1}^{D} \tilde{x}_{ijmd}}{D}$	(31)

Table 4. Fuzzy CoCoSo Procedure

Step	Equation	Equation Number
Integration of opinions	$\tilde{x}_{iju} = \frac{\sum_{d=1}^{D} \tilde{x}_{ijud}}{D}$	(32)
Normalization (benefit criterion)	$\tilde{r}_{ijl} = \frac{\tilde{x}_{ijl} - \min_j \tilde{x}_{ijl}}{\max_j \tilde{x}_{iju} - \min_j \tilde{x}_{ijl}}$	(33)
Normalization (benefit criterion)	$\tilde{r}_{ijm} = \frac{\tilde{x}_{ijm} - \min_j \tilde{x}_{ijl}}{\max_j \tilde{x}_{iju} - \min_j \tilde{x}_{ijl}}$	(34)
Normalization (benefit criterion)	$\tilde{r}_{iju} = \frac{\tilde{x}_{iju} - \min_j \tilde{x}_{ijl}}{\max_j \tilde{x}_{iju} - \min_j \tilde{x}_{ijl}}$	(35)
Normalization (cost criterion)	$\tilde{r}_{ijl} = \frac{\max_j \tilde{x}_{iju} - \tilde{x}_{iju}}{\max_j \tilde{x}_{iju} - \min_j \tilde{x}_{ijl}}$	(36)
Normalization (cost criterion)	$\tilde{r}_{ijm} = \frac{\max_j \tilde{x}_{iju} - \tilde{x}_{ijm}}{\max_j \tilde{x}_{iju} - \min_j \tilde{x}_{ijl}}$	(37)
Normalization (cost criterion)	$\tilde{r}_{iju} = \frac{\max_j \tilde{x}_{iju} - \tilde{x}_{ijl}}{\max_j \tilde{x}_{iju} - \min_j \tilde{x}_{ijl}}$	(38)
Total fuzzy weighted comparability sequence	$\tilde{s}_{il} = \sum_{j=1}^{n} \widetilde{w}''_{jl} \tilde{r}_{ijl}$	(39)
Total fuzzy weighted comparability sequence	$\tilde{s}_{im} = \sum_{j=1}^{n} \widetilde{w}''_{jm} \tilde{r}_{ijm}$	(40)
Total fuzzy weighted comparability sequence	$\tilde{s}_{iu} = \sum_{j=1}^{n} \widetilde{w}''_{ju} \tilde{r}_{iju}$	(41)
Total defuzzified weighted comparability sequence	$s_i = \frac{(\tilde{s}_{iu} - \tilde{s}_{il}) + (\tilde{s}_{im} - \tilde{s}_{il})}{3} + \tilde{s}_{il}$	(42)
Power fuzzy weighted comparability sequence	$\tilde{p}_{il} = \sum_{j=1}^{n} \tilde{r}_{ijl}^{\widetilde{w}''_{jl}}$	(43)
Power fuzzy weighted comparability sequence	$\tilde{p}_{im} = \sum_{j=1}^{n} \tilde{r}_{ijm}^{\widetilde{w}''_{jm}}$	(44)
Power fuzzy weighted comparability sequence	$\tilde{p}_{iu} = \sum_{j=1}^{n} \tilde{r}_{iju}^{\widetilde{w}''_{ju}}$	(45)

Table 4. Fuzzy CoCoSo Procedure

Step	Equation	Equation Number
Power defuzzified weighted comparability sequence	$p_i = \frac{(\tilde{p}_{iu} - \tilde{p}_{il}) + (\tilde{p}_{im} - \tilde{p}_{il})}{3} + \tilde{p}_{il}$	(46)
Aggregation strategy a	$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)}$	(47)
Aggregation strategy b	$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i}$	(48)
Aggregation strategy c	$k_{ic} = \frac{\lambda S_i + (1-\lambda)P_i}{\lambda \max_i S_i + (1-\lambda)\max_i P_i}$	(49)
Final value	$k_i = \sqrt[3]{k_{ia}k_{ib}k_{ic}} + \frac{k_{ia} + k_{ib} + k_{ic}}{3}$	(50)

$$i: alternative; i = 1,2,3, \dots, m$$

$$\tilde{x}_{ijld}: fuzzy\ performance\ lower\ value$$

$$\tilde{x}_{ijmd}: fuzzy\ performance\ the\ most\ promising\ value$$

$$\tilde{x}_{ijud}: fuzzy\ performance\ upper\ value$$

$$\tilde{x}_{ijl}: integrated\ fuzzy\ performance\ lower\ value$$

$$\tilde{x}_{ijm}: integrated\ fuzzy\ performance\ the\ most\ promising\ value$$

$$\tilde{x}_{iju}: integrated\ fuzzy\ performance\ upper\ value$$

$$\tilde{r}_{ijl}: normalized\ fuzzy\ performance\ lower\ value$$

$$\tilde{r}_{ijm}: normalized\ fuzzy\ performance\ most\ promising\ value$$

$$\tilde{r}_{iju}: normalized\ fuzzy\ performance\ upper\ value$$

$$\tilde{s}_{il}: total\ fuzzy\ weighted\ comparability\ sequence\ lower\ value$$

$$\tilde{s}_{im}: total\ fuzzy\ weighted\ comparability\ sequence\ most\ promising\ value$$

$$\tilde{s}_{iu}: total\ fuzzy\ weighted\ comparability\ sequence\ upper\ value$$

$$s_i: total\ defuzzified\ weighted\ comparability\ sequence\ of\ alternative\ i$$

$$\tilde{p}_i: the\ power\ fuzzy\ weight\ of\ comparability\ sequence\ of\ alternative\ i$$

$$\tilde{p}_{il}: power\ fuzzy\ weight\ of\ comparability\ sequence\ lower\ value$$

$$\tilde{p}_{im}: power\ fuzzy\ weight\ of\ comparability\ sequence\ most\ promising\ value$$

$$\tilde{p}_{iu}: power\ fuzzy\ weight\ of\ comparability\ sequence\ upper\ value$$

$$p_i: defuzzified\ power\ weighted\ comparability\ sequence\ of\ alternative\ i$$

$$k_{ia}: aggregation\ strategy\ a\ value\ for\ alternative\ i$$

$$k_{ib}: aggregation\ strategy\ b\ value\ for\ alternative\ i$$

$$k_{ic}: aggregation\ strategy\ c\ value\ for\ alternative\ i$$

$$\lambda: balance\ value\ (usually\ 0{,}5);\ 0 \leq \lambda \leq 1$$

$$k_i: final\ value\ of\ alternative\ i$$

4. APPLICATION

In this study, trailer alternatives in Turkey are evaluated. Firstly, the evaluation criteria are determined by interviewing with the experts. The expert group consists of three professionals. The first of these is the owner of one of the leading transportation companies operating in Turkey, and the other two are drivers with at least 10 years of experience working in this company. As a result of the interviews, the criteria determined as the common opinion of 3 experts and their explanations can be seen in Table 5.

Table 5. Criteria for the Trailer Selection Problem

Code	Criterion	Why it is essential?
K1	Light structure	It is important in accordance with the tonnage limits of the Turkish Republic Highways Trucks. The greater the load carried by logistics companies, the greater the profit. In other words, the lighter the trailer's curb weight, the greater the load it can carry within the limits.
K2	Solid Chassis	It is critical because these trailers will be subjected to heavy loads and harsh conditions for the duration of their service life.
K3	Strong Brake System	It appeared to be a powerful braking system. The importance of powerful and fast cooling brake systems in heavy-duty vehicles is growing at an exponential rate. For example, most accidents are caused by brake systems that fail to perform their duties due to overheating. As a result, trailer models with drum brake systems were excluded from the scope of our study.
K4	Driver's food cabinet	It appears as Driver's food cabinet. It has a very important place in Turkey culturally. Many drivers prefer to cook their own meals on the roads and this food cabinet can be used as a food preparation counter, a dining table, and a food cabinet. (cultural & driver comfort element)
K5	After-Sales Support	It has an important place in meeting the breakdown or spare part requirements that may occur after-sales. (warranty, service, and spare parts)

In the next step of the study, a questionnaire is formed for decision-makers. The first part of the questionnaire includes questions for determining the weights of criteria. Table 6 depecits the relative importance taking into account of decision maker 1.

Table 6. Relative Importance for Decision Maker 1

	$\tilde{s}_{jl1}$	$\tilde{s}_{jm1}$	$\tilde{s}_{ju1}$
K1	-	-	-
K2	0.3330	0.4000	0.5000
K3	0.5000	0.6670	1.0000
K4	0.3330	0.4000	0.5000

K5	0.4000	0.5000	0.6670

Thanks to equations 2, 3, and 4, the opinions of the decision-makers are revealed (Table 7).

Table 7. Integrated Relative Importance

	$\tilde{s}_{jl}$	$\tilde{s}_{jm}$	$\tilde{s}_{ju}$
K1	-	-	-
K2	0.2877	0.3365	0.4053
K3	0.3625	0.4462	0.5848
K4	0.3165	0.3763	0.4642
K5	0.3763	0.4642	0.6059

The coefficient is calculated by employing Equations 5, 6, and 7 (Table 8).

Table 8. Coefficients

	$\tilde{k}_{jl}$	$\tilde{k}_{jm}$	$\tilde{k}_{ju}$
K1	1.0000	1.0000	1.0000
K2	1.5947	1.6635	1.7123
K3	1.4152	1.5538	1.6375
K4	1.5358	1.6237	1.6835
K5	1.3941	1.5358	1.6237

Thanks to equations 8, 9, and 10, fuzzy weights of criteria are calculated (Table 9).

Table 9. Fuzzy Weights

	$\tilde{q}_{jl}$	$\tilde{q}_{jm}$	$\tilde{q}_{ju}$
K1	1.0000	1.0000	1.0000
K2	0.5840	0.6011	0.6271
K3	0.3566	0.3869	0.4431
K4	0.2118	0.2383	0.2885
K5	0.1305	0.1551	0.2070

By taking into account of equations 11,12 and 13, relative weights of criteria are calculated (Table 10).

Table 10. Relative Weights

	$\tilde{w}_{jl}$	$\tilde{w}_{jm}$	$\tilde{w}_{ju}$
K1	0.3898	0.4199	0.4380
K2	0.2276	0.2524	0.2747
K3	0.1390	0.1625	0.1941
K4	0.0826	0.1001	0.1264
K5	0.0509	0.0651	0.0907

After calculating the weights of criteria with Fuzzy PIPRECIA, the inverse methodology of Fuzzy PIPRECIA method starts. Table 11 demonstrates inverse relative importance based on decision-maker 1.

Table 11. Inverse Relative Importance for Decision Maker 1

	$\tilde{s}'_{jl1}$	$\tilde{s}'_{jm1}$	$\tilde{s}'_{ju1}$
K5	-	-	-
K4	1.2000	1.3000	1.3500
K3	1.3000	1.4500	1.5000
K2	1.1000	1.1500	1.2000
K1	1.3000	1.4500	1.5000

Thanks to equations 15, 16, and 17, the opinions of the decision-makers are revealed (Table 12).

Table 12. Integrated Inverse Relative Importance

	$\tilde{s}'_{jl}$	$\tilde{s}'_{jm}$	$\tilde{s}'_{ju}$
K1	-	-	-
K2	1.3976	1.5953	1.6454
K3	1.2919	1.4332	1.4838
K4	1.3325	1.4984	1.5484
K5	1.2658	1.3982	1.4482

The inverse coefficient is calculated by using Equations 18, 19, and 20 (Table 13).

Table 13. Inverse Coefficient

	$\tilde{k}'_{jl}$	$\tilde{k}'_{jm}$	$\tilde{k}'_{ju}$
K1	0.3546	0.4047	0.6024
K2	0.5162	0.5668	0.7081
K3	0.4516	0.5016	0.6675
K4	0.5518	0.6018	0.7342
K5	1.0000	1.0000	1.0000

Inverse fuzzy weights are calculated by employing Equations 21, 22, and 23 (Table 14).

Table 14. Inverse Fuzzy Weights

	$\tilde{q}'_{jl}$	$\tilde{q}'_{jm}$	$\tilde{q}'_{ju}$
K1	4.7834	14.4408	21.9294
K2	2.8814	5.8442	7.7753
K3	2.0405	3.3124	4.0134
K4	1.3620	1.6616	1.8124
K5	1.0000	1.0000	1.0000

Inverse relative weights are calculated by using Equations 24, 25, and 26 (Table 15).

Table 15. Inverse Relative Weights

	$\tilde{w}'_{jl}$	$\tilde{w}'_{jm}$	$\tilde{w}'_{ju}$
K1	0.1309	0.5499	1.8173
K2	0.0789	0.2226	0.6443
K3	0.0559	0.1261	0.3326
K4	0.0373	0.0633	0.1502
K5	0.0274	0.0381	0.0829

Fuzzy PIPRECIA and inverse Fuzzy PIPRECIA weights are aggregated by using Equations 27, 28, and 29. Aggregated weights that demonstrate the fuzzy importance level of criteria based on Table 16 indicates fuzzy PIPRECIA-E method.

Table 16. Aggregated Weights

	$\tilde{w}''_{jl}$	$\tilde{w}''_{jm}$	$\tilde{w}''_{ju}$
K1	0.2604	0.4849	1,1276
K2	0.1532	0.2375	0.4595
K3	0.0974	0.1443	0.2633
K4	0.0599	0.0817	0.1383
K5	0.0391	0.0516	0.0868

After electing the weights of criteria, the trailer alternatives are analyzed based on Fuzzy CoCoSo method. In this study, the manufacturer that has the approval documents and the basic element determined at the point of choice among alternatives is the determination of the trailer tire sizes as 385/65 R22.5. However, trailers with tire sizes of 385/55 R22.5 and 435/50 R19.5 were excluded from the alternatives to avoid some issues with the ramps used in the loading and unloading areas in Turkish country conditions. Special care was taken to choose alternatives from among the models of firms that have proven their quality in the equivalent segment range. Premium trailer brands and products of foreign origin were excluded from the alternative list. To narrow the scope of the research, only the curtain sider trailer type, which is widely used for multi-purpose in Turkey's geography, has been evaluated. Finally, the trailer alternatives included in the study are as follows: A1: Tırsan.SCL X / 150 - 12/27 Trailer, A2: Krone Profiliner Trailer , A3: Serin Optima Light Trailer, A4: Çarsan Tautliner Trailer.

In the beginning of Fuzzy CoCoSo method, the decision-maker evaluates the performance of the alternatives. By taking into account of equations 30, 31, and 32, the opinions of the decision-makers are revealed. Table 17 depicits a part of the integrated fuzzy decision matrix (Criterion 1).

Table 17. A Part of the Integrated Fuzzy Decision Matrix (Criterion 1)

	$\tilde{x}_{i1l}$	$\tilde{x}_{i1m}$	$\tilde{x}_{i1u}$
A1	5.6667	7.6667	9.3333
A2	9.0000	10.0000	10.0000
A3	5.0000	7.0000	8.6667
A4	2.3333	4.3333	6.3333

In the next step of Fuzzy CoCoSo method, fuzzy performance values are normalized. Table 18 demonstrates a part of the normalized fuzzy decision matrix (Criterion 1).

Table 18. A Part of the Normalized Fuzzy Decision Matrix (Criterion 1)

	$\tilde{r}_{i1l}$	$\tilde{r}_{i1m}$	$\tilde{r}_{i1u}$
A1	0.4348	0.6957	0.9130
A2	0.8696	1.0000	1.0000
A3	0.3478	0.6087	0.8261
A4	0.0000	0.2609	0.5217

The total of the fuzzy weighted comparability sequence for each alternative is calculated by using Equations 39, 40, and 41 (Table 21). Fuzzy PIPRECIA-E results are used in this phase of Fuzzy CoCoSo method. Then, the total of the fuzzy weighted comparability sequence is defuzzified based on the best non-fuzzy performance (BNP) method in Equation 42 (Table 19).

Table 19. The Total of the Fuzzy Weighted Comparability Sequence and Defuzzification

	$\tilde{s}_{il}$	$\tilde{s}_{im}$	$\tilde{s}_{iu}$	s_i
A1	0.3886	0.8390	1.9775	1.0684
A2	0.3848	0.8594	1.9765	1.0736
A3	0.1716	0.5742	1.7073	0.8177
A4	0.0125	0.3081	1.2082	0.5096

The whole of the power fuzzy weight of comparability sequences for each alternative is calculated by using Equations 43, 44, and 45 (Table 22). The outputs of Fuzzy PIPRECIA-E are used in this phase of Fuzzy CoCoSo method. The whole of the power fuzzy weight of comparability sequences for each alternative is defuzzified according to BNP method in Equation 46 (Table 20).

Table 20. The Whole of the Power Fuzzy Weight of Comparability Sequences and Defuzzification

	$\tilde{p}_{il}$	$\tilde{p}_{im}$	$\tilde{p}_{iu}$	p_i
A1	4.7207	4.8248	4.9025	4.8160
A2	3.7897	4.7959	4.8732	4.4863
A3	4.2237	4.4761	4.6207	4.4402
A4	0.9103	4.0215	4.0969	3.0095

These values are aggregated with three different aggregation strategies. The aggregation strategies can be seen in Equations 47, 48, and 49 (Table 21).

Table 21. The Results of the Aggregation Strategies

	k_{ia}	k_{ib}	k_{ic}
A1	0.2910	3.6967	0.9991
A2	0.2750	3.5974	0.9440
A3	0.2600	3.0800	0.8927
A4	0.1740	2.0000	0.5975

In the last phase of Fuzzy CoCoSo method, final values of the alternatives are calculated by employing Equation 50. The final values of the alternatives and ranks can be seen in Table 22.

Table 22. Final Values and Ranks

Alternative	k_i	Rank
A1: Tırsan SCL X / 150 - 12/27 Trailer	2.6866	1
A2: Krone Profiliner Trailer	2.5829	2
A3: Serin Optima Light Trailer	2.3051	3
A4: Çarsan Tautliner Trailer	1.5163	4

When Table 22 is examined, it is seen that Tırsan SCL X / 150 – 12/27 trailer is in the first place. The correct perception of the Turkish market by the manufacturer and the fact that a product is offered that can appeal to all groups, including both the firm (Solid Chassis) and the driver (Food Cabinet), can be interpreted as the reason for this result. It is seen that Krone Profiliner Trailer takes the second place. This can be explained by the fact that the Krone Profiliner alternative is unrivaled in terms of lightness. Following the first two rank is the Serin Optima Light Trailer alternative. When the features of this alternative are examined, it is seen that this trailer performs slightly better than the average in terms of all criteria. In the last place, Çarsan Tautliner Trailer was obtained. The difference between the third-order alternative and the last-ranked alternative is striking. This can be explained by the fact that the 4th alternative is below the average in terms of all criteria. In addition, the user's perception of the brand and its relatively low awareness compared to other alternatives also confirm that Çarsan Tautliner Trailer is in the last place.

5. CONCLUSION

The study discussed the problem of trailer selection in a fuzzy environment. In the solution of this problem, Fuzzy PIPRECIA-E was preferred for the evaluation of the selection criteria and Fuzzy COCOSO method was preferred for the ranking of the alternatives. This study provides a resource to understand the position of brands in the Turkish market in terms of end users, rather than focusing only on technical data. In today's competitive environment, it is meaningless to find the best by focusing on a single criterion. Similarly, products designed without considering the driver's (user) opinion cannot achieve market success at the desired level. It makes no sense to offer the best in only one criterion in a competitive environment. Similarly, products that are designed without considering the driver and instead focus solely on the business will fail to achieve the desired market success.

A clear example of this is the rank difference between Alternative 1 and Alternative 2. In Turkey, there is a group of drivers who work for the company, as well as a group of owners who work on their own with their vehicles. Being successful in the market is not possible by ignoring cultural aspects and focusing only on businesses. Manufacturers who want to achieve market success should consider both segments and criteria as a whole, develop products, and focus on marketing activities that will positively affect brand perception and awareness. Therefore, the results obtained in the study show this situation. Despite meeting the quality standards in production, Çarsan Tautliner Trailer, which is in the last place, received low evaluation scores from end users as a result of poor marketing efforts. As a result of this working structure, this study sheds light on the trailer selection problem through comprehensive perspectives. This study will benefit the literature in terms of being the first study on trailer selection and the integrated application of the methods used in this study.

There are a few limitations of the study. In multi-criteria decision making problems, a single expert opinion is generally used. However, in some cases, there may be expert groups. A team of three experts contributed to this study. Therefore, it can be concluded that the findings are limited to the expertise of the expert team. In addition, the alternatives included in the study are limited to alternatives produced by manufacturers meeting certain criteria and those with a certain tire size.

In future studies, the same application can be repeated using different MCDM methods. The study can be handled by expanding the expert team or by diversifying the areas of expertise.In addition, the PIPRECIA Extended and Fuzzy CoCoSo methods, which are integrated in this study, can be used to solve a different transportation vehicle selection problem.

Conflict of interest

The authors declare that they have no conflict of interest.

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PROCESS-ORIENTED PERFORMANCE ASSESSMENT OF ONLINE LEARNING DURING THE COVID-19 PANDEMIC

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ABSTRACT

Lockdown and social distancing measures caused by the COVID-19 pandemic have led to focusing on online alternatives in education around the world. As a result, quick adoption necessity of new online learning facilities have led to several challenges to educators and students. Therefore, it is important to measure the quality and effectiveness of online education. The aim of this study is to exemplify the use of a process-oriented assessment tools for online education to improve the quality of learning process. Statistical process control (SPC) is one of the commonly accepted quality improvement approaches that utilizes quality control charts to inform decision-makers instantly to diagnose the origin of the problems. This paper demonstrates that SPC can be a functional tool to support the assessment of online learning. Hence, performance of the online students on weekly quiz questions in an undergraduate level accounting course has been monitored during the COVID-19 pandemic. Then, the C Control Chart has been drawn to investigate the performance of the students.

Keywords: *Online Learning, Process-Oriented Performance Assessment, Statistical Process Control, C Control Chart.*

1. INTRODUCTION

The COVID-19 pandemic has played an important role in the spread of remote working and distance learning practices (Szopiński & Bachnik, 2022). Successful e-learning adoption can be only achieved by the integration of modern education and information technologies (Qiu et al., 2022). Although in the last two decades, many higher education institutions started to adopted distance learning systems (Yeung & Yau, 2022), the COVID-19 pandemic has forced universities to immediately implement online learning activities, giving little time for educators and students to familiarize e-learning systems (Salas-Pilco et al., 2022).

Online education, which gained momentum with the COVID-19 pandemic, initially brought many challenges to both educators and students (Özcan, & Tunca 2021). One of the most prominent problems regarding online education is the quality and effectiveness (Szopiński & Bachnik, 2022). According to Hongsuchon et al. (2022), the effectiveness of online learning refers to "improving student's abilities via the learning process while using digital media and connecting online".

While some scholars argue that aspects of online learning experience differ from those of face-to-face teaching (Kim et al., 2022), some studies in the literature highlight that online learning outcomes of students have similarities to traditional face-to-face learning outcomes (Redpath, 2012). Krishnamurthy (2020), however, highlights that according to the suggestions of the previous studies in the literature, the performance of online students is better than students in traditional classroom environments.

In the literature, various approaches such as exam scores, student attitudes, and student satisfaction to assess the effectiveness of online learning in achieving learning outcomes (Robinson & Hullinger, 2008). Salas-Pilco et al. (2022) asserts that there still is a lack of studies in the literature that focus on the efficiency of the student engagement in online learning as majority of the previous studies solely focused on the students' engagement with digital technologies.

The objective of modern education is to improve the quality of learning experience by providing student-centered teaching methods. Such innovative teaching methods require new approaches to measure the performance of the education system by monitoring the outcomes. Therefore, in addition to traditional assessment methods, there are always increasing demand for alternative approaches (Wondimu, 2010).

Modern methods are particularly based on authentic measurement tools that allow reliable and accurate assessment of students existing knowledge and abilities. Such methods usually focus on students thinking and perception abilities (Dochy F. J. & McDowell, 1997). The logic of those methods lie behind the student oriented education systems. The main idea of the student-oriented education systems is the fact that the students are not passive minds to grab the knowledge from professionals but the architects of the key learning process, who start and control it. This process gives more freedom to students on learning speed and tools while limiting the traditional responsibilities of the educators (Barraket, 2005).

Assessment of accounting education needs to be conducted in three stages; input, transaction and output (Colarelli, 1991). While the inputs of accounting education are internal and external factors, the transaction process deals with the impact of the school on students. Finally, outputs of accounting education include the contributions of this process to the students (Torkzade & Moghadam, 2012).

The first stage of the performance assessment addresses the abilities of students that is used in the process. The second stage concentrates the service evaluation. In other words, this stage investigates the outcomes of the students, rather than their activities during the transaction process. The last stage, however, examines both the process and the outcomes together. As a result, it enables decision-makers to evaluate both the system as a whole and the students' success individually (Protheroe, 2001).

In this context, statistical process control (SPC) can be adopted to online accounting education assessment process as a valuable tool to determine the students' understanding of accounting knowledge and the progress of their learning experience to assess the performance of the e-learning system.

As details given in the following section, a SPC-based online accounting education assessment tool has been introduced in this study. After briefly presenting the SPC charts, a case study on the students of an online course, having accounting education at undergraduate level during the COVID-19 pandemic has been presented. The findings and the suggestions are given in the subsequent sections.

2. STATISTICAL PROCESS CONTROL

One of the prerequisites of Total Quality Management philosophy is ongoing quality control and improvements efforts. Statistical process control is one of the commonly accepted approaches to use in continuous quality control. SPC uses various control charts to determine problems in the process and alerts decision makers when out-of-control conditions happen. Hence, SPC is known as a significant supportive tool for executives to keep business processes under control (Evans & Lindsay, 1996).

Different control charts serve different needs. For instance, while the $\overline{X}$ control charts monitor a variable's data when samples are collected at regular intervals from a process, the p and the c charts monitor the proportion of nonconforming units in the sample (Nist/Sematech, 2012).

The p chart is used to determine if the fraction of defective items in a group of items is consistent over time. There are only two possible outcomes: either the item is defective, or it is not defective. The c chart is occasionally used to monitor the total number of events occurred in a given unit of time. It differs from the p chart in that it accounts for the possibility of more than one nonconformity per inspection unit, and that it requires a fixed sample size (Montgomery, 2005).

The control charts are used to detect whether a process is statistically stable. The process statistics are plotted as the center line along with the upper control limit (UCL) and lower control limit (LCL). The main principle of the control charts is to keep the data points between the control limits as any point beyond the limits suggests out-of-control conditions that require immediate action to find the source of the problem.

In the control charts, the quality of the individual points of a subset is determined unstable if any of the following occurs (Nist/Sematech, 2012):

- If one or more points falls outside of the upper or lower control limits.
- If two out of three successive data points fall in the area that is beyond two standard deviations from the process mean (center line).
- If four out of five successive data points fall in the area that is beyond one standard deviation from the process mean.
- If there is a run of six or more data points that are all either successively higher or successively lower in $\overline{X}$ control charts.
- If eight or more data points fall on either side of the process mean.
- If 15 points in a row fall within the area on either side of the center line that is one standard deviation from the process mean.

Although SPC is not a Decision Support System (DSS) that help decision makers to suggest the solutions for out-of-control conditions, it is an important tool to alert the executives to take necessary actions against the out-of-control conditions immediately. In other words, SPC only provides timely warnings about the unexpected problems in the process to figure out the reasons and to develop corrective decisions. Hence it is important for decision makers to understand the sources of the problems in the process to fix it (Tunca & Sutcu, 2006).

3. USE OF SPC TO ASSESS THE PERFORMANCE OF ONLINE STUDENTS

Even if the SPC charts have been widely used in manufacturing industry, there are several examples of its successful use in service industry (Guh et al. 1999). Nevertheless, there is no SPC use in education to best of the authors knowledge. Hence, in this paper it is aimed to exemplify the use of the SPC charts to examine the performance of online students.

In order to improve the quality of an online accounting course, the c control chart has been used to observe the weekly performance of the students during the term. In order to do that, every week, a quiz that consist of 10 questions about the teaching material has been provided to the students immediately after finishing the course to solve the questions in 15 minutes time. The number of wrong answers and the most common misunderstood subjects have been recorded every week. As a result, while collecting the data for the c control chart, it was also possible to determine which subjects online students mostly confuse to provide additional teaching sessions.

As seen in Table 1, the average number of unanswered or wrongly answered questions has been recorded as defected items to draw the c control chart in Figure 1, which is drawn by WinQSB software.

Table 1. Weekly Subjects and The Average Number of Unanswered or Wrongly Answered Questions

Week	Subject	Defected Items
1	General concepts	3
2	Principles of accounting	4
3	Balance sheet and income statement	3
4	Accounting plan	4
5	Accounting process and documents	2
6	Liquid assets	4
7	Marketable securities	3
8	Trade receivable	2
9	Inventories	4
10	Shot-term loans	3
11	Tangible fixed assets	2
12	Intangible fixed assets	2
13	Long term loans and equities	1

Notation of c control charts are given below:

C : Number of defective items

n : sample size

$\overline{C}$: Average number of defective items

Process mean = $\overline{C} = \dfrac{\sum C}{n}$

Upper control limit (UCL) = $\overline{C} + 3\sqrt{\overline{C}}$

Lower control limit (LCL) = $\overline{C} - 3\sqrt{\overline{C}}$

Figure 1. C Control Chart

As seen in Figure 1, the weekly observed data points fall ideally between the control limits. The distribution of the points suggests that there is no out-of-control condition exist in the learning process of the students.

Unlike the $\overline{X}$ control charts, the c charts aim to reduce the number of defective items in the process, where upward or downward trends of the data points to any control limit is acceptable. The downward trend of the data points to the lower control limit in the last five weeks suggest that the average ndesiumber of unanswered or wrongly answered questions tend to decrease, ie. students' learning abilities is incrementally improving.

4. CONCLUSION

Since exam is still the most important way in education system to assess students' performance even in online environments, it is important to determine the factors that influence the success of the students in exams. For instance, while sometimes poorly designed exams affect the students' success, sometimes the quality of the lectures or teaching materials could be the reasons of the failures. Hence, continuous efforts on improving the education and assessment system must be priority of the educators especially in online education.

In this study, Statistical Process Control is introduced as a tool for continuously observing the performance of online students. The online learning systems allow both educators and administratives to observe students' weekly performance to take immediate action as soon as their performance decreases.

The findings of this study suggest no significant decrease in students' performance. Hence, it was not necessary to take immediate action against the out-of-control conditions. The most important requirement of statistical process control is gathering indiscrete and standard observations. Under normal circumstances, at least 30 observations are expected for accurate results. In this study, only 13 observations have been used as the academic calendar reserve 13 weeks for lectures, and 3 weeks for mid-term and final exams. Nevertheless, it is important to repeat this process in the following terms for different courses to get sustainable results. Furthermore, in the further studies, different online student groups, having the same course in different programs can be investigated to observe the differences. of graduated students in addition to students' weekly performance.

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Original Paper

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AN EDAS METHOD-BASED CLUSTERING STUDY TO ASSESS THE LOGISTICS PERFORMANCES OF SELECTED COUNTRIES[1]

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ABSTRACT

The importance of environmentally friendly logistics activities is increasing day by day due to the intensifying globalization and increasing trade volumes of countries. Undoubtedly, the logistics industry contributes positively to national economies; however, this increasing contribution brings environmental concerns. The total amount of CO_2 emissions caused by transportation varies depending on the countries' efforts on green strategies. In this case, it is thought that clustering countries based on their logistics performance indices and CO_2 emissions from transportation may contribute to the sustainable development goals of actors that play an active role in global trade movements. This research study investigates Turkey's position in global trade logistics relative to its competitors, taking into account the Logistics Performance Index (LPI) and the total CO_2 emission values from transportation. For this purpose, the hierarchical K-means clustering analysis was conducted using the six criteria of the LPI published by the World Bank in 2018 and the CO_2 transport-related emission values of 44 countries. The R programming language was used for clustering analysis. According to the analysis results of the study, 44 countries were divided into 4 clusters in terms of their logistics performance and CO_2 emissions sourced by transportation. In addition, performance evaluations of clustered countries were carried out with the EDAS method, which is one of the Multi-Criteria Decision Making (MCDM) methods on each cluster basis. According to the results obtained from the EDAS method, the countries within each cluster are ranked from the best to the worst. This study can provide a practical framework for countries to improve their logistics performance with low carbon footprint applications.

Keywords: *Logistic Performance Index, CO_2 Emission, Hierarchical K-means, EDAS Method.*

1. INTRODUCTION

The global supply chain is so complex and multi-layered that maintaining logistics efficiency in such a challenging environment is vital thus; high levels of logistics efficiency represent good management of government services, transport investments, and policies. Concentrations of greenhouse gases (GHG) sourced by certain sectors have been increasing continuously in recent years. Mainly, transportation sectors have a large impact on climate change due to their high greenhouse gas emissions (Miklautsch & Woschank, 2022). The transportation sector makes an undesirable contribution to global greenhouse gas emissions standing out at 16.2% (Ritchie, Roser, & Rosado, 2020). As stated in the Paris Climate Agreement, where 196 countries around the world come together on a common ground perspective, several improvements need to be made in the transportation sector in order to reduce energy consumption and CO_2 emissions.

In order to minimize CO_2 emissions in logistics activities, especially in transportation, which is one of the key elements of international trade, it is necessary to maximize the efficiency of logistics performance. This ensures that CO_2 emissions from logistics activities are reduced to acceptable levels (Polat, Kara & Yalcin, 2022). In the studies that contribute some suggestions to the climate change problem, essential points about the CO_2 emissions from transportation are taken into consideration. With the determination of the CO_2 efficiency level, it is foreseen that the implementation of strong logistics and

[1] This study is an extended version of the abstract titled "Performance Evaluation through Clustering Analysis based on Logistics Performance Index and Transport Emissions: An Empirical Analysis" presented at the 10th EJSER symposium.

transportation strategies will positively contribute to preventing global climate change in the countries.

Generally, it is emphasized that there is causality in the CO_2 emissions in the Gross Domestic Product, foreign trade volumes, and logistics movements of the countries. It is seen that especially developed and developing countries are negative pioneers in CO_2 emissions (Antoni et al., 2015; Guo et al., 2016; Li et al., 2019; Jiang et al., 2020; Yang et al., 2019; Polat et al. 2022). Because of successful and effective steps that countries will take to improve their logistics performance, greater improvements will be experienced in this field, and they will contribute to sustainability as a result of their environmentalist approach. Due to this butterfly effect, a global healing movement will be triggered.

This study aims to cluster countries by using the LPI values and the CO_2 emissions from transportation. Following that, the performances of the clustered countries are ranked from best to worst for each cluster on each cluster basis. This study differs from the previous literature in some aspects. First, clustering analysis was performed based on transport–related CO_2 emission and LPI values, which have been understudied thus far. Second, the Hierarchical K-Means algorithm was used for clustering analysis, and the analysis was conducted using R language. Following this, each clustered country's performance was evaluated using the EDAS method within the cluster which they divided into.

This study contributes to the literature by clustering the countries according to the Transport CO_2 emission and LPI. In this research paper, the Hierarchical K-means algorithm was conducted for clustering, and the EDAS, one of the MCDM methods, was used for ranking analysis. The hierarchical K-means clustering analysis was performed by using R Software. The LPI and transport-related CO_2 emissions data (2018) of 44 countries were selected to perform the clustering analysis. The countries of each cluster from highest to lowest performance were ranked by using the EDAS method. The aim here is to compare the results of the EDAS method with the results of the clustering analysis so that the performance ranking of each country can be evaluated more effectively. Creating separate rankings for each cluster can help countries to assess their logistics performance more efficiently.

The paper is structured as follows: In the second section, the literature review of clustering analysis and MCDM on LPI is given. In the third section, data and methodology of the study are described. Subsequent section provides the findings of the empirical analyses. Finally, theoretical and methodological implications of the study are discussed in the conclusion section.

2. BACKGROUND

There is an important number of studies about the clustering of LPI in the literature. Popal et al. (2010) examined the logistics performances of countries by using the clustering analysis. It has been emphasized that Dynamic Clustering Analysis was useful in clustering countries. Danacı and Nacar (2017) carried out a comparative analysis with EU member countries by considering the logistics performance of Turkey's foreign trade activities in their research. The data used in the study are 2014 logistics performance indexes (LPI) and import/export values of EU 28 countries and Turkey, which is nominated for membership. The findings of the hierarchical clustering analysis depict the Turkey's position in foreign trade and the EU member states with which it has close relations were revealed.

Bayır and Yılmaz (2017) evaluated the importance of LPI sub-criteria. The authors found timeliness of the most crucial criterion. Roy et al. (2018) performed the clustering analysis with LPI and per capita GDP variables. In the research, the K-means algorithm was used for the clustering analysis, and multivariate adaptive regression spline (MARS) was used to find out the complex non-linear relationship between the variables. In the research, the authors clustered 129 countries. The dataset was formed based on per Capita GDP and Overall LPI Score. Upon the clustering analysis result of the 129 countries, five clusters were obtained. Rezaei et al. (2018) addressed the weights of six components used in LPI and infrastructure has been determined as the most important criterion.

Kısa and Ayçin (2019) revealed the importance of the weights of LPI's sub-criteria. The authors determined the most essential criteria as logistics service quality, infrastructure, and international shipment, respectively. According to the analysis result, Germany, the Netherlands, and Sweden were ranked as first, second, and third, respectively. Yıldız et al. (2020) determined the current situation of Turkey's position as 34th out of 90 countries by conducting a hierarchical clustering analysis. Işık et al. (2020) compared the importance weights of LPI's sub-criteria. The authors identified the most essential criterion as timeliness. According to the analysis results, the Czech Republic, Poland, and Hungary were ranked first, second, and third, respectively. Eren & Ömürbek (2021) clustered the logistic performances of OECD countries and Turkey. Polat et al. (2022) clustered the logistic performances of the same countries.

Table 1 lists studies that specifically evaluated LPI using MCDM and clustering methods. As seen in Table 1, the existing studies in the literature mainly focused on OECD countries, European Union countries, and G20 countries.

Table 1. Summary of the Existing Studies on Clustering Analysis and MCDM Methods in Logistics

Study	Variables	Methods	Findings
Popal et al. (2010)	Logistic Performance Index (LPI) data between 2007 and 2010	Dynamic Clustering Analysis	The positions and group members of Romania was detected.
Trappey et al. (2010)	Service needs, preferences, and outsourcing of 98 auto and auto part manufacturers	Ward clustering method and K-means algorithm	Distribution and distribution services have the highest percentage of outsourcing services.
Danacı & Nacar (2017)	2014 Logistics Performance Indexes (LPI) and import/export data of 28 EU countries	Hierarchical clustering analysis	The positions and group members of Turkey and other countries in foreign trade have been determined.
Bayır & Yılmaz (2017)	2014 Sub-criterias of Logistics Performance Indexes (LPI) of 20 European countries.	Analytical Hierarchy Process (AHP) and VIKOR	The importance of criteria's were found and the countries were ranked.
Roy et al. (2018)	2014 Logistics Performance Indexes (LPI), Gross Domestic Product (per capita)	Clustering by K-means data mining algorithm and multivariate adaptive regression spline (MARS)	The clusters of countries were obtained.
Rezaei et al. (2018)	Sub-criterias of Logistics Performance Indexes (LPI) of 107 countries	BWM	The importance levels of the criteria have been determined.
Kısa and Ayçin (2019)	Sub-criterias of Logistics Performance Indexes (LPI) data between 2012 and 2018 of OECD countries	SWARA, EDAS	The importance levels of the criteria have been determined and the countries were ranked.
Yıldız et al. (2020)	Logistics Performance Index (LPI) data from 2012 to 2018 of 90 countries.	Hierarchical clustering analysis. SPSS 22 statistical program was used.	The positions and group members of countries have been determined. Turkey was ranked 34th.
Işık et al. (2020)	Sub-criteria of Logistics Performance Index (LPI) of 11 European countries	SV, MABAC	The importance levels of the criteria have been determined and the countries were ranked.

Eren & Ömürbek (2021)	Logistic Performance Index (LPI) of OECD Countries	Canopy algorithm was applied by using Weka program.	Countries were divided into four clusters.
Polat et al. (2022)	Logistic Performance Index (LPI), CO_2 emissions per capita, CO_2 emissions efficiency per capita of 150 countries	Hierarchical & non-Hierarchical Clustering Analysis	Different clustering results were obtained from each method.

3. METHODOLOGY

The efficiency of the transportation systems of the countries and the profitability of foreign trade and industry are closely related. The sustainability of logistical agility and efficiency levels in operations is linked to transport infrastructure (Senir, 2021). Improving transport infrastructure has a significant impact on the productivity and cost structure of businesses (Haughwout 2001; Ojala & Çelebi, 2015). The Logistics Performance Index (LPI), which is released by the World Bank in every two years since 2007, is a global benchmarking tool created to help countries identify the challenges and opportunities of trade and transport. The latest LPI, which was provided by World Bank in 2018, covers 160 countries. The LPI matrix allows the countries to perform a comparative perspective on their logistics performance (Alyoubi, 2021). In addition, the countries use the LPI to improve their logistic performance and strategic movement skills in their supply chain process.

These countries participating in the LPI survey provide quantitative feedback on how easy or difficult it is to transport common goods. The six leading indicators of LPI combined the performance-related evaluations of logistics actors who have an active role in international trade on a five-point scale. Thereby, LPI helps policymakers, foreign trade companies, and national administrators to eliminate or reduce the barriers encountered in global trade and serves as a roadmap to develop transportation services.

The six dimensions below represent the main points of the logistics industry. These six dimensions that represent the logistics performance of countries are as follows, respectively:

Customs: It is an indicator of efficiency and productivity in the customs clearance process while performing foreign trade transactions of countries.

Infrastructure: It is an indicator of the quality and efficiency of countries' transport and trade infrastructures.

International Shipments: It is an indicator of the ease of shipping at competitive prices.

Logistics Competence: Efficiency, and quality of logistics services.

Tracking and Tracing: It is the ability to track the shipments in the most effective way.

Timeliness: It is the rate of delivery of the shipments to the recipient at the desired time as planned (Arvis, et al., 2018).

The other variable of this research is CO_2 emissions from transport (Tonnes of CO_2 equivalent, Thousands). The road transport mode covers almost three-quarters of the CO_2 emissions from transport (Yang et al., 2015). While economic sanctions related to energy consumption are effective on fuel consumption, it is still late to take environmentalist steps in the ongoing global goods transportation (Schipper, 2009). Insistent steps on climate change, which are especially suppressed by global dynamics, will result in favor of countries. In order to minimize the amount of transport-related CO_2 emissions, which is one of the most important indicators of sustainable transportation, it is thought that it can be beneficial for countries to see their current position through this research study, which includes this variable.

The purpose of this study is to cluster 44 countries in terms of logistics performance and Transport CO_2

emission values and rank the grouped countries in each cluster in terms of performance weights. For this purpose, the logistics performances of the countries are assessed according to the six criteria in the World Bank's LPI report, and the Transport CO_2 emission values are evaluated according to the Transport CO_2 emission values published by the Organization for Economic Co-operation and Development (OECD) database. Briefly, the dataset was obtained from the World Bank and the OECD database. Clustering analysis was performed with the R program. In this paper, the Hierarchical K-means algorithm was used for clustering the countries in terms of logistic performance. For evaluating the performance rankings of the countries the EDAS calculation steps were applied.

The limitations and constraints of the study were mainly experienced with the data set. The World Bank shared the latest calculated LPI values in 2018. Although the shared matrix include 160 countries, only 44 of them had relevant Transport CO_2 emissions data. Hence, the study covered only 44 countries, having 2018 Transport CO_2 emissions data which was shared by the OECD database. The data matrix was presented in Table 2.

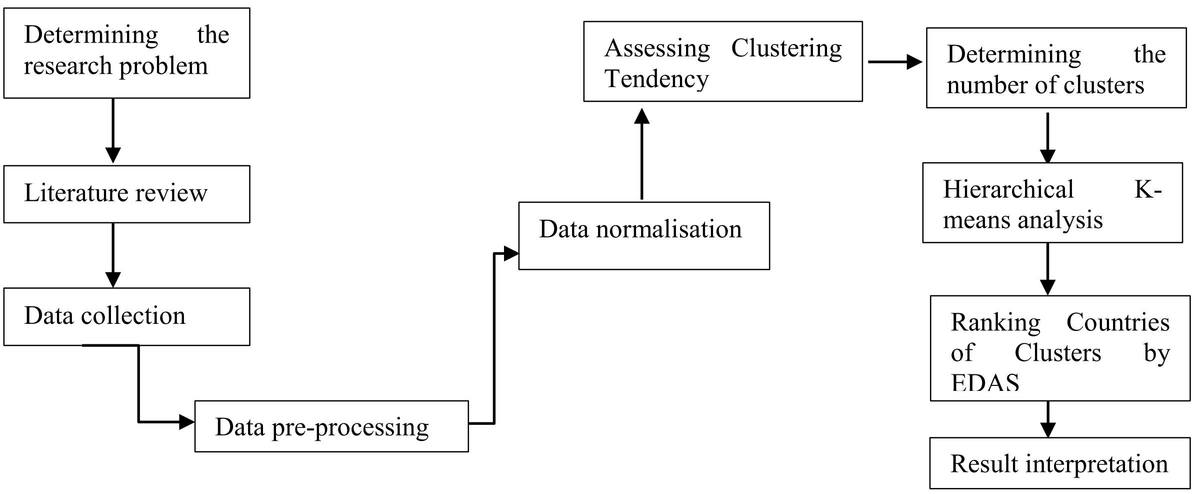
Table 2. Data Matrix

Country	Greenhouse Gases by transport sources (Tones of CO_2 equivalent, Thousands)	Customs	Infrastructure	International	Quality	Tracking	Timeliness
Australia	100262.00	3.87	3.97	3.25	3.71	3.82	3.98
Austria	24453.34	3.71	4.18	3.88	4.08	4.09	4.25
Belarus	4040.27	2.35	2.44	2.31	2.64	2.54	3.18
Belgium	26214.52	3.66	3.98	3.99	4.13	4.05	4.41
Bulgaria	9757.69	2.94	2.76	3.23	2.88	3.02	3.31
Canada	184832.06	3.60	3.75	3.38	3.90	3.81	3.96
Chile	28614.67	3.27	3.21	3.27	3.13	3.20	3.80
Croatia	6410.25	2.98	3.01	2.93	3.10	3.01	3.59
Cyprus	2107.37	3.05	2.89	3.15	3.00	3.15	3.62
Czech Republic	18897.68	3.29	3.46	3.75	3.72	3.70	4.13
Denmark	13705.30	3.92	3.96	3.53	4.01	4.18	4.41
Estonia	2468.41	3.32	3.10	3.26	3.15	3.21	3.80
Finland	11658.34	3.82	4.00	3.56	3.89	4.32	4.28
France	132929.12	3.59	4.00	3.55	3.84	4.00	4.15
Germany	163639.45	4.09	4.37	3.86	4.31	4.24	4.39
Greece	17444.38	2.84	3.17	3.30	3.06	3.18	3.66
Hungary	13869.73	3.35	3.27	3.22	3.21	3.67	3.79
Iceland	1150.68	2.77	3.19	2.79	3.61	3.35	3.70
Ireland	12202.06	3.36	3.29	3.42	3.60	3.62	3.76
Israel	18698.50	3.32	3.33	2.78	3.39	3.50	3.59
Italy	104276.16	3.47	3.85	3.51	3.66	3.85	4.13
Japan	204802.24	3.99	4.25	3.59	4.09	4.05	4.25
Kazakhstan	26150.75	2.66	2.55	2.73	2.58	2.78	3.53
Korea	98111.38	3.40	3.73	3.33	3.59	3.75	3.92
Latvia	3351.30	2.80	2.98	2.74	2.69	2.79	2.88
Lithuania	6077.07	2.85	2.73	2.79	2.96	3.12	3.65
Luxembourg	6027.14	3.53	3.63	3.37	3.76	3.61	3.90
Malta	671.39	2.70	2.90	2.70	2.80	2.80	3.01
Netherlands	31497.20	3.92	4.21	3.68	4.09	4.02	4.25
New Zealand	15126.26	3.71	3.99	3.43	4.02	3.92	4.26
Norway	13241.61	3.52	3.69	3.43	3.69	3.94	3.94

Poland	65150.96	3.25	3.21	3.68	3.58	3.51	3.95
Portugal	17256.61	3.17	3.25	3.83	3.71	3.72	4.13
Romania	18434.19	2.58	2.91	3.18	3.07	3.26	3.68
Russia	254077.22	2.42	2.78	2.64	2.75	2.65	3.31
Slovak Republic	7818.02	2.79	3.00	3.10	3.14	2.99	3.14
Slovenia	5841.65	3.42	3.26	3.19	3.05	3.27	3.70
Spain	90446.34	3.62	3.84	3.83	3.80	3.83	4.06
Sweden	17230.48	4.05	4.24	3.92	3.98	3.88	4.28
Switzerland	14925.51	3.63	4.02	3.51	3.97	4.10	4.24
Turkey	84616.68	2.71	3.21	3.06	3.05	3.23	3.63
Ukraine	34956.45	2.49	2.22	2.83	2.84	3.11	3.42
United Kingdom	122972.94	3.77	4.03	3.67	4.05	4.11	4.33
United States	1816671.44	3.78	4.05	3.51	3.87	4.09	4.08

The research algorithm of the study is presented in Figure 1. First of all, the research problem was determined. Following that, the literature background of the field was structured. The research sample data were collected from the databases. The data pre-processing was conducted. The dataset was normalized before analysis. Before clustering analysis, the tendency of clustering with the Hopkins statistic test was assessed. After that, the cluster numbers were determined with the Elbow method. Following that the Hierarchical K-means algorithm was applied to the normalized dataset with R language codes. In the next step, the countries were ranked by applying the EDAS method for each cluster. Finally, the results were interpreted.

Figure 1. Research Process



3.1. Hierarchical K-Means Clustering

Models in data mining can be divided into predictive and descriptive models (Han et al., 2006) In this research, the clustering analysis was applied which classified into descriptive models. Clustering analysis, which is frequently used in data mining, has become very popular because there is a lot of data accumulation today. Clustering analysis can be briefly mentioned as the process of separating data into clusters or classes in terms of similar characteristics. In the literature, there are many clustering methods such as hierarchical, density-based, partition-based, and artificial intelligence-based clustering (Jain et al, 1999; Berkhin, 2002; Kuo et al., 2005). Clustering analysis is a statistical technique aimed at classifying some objects into clusters according to their similarities (Suzuki & Shimodaira, 2006). Pvclust was designed for general hierarchical clustering complication. This allows researchers to easily obtain bootstrap p-values for their dataset and approved clustering method (Suzuki & Shimodaira, 2004).

If there is no output value in clustering methods, these inputs are grouped only according to their input values. Therefore, the purpose of clustering techniques is to discover groups of similar samples in the data (Balaban & Kartal, 2015) . Hierarchical clustering is a very advantageous and extensively used technique in data processing (Lu et al., 2008). For multiplex clustering involving large datasets and many dimensional attributes that are very difficult to visualize, hierarchical k-means can perform well in terms of both accuracy and agility (Arai & Ridho, 2007).

Clustering algorithms can be largely divided into two groups as hierarchical and divisive (Jain, 2010). Most hierarchical algorithms have quadratic or higher complexity in the number of data points and therefore are suitable for small datasets (Celebi et al., 2013). In the study, the clustering analysis is performed with the Hierarchical K-means algorithm by using the R program. The countries are divided into clusters in terms of their logistics performance and Transport-related CO_2 emission values. The Hierarchical K-means clustering has the skill to sense clusters of varying shapes and dimensions (Govender & Sivakumar, 2020). To conduct this, clustering analysis was performed using (factoextra) and (cluster) libraries of R. In R program the R function hkmeans() [in factoextra], provides a simple solution for computing hierarchical k-means clusters. The following steps were conducted for hierarchical clustering:

1st Step: Compute hierarchical clustering

2nd Step: Divide the tree into k clusters

3rd Step: Compute the center (mean) of each cluster.

4th Step: Run k-means using the set of cluster centers which was defiden in 3rd step as initial cluster centers. Optimize clustering. This causes the final optimized partitioning obtained in 4th Step to differ from that obtained in 2nd Step.

4. FINDINGS

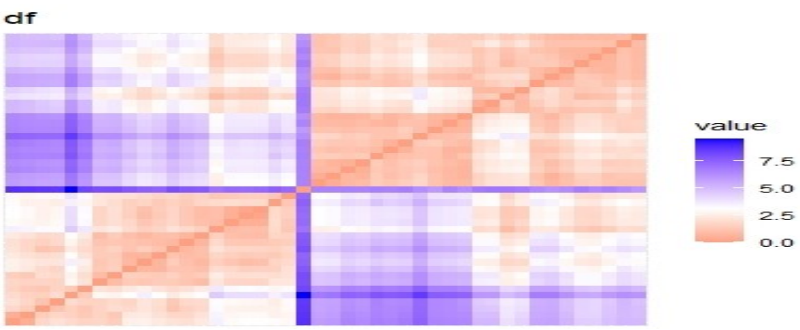
4.1. Assessing Clustering Tendency

For a given dataset, evaluating the clustering tendency evaluates whether the data has a non-random structure. Arbirtarily use of a clustering method to a dataset may hinder the accurate clusters. Clustering analysis of datasets is useful only when the data have a non-random structure.

In a research problem; the null hypothesis is the homogeneous hypothesis that D is uniformly distributed and thus contains no meaningful clusters. The nonhomogeneous hypothesis (i.e., that D is not uniformly distributed and thus contains clusters) is the alternative hypothesis. The Hopkins Statistic test can be conducted iteratively, using 0.5 as the threshold to reject the alternative hypothesis. That is, if $H > 0.5$, then it is unlikely that D has statistically significant clusters (Han et al., 2012).

In this research, the clustering tendency was measured by using the Hopkins statistic. As it is seen in Figure 2, the clustering tendency (VAT) analysis result shows that the dataset has a high tendency for clustering. According to the Hopkins statistic test result, the research data set is highly clusterable (the H value = 0.20 which is far below the threshold of 0.5). In addition to that, in order to visualize the research dataset as highly clusterable; the visual assessment of the cluster tendency approach was conducted.

Figure 2. The Visual Assessment of Cluster Tendency (VAT) Analysis Result

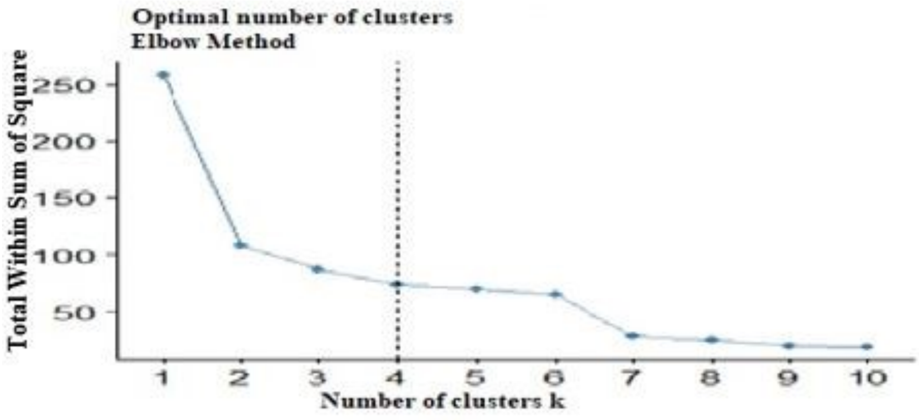


Red: high similarity (ie: low dissimilarity) | Blue: low similarity

4.2. Determining the Optimal Number of Clusters

In this study the value of k, that is, the number of clusters was systematically chosen by using the Elbow method. A technique known as the elbow method attempts to estimate how homogeneity or heterogeneity varies within a cluster for different values of k. This value of k is called the elbow dot because it looks like an elbow (Lantz, 2013). In this paper, the optimal number of cluster was found as 4 and presented in Figure 3.

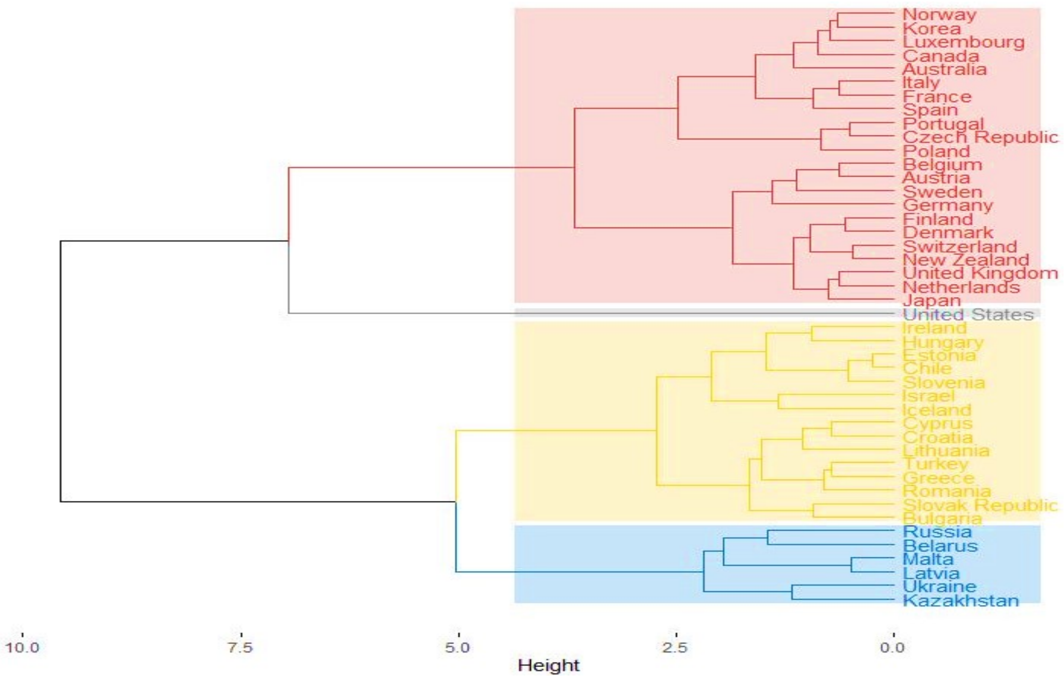
Figure 3. The Optimal Number of Cluster



4.3. Hierarchical K-Means Clustering Analysis Results

One of the advantages of hierarchical k-means clustering analysis is that it provides Dendrogram graphical representation (Govender & Sivakumar, 2020). A hierarchical method creates a hierarchical decomposition of the given set of data objects. A dendrogram is built due to the Tree of clusters. In clustering analysis, the results shown as tree diagrams are called dendograms (Sharma & Wadhawan, 2009). Every cluster node contains child clusters, and sibling cluster partition the points covered by their common parent.

Figure 4. Hierarchical K-means Cluster Dendrogram



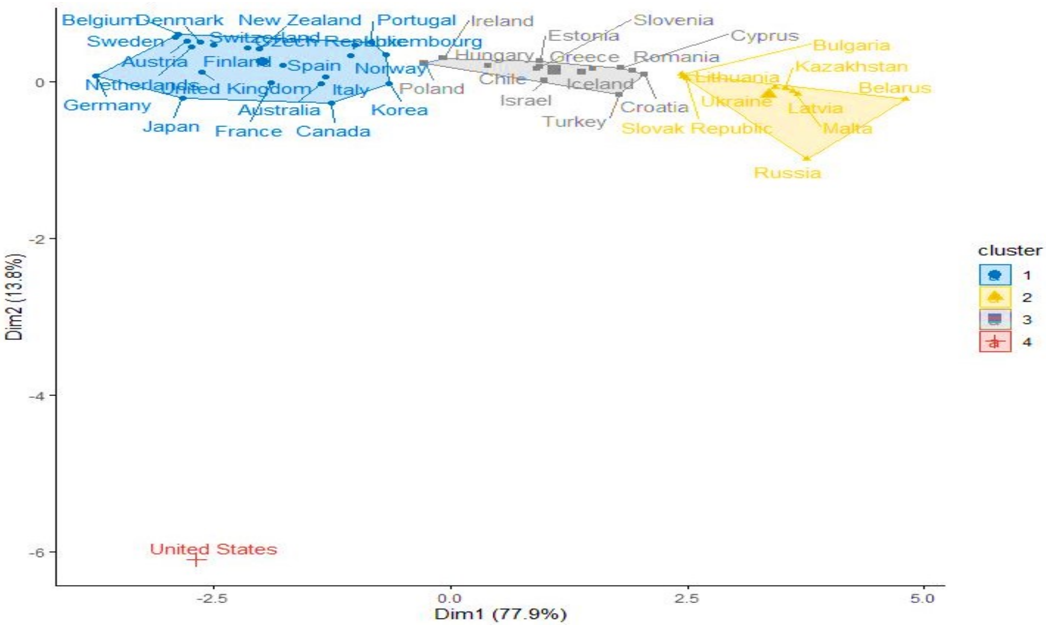
The hierarchical K-means cluster dendrogram is shown in Figure 4. According to the obtained dendrogram tree; the clusters in which the countries are classified are seen in four different colors blue, yellow, red, and gray.

According to the cluster dendrograms of Hierarchical K-means Russia, Belarus, Malta, Latvia, Ukraine, and Kazakhstan are divided into Blue Cluster. Following that, Iceland, Hungary, Estonia, Chile, Slovenia, Israel, Iceland, Cyprus, Croatia, Lithuania, Turkey, Greece, Romania, Slovak Republic, and Bulgaria was divided into Yellow Cluster which includes 15 countries. The United States is in Gray Cluster.

Finally, in the Red Cluster which includes 22 countries; Norway, Korea, Luxemburg, Canada, Australia, Italy, France, Spain, Portugal, Chech Republic, Poland, Belgium, Austria, Sweden, Germany, Finland, Denmark, Switzerland, New Zealand, United Kingdom, Netherlands, and Japan.

The Hierarchical K-means cluster plot is shown in Figure 5.

Figure 5. Hierarchical K-means Cluster Plot



The Hierarchical K-means cluster plot is shown in Figure 5. In order to better understand the clusters shown in the Hierarchical K-means cluster graph, they are presented in detail with the help of Table 3.

Table 3. Hierarchical K-means Clustering Results of Countries

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Australia	Belarus	Chile	United States
Austria	Bulgaria	Croatia	
Belgium	Kazakhstan	Cyprus	
Canada	Latvia	Estonia	
Czech Republic	Lithuania	Greece	
Denmark	Malta	Hungary	
Finland	Russia	Iceland	
France	Slovak Republic	Ireland	
Germany	Ukraine	Israel	
Italy		Poland	
Japan		Romania	
Korea		Slovenia	
Luxembourg		Turkey	
Netherlands			
New Zealand			
Norway			

Portugal Spain Sweden Switzerland United Kingdom			

The Hierarchical K-means clustering results of countries were presented in Table 3. When evaluated over the existing criteria, it has been understood that the countries in Cluster 4 and Cluster 1 are generally at the top of all criteria. United States was clustered in Cluster 4. The US has modern and developed transportation infrastructures. In addition to that United States is one of the giant economies globally. That means the transportation industry which is the most essential operating network of global trade, is developed. However, depending on the intensity of transportation, the amount of Greenhouse Gas Emissions from transportation is also extremely high.

According to the analysis results, besides the high logistics performance, it should consider its responsibilities towards the environment in transportation. At this point, the policymakers need to take strategic decisions to reduce transport-related CO_2 emissions. Countries in Cluster 1 such as Belgium, Germany, Japan, Spain, Netherlands, Norway, Denmark, Switzerland, United Kingdom, France, and Norway are the power representatives in the world's maritime trade. The countries in Cluster 1 are active in taking environmental steps and their implementation. In addition, the transportation infrastructures of the countries in this cluster are highly developed. However, Japan, Canada, Germany, France, United Kingdom, Italy, Australia, Korea, and Spain have active roles in international trade thus greenhouse gas emission rates increase caused by transportation. Therefore, it is strongly recommended to make environmentally friendly investments in transportation. Countries in Cluster 2 have low LPI values. However, especially since Russia is an important actor in world trade, the need to be active in transportation industry is quite high. Therefore, the amount of CO_2 emissions associated with transportation is high. In this case, it is vital for the countries in this cluster to improve their performance in the field of Logistics, while advancing with an environmentalist understanding. Turkey, which is an important representative in maritime transport, is in the 3rd Cluster. In Cluster 3 the countries have average scores in LPI. When we look at the other countries in the cluster, it is seen that they are among the developing economies. Turkey's high rate of transport-related CO_2 emissions from transportation supports sustainable developments in the logistics sector of environmentalist investments to be made in this field.

4.4. EDAS Method

In this study, the EDAS method was used to measure and rank the performance of clustered countries. The steps of the EDAS method can be summarized as follows (Özbek, 2021):

Step 1: *The initial matrix (X) is created.* Equation (1) shows the decision matrix. In this matrix xij; i option j. represents the performance according to the criteria.

$$X = [X_{ij}]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{i1} & x_{i2} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: *The average solution is determined according to all criteria*. This is done using equations (2) and (3).

$$AV_J = \frac{\sum_i^m \mathrm{x_{iJ}}}{m} \quad (2)$$

$$AV = \left[AV_j\right]_{1\mathrm{xn}} \quad (3)$$

Step 3: *Create a matrix of positive and negative distances from the mean.* For each criterion, a positive distance matrix (PDA) from the mean represented by Equation (4) and a negative distance matrix (NDA) from the mean by Equation (5) is formed. If the criterion is beneficial, the PDA and

NDA matrices are formed by Equations (6) and (7). If the criterion is non-beneficial, then the PDA and NDA matrices are calculated using Equations (8) and (9).

$$PDA = \left[PDA_{ij}\right]_{mxn} \quad (4)$$

$$NDA = \left[NDA_{ij}\right]_{mxn} \quad (5)$$

$$PDA_{ij} = \frac{max\left(0,(X_{ij}-AV_j)\right)}{AV_i} \quad (6)$$

$$NDA_{ij} = \frac{max\left(0,(AV_j-X_{ij})\right)}{AV_i} \quad (7)$$

$$NDA_{ij} = \frac{max\left(0,(AV_j-X_{ij})\right)}{AV_i} \quad (8)$$

$$PDA_{ij} = \frac{max\left(0,(X_{ij}-AV_j)\right)}{AV_i} \quad (9)$$

Step 4: *Calculate the weighted sum of the options.* The weighted total PDA and NDA are calculated for each option. vj, j. shows the weights of the criteria.

$$SP_i = \sum_{j=1}^{n} v_j \, PDA_{ij} \quad (10)$$

$$PN_i = \sum_{j=1}^{n} v_j \, NDA_{ij} \quad (11)$$

Step 5: *Normalize the weighted sum of the options.* For each option, the SP and SN values are normalized using Equations (12) and (13).

$$NSP_i = \frac{SP_i}{max_i(SP_i)} \quad (12)$$

$$NSN_i = 1 - \frac{SN_i}{max_i(SN_i)} \quad (13)$$

Step 6: *Calculate the ranking score.* The evaluation score (AS) is calculated using Equation (14) for all options.

$$AS_i = \frac{1}{2}(NSP_i - NSN_i) \quad (14)$$

AS_i value must satisfy the $0 \le AS_i \le 1$ condition.

Step 7: *Sort all the options.* The options are sorted in descending order of AS score. The first option is considered the best. The AS_i scores obtained after the implementation of Step 7 are presented in table 4.

Tablo 4. AS Scores and Ranks of Countries

Cluster 1			Cluster 2			Cluster 3			Cluster 4	
Countries	AS_i	Rank	Countries	AS_i	Rank	Countries	AS_i	Rank	Country	
Sweden	0.996	1	Slovak Republic	0.997	1	Iceland	0.965	1	United States	1
Denmark	0.974	2	Lithuania	0.981	2	Estonia	0.954	2		
Finland	0.971	3	Bulgaria	0.957	3	Ireland	0.893	3		
Austria	0.918	4	Malta	0.923	4	Slovenia	0.890	4		
Belgium	0.910	5	Latvia	0.917	5	Cyprus	0.877	5		
Switzerland	0.904	6	Belarus	0.815	6	Hungary	0.780	6		
New Zealand	0.889	7	Kazakhstan	0.647	7	Croatia	0.772	7		
Netherlands	0.866	8	Ukraine	0.581	8	Israel	0.639	8		
Luxembourg	0.841	9	Russia	0.016	9	Greece	0.575	9		
Norway	0.816	10				Romania	0.514	10		
Portugal	0.776	11				Chile	0.496	11		
Czech Republic	0.775	12				Poland	0.393	12		
Spain	0.415	13				Turkey	0.008	13		
Germany	0.398	14								
United Kingdom	0.384	15								
Australia	0.354	16								
Italy	0.316	17								
Korea	0.291	18								
France	0.261	19								
Japan	0.122	20								
Canada	0.020	21								

Table 4 shows the EDAS method results. Each cluster was analyzed independently by applying the EDAS method. According to the AS scores and ranks of countries the best country among the countries in cluster 1 is Sweden. The country with the best AS score in the second cluster was the Slovak Republic. The country with the best performance in Cluster 3 is Iceland, while the country with the worst performance is Turkey. Since only United States is included in Cluster 4, no calculations were made on this cluster. Considering the AS_i scores of the countries belonging to the clusters in Table 4: the AS_i value of the best performing country for Cluster 1 was found to be 0.996. In addition, the AS_i value of Canada, which has the worst performance value, is 0.020.

Furthermore, the AS_i value of Slovak Republic which has the best performance value in Cluster 2, is 0.997. In addition to that, the AS_i value of Russia, which has the worst performance value, is 0.016. Moreover, the AS_i scores is 0.965 of Iceland which was ranked in first rank in Cluster 3. Turkey was ranked 13th in Cluster 3 as it has the worst AS_i performance value of 0.008.

Table 5. Ranking Results of the Countries in the Clusters according to the EDAS Method

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Sweden	Slovak Republic	Iceland	United States
Denmark	Lithuania	Estonia	
Finland	Bulgaria	Ireland	
Austria	Malta	Slovenia	
Belgium	Latvia	Cyprus	
Switzerland	Belarus	Hungary	
New Zealand	Kazakhstan	Croatia	
Netherlands	Ukraine	Israel	
Luxembourg	Russia	Greece	
Norway		Romania	
Portugal		Chile	
Czech Republic		Poland	
Spain		Turkey	
Germany			
United Kingdom			
Australia			
Italy			
Korea			
France			
Japan			
Canada			

Table 5 shows the ranking results of the countries in the clusters according to the EDAS method. According to Table 5, Cluster 1 includes 21 countries which are ranked from best to worst as Sweden, Denmark, Finland, Austria, Belgium, Switzerland, New Zealand, Netherlands, Luxembourg, Norway, Portugal, Czech Republic, Spain, Germany, United Kingdom, Australia, Italy, Korea, France, Japan, Canada, respectively. Cluster 1 typically includes countries performing well on LPI and transport-related carbon footprint.

Even though the railway network of Korea and Japan is developed, these countries are ranked last in Cluster 1. Cluster 2 includes 9 countries that are ranked from best to worst Slovak Republic, Lithuania, Bulgaria, Malta, Latvia, Belarus, Kazakhstan, Ukraine, and Russia, respectively. Cluster 3 includes 13 countries which are Iceland, Estonia, Ireland, Slovenia, Cyprus, Hungary, Croatia, Israel, Greece, Romania, Chile, Poland, Turkey, form best performed to worst, respectively. Since Turkey is an important actor both in terms of being a corridor in global trade and in exports, the transportation sector has developed. However, since Turkey has the lowest performance in cluster 3, it is understood that it needs to increase its initiatives to improve both its transport-related carbon footprint and logistics performance indicators. Turkey's 169.5 billion Dollar export was transported by sea with 59.6 percentage in 2021. Road mode is in the second place with 31.2%, and airway is in the third place with 7.5% (https://ticaret.gov.tr/). This can affect the transport-related CO_2 emissions as the road is the second most preferred mode of transportation, which is a fast mode of transportation. Cluster 4 includes only

United States. As it can clearly seen in Table 2, United States was with the highest transport-related CO_2 emission amount in the research dataset. United states is an economy with the second highest share in the global trade arena. According to the U.S. Department of Transportation, water transport was the dominant mode of transport for the 41.1 percent of the total value of all goods traded into and from the United States (U.S.) in 2021. Air transport was responsible for 29.6 percent of the value of all U.S. trade that year (www.bts.dot.gov). As it can be understood from this, the increase in the United States' attempts to use sea and rail transportation modes can reduce the level of carbon footprint. When all clusters are examined, it can clearly understand that the countries that have the high usage transportation industry or make wrong transportation modes decisions are listed in the last place.

5. CONCLUSION

The importance of transportation for the continuity of the global supply chain is undeniable. However, transportation is one of the leading sectors in terms of energy consumption and CO_2 emissions. For this reason, as a result of the more sustainable initiatives of this sector, there will be some improvement in the carbon footprint. Efforts made by countries to reduce emission values in these leading sectors in terms of preventing global climate change are vital. In this study, it is aimed to classify countries by considering their logistics performance and CO_2 emissions from transportation. For this purpose, 44 countries with CO_2 emissions from transportation are grouped in terms of their logistics performance according to 7 criteria. After performing the clustering algorithm, the EDAS method was applied to rank the logistics performances of the countries within each cluster. The purpose of this is to rank the countries in each cluster according to their logistics performance in the cluster they are in and to facilitate comparisons with other countries in the same cluster. Thus, it will make it easier for countries to make self-evaluations in improving their logistics activities in terms of environmental responsibility, according to the competitors in the cluster. Clusters will help countries take the necessary precautions regarding CO_2 emissions while performing their logistics activities.

In the first stage of the empirical study, hierarchical clustering analysis was performed using Customs, Infrastructure, International Shipments, Logistics Quality, Monitoring and Monitoring, Timeliness, and CO_2 emissions from transport data. According to the hierarchical clustering analysis, countries are divided into 4 clusters. Countries in Cluster 1 are generally seen to have good LPI scores and low carbon footprints. The fact that the United States is in a cluster alone indicates that the amount of CO_2 emissions from transportation is more dominant than other variables in the classification. To make an assessment for Cluster 2 and Cluster 3, developing countries are generally clustered in these clusters. In addition, these countries have lower LPI scores than Cluster 1. According to the EDAS method results: In Cluster 1 Sweeden has the best performance value, besides the country which has the worst performance was Canada. As it can be understood from here, Canada's carbon footprint is higher than Sweeden's. Sweeden has a sense of environmentally responsible transportation and its impact is easily felt here as it is lower than Canada in terms of population. Besides, Canada's foreign trade volume is more intense than Sweeden. This triggers the need for transportation. While Slovak Republic ranked in 1st rank, Russia ranked in 13th rank with the worst performance value in Cluster 2. In addition to that, in Cluster 3 Iceland has the best performance value and it ranked in 1st rank. However, Turkey ranked in the 13th rank in Cluster 3. Although Turkey is a peninsula country surrounded by the sea on three sides, it is one of the most preferred modes of transport for road transport and transportation rather than the use of railways and seaways due to various foreign trade costs. Recently, the invesments to railway infustructures are ingreasing day by day in Turkey. While most of the population prefers the road in their transportation preferences, railway mode usage remains at low levels. There is no doubt that every investment to be made in the railway will be steps with high environmental responsibility. Policimakers, investors, and other actors should support initiatives that will facilitate the choice of low-carbon transportation vehicles by changing the mode preferences in transportation. Furthermore, it is very important to support the environmental sustainability dimension of the logistics industry, which plays a key role in the global and national economy.

The study has some limitations regarding the data sample due to the fact that CO_2 equivalent greenhouse gas emission values are not shared by some countries. Additionally, the other limitation of this study was the Hierarchical k-means clustering algorithm, which is another limitation of this study, can be compared with different clustering analysis techniques in future studies.

This study will be a roadmap for researchers to propose a country that can carry out effective initiatives on sustainability in the logistics sector. In future studies, the results can be compared by increasing the number of countries and using different clustering techniques.

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FORECASTING TÜRKİYE'S HOURLY ELECTRICITY PRODUCTION BY USING NONLINEAR AUTOREGRESSIVE MODELS

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ABSTRACT

Considering that industrialization is increasing rapidly, and technological enhancement is developing exponentially compared to the past, and considering that electrical energy is at the center of all these, it is one of the essentials of our age that this energy reaches its end users efficiently and at low cost. The aim of this study is to predict electricity generation with the help of the NARX model, an artificial neural network model, with the help of hourly data of Türkiye between 2016 and 2022 and to reveal the success of the model. As a result of the analysis, 99.83% coefficient of determination value was obtained with the NARX model.

Keywords: *Electricity Production, Forecast, NAR, NARX.*

1. INTRODUCTION

Energy resources are basically divided into two areas. These are primary and secondary energy sources. Primary energy sources are also divided into traditional and renewable energy sources. Oil, natural gas, and coal are traditional energy sources and wind, solar, and hydro powers are renewable energy sources. Electricity generated using these sources plays a central role in people's professional and daily work. As a result of the rapid development and changes in technology and industry, our need for electricity in almost every field is increasing day by day. With this increase in energy demand, it is possible to prevent uncertainties, supply-demand imbalances, and disruptions that may occur in the sector by using a reliable forecasting method. It can be said that the use of reliable forecasting methods in the energy sector reduces energy costs as well as provides uninterrupted energy (Soliman and Al-Kandari 2010).

In order to manage energy policies well, it is very important for countries to determine their future energy needs. There are basically three time horizons in electrical energy forecasting: short-term load forecasting, medium-term load forecasting and long-term load forecasting. These load forecasts are highly affected by periodic events and situations. There are significant differences between the electricity required in summer and winter, and these differences can be daily and weekly. By making short-term load forecasts, a significant cost reduction in electricity prices can be achieved. In line with an accurate forecast, a 1 percent reduction in the margin of error for a 10 GW service can result in a profit of approximately 1.6 million dollars (Dudek 2015). One-hour-ahead forecasting is an important element of the intraday electricity market and is also an important component and complement to the day-ahead market. Machine learning and deep learning techniques are frequently used to forecast electricity generation data. In addition, machine learning techniques produce much more successful results in situations where the amount of data is quite high, such as one hour ahead and a day-ahead, and therefore play a major role in stakeholder decision-making (Lantz 2019). When the studies using electric energy data are examined, it is seen that artificial neural networks are also used quite frequently in studies. Nonlinear Autoregressive (NAR) and Nonlinear Autoregressive model with exogenous variable (NARX) models, which are also used in this study, are also used for different purposes with similar data.

In this context, Türkiye, as a developing country, can have the opportunity to consolidate its position in the region and keep up with the progress of developed countries more easily by managing its energy policies correctly and increasing energy efficiency. According to the daily production amounts announced by the Energy Exchange Istanbul (EXIST), Türkiye's average hourly electricity demand is 28000 megawatt hours. This amount varies during the day. These data have been available since 2012. Approximately 20 percent of the hourly average electricity demand of 28000 MWh is met from coal, 19 percent from dams, 16 percent from wind and the rest from various other sources.

A brief review of the recent literature on forecasting the production, consumption and prices of electricity energy reveals that some authors forecast demand, some forecast price and some forecast load. In the studies on electricity load forecasting, authors have made short-term load forecasts using various models for only one region with a narrow scope (Şeker 2022; Shirzadi et al. 2021) and emphasized that the NARX model gives the most accurate results (Kim, Son, and Kim 2019). They have also forecasted long-term electricity load forecasts for the whole country using several models, including the NAR and NARX models (Essallah and Khedher 2022). In addition, some authors have also investigated price forecasting in addition to load forecasting and proposed a new NARX model (Mujeeb and Javaid 2019). It has been argued that by combining different models, they overcome each other's weaknesses and increase the success of the models in predicting electricity prices (Lehna, Scheller, and Herwartz 2022).

There are studies in the literature where energy demand is met by using renewable energy sources and this demand is estimated using artificial neural networks, machine learning and other methods. Some of these studies used solar energy data, which is one of the renewable energy sources, and made forecasts with artificial neural networks and machine learning algorithms (Demolli et al. 2019; Gök, Yıldız, and Şekkeli 2019; Yousif and Kazem 2021). Krechowicz et al. (2022) examined the studies on machine learning forecasting using data from three different renewable energy sources and concluded that it has an important place in recent studies. In this study, forecasting is performed with the NARX model using hourly electricity data published by EXIST between 2012 and 2022.

2. MATERIAL AND METHOD

The data is collected from EXIST website for Türkiye with a time array of 2016 and 2022. The production and consumption values are normalized in order to get better results from the analysis. All the analyses are conducted using the MATLAB R2022a program. The normalization is done with MATLAB with the range between [0,1] and the code used for normalization was; "normalize(variable_name,'range')".

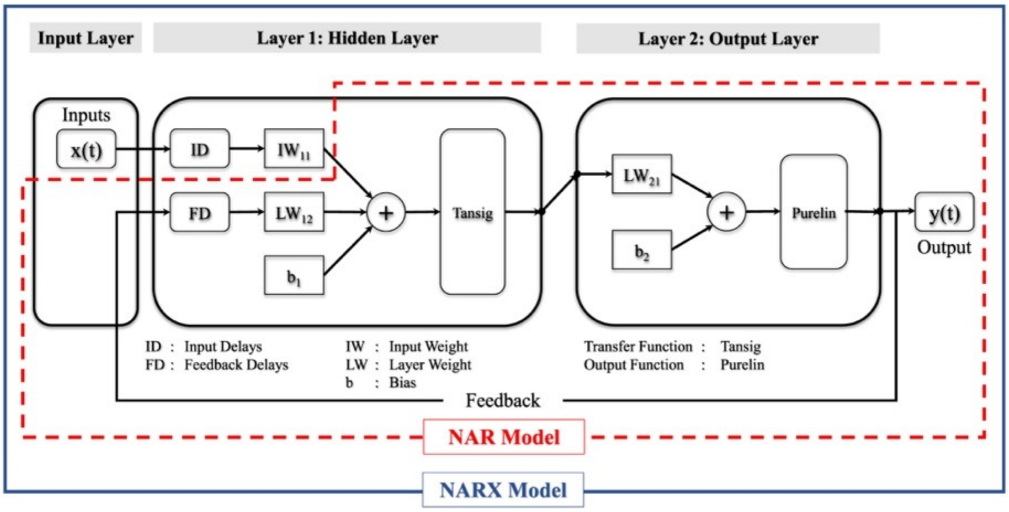
The Nonlinear Autoregressive (NAR) and with exogenous (NARX) neural network models used in the study are input-output based Recurrent Neural Networks (RNN) (Leontaritis and Billings 1985). NAR uses historical data to forecast the future of the same data. In addition to NAR, NARX uses exogenous input data together with the output data (Rogier and Mohamudally 2019). The NAR model can be interpreted mathematically in Equation 1 and the NARX model in Equation 2.

$$y(t) = f[y(t-1), y(t-2), \ldots, y(t-dy)] \tag{1}$$

$$y(t) = f[y(t-1), y(t-2), \ldots, y(t-dy), x(t-1), x(t-2), \ldots, x(t-dx) \tag{2}$$

where f is the nonlinear function; $y(t-1)$, $y(t-2)$, $\cdots$, $y(t-dy)$ are the past values of the time series y; $x(t)$, $x(t-1)$, $\cdots$, $x(t-dx)$, are the current and past values of the exogenous time series x.

Figure 1. The Visualization of NAR and NARX Models



Source : (Chreng, Lee, and Tuy 2022)

The performance of the models was determined by the coefficient of determination (R^2) and mean squared errors (MSE). The mathematical interpretations of the values are given in Equations 3 and 4, respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(P^i_{predicted} - P^i_{actual})^2}{\sum_{i=1}^{N}(P^i_{actual} - P^i_{predicted})^2} \tag{3}$$

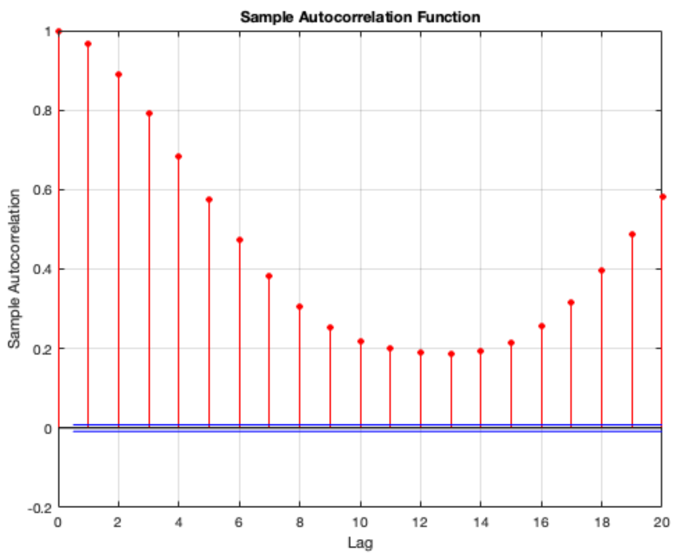
$$MSE = \frac{1}{N}\sum_{i=1}^{N}(P^i_{predicted} - P^i_{actual})^2 \tag{4}$$

where P^i_{actual}, $P^i_{predicted}$ are the i_{th} actual and predicted values, N is the period. The coefficient of determination refers to how well the data fits, and the degree of the fit is evaluated by its distance to 1.

3. FINDINGS

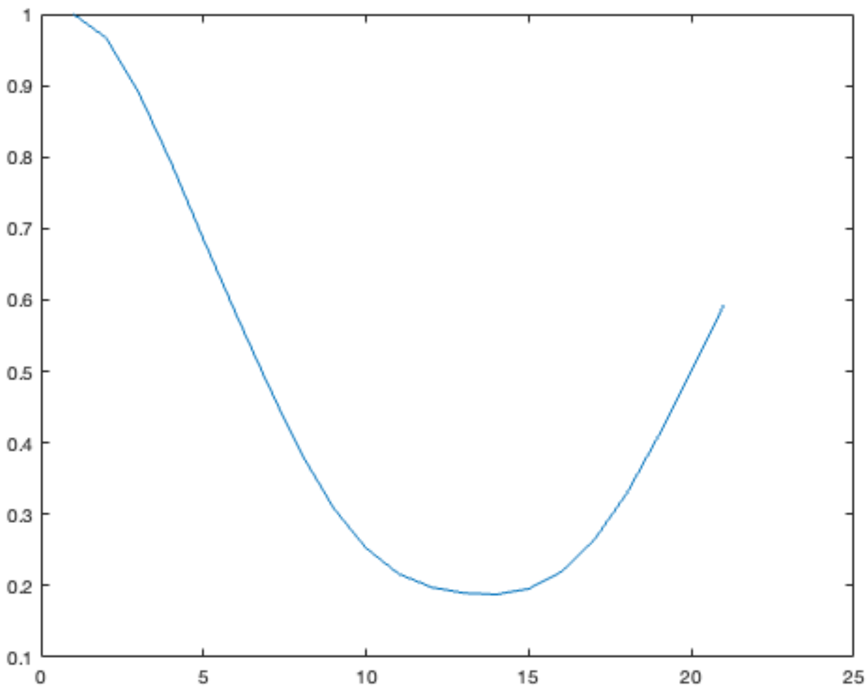
Since the NAR and NARX models used in the study contain autoregressive conditions, correlation test was first applied to both electricity generation and consumption data. As a result of the test, the autocorrelation of generation data is shown in Figure 2 and consumption data in Figure 3. As can be seen from the figure, the auto-correlation of both data sets is almost the same. The analysis shows that the correlation first decreases and then increases again as the lag increases.

Figure 2. Autocorrelation of Electricity Production



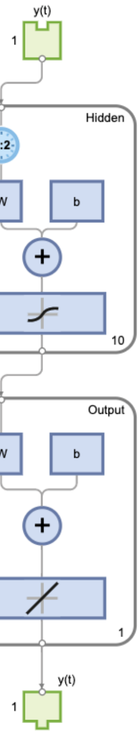
A correlation value of 50% was determined for the lag to be used in both data sets and this percentage corresponds to a lag of 5 units in the data sets. Therefore, while constructing the NARX model, a lag of 5 lines was applied to both production and consumption data and the model was made ready for analysis.

Figure 3. Autocorrelation of Electricity Consumption



The NAR model using lagged data is shown in Figure 4. In the model, electricity generation data is used both as input and output. 70% of the data is allocated for training, 15% for validation, and the remaining 15% for testing. Levenberg-Marquardt algorithm was used for training the network. The success of the algorithm in solving non-linear real-life problems and its ability to produce fast solutions played a major role in the selection of this algorithm. Since there is no definite rule for determining the number of hidden layers and the number of layers is determined by trial and error in the literature, the trial-and-error method was used in this study.

Figure 4. NAR Model with 10 Hidden Layers for Electricity Production



In the NAR model, models with 2, 5, 10, 15, 20, and 40 hidden layers were created and analyzed respectively. When the R^2 and MSE values of the models were examined, no significant difference was observed and it was concluded that increasing the number of layers would only increase the analysis time and the performance of the NAR models with only 10, 15, and 20 hidden layers are given in Table 1 below.

Table 1. Performance Values of NAR Models with Different Hidden Layers

Number of Hidden Layers	R^2	MSE
10	0.9846	0.0009156
15	0.9848	0.0009063
20	0.9850	0.0008952

When the results are analyzed, it is seen that the 20-layer model performs better with the lowest error and the highest level of coefficient of determination. The performance values of the 20 hidden layer NAR model for training, validation, and test data are also given in Figure 5.

Figure 5. The Performance Values of the NAR Model with 20 Hidden Layers

Model Summary

Train a neural network to predict series y(t) from past values of y(t).

Data

Responses: output - [61196x1 double]

output: double array of 61196 time steps with 1 features.

Algorithm

Data division: Random

Training algorithm: Levenberg-Marquardt

Performance: Mean squared error

Training Results

Training start time: 28-Dec-2022 05:25:16

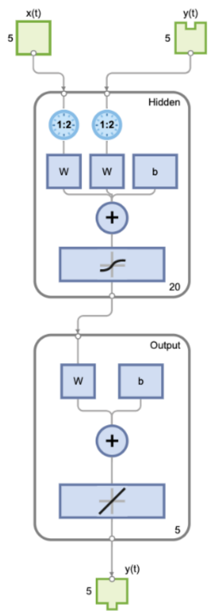
Layer size: 20

Time delay: 2

	Observations	MSE	R
Training	42836	8.9529e-04	0.9850
Validation	9179	9.4537e-04	0.9842
Test	9179	9.1097e-04	0.9848

After the analysis results of the NAR model are obtained, production and consumption data with 5 hours lags are used in the NARX model as explained earlier. As in the NAR model, 75% of the data is reserved as training data and the Levenberg-Marquardt algorithm is again chosen as the training algorithm. The NARX model with 20 hidden layers and 2 input and 1 output variable is shown in Figure 6.

Figure 6. NARX Model with 20 Hidden Layers to Forecast Electricity Production by Using Electricity Consumption



In the NARX model, as in the NAR model, models with 2, 5, 10, 15 and 20 hidden layers were created respectively. Although there is almost no performance difference between these models, the best performance, albeit very small, is obtained from the model with 20 hidden layers. The R^2 and MSE values of the models are given in Table 2.

Table 2. Performance Values of NARX with Different Hidden Layers

Number of Hidden Layer	R^2	MSE
10	0.9982	0.00010596
15	0.9982	0.00011014
20	0.9983	0.00010269

As a result of the analysis of NARX models, the highest R^2 value of 0.9983 was obtained. This high value indicates the success of the prediction performance of the model. In addition, compared to the NAR model, an R^2 increase of more than 1% and a lower error rate were obtained.

4. CONCLUSION

Regardless of the source, the uninterrupted, high quality, and low cost of the electrical energy produced affect both the daily and professional lives of people. Considering that industrialization is increasing rapidly, and technological enhancements are developing exponentially compared to the past, and considering that electrical energy is at the center of these, it is one of the essentials of our age that this energy reaches its end users uninterrupted, efficiently, and at low cost.

In this study, Türkiye's hourly electricity generation planning is forecasted by including both its own data and hourly electricity consumption data. With this forecasting, the performances of NAR and NARX models from RNN models were compared, and according to the results of the analysis, the NARX model, that is, the use of past and delayed data of electricity consumption as well as past and delayed data of electricity generation, increased the performance in the forecasting of hourly generation and allowed to obtain a result that will contribute to the planning for the uninterrupted supply of electricity with less margin of error. At the end of the study, a prediction accuracy of 99.83% was obtained with the NARX model, which shows the success of the model. Likewise, the error rate measured by the MSE value of the model was also found to be quite low.

When the analysis results are analyzed, it is seen that increasing the number of hidden layers does not affect the model performance to a great extent. This is thought to be due to the high autocorrelation with 61,196 lines of hourly data between 2016 and 2022. It is also thought that the study can be improved by adding other variables affecting electricity generation to the model. In addition, it is thought that more meaningful and useful results can be obtained from electrical energy data by using different machine learning and deep learning methods if sufficient data is available.

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