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Evaluation of Railway Infrastructure Managers' Efficiency Using a Pearson's Correlation-Based DEA Method Model

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Abstract: Efficient management of railway infrastructure is recognized as a cornerstone for the sustainable development of the transport sector, as it plays a critical role in reducing congestion, mitigating environmental pollution, and enhancing mobility. The modernization and optimization of railway systems are essential for the optimal utilization of resources and the advancement of a more competitive and environmentally sustainable sector. Railway infrastructure managers (RIMs) are entrusted with the responsibility of ensuring efficient infrastructure management, maintenance, and modernization, thereby guaranteeing the safety, reliability, and sustainability of railway systems. In this study, a methodological framework was proposed for evaluating the efficiency of RIMs by integrating Pearson's correlation and the Data Envelopment Analysis (DEA) method. The efficiency evaluation was conducted based on key performance indicators (KPIs) associated with railway infrastructure management. Pearson's correlation was employed to analyze the relationships among 35 KPIs, while the DEA method was utilized to identify efficient managers. The developed framework offers a novel approach for creating analytical tools tailored to RIMs, providing regulatory bodies and decision-makers with a valuable toolset to implement best practices and enhance competitiveness. The findings of this study have practical implications, enabling performance comparisons, the development of management strategies, and the formulation of policies aimed at fostering a more sustainable and efficient railway industry.

Keywords: Pearson's correlation; Data envelopment analysis method; Key performance indicators; Evaluation; Railway infrastructure managers

1. Introduction

Efficient management of railway infrastructure is the foundation for the optimal functioning of the railway system, which occupies a central role in the transport network of every country. As one of the most efficient and environmentally friendly modes of transport, railways play a significant role in achieving sustainable development goals and transitioning to a greener economy. The European Union, through strategic documents such as the White Paper on Transport, clearly emphasizes the need to shift freight and passenger traffic from road to rail to reduce environmental impacts, increase energy efficiency, and ensure sustainable mobility (European Communities-Commission, 1992). Additionally, railways play a key role in achieving the goals of the European Green Deal, which aims to reduce CO_2 emissions by at least 90% by 2050 (Fetting, 2020). Ensuring efficient and sustainable railway infrastructure management enables the growth of this sector, increases its attractiveness, and contributes to achieving broader modal shifts, which is one of the primary prerequisites for a more sustainable transport system. RIMs bear the crucial responsibility for the safety, reliability, and efficiency of railway operations. They must ensure that resources are used in the most efficient way to achieve high levels of operational efficiency and sustainable development (Makovsek et al., 2015). Their role goes beyond the technical aspect of infrastructure management, as their efficiency directly affects the quality of services, operational costs, and user satisfaction. Inefficient management can lead to serious consequences, including increased maintenance costs, transportation delays, and reduced user trust, further diminishing the competitiveness of the railway sector compared to other modes of transport. Analyzing and identifying best practices among efficient RIMs offers significant benefits not only for optimizing existing resources but also for setting standards that can serve as a reference for other managers. Researching and identifying efficient RIMs not only provides insights into best practices in railway infrastructure management but also enables the implementation of strategies that can be key to optimizing railway services and resources for better customer service and more economical operations (European Commission, 2020b). These practices include innovative solutions such as digitization, process automation, and the use of advanced technologies for maintenance, which directly contribute to reducing costs and increasing operational efficiency. Furthermore, improving interoperability on international railway corridors further enhances efficiency and facilitates the development of multimodal transport systems. The railway sector has untapped potential in providing a sustainable and competitive form of transport. Identifying KPIs and developing guidelines based on best practices not only improves service quality but also contributes to a more cost-effective and environmentally responsible functioning of the entire transport system. Research on efficient railway infrastructure management and analysis of best practice examples is an important step toward modernizing and improving the railway sector, making it better suited to the challenges of today and the needs of future generations.

This study aims to identify efficient RIMs using Pearson's correlation and the DEA method. Pearson's correlation was used to analyze the correlation between KPIs, while the DEA method was applied to assess the efficiency of the managers. This combination enables the optimization of analysis by reducing the number of variables entering the DEA method, thus avoiding the complexity problem and reducing the possibility of overestimating the efficiency of decision-making units (DMUs) when working with a large number of inputs and outputs (Alirezaee et al., 1998). The research included nine RIMs and 35 KPIs. Using Pearson's correlation, KPIs with high correlation were identified and excluded to reduce data redundancy and increase the accuracy of the DEA method's results. After identifying correlations and eliminating highly correlated KPIs, efficiency analysis using the DEA method was performed based on eight variables (KPIs), three of which were inputs and five were outputs. The results of the DEA analysis revealed significant differences in efficiency among the managers. Of the nine managers analyzed, some exhibited a high level of efficiency, while others were identified as less efficient, indicating the need for optimization of their resource management and operations.

The main contribution of this study is the development of an analytical framework for evaluating the efficiency of RIMs through the combination of Pearson's correlation and the DEA method. The application of this methodology allows for more precise and reliable analysis by reducing the number of KPIs through the identification and elimination of highly correlated performance indicators. The results of the research hold significant practical value as they provide a foundation for benchmarking among RIMs, the development of standards and guidelines for improving managerial practices, and the formulation of informed policies that support more sustainable and efficient development of the railway sector. Furthermore, this study contributes to a broader understanding of sustainable transport strategies, particularly in the context of the role of railways in reducing emissions and increasing energy efficiency. By laying the foundation for future research and training program development, this research provides both theoretical and practical contributions to the improvement of the railway infrastructure sector.

The rest of the study is structured as follows: Chapter 2 provides an overview of the relevant literature, including key studies on efficiency in the railway sector, methods of efficiency evaluation, Pearson's correlation, and the DEA method, as well as efficiency in railway infrastructure management. Chapter 3 presents a detailed description of the combined methodology of Pearson's correlation and the DEA method. Chapter 4 demonstrates the application of the methodology to a specific sample of nine RIMs, along with input variables and the obtained results. Chapter 5, the discussion, examines the results, analyzing factors contributing to efficiency, the limitations of the methodology, and the theoretical and practical implications. Finally, Chapter 6 presents the conclusions of this study and suggests directions for future research.

2. Literature Review

Efficiency in the railway sector plays a crucial role in enhancing sustainability and competitiveness. Efficiency is reflected in the ability of railway systems to optimally utilize resources to reduce operational costs, increase capacity, and improve service quality. In European countries, the restructuring process of railway companies, initiated by Directive 91/440/EEC, resulted in the separation of infrastructure management from operational activities (Council of the European Communities, 1991). This reform laid the foundation for adopting new approaches to efficiency in the railway sector, allowing for greater transparency and fostering competition. Railway sector efficiency has been explored through various aspects, including technical, allocative, and operational efficiency (Zhang et al., 2022). Factors that influence the efficiency of the railway sector include the size of the network, technical equipment, level of investment, and regulations. The development of methodologies for measuring efficiency, particularly in the last three decades, has helped identify key factors affecting performance and efficiency in the railway sector. A review of previous research on efficiency in the railway sector analyzes key studies focusing on efficiency, the methods used, and specific challenges in infrastructure management, aiming to provide a comprehensive insight into previous research and identify future directions. Litman & Burwell (2006) emphasized how economic and ecological factors play a key role in achieving sustainable efficiency. Catalano et al. (2019) investigated the approaches applied in efficiency analysis in the railway sector, finding that in most cases, the railway operator, or the company as a whole, is used as the basic unit of analysis (70 out of 100 studies). In 24 studies, efficiency was examined on a broader scale, such as national or regional levels, which is common in international comparative studies of efficiency between different countries. Particular emphasis was placed on the importance of careful selection and compilation of country-specific data, including inputs from both infrastructure managers and operators. In the review of previous research, DEA and Stochastic Frontier Analysis (SFA) are the most commonly used methods for assessing efficiency. Input and output parameters are used in these methods to measure technical and allocative efficiency in railway systems and are frequently applied to compare the efficiency of different railway companies or countries (Oum et al., 1999). The DEA method is used to analyze the relative efficiency between different railway companies, operators, or infrastructure managers. In contrast to the DEA method, SFA provides a deeper analysis through stochastic modeling of random errors and technical inefficiencies (Makovsek et al., 2015). The first DEA model, the CCR model, was developed by Charnes et al. (1978) based on the assumption of constant returns to scale. Later, Banker et al. (1984) developed the BCC model, which allows for variable returns to scale.

The application of the DEA method in many areas highlights its adaptability and practical value in various situations. It has been used to evaluate the efficiency of intermodal terminals (Krstić et al., 2020), analyze collaborative development in e-commerce and logistics (Wang et al., 2017), determine optimal investment strategies (Zhang et al., 2016), assess the efficiency and effectiveness of state-owned transport companies (Singh & Jha, 2017), investigate the efficiency of commercial banks (Fan, 2016), analyze port efficiency (Birafane & El Abdi, 2019), and evaluate the efficiency of primary healthcare and medical institutions (Tan & Li, 2020).

The application of the DEA method in the railway sector most often focuses on five main areas: (a) performance analysis of railway companies in passenger and freight transport (Hilmola, 2007; Kutlar et al., 2013; Maltseva et al., 2020), (b) performance assessment considering environmental factors (Lan & Lin, 2005; Michali et al., 2021; Song et al., 2016), (c) locating urban railway stations and evaluating efficiency (Haghighi & Babazadeh, 2020; Mohajeri & Amin, 2010; Sameni et al., 2016), (d) investigating the impact of the private sector, management structure, new investments, and infrastructure on efficiency (Cantos et al., 1999; Cantos et al., 2012; Sueyoshi & Yuan, 2017; Tomikawa & Goto, 2022), and (e) analysis of efficiency changes over time (Hadjar Soumai & Yassine, 2021; Mahmoudi et al., 2020; Yu, 2008). The DEA method is a non-parametric approach that allows for the measurement of technical and allocative efficiency among different entities. Oum et al. (1999) applied DEA to 19 railway companies in Organization for Economic Co-operation and Development (OECD) countries over ten years and identified significant differences in efficiency caused by different regulatory frameworks and market conditions. This study is pioneering in exploring how market liberalization contributes to improvements in technical and operational efficiency. Hilmola (2007) analyzed the efficiency and productivity of European freight rail transport from 1980 to 2003 using the DEA method and partial productivity analysis. The study shows that countries with the highest levels of efficiency in the 1980s experienced a collapse of efficiency in the 1990s, particularly those from the former Eastern Bloc and Western Europe. Jitsuzumi & Nakamura (2010) investigated the causes of inefficiency in Japanese railways and proposed the DEA approach for calculating optimal subsidies tailored to railway companies operating under regulated operational constraints. The study identified inefficiency causes in 53 railway operators, distinguishing between those caused by management-controlled factors and those resulting from external conditions. Chen (2012) examined the impact of high-speed rail on regional economic efficiency in western Taiwan using DEA and Tobit regression models. The study showed that economic efficiency in these regions worsened after the commencement of the railway, indicating that negative effects outweigh the positive ones in the long term. The need for further research on the impact of railway infrastructure on regional development was emphasized. Lan & Lin (2005) developed a four-stage DEA approach to correct the shortcomings of conventional DEA models, such as the CCR and BCC models, which do not adjust for environmental impacts, statistical noise, and "slacks" when measuring efficiency. Their method considers heterogeneous operating conditions to avoid biased comparisons among DMUs. Based on empirical data from 44 railway operators in different countries over seven years, it was found that without this adjustment, efficiency and productivity results were often overestimated. The SFA method, developed by Aigner et al. (2023), enables stochastic modeling of inefficiencies in production systems. These models allow for the separation of random variations in data from actual technical inefficiencies, making SFA useful in efficiency analysis in the railway sector, especially in large and complex systems. Couto & Graham (2009) applied SFA to assess cost efficiency in European railways for the period from 1972 to 1999. Their analysis highlights significant cost inefficiency, with allocative inefficiency being more pronounced than technical inefficiency. Furthermore, productivity improvements were attributed to technological progress rather than increased efficiency of railway companies concerning frontier efficiency. Farsi et al. (2005) analyzed the cost efficiency of 50 Swiss railway companies during the period from 1985 to 1997 using the SFA method through the Cobb-Douglas cost function. Their research showed that the estimation of cost inefficiency depends on the panel model used and emphasized the need to distinguish between inefficiency and company-specific characteristics to avoid overestimating inefficiency. Lan & Lin (2006) used two stochastic distance functions to assess the efficiency of railway systems. First, a stochastic input distance function with an inefficiency effect was used to measure technical efficiency through input variables such as the number of passenger and freight cars and employees. Second, a stochastic output distance function with an inefficiency effect was used to measure service effectiveness using output variables such as passenger and freight kilometers. This method allows for distinguishing technical inefficiency from service inefficiency, taking into account external factors such as gross national income and network density. Holvad (2020) provided a comprehensive review of efficiency analysis in the railway sector, focusing on frontier-based efficiency methods, particularly through techniques like DEA and SFA. The paper analyzes various aspects of the application of these methods in the railway sector, including input and output variables, geographical variations, and key findings from previous studies. It also highlights challenges in applying these methods and suggests directions for future research, particularly regarding the adaptation of qualitative aspects of provided services in efficiency measurement.

After reviewing the literature on the application of various methods for measuring efficiency in the railway sector, particularly DEA and SFA methods, it is clear that research has mainly focused on analyzing the performance of railway companies in passenger and freight transport and the general railway sector. However, the efficiency of railway infrastructure management, which is crucial for optimal resource use and service quality improvement, has not been extensively studied. Efficient railway infrastructure management becomes especially important in the context of expanding market liberalization. The role of RIMs is critical to ensuring optimal use of infrastructure, reducing congestion, and improving services for end-users. The European Union, through the Platform for Infrastructure Managers (PRIME), monitors the performance and development of efficiency among managers using KPIs (European Commission, 2020a). Kalem et al. (2023) analyzed the performance of RIMs through a range of KPIs, covering aspects such as safety, operational performance, financial efficiency, and capacity for growth. Additionally, Kalem et al. (2024a) used the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to evaluate the impact of geographical, economic, and technological factors on efficiency, enabling a comprehensive view of railway infrastructure performance. Despite the importance of infrastructure managers, research in this area is sparse, which opens up opportunities for further studies. A greater focus on the efficiency of RIMs would provide a more accurate understanding of the challenges and opportunities in this segment, thereby contributing to the competitiveness of the sector in the context of increasing market competition and restructuring (Kalem et al., 2024b). This study proposes a methodology that combines Pearson's correlation and the DEA method to identify efficient RIMs. The application of the DEA method enables the identification of efficient RIMs through the analysis of multiple inputs and outputs, while Pearson's correlation was used to reduce the number of variables in the DEA analysis. The application of Pearson's correlation before the DEA analysis is still underrepresented in literature dealing with infrastructure manager efficiency, although it is recognized as a useful tool in other research areas. Djordjević et al. (2021) combined Pearson's correlation and the DEA method to assess the sustainability of the railway system. Pearson's correlation was used to examine the interdependencies between key sustainability indicators for railways, while the DEA method was applied to evaluate efficiency based on these indicators. In this case, Pearson's correlation was applied to determine the interrelationships between various indicators, such as the length of electrified railway networks, the volume of passenger traffic, and greenhouse gas emissions. Banjerdpaiboon & Limleamthong (2023) used the DEA super-efficiency model and the Malmquist productivity index to assess circular economy performance among European countries. Combining these methods allows for evaluating efficiency and monitoring performance changes over time, providing deeper insights into sustainable practices at the national level. Pearson's correlation was applied to investigate the correlations among indicators, which contributes to understanding the interconnections between variables, but was not used to reduce the number of variables in the DEA analysis. Chen & Chen (2009) used the DEA method to assess operational efficiency in the silicon semiconductor wafer manufacturing industry in Taiwan. The aim of the study was to determine the efficiency of companies by analyzing three input variables (total assets, operating costs, and operating expenses) and one output variable (net sales). To ensure data validity for the DEA analysis, Pearson's correlation was applied to analyze the relationship between input and output variables, confirming their positive correlation.

The combination of methods proposed in this study, Pearson's correlation and the DEA method, represents a significant gap in previous research and offers considerable potential to improve the efficiency analysis of RIMs. Djordjević et al. (2021) used the combination of Pearson's correlation and the DEA method to assess the sustainability of the railway system through the analysis of KPIs covering economic, ecological, and social aspects of sustainability. Unlike this study, which focuses on identifying correlations using the Pearson test and verifying those correlations through the DEA method to exclude strongly correlated KPIs, the goal of thisstudy is not only to identify correlations but also to use the Pearson test as a tool for reducing the number of input and output variables in the DEA analysis. This approach allows for greater efficiency in the DEA method, avoiding the generation of numerous DMUs with maximum efficiencies, and provides clearer and more practical results in assessing the performance of RIMs.

3. Methodology

This research applies a combination of Pearson's correlation and the DEA method to assess the efficiency of RIMs. The objective of this approach is to identify the most efficient RIMs through DEA analysis while reducing the number of variables (inputs and outputs) included in the model using Pearson's correlation. This step enables model optimization and mitigates the issue of "model overfitting," which can occur when there are too many variables, leading to a large number of efficient DMUs and making it difficult to accurately identify truly efficient RIMs. Figure 1 illustrates the proposed framework for evaluating the efficiency of RIMs. This framework consists of three key stages. The first stage involved defining the problem structure, where relevant KPIs were identified to be used as inputs and outputs. In the second stage, Pearson's correlation was employed to reduce the number of variables, enabling more efficient application of the DEA method. In the third stage, DEA analysis was applied to the optimized set of KPIs, allowing for the identification of efficient and inefficient managers. The results of this analysis can serve as a foundation for further recommendations and benchmarking.

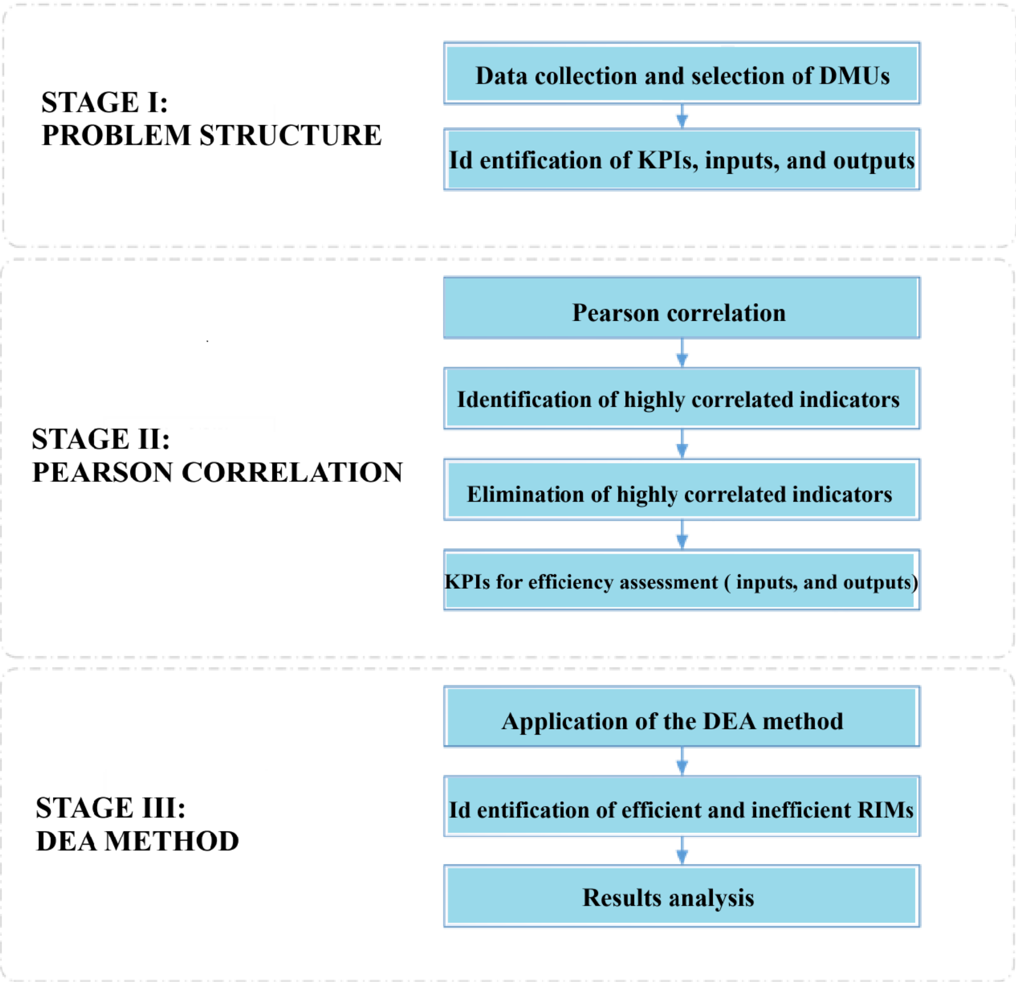

Figure 1. Methodology for assessing the efficiency of RIMs

Stage I: Problem structure

In this stage, the goal is to define the problem structure by identifying the relevant DMUs and KPIs tobe used in the efficiency analysis of RIMs. The first step involves the precise selection of DMUs, which represent different RIMs, and the identification of specific KPIs that serve as inputs and outputs in the DEA method. This stage includes the selection of indicators that are essential for assessing efficiency while drawing on performance metrics established in the literature, such as those from the study by Kalem et al. (2024b). In this way, the problem structure lays the foundation for the subsequent steps in the analysis by defining the DMUs and selecting the KPIs relevant for effective decision-making and evaluation.

Stage II: Pearson correlation and KPI reduction

Stage II involves the application of the Pearson correlation to reduce the number of KPIs tobe used in the DEA analysis. The Pearson correlation allows for the reduction of highly correlated variables (KPIs), which increases the accuracy of the results and minimizes the risk of having an excessive number of efficient DMUs in the analysis. First, the Pearson correlation was calculated between the KPIs to identify variables with high mutual correlation. Based on the obtained results, variables that show a high degree of correlation with other variables were recognized and adjusted for further analysis. The criterion for eliminating variables was a correlation threshold of ±0.70—variables with correlations equal to or greater than this threshold were considered redundant and removed from further analysis. This process helps avoid redundant data, thus enhancing the precision and clarity of the model in evaluating the efficiency of RIMs. In this way, the refined set of KPIs represents the final inputs and outputs for the DEA analysis, enabling a more efficient evaluation.

Pearson's correlation (*r*) between two variables *x* and *y* can be calculated using the following formula (Mukaka, 2020):

$$r = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sqrt{[\sum_{i=1}^{n}(x_i - \bar{x})^2][\sum_{i=1}^{n}(y_i - \bar{y})^2]}}, \tag{1}$$

where, x_i and y_i are the values of *x* and *y* for the *i*-th observation; and$\bar{x}$ and $\bar{y}$ represent their mean values, which are calculated as:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \tag{2}$$

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{3}$$

The value of the Pearson correlation ranges from -1 to 1. Values close to 1 or -1 indicate a strong positive or negative correlation, respectively, while values close to 0 indicate a weak or no correlation between the variables.

Stage III: Application of the DEA method

In the third stage, the DEA method was used to assess the efficiency of RIMs. The input and output variables represent the optimized set of KPIs obtained through Pearson correlation, which allows for the identification of efficient and inefficient managers. The DEA method can be presented as a linear program to maximize the output-to-input ratio for each DMU. Suppose there are DMUs, each utilizing *m* inputs to produce outputs. The efficiency of the *h*-th DMU is determined by solving the following formula (Charnes et al., 1978):

$$\max h_0 = \frac{\sum_{t=1}^{s} w_t z_{to}}{\sum_{k=1}^{m} u_k q_{ko}}, \tag{4}$$

The constraint is as follows:

$$\frac{\sum_{t=1}^{s} w_t z_{tj}}{\sum_{k=1}^{m} u_k q_{kj}} \leq 1, j = 1,2,..,p, \tag{5}$$

$$w_t\ , u_k \geq 0, \forall t, k \tag{6}$$

where, z_{tj} is the value of output *t* for DMU *j*; q_{kj} is the value of input *k* for DMU *j*; w_t is the weight coefficient for output *t*; and u_k is the weight coefficient for input.

4. Case Study-Determining the Efficiency of Rims

This chapter validates the previously described methodology for determining the efficiency of RIMs using a combination of Pearson's correlation test and the DEA method. The analysis includes nine European RIMs. Data for these RIMs were sourced from the PRIME report for 2021 (Platform of Rail Infrastructure Managers in Europe, 2021). To ensure confidentiality, the identities of the managers were anonymized and labeled as *RIM*1, *RIM*2, and so forth.

The dataset for the analysis consists of 35 KPIs defined in the study by Kalem et al. (2024b). These indicators provide insight into various aspects of RIM operations and encompass a wide range of operational characteristics important for efficiency analysis. The collected KPIs include metrics related to safety, performance, costs, and the utilization of resources and network capacity. The software Minitab was used to calculate Pearson's correlation between the selected indicators. The correlation results are presented in Appendix Table A1.

The results of the first stage of the analysis demonstrate the successful reduction of the number of KPIs through the application of Pearson's correlation, as per Eqs. (1)-(3). This reduction minimized redundancy in the model and improved the interpretability of the results. Using a correlation threshold set at ±0.70, Pearson's correlation facilitated the identification and elimination of indicators that exhibited a high degree of interconnection. Indicators with correlations exceeding this threshold were deemed redundant and excluded from further analysis to ensure the accuracy of the DEA model and avoid overlapping information. The final set of retained indicators includes a total of eight key KPIs, as shown in Table 1. These indicators were retained because they have correlations below the defined threshold, providing a clearer insight into the efficiency of RIMs.

Table 1. Inputs and outputs of DMUs

Category		**KPIs**	**KPI unit**
Inputs	*D*4	Power supply failures in relation to network size	Number per thousand main track-km
	*F*2	Maintenance expenditures in relation to network size	Euro per main track-km
	*F*3	Capital expenditures (CAPEX) in relation to network size	Euro per main track-km
Outputs	*S*1	Significant accidents	Number per million train-km
	*S*2	Fatalities and serious injuries	Number per million train-km
	*S*3	Infrastructure manager-related precursors to accidents	Number per million train-km
	*P*3	Delay minutes caused by the infrastructure manager	Minutes per train- km
	*F*5	Track Access Charges (TAC) revenue in relation to network size	Euro per main track-km

Inputs represent the resources and costs allocated for maintenance and capital investments in railway infrastructure, while outputs reflect key indicators of safety, network performance, and generated revenues. Table 2 presents the input and output values for the RIMs. Following the previously described methodology and using Eqs. (4)-(6), the DEA method was applied to the optimized set of KPI indicators, with the primary goal of assessing the efficiency of each infrastructure manager relative to the other analyzed units.

Table 2. Inputs and outputs data for the DEA method

	Inputs					**Outputs**		
DMUs	*D*4	*F*2	*F*3	*S*1	*S*2	*S*3	*P*3	*F*5
*RIM*1	58	37.00	264	0.52	0.09	2.7	8	8
*RIM*2	1	39.00	158	0.29	0.1	0.16	2.5	95
*RIM*3	36	48.00	86	0.95	0.54	1.75	24	25
*RIM*4	149	52.00	168	0.8	0.61	2.8	8	30
*RIM*5	35	81.00	159	0.18	0.07	0.5	9	50
*RIM*6	29	59	214	0.2	0.15	0.2	2	62
*RIM*7	10	57	110	0.31	0.12	0.9	6.5	103
*RIM*8	134	90	50	0.1	0.45	0.01	20	18
*RIM*9	74	38	139	0,.2	0.1	3.7	6.5	15

The obtained results, presented in Table 3, indicate that *RIM*2 is the most efficient manager with an efficiency score of 1.000, positioning it as the benchmark unit for others. *RIM*6 and *RIM*7 also demonstrated a high level of efficiency, with only slight deviations from the maximum value, indicating minimal opportunities for improvement. Other units, such as *RIM*1, *RIM*3, and *RIM*4, achieved significantly lower scores, highlighting substantial untapped potential and the need for resource optimization to enhance productivity. The ranking order further reflects the relative efficiency of each unit compared to the others, with lower scores associated with greater disproportions between inputs and outputs in their operations. This provides a valuable tool for identifying areas for improvement and making strategic decisions aimed at increasing efficiency.

Table 3. Results of the ranking using DEA

DMUs	**DEA CCR**	**DEA rank**
*RIM*1	0.539	7
*RIM*2	1,000	1
*RIM*3	0.183	9
*RIM*4	0.302	8
*RIM*5	0.852	4
*RIM*6	0.930	2
*RIM*7	0.922	3
*RIM*8	0.565	6
*RIM*9	0.589	5

*RIM*2 was recognized as the most efficient RIM, suggesting an optimal balance between the input and output parameters defined in the analysis. Its success can likely be attributed to a low level of power supply failures and well-managed maintenance costs, indicating the adoption of modern technologies and efficient procedures. Furthermore, capital investments are likely directed toward projects with long-term benefits, such as infrastructure upgrades and safety systems, reducing significant accidents, fatalities, and serious injuries. Lower accident rates linked to infrastructure management, along with fewer train delay minutes per kilometer, highlight high operational efficiency. Additionally, revenue from TAC relative to the network size reflects a balanced approach to financial management and the provision of high-quality services to users. This combination of factors suggests that *RIM*2 serves as a model of best practices in railway infrastructure management.

5. Discussion

The research problem of this study was to identify efficient RIMs based on KPIs, using Pearson's correlation and the DEA method, to analyze the relationships among KPIs and evaluate the relative efficiency of each manager. Based on the results and outputs of the DEA analysis, differences in efficiency among RIMs were observed. These differences can be explained by varying approaches to resource management, technology implementation, and work organization strategies. Managers with higher efficiency levels, such as *RIM*2, likely have better-optimized maintenance processes that reduce power failures and maintenance costs relative to the size of the network. Additionally, more efficient managers invest in capital projects that directly contribute to improving safety and reducing the number of accidents, serious injuries, and train delays. On the other hand, less efficient managers may face challenges such as outdated infrastructure, suboptimal investment strategies, or weaker maintenance process organization. These factors can lead to higher costs, more frequent failures, and a greater number of safety incidents. The difference in efficiency may also result from the level of income from TAC, where more efficient managers better balance their tariffs and the quality of services provided. Finally, the degree of adoption of modern technologies and innovations, as well as approaches to training and staff development, also significantly influence efficiency differences between various managers.

The combination of Pearson's correlation and the DEA method for evaluating the efficiency of RIMs represents an advancement over previous research in the field of railway infrastructure management and is a significant contribution to this study. While earlier studies, such as the study by Djordjević et al. (2021), applied this combination to analyze the sustainability of railway systems, this study focuses on a specific aspect of the efficiency of RIMs, with a detailed analysis of KPIs. The methodology applied in this study provides a foundation for benchmarking among different RIMs, offering a basis for formulating strategies to improve efficiency and optimize resources. This contributes not only to the theoretical framework for analyzing efficiency in the railway sector but also to practical recommendations for improving infrastructure management practices, which is crucial for the future development of railway systems.

Although the methodology proposed in this study makes a significant contribution to the analysis of the efficiency of RIMs, it contains several key limitations that should be considered. The availability of high-quality data represents a challenge, as the accuracy and consistency of the data directly affect the reliability of the Pearson correlation and DEA analysis results. Quality data are crucial for obtaining accurate and valid efficiency estimates. One of the key limitations of the approach used in this study is that the classical DEA method may overlook the weights of some inputs and outputs, which can lead to insufficiently precise efficiency estimates. In the traditional DEA approach, some inputs or outputs may receive a weight of 0, implying their complete irrelevance in the analysis, which can undermine the model's accuracy. To overcome this issue, the introduction of Assurance Region (AR) DEA methods was proposed, which introduces safety regions into the optimization process, ensuring that the weights of all relevant variables are considered (Tadić et al., 2019). These safety regions can be generated using multi-criteria optimization (MCO) methods, allowing for better management of input and output weights. This approach represents a potential direction for future research, enabling a more precise evaluation of the efficiency of RIMs and reducing the likelihood of overlooking key indicators that affect efficiency. The study establishes a framework for further research, allowing future researchers to refine the methodological approach to efficiency analysis in the infrastructure sector. On a practical level, the results of this research can serve as a valuable resource for regulators and policymakers to identify best practices and direct resources to areas with the greatest potential for efficiency improvements. Furthermore, railway infrastructure management and sector analysts can use these findings as a basis for benchmarking processes and developing strategies aimed at increasing operational efficiency.

6. Conclusions

The efficiency of railway infrastructure management is crucial for achieving sustainability, optimal resource utilization, and high-quality services in the railway sector. As a vital component of the transport network, efficient infrastructure management directly contributes to safety, reduction of operational costs, and increased system reliability, which is particularly important in the context of market liberalization and growing competition in the sector. The goal of this study is to develop and apply a methodological framework for assessing the efficiency of RIMs by combining the Pearson correlation and DEA methods. This approach allows for the optimization of the number of variables for DEA analysis, reducing redundancy and focusing on the most important KPIs. Based on the proposed methodological framework, efficient managers were identified, establishing a reference framework for benchmarking and improving management practices in the railway infrastructure sector. The contribution of this study lies in improving methodological approaches for assessing efficiency in infrastructure by using the Pearson correlation and DEA method, enhancing the precision and interpretative value of the results. The findings are useful for regulators and policymakers in the sector, enabling them to identify best practices and direct resources to areas with the greatest potential for efficiency improvement. Future research should test the methodology on a larger group of RIMs to improve its generalizability. One of the main limitations of the approach applied in this study relates to the fact that the classical DEA method has a drawback, as it may overlook the weights of certain inputs and outputs, leading to inaccurate efficiency estimates. In classical DEA analysis, some inputs or outputs may receive a weight of 0, making them irrelevant in the analysis and compromising the precision of the results. To overcome this limitation, the AR DEA method can be applied, which incorporates safety zones into the optimization process, ensuring that all key factors are properly evaluated. Safety zones can be generated using MCO methods, allowing for better management of input and output weights. This approach represents a step forward in more accurately assessing the efficiency of RIMs and reduces the risk of overlooking factors critical to the accuracy of the model. This research direction can open opportunities for further development of the methodology and its application in a broader context.

Author Contributions

Conceptualization: A.K., S.T. and M.K.; Methodology: A.K., S.T. and M.K.; Software: M.K.; Validation: S.T. and M.K.; Formal analysis: A.K., S.T., N.Č., A.M. and N.B.; Investigation: A.K. and S.T.; Data curation: A.K. and S.T.; Writing—original draft preparation: A.K., S.T., M.K., N.C.: A.M. and N.B.; Writing-review and editing: S.T. and M.K.; Visualization: A.K.; Supervision: S.T., A.M., N.Č. and N.B. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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Appendix

Table A1. Pearson correlation between KPIs

	C1	C2	C3	C4	C5	C6	C7	S1	S2	S3	S4	S5	P1	P2	P3	P4	D1	D2	D3	D4	D5	D6	F1	F2	F3	F4	F5
C1						-0,76					-0,81	0,808									-0,74						
C2						-0,8																					
C3						-0,76																					
C4					0,915																						0,792
C5				0,915			0,701																				0,799
C6	-0,76	-0,8	-0,76																								
C7					0,701																	0,71					
S1																											
S2															0,666					0,669							
S3																							-0,76				
S4	-0,81													-0,73			0,704										
S5	0,808													0,729			-0,7										
P1																				-0,78							
P2											-0,73	0,729									-0,7						
P3									0,666																		
P4																											
D1											0,704	-0,7						0,853	0,928		0,923						
D2																	0,853		0,827		0,739					-0,76	
D3																	0,928	0,827		0,699	0,965			0,774			
D4									0,669				-0,78						0,699		0,723						
D5	-0,74													-0,7			0,923	0,739	0,965	0,723				0,691			
D6							0,71																				
F1										-0,76																	
F2																			0,774		0,691						
F3																											
F4																		-0,76									
F5				0,792	0,799																						
F6																0,72											
F7				-0,71	-0,67																		0,758				
G1		0,696											0,69										0,851				
G2													0,729										0,837				
G3			0,785			-0,91																					
G4		0,842				-0,88																	0,675				
G5													0,682							-0,83						0,723	

G6	G5	G4	G3	G2	G1	F7	F6	
								C1
		0,842			0,696			**C2**
			0,785					**C3**
						-0,71		**C4**
						-0,67		**C5**
		-0,88	-0,91					**C6**
								C7
								S1
								S2
								S3
								S4
								S5
	0,682			0,729	0,69			**P1**
								P2
								P3
							0,72	**P4**
-0,71								**D1**
-0,81								**D2**
-0,68								**D3**
	-0,83							**D4**
								D5
								D6
-0,7		0,675		0,837	0,851	0,758		**F1**
								F2
								F3
	0,723							**F4**
								F5
								F6
		0,681		0,747	0,729			**F7**
		0,731		0,984		0,729		**G1**
					0,984	0,747		**G2**
		0,752						**G3**
-0,71			0,752		0,731	0,681		**G4**
								G5