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Development of a Model for Evaluating the Efficiency of Transport Companies: PCA–DEA–MCDM Model

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Abstract: The efficiency of transport companies is a very important factor for the companies themselves, as well as for the entire economic system. The main goal of this paper is to develop an integrated model for determining the efficiency of representative transport companies over a period of eight years. An original model was developed that includes the integration of DEA (Data Envelopment Analysis), PCA (Principal Component Analysis), CRITIC (Criteria Importance Through Inter criteria Correlatio), Entropy and MARCOS (Measurement Alternatives and Ranking according to the COmpromise Solution) methods in order to determine the final efficiency of transport companies based on 10 input–output parameters. The results showed that the most efficient business performance was achieved in the period 2014–2017, followed by slightly less efficient results. Then, extensive sensitivity analysis and comparative analysis were performed, which confirmed, to some extent, the previously obtained results. In the sensitivity analysis, 30 scenarios with changes in the weights of criteria were created, while the comparative analysis was carried out with three other MCDM (Multi-Criteria Decision-Making) methods. Finally, the rank correlation index was determined using the Spearman and WS (Wojciech Salabun) correlation coefficients. According to the final results, very efficient years can be separated that can be the benchmark for furthering the business.

Keywords: PCA–DEA; efficiency; transport; MARCOS; costs; logistics

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Citation: Stević, Ž.; Miškić, S.; Vojinović, D.; Huskanović, E.; Stanković, M.; Pamučar, D. Development of a Model for Evaluating the Efficiency of Transport Companies: PCA–DEA–MCDM Model. *Axioms* **2022**, *11*, 140. https://doi.org/10.3390/axioms11030140

Academic Editor: Hans J. Haubold

Received: 7 February 2022
Accepted: 10 March 2022
Published: 18 March 2022

1. Introduction

Better logistics performance is associated with trade expansion, export diversification, the ability to attract foreign direct investment, and economic growth. The significance of transportation infrastructure and logistics in trade should not be neglected, as the private sector (logistics providers) plays a large and relevant role in practice [1]. The increases in global production networks and competition underline the strategic function of logistics performance in improving competitiveness. It allows countries to perform better in globalized markets, a critical aspect for developing countries in harnessing economic benefits. Logistics performance is associated with proven service opportunities for increasing exports as a result of production networks. Therefore, its importance is becoming more relevant as facilitating trade and transport are commonalities for integrated markets and firms' engagement in modern production processes. Logistics at a national level facilitates distributions from the origin to the final destination, becoming a core component of the GDP of industrialized countries [2]. The research results in [3] show that there is a positive statistical significance and impact of logistics on bilateral trade between CEECs and that logistics justify the role of a trade facilitator. Better logistics performance in trading countries will lead to increased bilateral trade and reduced trade costs. Due to globalization and internationalization, logistics is becoming more and more open. Modern logistics is greatly influenced by the processes of managerial evaluation of the logistics performance and its dependencies on economies in selected countries. In the rapidly developing process of economic globalization, transportation management issues are of great importance [4]. Transport is one of the most important subsystems of logistics and elements of the economic system in general [5]. Certainly, in order for transport to be carried out successfully, it is necessary to have a good infrastructure, as well as the interaction of all other logistics subsystems, witnessing its development on a daily basis [6]. There are more and more companies in B and H (Bosnia and Herzegovina) that perform domestic and international transport of goods. Since B and H is not a member of the EU (European Union), transport companies receive a number of bilateral and multilateral permits for providing international transport every year. It is an aggravating circumstance and a limiting factor significantly affecting the efficiency and effectiveness of transport. However, despite this limitation, transport companies strive to provide the highest quality service in the market where they operate. Depending on the requirements of service users, transport companies adjust their resources. The most important is the selection of the appropriate means of transport, the selection and creation of transport units, all technical and economic procedures, as well as the application of an appropriate information system. As transport is an active process, it is necessary to check all these procedures several times a day, as well as to monitor the whole process in order for the service to be at a satisfactory level. For every transport company, the most important thing is that vehicles are in operation and that they safely transport goods from point A to point B. Through the realization of a tour or route, it is necessary that responsible persons calculate the cost-effectiveness, taking into account all the costs in order to determine the company's profit. Fuel costs, as well as tolls, have been constantly rising in the last few years and this has a negative impact on the operations of transport companies, so ways to save money have to be found on a daily basis. In addition, B and H transport companies must take into account the costs of customs clearance of goods since all goods must enter import/export customs upon entry to and exit from B and H. However, although there are many difficulties for B and H transport companies, statistics show that there was an increase in imports and exports of goods from B and H in the period from 2015 to 2019. All these data, as well as daily changes in transport, were the first motive for this research. Many companies record such and similar data, however, due to their complexity, it is rare for a company to determine which business year was more or less successful. The data are constantly changing, and by observing only some data, a certain year can be seen as successful, but after integrating them with other data, completely different values are obtained. This is the second motive for performing such a study. In this paper, the efficiency of representative transport companies in B and H over a period of eight years (2013–2020) was determined by considering a total of 10 parameters that represent a combination of inputs and outputs, and relate to quantitative numbers and cost parameters.

Through this research, it is possible to single out several goals reflecting the contributions of the paper. The first goal is to determine the efficiency of transport companies for a long period of time, which can positively affect their further business performance and increase efficiency in their further operations. Additionally, the most efficient business years can serve as a benchmark for other transport companies to improve their business operations by adopting best practices, which is another goal and contribution of this research. There are different models for determining efficiency, as shown extensively in Section 2. An integrated PCA–DEA–CRITIC–ENTROPY–MARCOS model was presented for the first time in the literature, which is a very important contribution from a methodological point of view. Therefore, the development of the integrated original model for determining the efficiency of transport companies is the third goal of the paper, which fills the gap in the current literature in a certain way. The advantages of the developed model were manifested through measuring the efficiency of two transportation companies (TC). However, this model can be applied in other fields, of course, using different data depending on the concrete case. Taking into account the previously mentioned facts, it can be concluded that the model can be applied as a generalized method.

In addition to introductory considerations, the paper is structured with several other sections. In Section 2, an extensive review of the literature on efficiency models, primarily DEA or a combination of PCA–DEA, and the application of MCDM methods is presented. Section 3 refers to the development of the integrated model with a detailed presentation of the overall methodology and explanations of its application. The steps of the DEA, PCA, CRITIC, Entropy, and MARCOS methods are shown. Section 4 provides an analysis of quantitative business parameters of representative transport companies, which relates to a comparative analysis of inputs and outputs for a whole observation period of eight years. Also, presents the application of the developed original model for determining the efficiency of transport companies, while a sensitivity analysis and a comparative analysis are performed in Section 5. The correlation coefficients of the ranks obtained are also calculated. Discussion is provided in Section 6, and concluding remarks in Section 7.

2. Literature Review

The measurement of the business efficiency of transport companies was performed by applying the DEA model, i.e., by applying an integrated PCA–DEA model in the initial phase. The mentioned models were applied in many studies for the purpose of measuring the efficiency of different areas of transport. In the research [7], an overview of the DEA model for measuring the efficiency of supply chains was made. Some of the studies will be given below and in Table 1.

Table 1. The overview of a method for evaluating the efficiency in the field of transport and supply chain.

Method	Findings	Observed Inputs and Outputs	Authors
DEA	Analysis of the efficiency of the bus subsystem of public passenger transport	Realized kilometers, realized places/kilometers and number of operationally ready vehicles	Despić et al. [8]
AHP and DEA	The analysis of the efficiency of airlines in the European Union	Operational costs, number of employees and offered capacity and realized passenger kilometers	Dožić and Babić [9]
DEA	Efficiency analysis of the European inland trimodal terminals	Terminal area, total track length, total operational shore length, maximum draft depth, storage capacity and annual terminal capacity	Krstić et al. [10]
DEA	An assessment of intermodal container transportation	The sum of transportation costs, time travel utilization, transportation work and strategy resistance factor	Radonjić et al. [11]
DEA, PCA and VIKOR	Supplier selection and evaluation in the garment supply chain	Quality, price, location, lead-time, monetary position (variability), financial position, on-time delivery, ability to produce, support and service and technical capacity	Karami et al. [12]
PCA and DEA	Developing A strategy-based framework for supplier selection	Delivery time, service relation combination, cost and organizational management	Hatami-Marbini et al. [13]
PCA, DEA and MLR	An assessment of the Eco-Efficiency of Transport-Related Particulate Matter Pollution	Fuel consumption, the number of employees, trips per day, pollution and emissions of various harmful gases	Muge [14]

Table 1. *Cont.*

Method	Findings	Observed Inputs and Outputs	Authors
DEA	Research in the new framework for logistics performance index	Freight price, logistic loss, fuel consumption, on-farm storage capacity, emissions (Eq. CO2/transported t), length of the route, production, corridor exports and inverted emission	Melo [15]
ANP and DEA	Measuring the efficiency of transport infrastructure projects	15 inputs/outputs related to energy, quality, operational indicators, utilization and resource indicators	Ivanović et al. [16]
DEA, CRITIC and MARCOS	An assessment of Traffic Safety in South Africa	The average number of accidents (per km), the number of access (per km), road width, the number of lanes	Stević et al. [17]

Analytic Hierarchy Process (AHP); Multiple linear regression (MLR); Analytic Network Process (ANP)

2.1. Review of Applying the DEA Method for Evaluating the Efficiency in the Field of Transport

The process of measuring efficiency in manufacturing companies differs greatly from the process of measuring efficiency in service companies. It was concluded that in order to successfully measure efficiency in logistics, it is necessary to consider a large number of inputs and outputs that are different in nature (financial, technical, environmental, energy, social, etc.) and expressed by different measuring units. In this regard, it is possible to measure energy, environmental, cost, and other types of efficiency in logistics. Despić et al. [8] apply the DEA model in order to analyze the efficiency of the bus subsystem of public passenger transport in Belgrade, on a sample of five small, three medium, and two large companies. The authors have concluded that efficiency is essential when considering the success of a company.

Economic efficiency expresses the efficiency of performing the economic processes of the company or the company's efforts to complete the tasks selected as successfully as possible. In addition, in terms of the DEA model, it is important to note that when using this model, the size of the company must be taken into account, which is the object of analysis. The subject of the research in [9] is the analysis of the efficiency of airlines in the European Union in 2012, where, by applying the DEA model, the individual efficiency of each airline was assessed, and inefficient business elements that could be improved were identified. The efficiency of the airline, as for other branches of the economy, was measured as the amount of output produced per unit of input. It was observed that the DEA model greatly contributes to the improvement of business operations since it allows the identification of efficient or inefficient companies. Accordingly, it is possible to react in time and provide guidelines for potential efficiency improvement of each company that was identified as inefficient, i.e., it is possible to determine how much each business element should be reduced or increased in order for a given company to become relatively efficient.

Blagojević et al. [18,19] proposed a model for evaluating the efficiency and effectiveness of railway operators for passenger transport based on the DEA model, which enables the comparison of the efficiency of comparable units, in this case, groups of operators with a large number of input and output variables, which can greatly increase the competitiveness of railway operators in the railway market. The proposed model was tested on real examples of selected operators from Europe. The authors chose the DEA model to assess the efficiency and effectiveness of railway operators since it enables the analysis of mutually comparable units despite heterogeneous data, which are expressed by different measurement units and affect business efficiency in different ways. Similar research was performed in the paper [20]. In this research, an analysis of the efficiency of selected railway operators in the transport of goods from EU countries was conducted, using the DEA analysis method. The aim of the analysis was to show that using a relatively small number of indicators, useful information, which can guide the business policy of the operator aimed at improving business performance can be obtained. The advantage of this analysis is that inputs and outputs do not have to be directly functionally dependent, whereby the DEA analysis can determine the indirect dependence of inputs and outputs.

Additionally, there is no limit to the number of inputs and outputs with DEA analysis, which allows for a comprehensive analysis depending on the requirements. The results obtained can be used as guidelines for improving the efficiency of other railway operators. Batur and Nikolić [21] applied the DEA model to measure port and terminal efficiency. The authors pointed out certain benefits and negative aspects of the DEA approach. As its benefit, it can be pointed out as a characteristic that it does not impose any functional form with regard to the production function nor the form for achieving a certain degree of productivity.

The possibility of using DEA analysis in multiple output processes is also its advantage, especially when considering port activities with different loads and when it is obvious that there is a certain degree of homogeneity in production processes in many ports. The negative aspect of this method is reflected in its deterministic nature, which does not allow random errors or erroneous measurements to be isolated when measuring only inefficiency. Andrejić and Kilibarda [22] point to the problem that may arise when applying the DEA model in order to measure the efficiency of linked systems and multiphase processes in the field of product distribution. One of the possible problems is a very large number of linear programming tasks that are difficult to solve in the case of a large number of DMUs and more complex chains. Since DEA is an extreme point method, small errors in input and output variables can lead to erroneous solutions.

However, despite all the disadvantages, this method with all its benefits is an excellent basis for the development of tools for measuring the efficiency of complex systems with a large number of participants. Krstić et al. [10] carried out the analysis of the efficiency of intermodal terminals with the aim of identifying terminals that would serve as models for the improvement of current and development of new terminals, as well as determining the parameters for making them efficient. The DEA method was used to determine the efficiency of the terminals, and the research was conducted on a sample of 35 real land trimodal terminals in Europe. The results of the research showed that, for the defined sample, storage capacity and length of railway tracks had the greatest influence on achieving the efficiency of the terminal. Kampf et al. [23] use the DEA model to efficiently assess the economic situation of a particular transport company in order to determine whether its business is economically attractive. In the study, the CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Chames, and Cooper) models of the DEA approach were applied. The DEA models, in addition to measuring effectiveness, can be also used, at times, to set benchmarks, benefits of scale, ranking objects, as well as to find ways of improving efficiency and the structure of optimal technologies for inefficient objects [24].

An important advantage of the DEA method is its non-parametric nature, enabling its use without the knowledge of functional dependencies between outputs and inputs. In order to assess the intermodal transport of containers as successfully as possible, Radonjić et al. [11] have analyzed the application of the DEA model in deciding on the most favorable line of containers. Although the DEA method is not a ranking method, many authors have used it for ranking purposes for practical reasons. Azadeh and Salehi [25] use the DEA model for modeling and optimizing efficiency gaps between managers and operators in integrated resilient systems. In addition, the application of this model identifies the gaps in the systems. The authors state that the level of durability of the system depends on the number of gaps. The smaller the gaps in the functioning between the operator and the manager, the more efficient the company's performance will be in terms of challenges and difficulties in real work.

2.2. Review of Applying the PCA–DEA Model for Evaluating the Efficiency in the Field of Transport and the Supply

Davoudabadi et al. [26] present an integrated efficiency measurement model that combines statistical techniques and mathematical programming for supplier analysis.

Supplier selection is one of the crucial issues in supply chain management, and great attention should be paid to the balance between price, time, and quality. Thus, in the study, the PCA approach is used to reduce the dimensions and the correlation between the criteria, while DEA is used in order to rank suppliers. A similar study was performed in the paper [12]. In the study, the PCA–DEA model was used in combination with other methods in order to evaluate and select suppliers in the garment industry. Decisions related to the purchase and supply of raw materials play a key role in business logistics. In this regard, it is very important to develop models that will enable the selection of the best supplier and thus long-term business cooperation with the desired suppliers without unforeseen changes in supply that may have a negative impact on the business. Hatami et al. [13] apply the PCA–DEA model when forming a strategy framework for the selection of suppliers in supply chains in the agri-food industry. Deng et al. [27] apply an integrated PCA–DEA approach with the aim of assessing carbon emissions and negative impacts in the implementation of logistics activities. The PCA model was applied to reduce the dimensionality of the observed indicators, and then the DEA method was applied to measure and assess the logistics performance with and without carbon emission constraints in 30 provinces in China. It was concluded that low efficiency is an important factor limiting logistics development and that regional economic and logistics development has a positive impact on the overall logistics efficiency, while the energy structure and the influence of the government have a negative effect. The efficiency evaluation of distribution centers is based on the assessment of any logistics operator's performance. Due to the huge number of potential indicators, the main issue is how to select adequate efficiency indicators. Accordingly, Layeb et al. [28] conduct an analysis of the efficiency of a logistics service provider operating in Tunisia. The paper uses the PCA approach to select adequate indicators, followed by the DEA method for measuring the efficiency of all warehousing and transport activities. The purpose of the research [14] is to determine the level of eco-efficiency of particulate matter air pollution caused by the transport sector in Nairobi City by identifying sources of particulate matter, determining the eco-efficiency of transport, and assessing the impact of various transport parameters on eco-efficiency. Therefore, an integrated approach is proposed, which includes, among other things, the application of the PCA model in order to process the parameters related to transport and assess the eco-efficiency of the transport sector using the DEA model. Melo et al. [15] use the DEA model to analyze the efficiency of long-distance freight transport, more precisely, to analyze the efficiency of soybean transport from production regions to export ports in Brazil. Ivanović et al. [16] propose a hybrid PCA–DEA model for measuring the efficiency of public–private partnership transport infrastructure projects using key performance indicators that are defined in accordance with the estimated stakeholder impact. The authors conclude that it is necessary to increase the discrimination power of the DEA model by using PCA as a method to reduce the number of KPIs (Key Performance Indicators) with minimal loss of information from the original set of indicators when the application of the DEA model does not provide adequate results. The above is confirmed by the research [29], in which the PCA–DEA approach was applied to measure the efficiency and selection of certain types of distribution.

Adler and Golany [30] presented the combined use of principal component analysis and the DEA model. The authors proved that PCA additionally strengthens the discrimination power of the DEA model. A similar study was performed in the paper [31], where it is once again proven that the use of principal component analysis can significantly improve the strength of the DEA model and can be used to validate the results of the DEA model. In the paper [32], the measurement of global logistics efficiency was performed using the PCA–DEA approach. It was concluded that the proposed model can be used to assess logistics activities at a global level and to improve current approaches.

2.3. Review of Applying Integrated Models in the Field of Transport

In the paper [17], an integrated model for identifying road safety indicators that are crucial for improving overall traffic safety was developed. The model encompasses the CRITIC method, which was used to determine the significance of the criteria, two DEA models, which were applied to calculate criterion weights, and finally the MARCOS method, which was used to rank the alternatives. Wu et al. [33] evaluated the safety of urban rail transit, developing a new integrated model for the evaluation of rail transit operation safety, which included, among other things, the application of the CRITIC method for determining the weight values of criteria. In the paper [34], a comparative assessment of the performance of social sustainability is performed. Evaluation of countries is carried out through a novel integrated data-driven weighting system based on the CRITIC and Shannon's Entropy methods, and the CoCoSo (Combined Compromise Solution) method. The proposed integrated data-driven weighting system is designed to remove the biasedness and subjectivity of experts' opinions that can happen using other weighting methods. Ranking of decision-making units can be performed using many models, but each of the ranking models can provide different ranking results for a similar problem. Therefore, it is necessary to test different ranking models, combine the results obtained and find out which of the models provides the most reliable results. Multi-criteria decision-making methods are often applied in logistics to create different strategies and assessments, so in the paper [35], different MCDM methods were used to assess human resources in an international transport company. The MARCOS method was used to rank 23 drivers on the basis of five criteria. Biswas [36] carried out a comparative analysis of the supply chain performance of leading healthcare organizations in India using different MCDM methods and ranking the alternatives by applying the MARCOS method. The importance of applying the MARCOS model is also discussed by Zolfani et al. [37]. The authors proposed a combined approach of SFA (Suitability–Feasibility–Acceptability) with MCDM methods in order to explore the complexity of dressing the appropriate target market for the Chilean fish market. Ecer in [38] proposes an integrated model, which includes the application of the MARCOS method in order to assess the performance of battery-powered electric vehicles. It was concluded that the proposed framework can be utilized as a basis for more detailed purchasing decisions. Ecer and Pamucar in [39] apply the MARCOS method to rank insurance companies. It was concluded that the introduced approach met the insurance assessment problem during the COVID-19 pandemic in a very satisfactory manner. Lee et al. [40] assess sustainable urban transport development, creating a new integrated assessment model based on the Entropy method. The weight values of the criteria defined (urban economic development, transport demand, environment quality, and energy consumption) were obtained by applying the Entropy method. It was concluded that the method could be used in a very simple and efficient way for a comprehensive assessment of urban transport development. A similar study was conducted in the paper [41], where the Entropy method was also applied. The paper evaluates the economic and social development of 287 cities in China using an integrated TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) Entropy model, where the results of the applied model show that the overall level of urban sustainable development in China is not high and that the developed model can be successfully used to assess sustainable development.

Popović in [42] shows how multi-criteria decision-making methods can improve the DEA model, i.e., eliminate shortcomings in the application of the DEA model when measuring efficiency. Given the large number of inputs and outputs used in DEA, the essential problem in its application is in the fact that it is often not clear which inputs and outputs to select when evaluating efficiency. For these reasons, Popović [42] believes that the problem of adequate selection of inputs and outputs becomes an important issue for improving the discrimination power of the method. Considering the observed problems for selecting and summarizing relevant criteria, hybrid models were developed for linking with multi-criteria decision-making methods. In addition, the research in [43] proposed a model for measuring the efficiency of connected logistics systems based on the DEA method and game theory. The main problem of measuring the efficiency of connected logistics systems is due to the fact that each system has its own strategy for achieving efficiency. In the paper [44], the fuzzy-DEA model was applied to assess the efficiency of the public transport system, showing how it is possible to take advantage of the combination of fuzzy logic and the DEA model in order to obtain the most precise results.

2.4. A Review of Studies of Pandemic Impact on Transport and the Supply Chain

In the following, several papers analyzing the COVID-19 (Coronavirus disease) pandemic impact on transport and the supply chain will be mentioned. Bašnec [45] points to the fact that the pandemic does not have the same influence dynamics in the world. That is precisely why in some countries there is a sharp decline in the volume of transport and trade, while in others there is a slight increase in the volume of trade and transport. One of the key issues in analyzing the impact of the pandemic relates to transport and mobility in the post-COVID-19 world. Cui et al. [46] analyzed the impact of the COVID-19 pandemic on transport in China. It was concluded that the volume of passenger transport by water declined the most, by 11.44%, in 2020, followed by road passenger transport, by 8.96%, and air passenger transport, by 5.26%. Compared to these modes of passenger transport, the decline in rail passenger transport is relatively smaller, by 3.08%, but is still higher than the share in all freight transport sectors. Compared to the passenger transport sectors, the freight transport sector has a significantly smaller decline, as they are mostly indirectly affected by the pandemic, which reduces the demand of households and manufacturing sectors for transport. Among them, the largest decline was recorded by pipeline transport, 2.85%. Airfreight transport recorded a large decline by 2.81%, but significantly lower than air passenger transport (5.26%). It is predicted that the use of road freight transport will decrease by 2.20%, followed by other modes of transport (1.84%) and rail freight (1.39%). Loske [47] conducted a similar study which confirmed the above, that the pandemic had a much greater impact on the decline in passenger transport compared to freight transport. Ivanisevic and Simović [48] analyzed the transport of goods by courier services during the pandemic, with an increase in demand for courier services as a result of the increase in the volume of purchases via the Internet. Zhang et al. [49] examined the impact of the pandemic on transport and came to the conclusion that from February to May 2020, the global decline in the use of public transport was 28.3%. The authors believe that the expected changes will contribute to improving the resilience and sustainability of the transport and logistics sector. A similar study was conducted in [50], where the impact of COVID-19 was analyzed on everyday public transport in the three most populous regions in Sweden (Stockholm, Västra Götaland, and Skåne) in 2020. The reduction in the number of passengers on public transport (40%–60% by regions) was serious compared to other modes of transport. According to [51], preventive isolation measures caused a reduction in flight volume between 40% and 60%. The decline in the number of freight trips after 25 March 2020 is also evident. Freight trips decreased by an average of about 38% during mandatory quarantine. Budd and Ison [52] analyzed the impact of the pandemic on air transport, where it was concluded that the global number of passengers was 80% lower in 2020 than in 2019.

In this paper, a new integrated model for evaluating the efficiency of transport companies is developed. The developed model includes the integration of the PCA, DEA, CRITIC, Entropy, and MARCOS method in order to evaluate the efficiency of two representative transport companies. The formation and application of such an integrated model bring many advantages to companies. The developed model enables companies to determine efficient or inefficient business periods in a very precise way, which can further influence the improvement of the overall business, increase efficiency in further work and increase the competitiveness of the transport company in the market. One of the many advantages of the developed model is that it gives precise and clear results and insight into business efficiency regardless of the number of observed parameters and the observed business period.

3. Methodology

The comprehensive methodology of the paper is shown in Figure 1, where it is easiest to see what models for calculating efficiency were applied in the paper and what steps were taken to determine the business efficiency of representative transport companies.

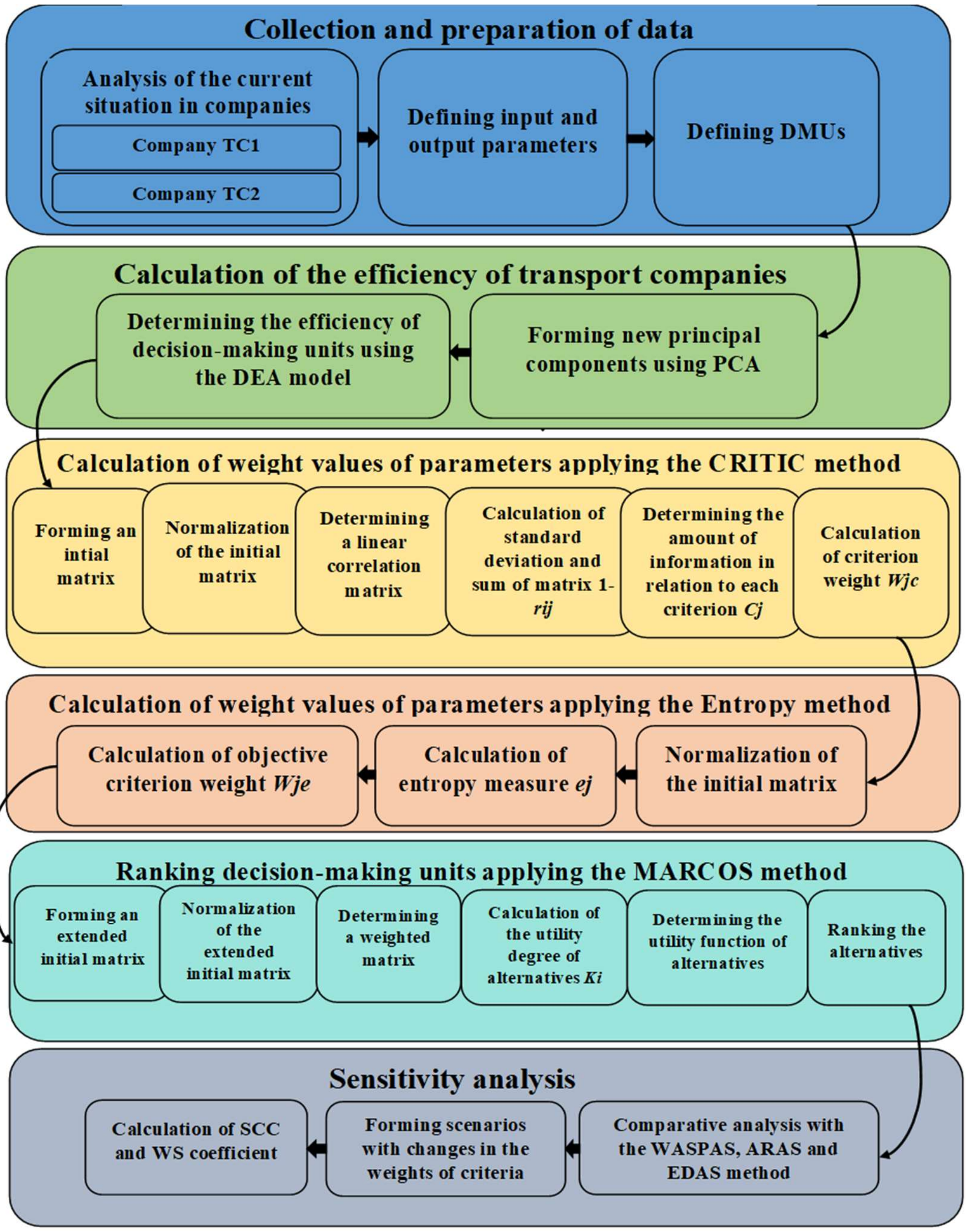


Figure 1. Applied methodology.

The paper analyzes the business efficiency of two companies from Bosnia and Herzegovina which provide services of domestic and international transport of goods. The methodology of the paper consists of six phases. The first phase includes an analysis of the business performance of representative transport companies in the last eight years, and the definition of input and output parameters and decision-making units. Based on data availability and the literature review [7,16,18,22,43,53], six inputs and four outputs were defined. The inputs are: the total number of vehicles, number of drivers, number of operating hours, vehicle maintenance costs, fuel costs per total kilometers traveled, and transport staff costs. The outputs are: the total number of deliveries, total quantity transported, total kilometers transported, and profit. Data on input and output values were collected for all eight decision-making units. The data collected represent the basis for the realization of the second phase, i.e., the foundation for determining the efficiency of companies using an integrated PCA–DEA model. In the paper, a procedure for determining efficiency by applying the PCA–DEA model and MCDM methods is carried out, observing both transport companies individually, but also observing the companies together, i.e., comparing the efficiency of the decision-making units of both companies together. DEA (Figure 2) is used to evaluate the relative efficiency of a homogeneous set of DMUs characterized by multiple inputs and outputs. If the value of results of DEA = 1, the model shows efficiency, and if the value of results of DEA < 1, the model shows inefficiency. Decision-making units that have a value of one are further implemented in the model. PCA is used to further strengthen the discrimination power of the DEA model, by creating new major variables that represent linear combinations of initial variables. The main steps in the analysis of principal components are: standardization of variables, calculation of the matrix of correlations between all initial standardized variables, finding eigenvalues of principal components, rejection of the components that are carriers of a proportionally small share of variance [49]. The third phase includes the calculation of weight values of all defined input and output parameters using the CRITIC method and then using the Entropy method in the fourth phase (Figure 3). The methods are of objective nature, and their individual application, through a few simple steps, leads easily to the weight values of the criteria. The CRITIC method includes the following six steps: formation of an initial matrix, normalization of the initial matrix depending on the type of criteria, determination of symmetric matrix of linear correlation, calculation of standard deviation, and calculation of the sum of matrix 1–*rij* (matrix of linear correlation), determination of information in relation to each criterion and calculation of criterion weights. The Entropy method is carried out through the following three steps: normalization of the initial matrix, calculation of the entropy measure, and objective calculation of the weight value of the criterion. Using the MARCOS method, in the fifth phase, the ranking of alternatives, i.e., the efficiency of selected decision-making units based on the final value of the utility function is performed. The MARCOS method is conducted through the following steps: formation of the initial decision matrix, formation of the extended decision matrix, normalization of the extended initial matrix, determination of the weighted matrix, calculation of the utility degree of alternatives, determination of the utility function of alternatives and, finally, ranking the alternatives. In the final phase, the sensitivity analysis of the results obtained is performed. A comparative analysis of the MARCOS method with other MCDM methods is performed, in this case with the WASPAS (Weighted Aggregates Sum Product Assessment), EDAS (Evaluation based on distance from average solution), and ARAS (additive ratio assessment) method. In addition, 30 new scenarios are formed, which include changes in the weight values of the most important criteria. To test the similarity of the rankings, the WS coefficient is calculated, as well as the SCC (Spearman's correlation coefficient) to determine the correlation of the initial solution with all scenarios. Finally, a discussion of the results obtained is performed.

3.1. DEA Model

This section presents two DEA CCR models [54] that were applied to obtain the values of alternatives (Figure 2), i.e., DMUs according to an input-oriented model (min) and an output-oriented model (max). The DEA CCR input-oriented model (min) is as follows:

$$\begin{array}{c} DEA_{input} = \min \sum\limits_{i=1}^{m} w_i x_{i-input} \\ st: \\ \sum\limits_{i=1}^{m} w_i x_{ij} - \sum\limits_{i=m+1}^{m+s} w_i y_{ij} \geq 0, \; j = 1, \ldots, n \\ \sum\limits_{i=m+1}^{m+s} w_i y_{i-output} = 1 \\ w_i \geq 0, \; i = 1\mathrm{I}., m+s \end{array} \tag{1}$$

Algorithm: Pseudo-code of DEA CCR min/max model

Input: *m* transport companies; *n* criteria for assessing the efficiency of companies
Output: Efficiency of transport companies (DMU)
Initialize each transport company as DMU
Determine the relative performance of transport companies using the input oriented DEA methodology.
Determine the relative performance of transport companies using the output oriented DEA methodology.
If θ=1
then
DMU is on the efficient frontier
else
DMU is inefficient.
Rank the transport companies based on relative efficiency score.
Select the efficient transport companies for the next stage of the evaluation

Figure 2. Pseudo-code for DEA model.

Algorithm: Pseudo-code of CRITIC and Entropy methods

Input: The decision matrix (X)
Output: The weight coefficients of criteria/sub-criteria

j=1;
while ($j \leq count\ (C)$) do
if $C_j = +$
then
$r_{ij}=(x_{ij}-\min(x_{ij}))/(\max(x_{ij})-\min(x_{ij}))$
$p_{ij}=x_{ij}/\mathrm{sum}(x_{ij})$
else
$r_{ij}=(x_{ij}-\max(x_{ij}))/(\min(x_{ij})-\max(x_{ij}))$
$p_{ij}=x_{ij}/\mathrm{sum}(x_{ij})$
For all j in C calculate symmetric linear correlation matrix eq. (6)
For all j in C calculate the entropy measure eq. (9)
Calculation of CRITIC and Entropy criteria weights

Figure 3. Pseudo-code for CRITIC and Entropy methods.

DMUs consist of m input parameters for each alternative x_{ij}, while s represents the output parameters for each alternative y_{ij}, taking into account weights of the parameters denoted by w_i, and n represents the total number of DMUs. The DEA CCR output-oriented model (max) is as follows:

$$\begin{gathered} DEA_{output} = \max \sum_{i=m+1}^{m+s} w_i y_{i-output} \\ st: \\ -\left(\sum_{i=1}^{m} w_i x_{ij}\right) + \sum_{i=m+1}^{m+s} w_i y_{ij} \leq 0, \ \ jI, \ldots, n \\ \sum_{i=1}^{m} w_i x_{i-input} = 1 \\ w_i \geq 0, \mathrm{I} = 1, \ldots, m+s \end{gathered} \tag{2}$$

3.2. PCA Model

PCA is a method that reduces dimensionality and is used to achieve visibility and simplify a large dataset. Principal Component Analysis is a technique of forming new ("artificial") variables which are linear combinations of initial variables. The maximum number of new variables that can be formed is equal to the number of initial ones. The new variables are not correlated with each other. The main aspects of the analysis of principal components are the summarization and analysis of the linear relationship of a large number of differently distributed, quantitative, mutually correlated variables, into a smaller number of components, new variables, mutually uncorrelated, with minimal information loss. Thus, we transform initial variables into new variables, i.e., linear combinations, which are called principal components. The first principal component is constructed to cover the largest part of the variance of an original dataset, and the following components include the part of the variance that is not covered by previously singled out components.

PCA is not sensitive to problems of normality, linearity, and homogeneity of variances. As stated, a certain degree of multicollinearity is also desirable. The main steps in the analysis of principal components are as follows [53]:

- Standardization of variables;
- Computation of the matrix of correlations between all initial standardized variables;
- Finding the eigenvalues of the principal components;
- Rejection of the components that are carriers of a proportionally small share of variance (usually the first several components carry 80–90% of the total variance).

Thus, out of a large number of initial variables, only a few principal components that carry most information and create the main form were formed. In the case where the initial variables are uncorrelated, the analysis does not provide satisfactory results. The best results can be achieved when initial variables are highly positively or negatively correlated. Then it can be expected that, e.g., 20–30 variables are covered with two or three principal components. The results of the principal components can primarily be used for further interpretation of the results. In addition to the above, the principal components can be used as input variables in other methods [53].

3.3. CRITIC Method

In the paper [55], the CRITIC method is introduced as a tool for determining the objective weights of criteria in MCDM problems. The steps of this method are presented as follows.

Step 1: Forming the decision matrix (X).

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} i = 1, 2, \ldots, m; \ j = 1, 2, \ldots, n \tag{3}$$

Step 2: Normalization of initial decision matrix depending on a criterion type.

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \; if\, j \in B \rightarrow \max \tag{4}$$

$$r_{ij} = \frac{x_{ij} - \max_i x_{ij}}{\min_i x_{ij} - \max_i x_{ij}} \; if\, j \in C \rightarrow \min \tag{5}$$

Step 3. Calculation of symmetric linear correlation matrix r_{ij}.

$$r_{ij} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - \left(\sum x_i\right)^2} \cdot \sqrt{n\sum y_i^2 - \left(\sum y_i\right)^2}} \tag{6}$$

Step 4. Determination of objective weights.

$$W_j = \frac{C_j}{\sum_{j=1}^{n} C_j}, C_j = \sigma \sum_{j'=1}^{n} 1 - r_{ij}, \sum_{j=1}^{n} \left(1 - r_{ij}\right), \sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{7}$$

3.4. Entropy Method

The Entropy method [56] consists of the following steps.

In the first step, it is necessary to normalize an initial matrix by applying Equation (8).

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{8}$$

In the second step, the computation of the entropy measure is performed by applying Equation (9).

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} r_{ij} \ln\left(n_{ij}\right) \tag{9}$$

In the third step, the values of the objective calculation of criterion weight are obtained by applying Equation (10).

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} \left(1 - e_j\right)} \tag{10}$$

3.5. MARCOS Method

The MARCOS method (Figure 4), developed by Stević et al. [57], consists of the following steps [58]:

Step 1: Formation of an initial decision matrix.

Step 2: Formation of an extended initial matrix. In this step, the extension of the initial matrix is performed by defining the ideal (AI) and anti-ideal (AAI) solutions.

$$X = \begin{array}{c} \\ AAI \\ A_1 \\ A_2 \\ \cdots \\ A_m \\ AI \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{aa1} & x_{aa2} & \cdots & x_{aan} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{22} & \cdots & x_{mn} \\ x_{ai1} & x_{ai2} & \cdots & x_{ain} \end{bmatrix} \end{array} \tag{11}$$

Algorithm: Pseudo-code of MARCOS method

Input: Transport companies – alternatives (A_i); w_j= weights of criteria
Output: Best A_i $(i=1,2,...,M)$
while $(M \neq NULL)$ do
Create a Decision Matrix X // equation (11)
for x_{ij} *in X do*
if $C_j = +$
then
$n_{ij}=x_{ai}/x_{ij}$
else
$n_{ij}=x_{ij}/x_{ai}$
end for
$v_{ij}=n_{ij}*w_j$// Weighted normalized matrix
while $(j \leq count\ (n))$ do
$S_i=sum(v_{ij})$
$K_i^+=S_i/S_{aai}$
$K_i^-=S_i/S_{ai}$
end while
for each A_i $(i=1,2,...,M)$ **do**
$f(K_i)=(K_i^++K_i^-)/(1+(1\text{-}f(K_i^+))/f(K_i^+)+(1\text{-}f(K_i^-))/f(K_i^-))$
end for
Rank all A_i based on $f(K_i)$

Figure 4. Pseudo-code for MARCOS method.

The anti-ideal solution (AAI) is the worst alternative, while the ideal solution (AI) is an alternative with the best characteristic defined by applying Equations (12) and (13):

$$AAI = \min_i x_{ij}\ if\ j \in\ B\ and\ \max_i x_{ij}\ if\ j \in C \tag{12}$$

$$AI = \max_i x_{ij}\ if\ j \in\ B\ and\ \min_i x_{ij}\ if\ j \in C \tag{13}$$

where B represents a benefit group of criteria, while C represents a group of cost criteria.

Step 3: Normalization of the extended initial matrix (X). The elements of the normalized matrix $N = [n_{ij}]_{mxn}$ are obtained by applying Equations (14) and (15):

$$n_{ij} = \frac{x_{ai}}{x_{ij}}\ if\ j \in\ C \tag{14}$$

$$n_{ij} = \frac{x_{ij}}{x_{ai}}\ if\ j \in\ B \tag{15}$$

where elements x_{ij} and x_{ai} represent the elements of matrix X.

Step 4: Determination of the weighted matrix $V = [v_{ij}]_{mxn}$, Equation (16).

$$v_{ij} = n_{ij} \times w_j \tag{16}$$

Step 5: Calculation of the utility degree of alternatives K_i applying Equations (17) and (18).

$$K_i^- = \frac{S_i}{S_{aai}} \tag{17}$$

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{18}$$

where S_i (i = 1,2, ... , m) represents the sum of the elements of the weighted matrix V, Equation (19).

$$S_i = \sum_{i=1}^{n} v_{ij} \tag{19}$$

Step 6: Determination of the utility function of alternatives $f(K_i)$ defined by Equation (20).

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1-f(K_i^+)}{f(K_i^+)} + \frac{1-f(K_i^-)}{f(K_i^-)}}; \tag{20}$$

where $f(K_i^-)$ represents the utility function in relation to the anti-ideal solution, while $f(K_i^+)$ represents the utility function in relation to the ideal solution.

Utility functions in relation to the ideal and anti-ideal solution are determined by applying Equations (21) and (22).

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{21}$$

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{22}$$

Step 7: Ranking the alternatives. The ranking of the alternatives is premised on the final values of utility functions. It is desirable that an alternative has the highest possible value of the utility function.

4. Integrated Model for Determining the Efficiency of Transport Companies

This section presents in detail the application of a model for determining the efficiency of transport companies, which is based on the PCA–DEA approach and MCDM methods. The procedure for determining efficiency was carried out by applying the integrated model, observing both transport companies individually, but also observing the companies together, i.e., comparing the efficiency of the decision-making units of both companies together. The main goal of this research is to determine the efficiency of transport companies for the period observed, i.e., identify efficient or inefficient business years, and thus provide a more detailed insight into the business performance and possible guidelines for improving the efficiency of transport companies.

4.1. Analysis of Representative Transport Companies

In this section, an analysis of representative transport companies is performed. Efficiency is analyzed in two transport companies in Bosnia and Herzegovina. (Figure 5) The companies provide domestic and international road transport services of goods. These companies were chosen as representatives for the following reason: they have asked for measurement of their efficiency through the mini-project. This paper is part of it. Due to data protection, the names of the companies will not be stated nor any other data that may reveal their identity. That is the reason the code TC1 is assigned to the transport company, which is the first object of analysis, and the code TC2 is applied to the second analyzed transport company. The analysis of the transport system of representative companies was performed individually, for the last eight years, and after that, a comparative analysis of the transport system of the given companies was performed. Thus, the values of the previously analyzed indicators of TC1 and TC2 were compared. First, a comparison of the number of vehicles and drivers of transport companies was made, which is shown in Figure 6.

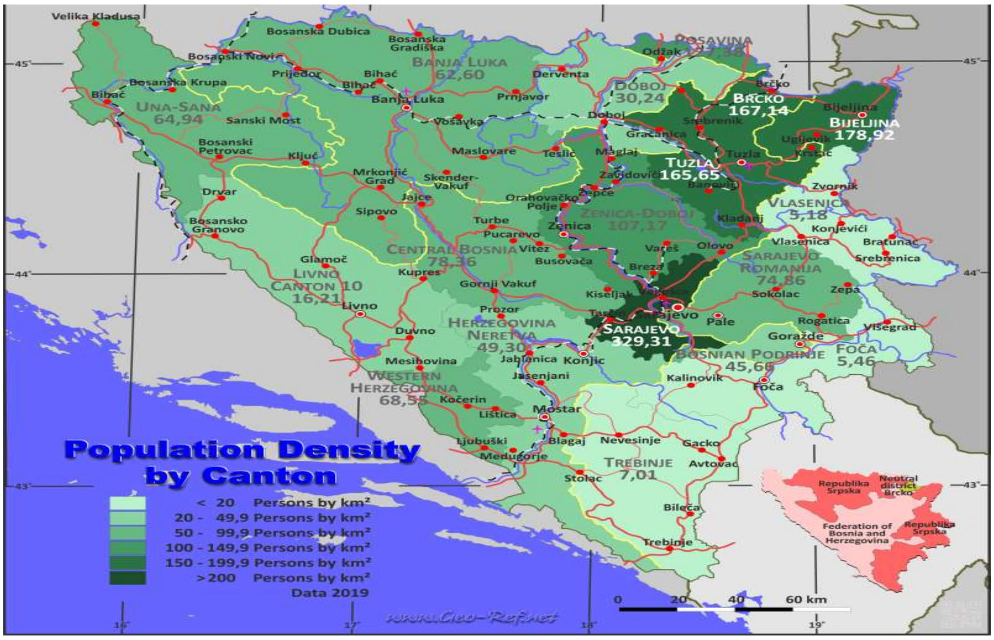


Figure 5. Population density and maps of B and H.

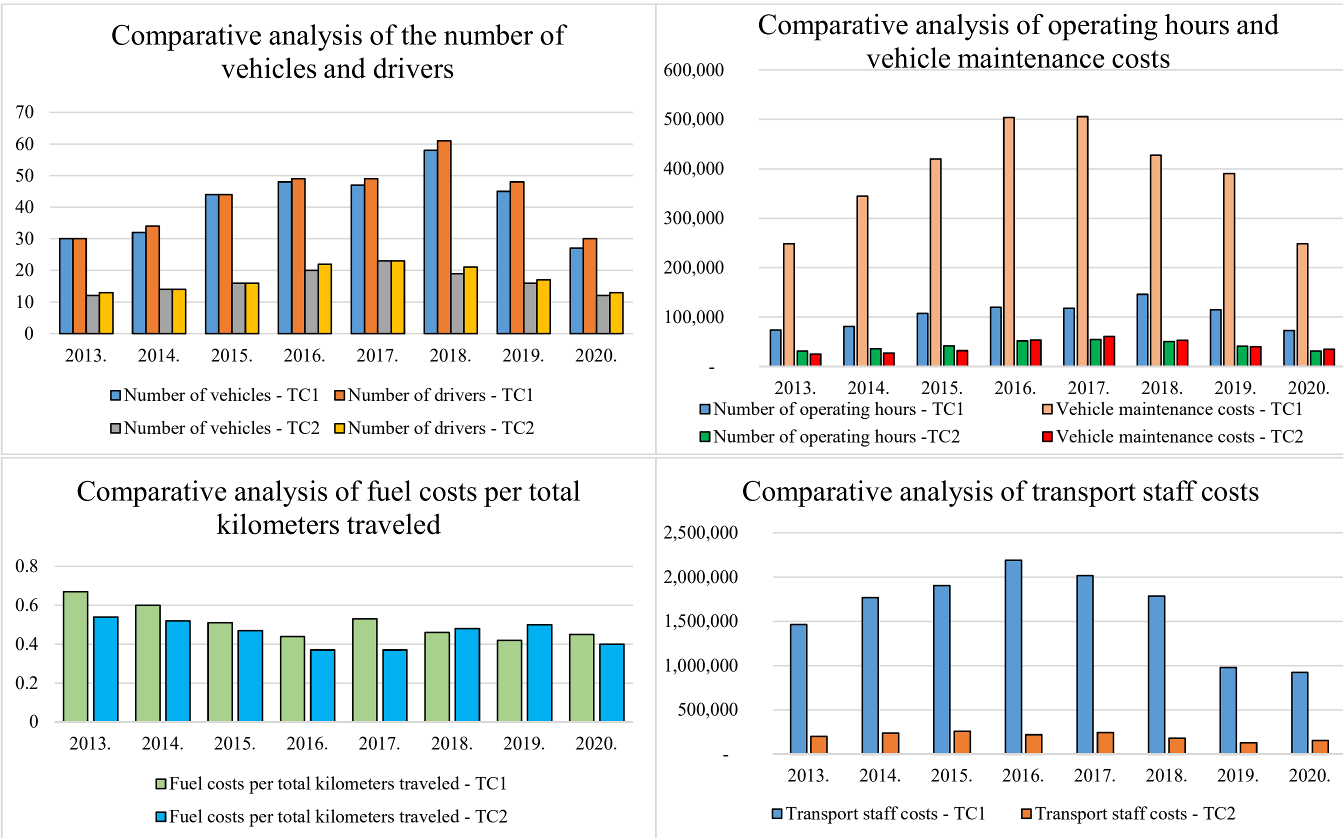


Figure 6. Graphical representation of a comparative analysis of the number of vehicles, drivers, operating hours, vehicle maintenance costs, fuel costs, and transport staff costs.

In addition, Figure 6 provides a graphical representation with a comparative analysis of operating hours and vehicle maintenance costs and then shows a comparative analysis of fuel costs per kilometers traveled and transport staff costs. It is evident that the company TC1 has a significantly larger number of vehicles at its disposal, as well as drivers employed during the entire observation period. The biggest difference can be seen in 2018, when the company TC1 had 39 vehicles more at its disposal compared to the company TC2. In the same year, TC1 had employed 40 drivers more than TC2. Consequently, the vehicle maintenance costs of TC1 are significantly higher. When comparing maintenance costs, it can be concluded that the costs of TC1 are higher than the costs of TC2 by 86%–92%, depending on the period observed. The large difference in total vehicle maintenance costs is because of the large difference in the number of vehicles of the analyzed transport companies. If we compare the average vehicle maintenance costs of companies, the above-mentioned difference is still obvious, so, for example, the average vehicle maintenance costs of TC1, at the beginning of the period observed, are 75% higher than the average maintenance costs of TC2. When comparing the number of operating hours, it can also be concluded that the company TC1 achieved a higher number by 53–65% depending on the observation period. When it comes to fuel costs per total kilometers traveled, there is no significant difference in the value of this indicator in the comparative analysis. However, when it comes to transport staff costs, a huge difference between the companies is obvious.

The huge difference in transport staff costs, among other things, is influenced by the large difference in the number of drivers employed. The greatest difference in the costs was recorded in 2016 when the company TC1 had 90% higher costs compared to the company TC2. A graphical representation of the comparative analysis of the number of deliveries, quantity transported, kilometers traveled and profit is given in Figure 7. The company TC1 has a much larger number of vehicles and drivers, therefore it is able to carry out a larger number of deliveries and transport a larger quantity of goods. The biggest difference can be observed in 2015 when the company TC1 performed 1380 deliveries more than the company TC2. When it comes to the quantity transported, the company TC1 transported a larger quantity in the entire observation period, and the difference is most visible in 2015 when the company transported 27,720 tons more goods. In addition, the company has an advantage when it comes to the total number of kilometers traveled. The largest difference in the number of kilometers traveled was recorded in 2018 and was 4,036,000 km.

At the beginning of the period observed, the company TC1 makes a significantly higher profit compared to the company TC2 and maintains this trend until 2020, when it makes a loss of BAM 205,389 due to the previously explained reason, while the company TC2 operates with a profit of BAM 33,000. Figure 8 shows a graphical representation of the comparative analysis of turnover for the month of April, based on which it can be concluded that in this case, too, the company TC1 has an advantage, i.e., the company achieved significantly higher turnover compared to TC2 during all the years covered by the analysis.

4.2. Data Collections for Inputs and Outputs

Thus, the PCA–DEA model is applied in order to solve the problem of a relatively small number of DMUs in relation to a relatively large number of parameters, i.e., when the application of the DEA method in assessing the efficiency of companies does not provide adequate results. At the very beginning, it is necessary to define input and output parameters that represent the basis for calculating the efficiency of transport companies. Six input parameters and four output parameters were defined, which are stated and explained above. After defining the input and output parameters, data were collected on the values of the defined parameters for all eight years which, in this case, represent decision-making units. Table 2 shows the values of input and output parameters for the company TC1, while Table 3 shows the values of the parameters for the company TC2.

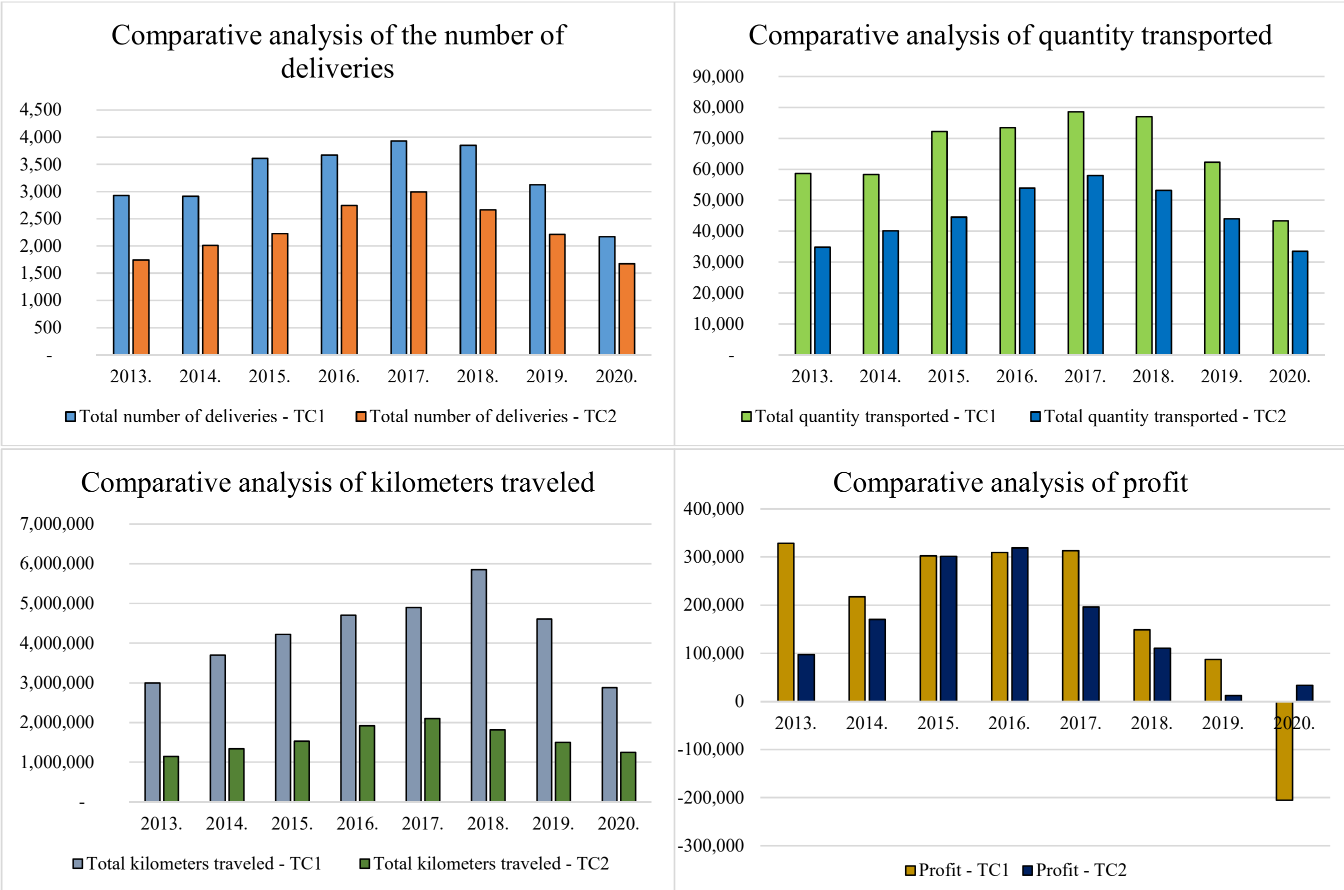


Figure 7. Graphical representation of a comparative analysis of the number of deliveries, quantity transported, kilometers traveled, and profit.

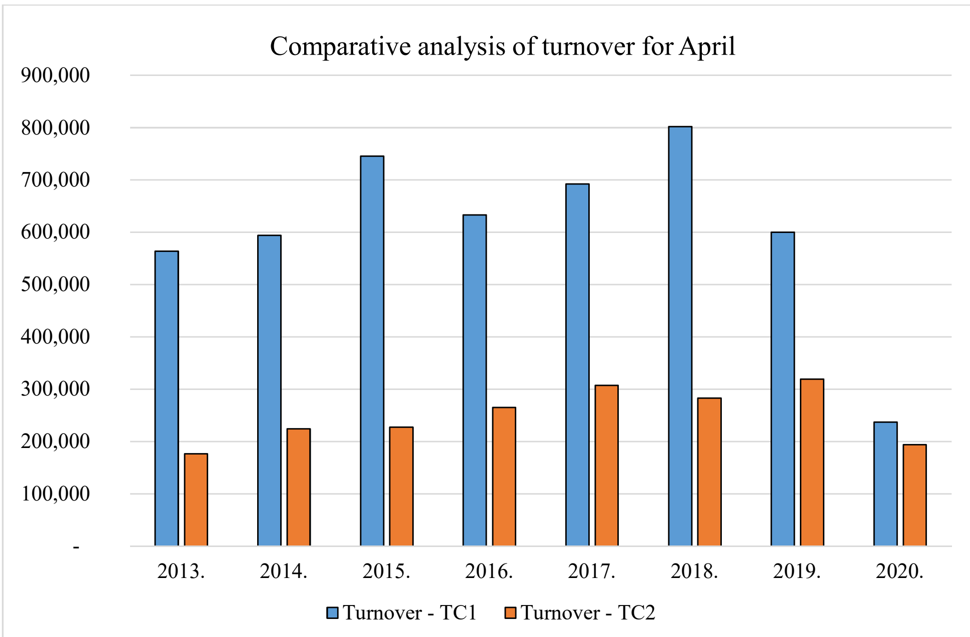


Figure 8. Graphical representation of comparative analysis of turnover for April.

Table 2. Input and output parameters of company TC1.

Year-DMU	Input Parameters						Output Parameters			
	Number of Vehicles	Number of Drivers	Number of Operating Hours	Vehicle Maintenance Costs	Fuel costs Per Kilometers Traveled	Transport Staff Costs	Total Number of Deliveries	Quantity Transported	Kilometers Traveled	Profit
2013	30	30	74,000	248,505	0.67	1,463,427	2931	58,620	3,000,000	328,675
2014	32	34	81,000	344,852	0.60	1,769,294	2917	58,340	3,700,000	217,144
2015	44	44	107,000	419,855	0.51	1,904,486	3611	72,220	4,224,000	302,445
2016	48	49	119,600	503,687	0.44	2,190,264	3672	73,440	4,704,000	309,331
2017	47	49	117,600	505,906	0.53	2,016,107	3930	78,600	4,900,000	313,002
2018	58	61	146,000	427,432	0.46	1,785,322	3849	76,980	5,856,000	148,554
2019	45	48	115,000	390,278	0.42	981,066	3126	62,250	4,608,000	86,743
2020	27	30	73,000	248,505	0.45	925,000	2168	43,360	2,880,000	−205,389

Table 3. Input and output parameters of company TC2.

Year-DMU	Input Parameters						Output Parameters			
	Number of Vehicles	Number of Drivers	Number of Operating Hours	Vehicle Maintenance Costs	Fuel costs Per Kilometers Traveled	Transport Staff Costs	Total Number of Deliveries	Quantity Transported	Kilometers Traveled	Profit
2013	12	13	31,000	25,000	0.54	200,000	1741	34,800	1,150,000	97,000
2014	14	14	36,000	27,000	0.52	240,000	2007	40,100	1,344,000	170,000
2015	16	16	41,500	32,000	0.47	260,000	2230	44,500	1,530,000	301,000
2016	20	22	51,800	54,000	0.37	220,000	2744	54,000	1,920,000	319,000
2017	23	23	55,000	61,000	0.37	245,000	2995	58,000	2,100,000	196,000
2018	19	21	50,400	53,000	0.48	180,000	2662	53,200	1,820,000	110,000
2019	16	17	41,000	40,000	0.5	130,000	2214	44,000	1,500,000	12,000
2020	12	13	31,000	35,000	0.4	155,000	1675	33,500	1,250,000	33,000

4.3. Determining Efficiency Using an Integrated PCA–DEA Model

The next step involves applying PCA to the input and output parameters in order to create principal components. By applying the program for statistics–SPSS, eight decision-making units were analyzed, and the average values and values of standard deviation by variables were obtained. Finally, the efficiency was determined by applying the previously mentioned model by observing both companies together, and the results of the calculation are given below. Accordingly, using the SPSS program, 16 decision-making units were analyzed, and average values and values of standard deviation by variables were obtained. Using the PCA model, two principal components were isolated from the set of input parameters, which contain 95% of the information of the original set of parameters. Additionally, two principal components from the set of output parameters were singled out. The next step is to apply the DEA model in order to determine the efficiency of decision-making units. The final results obtained using the PCA–DEA model are shown in Table 4.

Table 4. Results of PCA–DEA models for both companies depending on the number of parameters.

	DEA	**PCA–DEA**			
	6-4	**3-3**	**3-2**	**2-2**	**1-1**
DMU_1	0.966	0.942	0.756	0.609	0.593
DMU_2	1.000	1.000	0.722	0.616	0.524
DMU_3	0.969	0.954	0.900	0.842	0.532
DMU_4	1.000	1.000	1.000	0.953	0.496
DMU_5	1.000	1.000	0.941	0.881	0.530
DMU_6	1.000	1.000	1.000	1.000	0.475
DMU_7	1.000	1.000	0.936	0.935	0.485
DMU_8	0.987	0.939	0.682	0.633	0.416
DMU_9	1.000	0.989	0.987	0.985	0.807
DMU_{10}	1.000	1.000	1.000	1.000	0.888
DMU_{11}	1.000	1.000	1.000	1.000	0.970
DMU_{12}	1.000	1.000	1.000	1.000	1.000
DMU_{13}	1.000	1.000	1.000	1.000	0.950
DMU_{14}	1.000	1.000	1.000	0.999	0.888
DMU_{15}	1.000	1.000	1.000	0.997	0.821
DMU_{16}	1.000	1.000	0.980	0.980	0.817

After the application of the DEA model, all decision-making units except DMU1, DMU3, and DMU8 show efficiency, while by applying the integrated PCA–DEA model that is based on three input and three output principal components, ineffective decision-making units are the following: DMU1, DMU3, DMU8, and DMU9. The model that determines efficiency based on three input components and two outputs shows the efficiency of eight decision-making units (DMU4, DMU6, DMU10, DMU11, DMU12, DMU13, DMU14, and DMU15), while the model that is based on two input components and two principal output components shows the efficiency of five decision-making units (DMU6, DMU10, DMU11, DMU12, DMU13). Finally, the model based on one principal input component and one output component shows only the efficiency of DMU12. In the ranking model using the MARCOS method, the following efficient decision-making units were implemented: DMU6, DMU10, DMU11, DMU12, and DMU13.

4.4. Determining the Weight Values of Parameters Applying the CRITIC Method

In this section of the paper, the CRITIC method, by which it is necessary to determine the weight values of the criteria, is used, i.e., defined input and output parameters. Accordingly, the first criterion is the number of vehicles, the second criterion is the number of drivers and the third criterion is the number of operating hours. These three criteria need to be maximized because they belong to the benefit group of criteria. Vehicle maintenance costs are the fourth criterion, while fuel costs per total kilometers traveled and transport staff costs are the fifth and sixth criteria. These criteria are of a cost type and need to be minimized. The last four criteria need to be maximized, and they are: the total number of deliveries as the seventh criterion, the total quantity transported, i.e., the eighth criterion, followed by the total number of kilometers traveled as the ninth criterion, and profit representing the tenth criterion. The decision-making units, i.e., the observed business years from the previous model, in this case, represent alternatives. The calculation of the weight values of the criteria for the company TC1 is briefly presented below. The first step is the formation of an initial matrix, while the second step is the normalization of the initial matrix by applying Equation (4) for the benefit criteria and (5) for the cost criteria. An example of normalization is as follows:

$$x_{11} = \frac{30 - 27}{58 - 27} = 0.096;\ x_{14} = \frac{248{,}505 - 505{,}906}{248{,}505 - 505{,}906} = 1.00$$

The third step is to determine the symmetric matrix of linear correlation using Equation (6), and the fourth step is to calculate the standard deviation (σ) and the sum of the matrix 1-rij. Forming the matrix is completed by subtracting the correlation matrix from one, after which it is necessary to sum up the values by columns for all criteria. The fifth step involves determining the amount of information in relation to each criterion using Equation (7). Thus, the value of C_j is obtained by multiplying the value of standard deviation by the previously obtained individual value of the sum per column. The values obtained in this way, as well as the final values of the weights of the criteria, are given in Table 4. The final values of the weight coefficients are obtained when the individual value of C_j is divided by the previously calculated sum of C_j, i.e., by applying Equation (7). The sum of C_j, in this case, is 25.834.

Based on Table 5, it can be concluded that the most important is the fourth criterion, i.e., vehicle maintenance costs. The second most important is the sixth criterion, which refers to transport staff costs, while the third most important is the tenth criterion, i.e., profit. Fuel costs per total kilometers traveled is ranked fourth, and the total quantity transported is fifth in relation to other criteria. The values of the criteria that are in fifth and sixth place are very close and differ only in the fourth decimal. The sixth place is occupied by the total number of deliveries, while the number of operating hours is in seventh place. It is followed by the number of drivers and the total number of kilometers traveled, and the criterion referring to the total number of vehicles is in last place.

Table 5. Values of C_j and weight values of criteria–TC1.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**
C_j	1.636	1.692	1.697	5.549	2.561	4.555	1.848	1.854	1.644	2.797
w_j	0.063	0.065	0.066	0.215	0.099	0.176	0.072	0.072	0.064	0.108

Based on the results presented in Table 6, the most important is the fourth criterion, i.e., vehicle maintenance costs, while the second most important is the sixth criterion, i.e., transport staff costs. The third most important is the tenth criterion referring to profit. After that, the fourth place is occupied by fuel costs per total kilometers traveled, while the fifth place is occupied by the total number of drivers. This is followed by the number of operating hours, the total quantity transported, and the total number of deliveries. The total number of vehicles is in ninth place, and the total number of kilometers traveled is in tenth place. After calculating the weight values of the criteria for the company TC1 and the company TC2 individually using the CRITIC method, the weight values of the criteria were calculated in the same way considering both companies together. In this way, the following values of the criterion weights were obtained:

$$w_1 = 0.071;\ w_2 = 0.071;\ w_3 = 0.071;\ w_4 = 0.206;\ w_5 = 0.091$$

$$w_6 = 0.196;\ w_7 = 0.069;\ w_8 = 0.069;\ w_9 = 0.074;\ w_{10} = 0.082$$

Table 6. Values of C_j and weight values of criteria–TC2.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C_j	1.511	1.726	1.637	5.833	2.374	4.165	1.537	1.575	1.482	2.530
w_j	0.062	0.071	0.067	0.239	0.097	0.171	0.063	0.065	0.061	0.104

Based on the results obtained, it is possible to conclude that the most important is the fourth criterion, which represents vehicle maintenance costs, and then the second most important is the sixth criterion, i.e., transport staff costs. After that, fuel costs per total kilometers traveled, profit and total kilometers traveled are in third, fourth, and fifth place, respectively. The weight values of the criteria that are in sixth, seventh and eighth place are very close and differ only in the fourth and fifth decimal. The sixth place is occupied by the total number of vehicles, while the seventh and eighth places are occupied by the number of operating hours and the number of drivers. The eighth criterion relating to the total quantity transported is in ninth place, and the seventh criterion representing the total number of deliveries is in tenth place.

4.5. Determining the Weight Values of Parameters Applying the Entropy Method

In this section of the paper, the calculation of the weight values of criteria using the Entropy method for the company TC1, then the company TC2 and, finally, the calculation of the weight values of the criteria observing both companies together is performed. Entropy is a simple method of objective nature that is carried out through only three steps. At the very beginning, the calculation of the weight values of the TC1 criteria is presented. The first step is to normalize the initial matrix by applying Equation (8). An example of normalization is as follows:

$$x_{11} = \frac{30}{331} = 0.091;\ x_{12} = \frac{30}{345} = 0.087$$

The next step is to calculate the entropy measure ej. An example of the calculation is as follows:

$$e_1 = -\frac{1}{\ln(m)}\sum_{i=1}^{m} r_{11}\ln(n_{11}) = -\frac{1}{\ln(8)}\,(-2.050) = 0.986$$

Other values are obtained in the same way.

$$e_1 = 0.986;\ e_2 = 0.986;\ e_3 = 0.987;\ e_4 = 0.985;\ e_5 = 0.994;$$

$$e_6 = 0.981;\ e_7 = 0.993;\ e_8 = 0.993;\ e_9 = 0.988;\ e_{10} = 0.926$$

In the third step, the values of the objectively calculated criterion weight w_j are obtained by applying Equation (10). An example of the calculation is as follows:

$$w_1 = (1 - e_1)/\sum_{j=1}^{n}(1 - e_1) = (1 - 0.986)/\ 0.181 = 0.079$$

Other weight values of the criteria are obtained in the same way.

$$w_1 = 0.079;\ w_2 = 0.076;\ w_3 = 0.073;\ w_4 = 0.082;\ w_5 = 0.033;$$

$$w_6 = 0.103;\ w_7 = 0.0409;\ w_8 = 0.0410;\ w_9 = 0.066;\ w_{10} = 0.408$$

Based on the obtained weight values of the criteria, it can be concluded that the most important is the tenth criterion, i.e., profit. The sixth criterion, which refers to transport staff costs, is in second place while vehicle maintenance costs are in third place. The fourth most important is the first criterion, i.e., the total number of vehicles and the fifth most important is the number of drivers. It is followed by other criteria in the following order: the number of operating hours, the total number of kilometers traveled, the total quantity transported, the total number of deliveries, and finally, fuel costs per total kilometers traveled.

After that, by applying the third step, i.e., Equation (10), the following values of the criterion weights for the company TC2 were obtained:

$$w_1 = 0.052; w_2 = 0.051; w_3 = 0.046; w_4 = 0.101; w_5 = 0.020;$$

$$w_6 = 0.049; w_7 = 0.041; w_8 = 0.037; w_9 = 0.042; w_{10} = 0.561$$

It is clear that the most important is the tenth criterion referring to profit. It is followed by vehicle maintenance costs and the total number of vehicles in second and third place, respectively. The fourth place is occupied by the number of drivers, while the fifth place is occupied by transport staff costs. After that, the number of operating hours is in sixth place, and the total number of kilometers traveled is seventh. The total number of deliveries is in eighth place, and the total quantity transported is in ninth place. The last place is occupied by the fifth criterion, which refers to fuel costs per kilometer traveled.

After calculating the weight values of the criteria for the company TC1 and the company TC2 individually using the Entropy method, the calculation of the weight values of the criteria was performed in the same way, observing both companies together. The following values of criterion weights were obtained:

$$w_1 = 0.075; w_2 = 0.073; w_3 = 0.072; w_4 = 0.249; w_5 = 0.008;$$

$$w_6 = 0.231; w_7 = 0.0200; w_8 = 0.0201; w_9 = 0.080; w_{10} = 0.172$$

Thus, the most important is the fourth criterion, i.e., vehicle maintenance costs. The second most important is the sixth criterion related to transport staff costs, while the third most important criterion is related to the number of operating hours. The number of drivers takes fourth, and the total number of kilometers traveled is in fifth place in relation to other criteria. After that, the sixth place is occupied by the total number of vehicles, while the seventh place is occupied by fuel costs per total kilometers traveled. It is followed by the total quantity transported and the total number of deliveries, and the criterion related to profit is in last place.

Finally, it is necessary to average the weight values obtained using the CRITIC method and the weight values of the criteria obtained using the Entropy method in order to obtain the final weight values that will be further used when applying the MARCOS method. In this way, the final weight values of the coefficients are obtained, which will be further used when applying the MARCOS method, but also other MCDM methods in the sensitivity analysis. The values obtained in this way are presented in Table 7.

Table 7. Final weight values of the criteria.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
TC1	0.071	0.071	0.069	0.148	0.066	0.139	0.056	0.056	0.065	0.258
TC2	0.057	0.061	0.056	0.170	0.059	0.110	0.052	0.051	0.052	0.332
Both companies	0.073	0.072	0.071	0.227	0.049	0.214	0.044	0.044	0.077	0.127

4.6. Ranking the Alternatives Applying the MARCOS Method

When applying the MARCOS method, it is necessary to rank the alternatives, i.e., decision-making units that have proven to be efficient after applying the PCA–DEA model. When it comes to TC1, it is necessary to rank the following decision-making units: DMU1, DMU3, DMU5, and DMU7. First, it is necessary to form an initial decision matrix, and then to form an extended initial matrix by defining an ideal (AI) and anti-ideal solution (AAI). Depending on the nature of the criteria, AAI and AI are defined by applying Expressions (26) and (27).

After ranking the decision-making units, i.e., the efficient business years of TC1 and TC2, it is necessary to repeat the same for both companies together. In this case, it is necessary to rank the following decision-making units, which showed efficiency after applying the PCA–DEA model: DMU6, DMU10, DMU11, DMU12, and DMU13. DMU6 refers to 2018 of TC1, while DMU10 and DMU11 represent the efficiency in 2014 and 2015 of TC2. DMU12 and DMU13 also refer to the company TC2, i.e., to its efficiency in 2016 and 2017. The ranking process is performed in the same way as in the previous two examples, and the final results of applying the previously described steps of the MARCOS method are given in Table 8.

Table 8. Results of applying the MARCOS method–both companies.

	S_i	K_i^-	K_i^+	fK^-	fK^+	fKi^+	Rank
AAI	0.253	1.000					
DMU6	0.590	2.336	0.590	0.202	0.798	0.5615	5
DMU10	0.635	2.513	0.635	0.202	0.798	0.6042	3
DMU11	0.650	2.574	0.650	0.202	0.798	0.6187	2
DMU12	0.656	2.595	0.656	0.202	0.798	0.6239	1
DMU13	0.591	2.339	0.591	0.202	0.798	0.5623	4
AI	1.000		1.000				

Based on the previous table, it is clear that the most efficient business of the company TC2 was in 2016, and then in 2015. This is followed by the efficiency achieved in 2014 and 2017, which also refers to the company TC2. In last place is DMU6, which refers to the efficiency of the company TC1 in 2018.

5. Sensitivity Analysis and Comparative Analysis

A sensitivity analysis was performed, which includes a comparative analysis of the MARCOS method with other methods of multi-criteria decision-making in the first part, while the second part of the sensitivity analysis refers to the creation of 30 new scenarios involving changes in weight values of the most important criteria. To test the similarity of the rankings, the WS coefficient is calculated [59–61], as well as the SCC to determine the correlation of the initial solution with all scenarios.

5.1. Comparative Analysis with Other MCDM Methods

A comparative analysis of the MARCOS method was performed with other MCDM methods, in this case with the WASPAS, EDAS, and ARAS methods. The results obtained by applying the methods are presented below. Table 9 shows the results of comparative analysis for both companies.

Table 9. Comparative analysis for both companies.

	MARCOS		WASPAS		ARAS		EDAS	
	fK_i	Rank	A	Rank	K_i	Rank	AS_i	Rank
DMU6	0.562	5	0.464	5	0.615	1	0.500	5
DMU10	0.604	3	0.589	3	0.604	4	0.734	4
DMU11	0.619	2	0.617	2	0.613	2	0.770	2
DMU12	0.624	1	0.627	1	0.611	3	0.792	1
DMU13	0.562	4	0.572	4	0.558	5	0.740	3

Based on Table 9, it can be concluded that the application of the MARCOS and WASPAS methods yield the same ranks of decision-making units, while the ranks obtained using the EDAS method differ to a lesser extent. Accordingly, DMU12 ranks first, while DMU11 ranks second. The third place by EDAS is taken by DMU13, while DMU10 is in the same place by the other two methods. DMU10 is ranked fourth using the EDAS method, while DMU13 is in fourth place by the other two methods. DMU6 is in last place by all three methods. The ranking results obtained using the ARAS method are completely different from the results obtained using the afore-mentioned three methods. The final values of the utility degree, on the basis of which the ranking is performed, are very close and differ only in the third decimal, and this is precisely the reason for the large deviation of the ranks. The best alternative in relation to all defined criteria using the EDAS method is DMU6. DMU11 is in second place, while DMU12 is in third place. It is followed by DMU10 and DMU13 in fourth and fifth place, respectively.

To obtain a more detailed insight into the similarity of the rankings, the WS coefficient was calculated using Equation (23), as well as the SCC to determine the correlation of the rankings with the initial rank obtained using the MARCOS method.

$$WS = 1 - \sum_{i=1}^{n} \left(2^{-R_{xi}} \cdot \frac{|R_{xi} - R_{yi}|}{\max\{|1 - R_{xi}|, |N - R_{xi}|\}} \right) \tag{23}$$

Figure 9 shows a graphical representation of the correlation of ranks for both companies together, i.e., the values of statistical correlation for SCC and the obtained values of WS are shown.

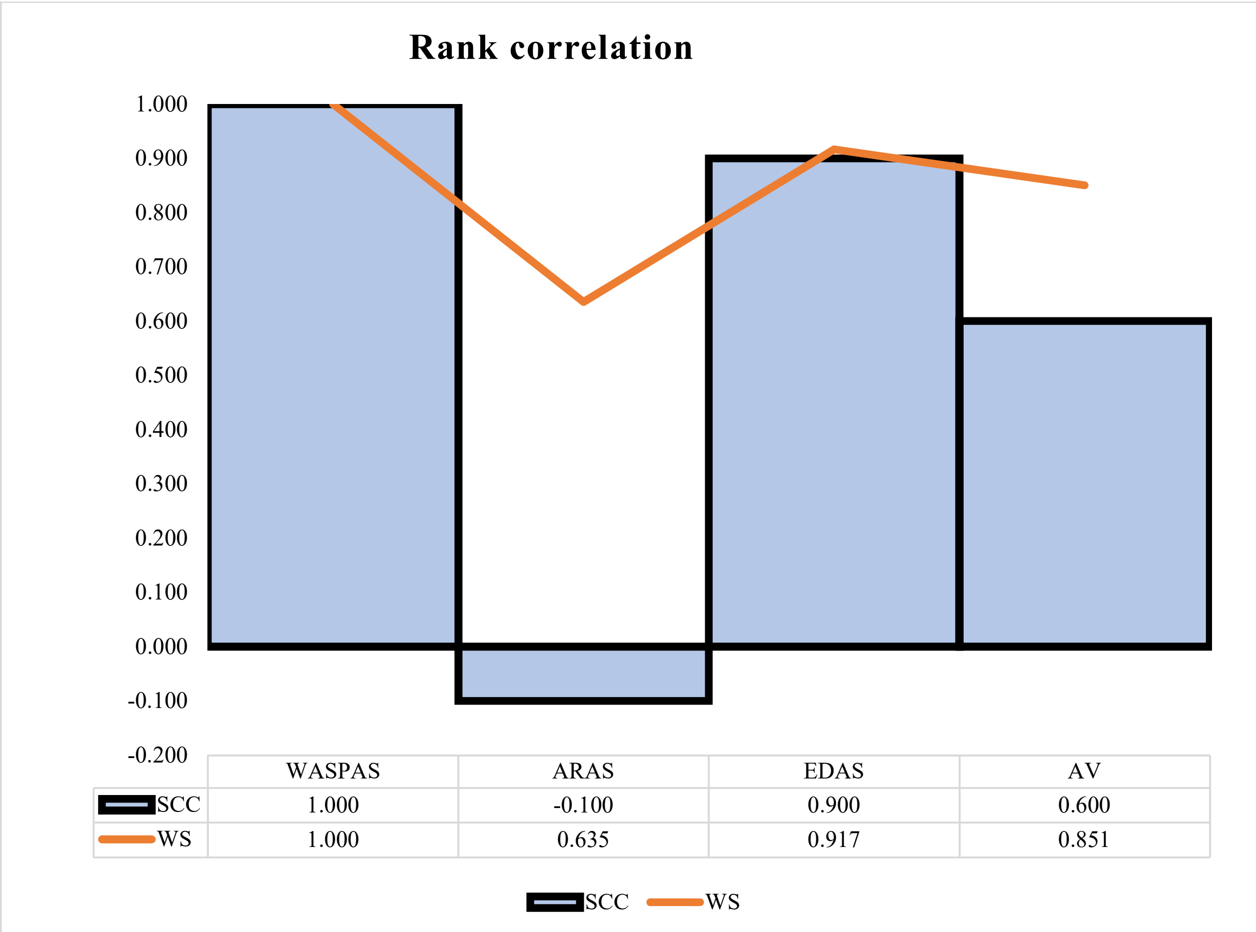


Figure 9. Correlation of ranks calculated with SCC and WS coefficients.

Observing the results obtained for both companies together, it can be seen that a complete correlation of the WASPAS method with the MARCOS method is achieved, while the correlation with the EDAS method is relatively high (SCC = 0.900). A negative SCC value (SCC = −0.100) indicates that there is no correlation between the ranks of the MARCOS method and ARAS. The WS coefficient shows different values from SCC depending on changes in ranking because the positions at the top of the ranking have a more significant impact on the similarity than those positioned lower in the ranking. The WS coefficient, as well as SCC, shows a complete correlation with the WASPAS method and is relatively high with EDAS (WS = 0.917). The correlation achieved with the ARAS method is very low (WS = 0.635). When it comes to the company TC1, a complete correlation of the ranks of the MARCOS method with the EDAS and WASPAS method is achieved, while the correlation of the ranks with the ARAS method is very low (SC = 0.400; WS = 0.667).

5.2. Changes in Parameter Significance

In the following, 30 scenarios are formed that refer to changes in the weights of the five most important criteria of both companies together, when the values of the following criteria were reduced: C4, C6, C10, C9, and C1. Accordingly, there is a change in the most significant criterion, C4 in scenarios S1–S6, criterion C6 in scenarios S7–S12, criterion C10 in scenarios S13–S18, criterion C9 in scenarios S19–S24, and criterion C1 in scenarios S25–S30. The influence of percentage decrease in the weight values of the criteria on the changes in ranks through 30 scenarios is shown in Figure 10.

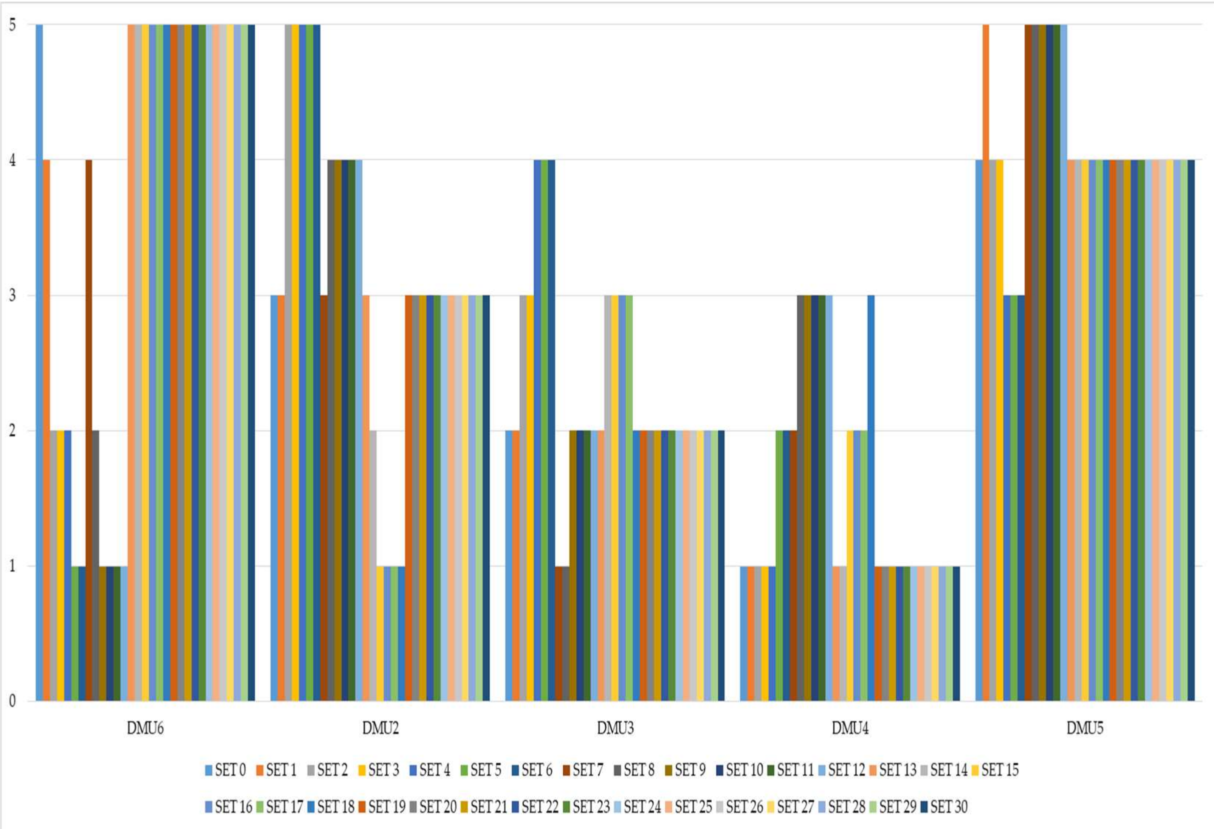
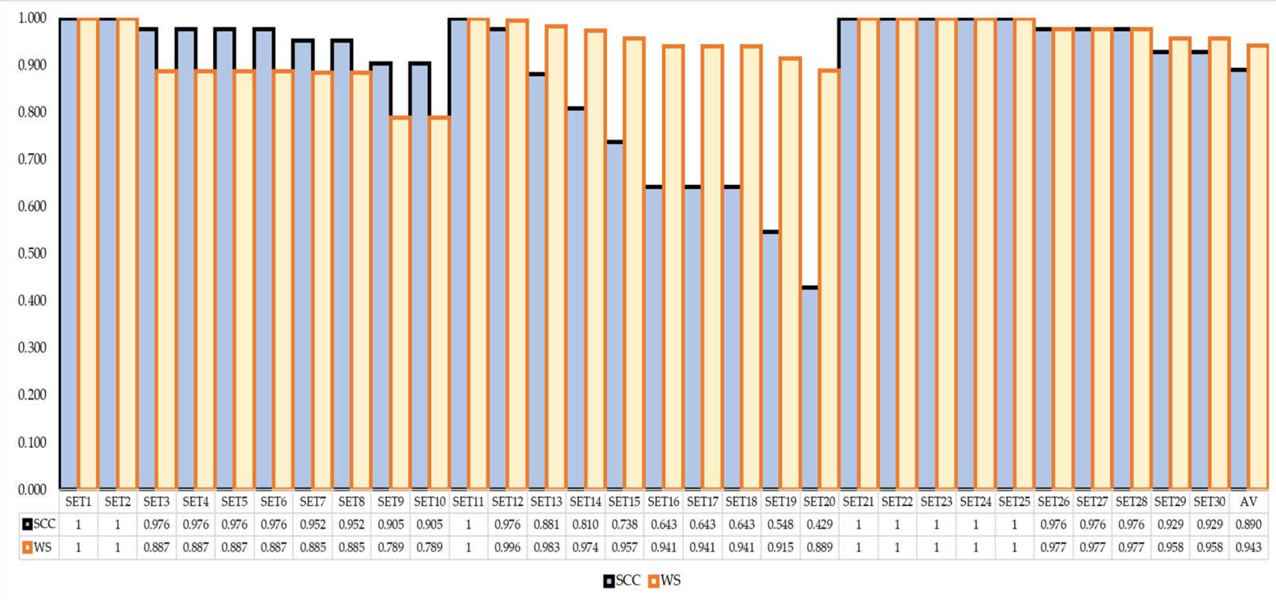


Figure 10. Results of sensitivity analysis for 30 newly formed scenarios for both companies.

Based on Figure 6, it can be concluded that there are large changes in the ranks of all decision-making units through different scenarios, i.e., decision-making units drastically change their positions depending on the scenario formed. The most significant change in rank is observed when the weight value of the most important criterion C4 was reduced by 30–90%, but also when the value of the second most important criterion C6 was reduced.

For example, DMU4 represents the most significant alternative in the original model, and it is now in third place in five scenarios (S9, S10, S11, S12, S18). Likewise, DMU6 moves from the last place of the original model to the first place within six scenarios (S5, S6, S9, S10, S11, S12). Large differences in ranking results are also present for the DMU2 alternative, which, for example, is in first place in four scenarios (S15–S18), while it is in fifth place in five scenarios (S2–S6). Slightly smaller are the rank changes of DMU5 alternative, which was originally in fourth place, and now ranks fifth in seven scenarios (S1, S7, S8, S9, S10, S11, S12), and third in three scenarios (S6, S6, S7).

It is very easy to conclude that there is a significant change in the results compared to initial results, i.e., it was proved that the model is highly sensitive to changes in the weight values of the criteria, therefore it is calculated SCC and WS coefficients that accurately determine the correlation value of new results in relation to initial ones. A graphical representation of the correlation of rankings for both companies, as well as the SCC and WS values, is given in Figure 11.



	SET1	SET2	SET3	SET4	SET5	SET6	SET7	SET8	SET9	SET10	SET11	SET12	SET13	SET14	SET15	SET16	SET17	SET18	SET19	SET20	SET21	SET22	SET23	SET24	SET25	SET26	SET27	SET28	SET29	SET30	AV
SCC	1	1	0.976	0.976	0.976	0.976	0.952	0.952	0.905	0.905	1	0.976	0.881	0.810	0.738	0.643	0.643	0.643	0.548	0.429	1	1	1	1	1	0.976	0.976	0.976	0.929	0.929	0.890
WS	1	1	0.887	0.887	0.887	0.887	0.885	0.885	0.789	0.789	1	0.996	0.983	0.974	0.957	0.941	0.941	0.941	0.915	0.889	1	1	1	1	1	0.977	0.977	0.977	0.958	0.958	0.943

Figure 11. SCC and WS values for 30 newly formed scenarios for both companies.

In two scenarios (S1 and S4), the SCC is 0.971, which shows a very high correlation, while in four scenarios (S15, S16, S17, and S18), the SCC is 0.700 or 0.600. Extremely low correlation is shown by S2 and S3 where a large difference between the values of the SCC and WS coefficient (SCC = 0.300: WS = 0.768) can be observed. The situation is similar in, e.g., the following scenarios: S5, S6, S9, S10, S11, and S12, when the SCC value ranges from −0.100 to −0.300, while the WS value ranges from 0.531 to 0.635. In general, if all correlation coefficients are taken into account and the average SCC is calculated, it can be seen that the ranks are not largely correlated (SCC = 0.607), while the average value of WS shows a relatively high correlation (WS = 0.817).

6. Discussion

6.1. Discussion of Obtained Results

In this section, the final results obtained during the research, which includes measuring the efficiency of two transport companies, are analyzed. In addition to the PCA–DEA model, the following methods of multi-criteria decision-making are applied in the research: CRITIC, Entropy, MARCOS, ARAS, EDAS, WASPAS.

The first phase includes the calculation of the efficiency of eight decision-making units using the PCA–DEA model, which, in this case, is based on six input and four output parameters. Input parameters are: total number of vehicles, number of drivers, number of operating hours, vehicle maintenance costs, fuel costs per total kilometers traveled, and transport staff costs. The output parameters are: total number of deliveries, total quantity transported, total number of kilometers traveled, and profit. The decision-making units are actually the business years of the companies, from 2013 to 2020. By applying the PCA model based on the defined parameters of the company TC1, two principal input components and two output components were created, which contain 90% of variance, i.e., information from the original set of parameters, while from the defined parameters of the company TC2, three principal input components and two output components were singled out, which contain 95% of variance. The PCA model was applied and observing the parameters of both companies together, two principal input components and two output components containing about 95% variance were formed. The final results of the PCA–DEA model obtained using Excel Solver are given in Table 10.

Table 10. Final results of the PCA–DEA model.

Both Companies			
DMU_1	0.609	DMU_9	0.985
DMU_2	0.616	DMU_{10}	1.000
DMU_3	0.842	DMU_{11}	1.000
DMU_4	0.953	DMU_{12}	1.000
DMU_5	0.881	DMU_{13}	1.000
DMU_6	1.000	DMU_{14}	0.999
DMU_7	0.935	DMU_{15}	0.997
DMU_8	0.633	DMU_{16}	0.980

When it comes to the company TC1, the results show the efficiency of business performance in 2013, 2015, 2017, and 2019. Observing the results of the PCA–DEA model for the company TC2, we can conclude that business performance was efficient from 2014 to 2019. However, when we perform the efficiency calculation by observing both companies together, we can see that the business efficiency was achieved in 2018 in the company TC1, and in 2014, 2015, 2016, and 2017 in the company TC2.

Observing the average weight values of the criteria, we can conclude that the most important is the tenth criterion for the company TC1, i.e., profit. Then, vehicle maintenance costs are in second place, while transport staff costs are in third place. The fourth place is occupied by the total number of vehicles, and the fifth and sixth place is occupied by the number of drivers and the number of operating hours, respectively. This is followed by fuel costs per total kilometers traveled, total kilometers traveled, total quantity transported and total number of deliveries. The most important criterion for TC2 is also profit, followed by vehicle maintenance costs and transport staff costs. The number of drivers is in fourth place, and the fuel cost per kilometer traveled is in fifth place. The sixth and seventh places are occupied by the total number of vehicles and the number of operating hours, while the eighth place is occupied by the total number of deliveries. This is followed by the total number of kilometers traveled and the total quantity transported, which is in last place. If the average weight values of the criteria of both companies are observed together, the most important criterion is vehicle maintenance costs, while transport staff costs are in second place. This is followed by other criteria in the following order: profit, number of kilometers traveled, total number of vehicles, number of drivers, number of operating hours, fuel costs per total kilometers traveled, total quantity transported and, finally, the total number of deliveries. The average values of the criteria will be used later when ranking decision-making units. The ranking of decision-making units was performed using the MARCOS method. In addition, the WASPAS, ARAS, and EDAS methods were applied in the sensitivity analysis in order to rank the decision-making units that showed efficiency after applying the PCA–DEA model.

In the case of TC1, four decision-making units (DMU1, DMU3, DMU5, and DMU7) were ranked using the steps shown above, providing the same ranking results with the

MARCOS, WASPAS, and EDAS methods, while the ARAS method ranking results differ. However, all ranking methods show that DMU5 is the most efficient decision-making unit compared to all observed criteria. It means that the most efficient business performance was achieved in 2017 referring to company TC1. Then, DMU3 is in second place (2015), when applying MARCOS, WASPAS and EDAS, i.e., DMU1 (2013) using the ARAS method. A difference also occurs when it comes to third and fourth place in the ranking, where DMU7 (2019) and DMU3 are positioned by the ARAS method, while DMU1 is in third place, and DMU7 is in fourth place using other methods.

Regarding TC2, six decision-making units (DMU2, DMU3, DMU4, DMU5, DMU6, and DMU7) were ranked and all ranking methods provide the same results. Thus with all the methods applied, the best alternative is DMU4 (2016) and then DMU3 (2015). DMU5 (2017) ranks third, while DMU2 (2014) and DMU6 (2018) are in fourth and fifth place. The last place in the ranking, when applying the MARCOS, WASPAS, ARAS and EDAS methods, is occupied by DMU7 (2019).

When ranking the efficient decision-making units of both companies together (DMU6, DMU10, DMU11, DMU12, DMU13), MARCOS, WASPAS, and EDAS show that DMU12 is the most efficient decision-making unit, with DMU6 in last place. Therefore, the most efficient business performance was achieved by the company TC2 in 2016, while the least efficient business performance was achieved by the company TC1 in 2018. In contrast, the ARAS method shows the most efficient business performance of TC1 in 2018, while the least efficient business performance of TC2 is in 2017 when considering the efficiency of both companies together.

6.2. Discussion Related to Other Studies

Although the application of the DEA model can very easily determine the efficiency or inefficiency of certain decision-making units, as with everything, this model has certain strengths and limitations. A few of the characteristics that make it powerful are: DEA can handle multiple input and multiple output models, it does not require an assumption of a functional form relating inputs to outputs, DMUs are directly compared against a peer or combination of peers, and inputs and outputs can have very different units [62].

The same characteristics that make DEA a powerful tool can also create problems. An analyst should keep these limitations in mind when choosing whether or not to use DEA. Since DEA is an extreme point technique, such as measurement error can cause significant problems. DEA is good at estimating the "relative" efficiency of a DMU but it converges very slowly to "absolute" efficiency. In other words, it can tell you how well you are doing compared to your peers but not compared to a "theoretical maximum." Since DEA is a nonparametric technique, statistical hypothesis tests are difficult and are the focus of ongoing research. Since a standard formulation of DEA creates a separate linear program for each DMU, large problems can be computationally intensive and it is difficult to perform a statistical test with the results. That is the reason why the DEA model in this paper is integrated with other models, i.e., in order to improve the DEA model and try to eliminate its limitations and weaknesses, this model is integrated with PCA and multicriteria decision-making methods. Thus, in order to strengthen the DEA model and increase its discriminatory power, the PCA model was applied, in the manner it was carried out in the paper [23,25,26]. The CRITIC and Entropy methods were used to calculate the weight values of the parameters in an objective way. Entropy is a commonly used weighting method that measures value dispersion in decision-making. The greater the degree of dispersion, the greater the degree of differentiation, and more information can be derived. Meanwhile, higher weight should be given to the index, and vice versa [16,51]. The CRITIC method estimates the objective determination of criteria weights while eliminating a subjective point of view of DMs. This method considers the intensity of the contrast in the structure of decision-making problems [28]. Unlike many other papers where only the DEA model [4,11,14] or PCA–DEA [24] was used to identify effective/ineffective DMUs, this paper also used the MARCOS method, which ranked all effective DMUs very successfully and determined which DMU was most effective in relation to all observed parameters. In general, we can conclude that by applying this integrated model we get a detailed insight into the efficiency of transport companies, i.e., based on the obtained results we can conclude which DMUs are efficient and which are inefficient, what is the importance of certain parameters for the company, which is the most efficient DMU from the whole set of DMUs that have shown efficiency, and we can perform a comparative analysis of business efficiency between companies.

Besides advantages, one of the limitations can be manifested through the following. The process of projecting orthogonally data onto lower-dimensional space unavoidably provokes information loss. This is one of the major limitations of the methods that use the PCA approach (even if combined with the DEA).

6.3. Managerial Implications

The proposed methodology has direct managerial implications. The efficiency of transport companies is an important factor for companies and for the entire economic system. The need for their efficiency is especially pronounced in the conditions of uncertainty and global crises such as the financial crisis of 2008 and unpredictable epidemics, such as COVID-19. In such circumstances, the efficiency of transport companies plays a key role as an element of financial balance at the company level. Performing direct benchmarking of the performance of transport companies and analyzing how companies combine their potentials can offer additional and valuable information from a business perspective. Therefore, it is obvious that defining the efficiency of companies is a useful way to eliminate unwanted consequences for society and the company.

By applying the methodology presented in this study, managers and investors would better understand the efficiency and sustainability of company operations. By applying the presented concept, managers and decision-makers who care about effectiveness can take preventive actions in order to improve the performance of their company. Additionally, the application of this methodology can influence the encouragement of companies to incorporate sustainability and effectiveness into their business performance and business strategies. In this way, decision-makers, managers, and investors would understand the importance of defining the future performance of companies through understanding the links between company performance and resources expended. In this context, great opportunities open up, especially for managers who properly analyze company performance data and combine it with financial data.

7. Conclusions

In this paper, the efficiency analysis of transport companies is performed using an integrated PCA–DEA model and multi-criteria decision-making methods. The research was conducted on a sample of two transport companies from Bosnia and Herzegovina, and the business performance was observed from 2013 to 2020. The advantage of the DEA model is the measurement of efficiency by considering many different input and output parameters, which are often in conflict with each other. In the paper, the PCA model is also used to create new principal components that are linear combinations of initial variables, thus increasing the power of the DEA model. CRITIC and Entropy are multi-criteria decision-making methods of objective nature, which were used in this paper to determine the weight values of defined input and output parameters. According to the results obtained, the most important parameter for the company TC1, as well as for the company TC2, is “profit”. However, if observing both companies together, the most important parameter is “vehicle maintenance costs”. In order to precisely determine which decision-making unit is the most efficient, ranking was performed using the MARCOS method. Based on the results, it can be concluded that the highest efficiency was achieved in 2017 regarding TC1, and in 2016 regarding the company TC2. Performing an analysis of the efficiency of both companies together, it can be concluded that the company TC2 operated more efficiently compared to the company TC1, i.e., the most efficient business performance of the company TC2 was in 2016. Therefore, the paper proves that the PCA–DEA approach in combination with multi-criteria decision-making methods is a very useful tool for determining the individual efficiency of transport companies, but also for a comparative analysis of efficiency between companies. While the PCA–DEA itself can determine which decision-making units are efficient and which are inefficient, the integrated model with multi-criteria decision-making methods also enables the accurate identification of a less efficient decision-making unit from a set of efficient units.

One of the limitations of the research conducted is the number of representative companies, as well as the absence of a larger volume of historical data of the companies considered. Additionally, the number of inputs and outputs is ten but can be larger. In these cases, very often the principal components obtained as a linear combination of the initial variables (i.e., by the features from the original data) are difficult to interpret. However, it is important to note that DMUs represent years of business and in such cases for managers is an important quantitative measure of efficiency as, according to this, they can model other similar activities. These limitations can be compensated through future research that will involve a larger number of companies or the application of this methodology in integration with some of the theories of uncertainty. Additionally, some directions for future studies can be manifested through comparing transport companies in different markets or different countries, as one of the directions for future studies can be defined monitoring of performances, their evaluation, and selection of key performance indicators. After that KPI can be divided into inputs and outputs and such research should be reproduced.

Author Contributions: Conceptualization, Ž.S. and S.M.; methodology, Ž.S. and S.M.; validation, D.V., M.S. and D.P.; formal analysis, M.S.; investigation, E.H.; writing—original draft preparation, Ž.S., M.S. and E.H.; writing—review and editing, D.V. and D.P.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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