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Efficiency of the rail sections in Brazilian railway system, using TOPSIS and a genetic algorithm to analyse optimized scenarios

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ABSTRACT

A railway system plays a significant role in countries with large territorial dimensions. The Brazilian rail cargo system (BRCS), however, is focused on solid bulk for export. This paper investigates the extreme performances of BRCS through a new hybrid model that combines TOPSIS with a genetic algorithm for estimating the weights in optimized scenarios. In a second stage, the significance of selected variables was assessed. The transport of any type of cargo, a centralized control of the operation, and sharing the railway track pushing competition, and the diversification of services are significant for high performance. Public strategies are discussed.

1. Introduction

The Brazilian rail cargo system (BRCS) has an extension of about 29,000 km deployed since the second half of the 19th century in a dispersed and isolated way (Munhoz, n.d.) where modern and obsolete infrastructure of the railway track and rolling stock can be found side by side. It is operated by private capital railway concessionaires broken down into subsystems that were granted by the federal government between 1996 and 1999. The concession model included, cumulatively, the granting of the right to use the railway along with the lease of the operational assets and the support facilities required for the operation. The concession term was for 30 years in most cases. The BRCS subsystem is translated into a regional sector and verticalized monopoly (Marchetti and Ferreira, 2012) with low inter-modal competition, even though there are operational regulations that seek to promote the increase of supply and competition on the network by means of the trackage right regime, where the access to the infrastructure of another concessionaire with its own trains is done in exchange for a fee, or the haulage right regime, where the owner of the railroad operates trains for another concessionaire in exchange for a fee (ANTT, 2011; Laurino et al., 2015).

The BRCS is heterogeneous, presenting different standards of efficiency among the operators and distinct physical and operational characteristics (Marchetti and Wanke, 2017). The main cargo on the tracks are mineral and agricultural commodities for export with a low diversification of scope, reaching up to 95% of its offer (EPL, 2016). It also includes different track gauges: metric (1.0 m), broad (1.6 m), and mixed. The subsystems are installed in all regions of the country, but with low connectivity and integration among them. There are railway sections with high daily circulation of trains and low idleness, but many stretches are little used or not used at all due to the sinuous, extended, and inefficient geometry of the track or even shortage of supply or demand. The technology of the operation comprises elements such as computers embedded in the locomotives, centralized control of the operation, auxiliary power along critical stretches, and the ability to transport hazardous materials. Its average speed is low (ANTT, 2013; Marchetti and Ferreira, 2012), which inhibits access to cargo of higher added value.

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Brazil has a cargo transportation modal network that is unbalanced when compared with countries of large territorial dimensions (EPL, 2016). The insertion of rail transport is low (15%) while road transport is the highest with a 65% market share, including for long distances trips. This is where the greatest economic, transportation, and environmental costs are concentrated. Public policies should attempt to change this reality in the long term in order to rebalance the Brazilian transportation network, reducing transportation and logistics costs, and the emission of pollutants produced from burning fuels in the transport sector in Brazil, which is twice the transport average emission registered in the world (Ferreira et al., 2016).

As the BRCS has a heterogeneous performance focused on bulk for export presenting low average efficiency and an economic impact lower than expected, the questions of this research are as follows: How can a high performance scenario be achieved in the BRCS? What are the significant characteristics of the high performance scenario in the BRCS?

The performance of the railway sections, which are the stretches between rail yards, was analysed to answer these research questions. The availability of a database with information of the physical and operational characteristics, transportation capacity, idleness, and the type of regulation of the railway sections of each concessionaire network enabled innovative conclusions about the entire BRCS's performance, which would not have been found with the traditional analysis of aggregate data. There were 7,351 railway sections selected from 2013 to 2016. The database comes from the Network Statement drawn up every year by the concessionaires and disclosed by the National Land Transportation Agency (ANTT, 2018).

This paper evaluates the efficiency of rail sections by using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) that combined with a Differential Evolution optimization genetic algorithm simulates the optimized behaviour of the scores in BRCS's low and high performance scenarios.

The methodology proposed differs from studies already done in the literature. Several articles have already used a hybrid methodology for analysing alternatives by using some genetic algorithm for a multi-objective optimization followed by TOPSIS for ranking solutions in different areas of application, as indicated in Section 2. However, using a genetic algorithm of Differential Evolution for identifying the weights to be assigned to the criteria selected in the TOPSIS model for building optimized scenarios was an innovation. As to the best of our knowledge, a simulation of the extreme scenarios in a (railway) system based on the characteristics of its network subparts (the rail sections) using a genetic algorithm to optimize the performance of the entire system according to the TOPSIS scores of the subparts is an innovative contribution of this research.

The determinants of BRCS's performance are revealed in the second stage and are additional contributions from the research. By using a Tobit model, the significance of the contextual variables selected in each scenario was analysed such as the technologies employed in the railroad operation, the type of cargo transported, the type of regulations regarding the use of the railway track (restrictive or open), among others. The significant attributes of low and high performance scenarios were highlighted. By analysing the score percentiles, the railway profile of each concessionaire was identified in the extreme deciles. The less efficient and most efficient railway sections of each scenario can be identified, offering an important contribution of an administrative and managerial nature.

The methodology proposed can be applied to different economic sectors treated as a network such as passenger and cargo railway systems and energy or telecommunication transmission lines.

The remainder of this paper is organized as follows. Section 2 presents the literature review and indicates the gap found. Section 3 describes the methodology used to analyse the data. The data are presented and the results are discussed in Section 4. Public policies to achieve high performance are discussed, as well as management insights due to the availability of the ranking of the concessionaires' railway sections per scenario. Section 5 concludes the discussion and shows the limitations of the research while giving suggestions for new studies for going deeper into BRCS's efficiency frontier.

2. Literature review

The objectives of the literature review were twofold. The first objective was to uncover the applications where there had been a selection of multi-criteria alternatives using TOPSIS in the infrastructure and transport sectors, and more specifically in the railway sector. The second more comprehensive objective was to identify the articles that used some genetic algorithm to solve multi-optimization problems together with the TOPSIS methodology, including different areas of interest. The strategy was to investigate how these methods, widely employed in studies that transcend the infrastructure, transport, and the railway sectors, were combined in the literature, concluding whether there is an innovative application in the present study. A comprehensive survey of the literature involved articles in English reviewed by peers on widely recognized databases.

2.1. TOPSIS in infrastructure, transport, and the railway sector

Several authors have used the TOPSIS methodology as a multi-criteria method for making decisions on ranking infrastructure alternatives in their studies, whether alone or in combination with other methods. The uncertainty as to the weights of the criteria was treated in different ways. The main methods to determine the criteria weights include Shannon Entropy, Analytic Hierarchy Process (AHP), Fuzzy AHP, and Delphi Survey. Other authors have used the Fuzzy-TOPSIS method for judging the relevance of the criteria, treating the uncertainty, and ranking the alternatives.

Askarifar et al. (2018) ranked the necessary public infrastructure requirements along the Mokran coast in Iran with Best Worst Method and TOPSIS to determine the priorities. The results show that ports and private terminals are the best choices for investment while security infrastructure, transport, and energy should be the public administration's priorities. Keshavarz-Ghorabaee et al. (2018) proposed a conceptual bridge design process under uncertainty by applying a modified Fuzzy TOPSIS method and compared the results with other multiple criteria decision making (MCDM) methods, concluding that the results were valid. Kannan et al. (2009) interpreted the 15 alternatives for choosing a third-party reverse logistics provider (3PRLP) in India using Interpretive Structural Modelling (ISM) and Fuzzy TOPSIS arriving at a decision-making tool for choosing a 3PRLP. Afful-Dadzie et al. (2015) applied Fuzzy TOPSIS to create a framework for selecting states for aid facilities. Farajpour and Yousefli (2018) identified the parameters that influence the supply chain information flow prioritized towards three criteria (measurability, being illustrative, and parameters relevancy) and applied a Fuzzy TOPSIS method to rank the parameters. They concluded that supply chain hardware capabilities and infrastructure; information software capabilities, sharing timeliness, and recency; and organizational rewards are the highest priorities while internal and interpersonal communications, and users' trust and tendency stand at the bottom of the ranking. Liu and Wei (2018) explored risk factors through a survey and calculated the overall risk levels of public–private partnership (PPP) projects for electric vehicle (EV) charging infrastructure with an integrated Fuzzy TOPSIS, then, ranked the alternatives. Rahdar and Khalily-Dermany (2017) proposed an optimization model for time-resource allocation in wireless ad-hoc networks applying Fuzzy TOPSIS to assign more appropriate time-slot to nodes, reaching the conclusion that the algorithm proposed is more efficient than the available ones. Onat et al. (2016) used a Fuzzy MCDM and TOPSIS method to rank the life cycle sustainability performance of alternative passenger vehicles. The results indicate that hybrid and plug-in hybrid EVs are the best alternatives for both Scenario 1 (existing electric power infrastructure in the US) and Scenario 2 (the electricity to power EVs is generated exclusively via solar stations). Celik et al. (2013) applied an interval type-2 Fuzzy MCDM method based on TOPSIS and Grey Relation Analysis (GRA) to estimate satisfaction and suggest improvements for public transport in Istanbul. Tian et al. (2018) proposed a hybrid method using Fuzzy TOPSIS to manage MCDM problems and applied BWM (Best-Worst Method) to determine the weights with respect to different criteria for solving a green supplier selection problem. Li et al. (2018) applied an improved entropy TOPSIS to evaluate the distribution capacity of 23 imported grain distribution nodes (IGDNs) of freight railways, waterways, and highways networks IGDNs, using four measures of centrality - the relative importance of a city based on its connections with other cities. They selected Guangzhou, Lianyungang, Shanghai, Tianjin, Chongqing, and Xi'an as the final imported grain distribution centres considering government policies and the Belt and Road routes that transport grain into China. Yan et al. (2017) analysed the inland waterway transportation congestion problem on the Yangtze River (China) using a hybrid cost-benefit ratio (CBR) and Fuzzy-TOPSIS to deal with different congestion risk conditions and ambiguity. They found out that channel dredging and maintenance; and prohibition of navigation are more cost-effective in high level congestion risk situation, while loading restriction; and crew management and training are more significant in low level congestion risk condition. The results were compared with those obtained with other MCDM methods, such as VIKOR (VIsekriterijumska optimizacija i KOmpromisno Resenje), ELECTRE (ELimination Et Choice Translating REality) and PROMETHEE (Preference Ranking Organization METHods for Enrichment Evaluation).

Applying a hybrid of the Fuzzy Delphi and TOPSIS methods, Pham et al. (2017) developed a methodology to choose the locations of logistics centres. According to the authors, the most important factors are demand, closeness to market, production area, customers, and transportation costs, and the provinces of Ho Chi Minh City were the best location for logistics centres in Vietnam. Jayasooriaya et al. (2018) applied a Delphi survey and TOPSIS to optimize green infrastructure treatment train configuration and the sizing combinations for stormwater management in industrial areas. The authors used a Delphi survey to identify the environmental, economic, and social performance measurements and to obtain the weights. The TOPSIS method was used to identify the optimum from 10 alternatives.

Huang et al. (2018), with a focus on identifying the level of third-party logistics service sites based on the Chinese railway stations, applied a two-stage model combining Entropy Weight Method (EWM) based on Shannon entropy and TOPSIS and concluded that the eight first-class railway logistic bases are Beijing, Harbin, Xi'an, Wuhan, Nanjing, Guangzhou, Chongqing, and Taiyuan. Another 28 cities were selected as the second-class railway logistic centres. Zhang et al. (2018) applied the structural Entropy-TOPSIS model to evaluate the performance of a public transport priority implementation in the city of Wuhan from 2006 to 2015, reaching the conclusion that the performance improved from poor to excellent. The weights were determined according to EWM. Bagheri et al. (2018) investigated the conditions of the tourism infrastructure from different provinces of Iran and used the VIKOR and TOPSIS methods to rank the cities according to the indicators selected. They used the Shannon Entropy method to determine the weights of the indicators. The authors reached the conclusion that the Province of Tehran is under the best conditions and that the province of Ilam is under the worst conditions.

Some authors used AHP to determine the weights of the selection criteria and combined with TOPSIS to rank the alternatives. Zhao et al. (2018) applied complex network theory combined with entropy based TOPSIS to identify which cities are the optimal consolidation centres of the China Railway Express operation according to a complex network (OBOR) aimed to open up new markets to Chinese goods, and they selected the cities of Taiyuan, Xi'an, Zhengzhou, Wuhan, and Suzhou. They used AHP to weigh the criteria. Moosivand and Farahani (2013) combined AHP and TOPSIS models to determine the factors attracting tourist in the Isfahan province (Iran) and to rank the cities, reaching the conclusion that Isfahan and Kashan are the top two tourist destinations in the province. Singh et al. (2018) used a Fuzzy AHP to determine the relative weights of the different criteria shortlisted and Fuzzy TOPSIS to rank the third-party logistics (3PL) for a cold chain and to select the best 3PL based on performance. The major reasons behind the top ranking are an emphasis on automation, innovation, tracking & tracing, and flexibility. Fabianowski and Jakiel (2018) used an innovative integrated calculation algorithm that uses the modified extent analysis method on the Fuzzy AHP (EA FAHP) method to obtain the weight vector of the criteria and Fuzzy TOPSIS to reflect the actual assessment processes of the technical condition of railway culverts. Zhang and Xu (2009) used AHP to evaluate weight criteria and an extension TOPSIS with triangle fuzzy numbers to determine the optimal choice in building or rebuilding projects of urban railway passenger stations.

Behzadian et al. (2012) identified that TOPSIS works satisfactorily across different application areas and then they conducted a literature survey on TOPSIS applications and methodologies containing 266 papers from 103 journals since 2000 separated into diverse areas including Supply Chain Management and Logistics. Finally, applying a different approach, Liu et al. (2017) used an Improved Analytic Hierarchy Process (IAHP) and EWM to calculate the weights and a cloud model to overcome the problem of fuzziness and randomness in emergency railway decision-making.

2.2. The applications of a genetic algorithm together with TOPSIS

Other studies used genetic algorithms for solving multi-objective optimization problems especially together with TOPSIS for ranking the alternatives. The interest of the research was to recognize the way that these methods were combined in the literature in different areas of interest, concluding for an innovative application in the present study.

Cheng et al. (2009) applied the non-dominated sorting genetic algorithm (NSGA-II) to solve optimization functions and the TOPSIS approach to identify the best solution from a Pareto optimal solution set. They reached the conclusion that the NSGA-II outperforms the other genetic algorithms to help manufacturers find an appropriate collaborative manufacturing chain for manufacturing complex products. Azadeh et al. (2011) created a hybrid genetic algorithm and TOPSIS simulation (HGTS) for determining the most efficient number of operators and labour assignment in cellular manufacturing systems. The entropy method was used to estimate the weight of the attributes. The authors concluded for the superiority and advantages of the HGTS proposed over TOPSIS, Data Envelopment Analysis (DEA), and Principal Component Analysis (PCA). Azzam and Mousa (2007) applied a combination of a genetic algorithm and the ϵ -dominance concept to solve the multi-objective reactive power compensation problem and used TOPSIS to assess the best solution from a set of alternatives. The results demonstrate the capabilities of the technique proposed in a single run. Cheng et al. (2006) presented a general framework for the multiple criteria parameter calibration problem by combining a genetic algorithm with TOPSIS for a rainfall-runoff model for flood forecasting in China. TOPSIS gave the ranking order of alternatives (chromosomes) and the attributes of multiple criteria are the flood characteristics. They concluded that the hybrid method is easier when compared with previous studies and feasible and robust to be applied in practice. Huang and Tang (2005) adopted the Taguchi method, neural networks, TOPSIS, and the genetic algorithm to develop an optimization system that evaluates simultaneously four qualities of as-spun polypropylene yarn rather than using engineering experience. The performance of the parameters was assessed with TOPSIS while the parameter measurements and the parameter combination were optimized with the genetic algorithm. The authors showed that the algorithm could obtain the smallest denier and breaking elongation, the second smallest denier variance, and the largest tenacity. Taleizadeh et al. (2009) used a hybrid method of Pareto, TOPSIS, and genetic algorithm to solve multi-periodic inventory control problems. Olçer (2008) employed a two-stage hybrid approach for solving a multi-objective combinatorial optimisation (MOCO) problem in ship design. In the first stage, through an evolutionary process, a genetic algorithm was used (Frontier) to determine the set of pareto-optimal solutions. TOPSIS was adopted to rank these solutions in the second stage. The author concluded that the model can be applied in various MOCO problems in ship design and shipping. Goyal et al. (2012) applied a NSGA-II to identify the pareto frontiers for machine selection based on machine reconfigurability and operational capability along with cost. Shannon entropy weighted the attributes and TOPSIS was employed to rank the pareto frontiers. The study reveals that the hybrid approach has a great potential in handling the reconfigurable manufacturing system optimisation. Li et al. (2008) presents an integrated methodology for designing and optimizing a chemical process based on the green chemical principles. They performed a multi-objective mixed integer non-linear mathematical model considering environmental and economic factors solved by NSGA-II. TOPSIS was used for identifying the set of optimal parameters. Dhanalakshmi et al. (2011) applied a modified NSGA-II (MNSGA-II) to solve the combined economic and emission dispatch problem with conflicting objectives such as fuel cost and emission. TOPSIS was used to identify the best solution. Jeyadevi et al. (2011) compared the performance of MNSGA-II, NSGA-II, and multi-objective particle swarm optimization (MOPSO) with respect to multi-objective performance measures optimal reactive power dispatch. TOPSIS was applied to determine a best compromise solution. The authors reached the conclusion that MNSGA-II performs better than NSGA-II.

The application of a genetic algorithm based on NSGA-II to simultaneously solve multi-objective functions and of decision making methods, including TOPSIS, LINMAP, and Fuzzy Bellman-Zadeh models, to acquire the ultimate optimum solution have been done in literature in several areas. Ahmadi et al. used NSGA-II and TOPSIS and LINMAP to solve the optimum solution in refrigeration systems (Ahmadi et al., 2016a, 2016b). More recently, Ahmadi et al. used NSGA-II and TOPSIS, LINMAP, and Fuzzy Bellman-Zadeh models to solve the optimum solution in hydrogen production system, and Diesel cycle (Ahmadi et al., 2018a, 2018b). Beyond the application of genetic algorithms together with TOPSIS, Chen et al. (2019) developed a hybrid atmospheric pollutant concentration forecasting model based on a particle swarm optimization (PSO) algorithm, the support vector machine (SVM) method, and a K-means clustering algorithm, conducting a case study in Beijing. Mohammadi et al. (2018) applied a multi-objective optimization with a genetic algorithm (NSGA-II) to satisfy the exergy efficiency and product cost rate at the same time of a combined gas turbine, steam, and organic Rankine cycle. The minimum distance method was applied to choose the optimal point. Wang et al. (2018) proposed two distance methods to deal with the problem of linguistics preference information under multi-criteria group decision making and applied the TOPSIS-VIKOR method (Baccour, 2018) and TODIM (an acronym in Portuguese for interactive and multiple attribute decision making) to weight and order the probabilistic alternatives.

The gap in the literature was found, after identifying the articles that used TOPSIS in the infrastructure, transport, and in the railway sectors, whether alone or in combination with other methods, and the studies that especially applied TOPSIS together with genetic algorithms in diverse areas. To the best of our knowledge, no study has been developed using a genetic algorithm for determining the weights of the criteria selected in the TOPSIS model in order to build optimized scenarios, which constitutes the gap that this article seeks to fill. The use of railway sections is also an innovation that makes it possible to associate efficiency with the physical and operational characteristics, the transportation capacity, idleness, and the type of regulation of each railway section.

Table 1 summarises the references.

Table 1
References summary.

authors	year	sector	methodology	weighting/ranking method
TOPSIS in infrastructure, transport, and railways				
Askarifar et al.	2018	public infrastructure	BWM	TOPSIS
Keshavarz-Ghorabaee et al.	2018	bridge design (infrastructure)	Fuzzy-TOPSIS	Fuzzy-TOPSIS
Kannan et al.	2009	third-party logistics	ISM and Fuzzy-TOPSIS	Fuzzy-TOPSIS
Afful-Dadzie et al.	2015	aid facilities (infrastructure)	Fuzzy-TOPSIS	Fuzzy-TOPSIS
Farajpour and Yousefli	2018	supply chain	Fuzzy-TOPSIS	Fuzzy-TOPSIS
Liu and Wei	2018	electric vehicle infrastructure	Fuzzy-TOPSIS	Fuzzy-TOPSIS
Rahdar and Khalily-Dermany	2017	wireless network (infrastructure)	Fuzzy-TOPSIS	Fuzzy-TOPSIS
Onat et al.	2016	electric vehicle infrastructure	Fuzzy MCDM	Fuzzy-TOPSIS
Celik et al.	2013	public transport	Fuzzy MCDM based on TOPSIS and GRA	Fuzzy-TOPSIS and Fuzzy GRA
Tian et al.	2018	green supplier	Fuzzy TOPSIS	BWM
Li et al.	2018	grain distribution centre	TOPSIS	EWM
Yan et al.	2017	inland waterway transportation	Fuzzy-TOPSIS	CBR/Fuzzy-TOPSIS, VIKOR, ELECTRE and PROMETHEE (I and II)
Pham et al.	2017	logistic centre	hybrid Fuzzy method	Fuzzy Delphi/TOPSIS
Jayasooriaya et al.	2018	green infrastructure	TOPSIS	Delphi survey/TOPSIS
Huang et al.	2018	third party logistics	TOPSIS	EWM
Zhang et al.	2018	public transport	TOPSIS	EWM
Baghery et al.	2018	tourism infrastructure	VIKOR and TOPSIS	EWM
Zhao et al.	2018	Railways	TOPSIS	AHP (two-phased method)
Moosivand and Farahani	2013	tourism infrastructure	TOPSIS	AHP
Singh et al.	2018	third-party logistics	Fuzzy-TOPSIS	Fuzzy AHP
Fabianowsky and Jakiel	2018	Railways	Fuzzy-TOPSIS	Fuzzy AHP
Zhang and Xu	2009	Railways	Fuzzy-TOPSIS	AHP
Behzadian et al.	2012	diverse (including supply chain management and logistics)	TOPSIS	–
other reference				
Liu et al.	2017	Railways	cloud model	improved AHP and EWM
genetic algorithm together with TOPSIS				
Cheng et al.	2009	Manufacturing	NSGA-II	TOPSIS
Azadeh et al.	2011	Manufacturing	HGTS	EWM/TOPSIS
Azzam and Mousa	2007	Manufacturing	genetic algorithm and ϵ -dominance concept	TOPSIS
Cheng et al.	2006	flood forecasting	genetic algorithm	TOPSIS
Huang and Tang	2005	Manufacturing	Taguchi method, neural networks, TOPSIS, genetic algorithm	TOPSIS
Taleizadeh et al.	2009	inventory control	hybrid Pareto, TOPSIS, genetic algorithm	TOPSIS
Ölçer	2008	ship design	MOCO and Frontier (genetic algorithm)	TOPSIS
Goyal et al.	2012	machine selection	NSGA-II	EWM/TOPSIS
Li et al.	2008	chemical process	NSGA-II	TOPSIS
Dhanalakshimi et al.	2011	emission dispatch (power system)	MNSGA-II	TOPSIS
Jeyadevi et al.	2011	power dispatch	MNSGA-II, NSGA-II, MOPSO	TOPSIS
Ahmadi et al.	2016a	refrigeration system	NSGA-II	TOPSIS, LINMAP
Ahmadi et al.	2016b	refrigeration system	NSGA-II	TOPSIS, LINMAP
Ahmadi et al.	2018a	hydrogen production system	NSGA-II	TOPSIS, LINMAP, Fuzzy
Ahmadi et al.	2018b	Diesel cycle	NSGA-II	TOPSIS, LINMAP, Fuzzy Bellman-Zadeh
other references				
Chen et al.	2019	pollutant concentration forecasting	hybrid PSO algorithm-SVM method	K-means clustering algorithm
Mohammadi et al.	2018	gas turbine	NSGA-II	minimum distance method
Wang et al.	2018	–	two distance methods	TOPSIS-VIKOR and TODIM

TOPSIS = Technique for Order Preference by Similarity to Ideal Solution; BWM = Best-Worst Method; ISM = Interpretive Structural Modelling; MCDM = Multiple Criteria Decision Making; GRA = Grey Relation Analysis; NSGA-II = Non-dominated Sorting Genetic Algorithm; HGTS = Hybrid Genectic algorithm and TOPSIS Simulation; MOCO = Multi-Objective Combinatorial Optimisation; MNSGA-II = Modified NSGA-II; MOPSO = Multi-Objective Particle Swarm Optimization; PSO = Particle Swarm Optimisation; SVM = Support Vector Machine
EWM = Entropy Weight Method; CBR = cost-benefit ratio; AHP = Analytic Hierarchy Process; VIKOR = VIseKriterijumska Optimizacija I Kompromisno Resenje a Serbian name; ELCTRE = ELimination Et Choice Translating REality; PROMETHEE = Preference Ranking Organization METHods for Enrichment Evaluation; LINMAP = Linear Programming Technique for Multidimensional Analysis of Preference; TODIM = interactive and multiple attribute decision making (Portuguese acronym)

3. Methodology

The methodology proposed uses a genetic algorithm of a differential evolution to change the weights of the criteria (mutation) and to optimize the objective function, the median of the TOPSIS scores of the railway sections, simulating virtual optimized scenarios of low and high performance whose characteristics will be evidenced by a Tobit model. The methods are presented below.

3.1. Topsis

The Technique for Order Preference by Similarity to Ideal Solution developed by Hwang and Yoon (1981) is a multi-criteria decision making (MCDM) technique based upon the concept that the alternative chosen should have simultaneously the shortest distance to a (positive) ideal solution (A^+) and the farthest distance from a negative ideal solution (A^-). The ideal solution maximizes the benefit and also minimizes the total cost while the negative-ideal solution minimizes the benefit and also maximizes the total cost (Azadeh et al., 2011). The TOPSIS method measures the weighted Euclidian distances, as showed in Fig. 1.

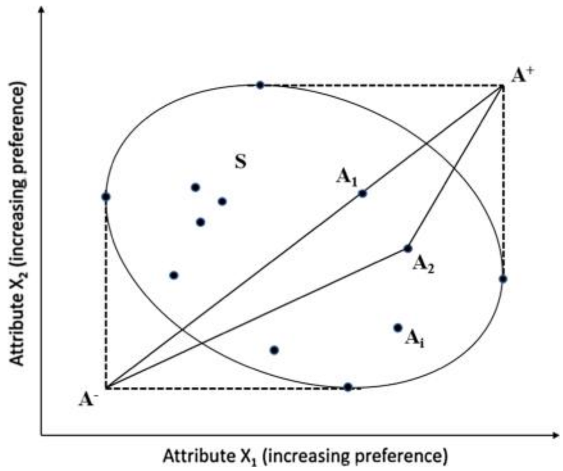

Fig. 1. Euclidean distances to the ideal and negative-ideal solutions. Source: Hwang, C. L. and Yoon, K. (Hwang and Yoon 1981).

The TOPSIS analysis starts with normalizing the decision matrix that can reduce the computational problems that may occur due to different units and measurements of the criteria selected (Jayasooriya et al. 2018). The successive steps present the TOPSIS method.

Step 1 is to construct the normalized decision matrix (NDM) whose element r_{ij} is calculated by:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{1}$$

where x_{ij} = outcome of i^{th} alternative with respect to the j^{th} criterion.

Step 2 is to multiply the columns of the NDM by the associated weights (w_j), finding the weighted NDM with (v_{ij}) components.

$$(v_{ij})_{mxn} = (w_j.\ r_{ij})_{mxn} \tag{2}$$

Step 3 is to determine the ideal solution [A^+], which is the best performance in each positive and negative criteria (the perfect alternative), and negative ideal solution [A^-].

$$A^+ = \{(\max_i v_{ij} \mid j \in J), (\min_i v_{ij} | j \in J') | i = 1, 2, \cdots, m\} = \{v_1^+, v_2^+, \cdots, v_j^+, \cdots, v_n^+\} \tag{3}$$

$$A^- = \{(\min_i v_{ij} | j \in J), (\max_i v_{ij} | j \in J\hat{A}) | i = 1, 2, \cdots, m\} = \{v_1^-, v_2^-, \cdots, v_j^-, \cdots, v_n^-\} \tag{4}$$

where J = {j = 1, 2, …, n | j, associated with benefit criteria} and

J́ = {j = 1, 2, …, n | j, associated with cost criteria}.

Step 4 is to calculate the Euclidean distance for vectors [A +] and [A^-] for each component of the sample from the ideal alternative (v_j^+) and from the non-ideal alternative (v_j^-), saving [d_i^+] and [d_i^-], where:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad \mathrm{i} = 1, 2, \cdots, \mathrm{m};\ 0 < d_i^+ < 1 \tag{5}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \quad \mathrm{i} = 1, 2, \cdots, \mathrm{m};\ 0 < d_i^- < 1 \tag{6}$$

Step 5 is to calculate the relative closeness of a particular alternative (A_i) to an ideal solution [ξ], where:

$$\xi = \frac{d_i^-}{(d_i^+ + d_i^-)};\ 0 < \xi < 1 \tag{7}$$

Step 6 is to rank the alternatives by the highest scores [ξ].

In the TOPSIS method, the relative importance of each criteria is exogenously defined, which is different from other nonparametric MCDM models that determine performance levels of units. Although computationally simple and with no constraints as to the number of criteria, determining the weights can be an issue for the researcher (Aye et al., 2017). Besides, the TOPSIS method does not offer details about the determinants of the scores. To solve these issues, a genetic algorithm was applied to determine the weights considering the optimized objective function, thus building two extreme scenarios. In a second stage approach, the Tobit regression revealed the determinants of the scores according to the different optimal scenarios found.

3.2. Genetic algorithm

The genetic algorithm (GA) is one of the optimization algorithms, usually called evolutionary algorithms (EA), which was created by Holland (1975) in the 1960 s inspired by the process of natural selection. It is commonly used to generate high quality solutions for global and combinatorial optimization by bio-inspired logical operators. The solution (chromosome) is repeatedly evolved until the best solution is attained. The GA creates a population of solutions and applies genetic operators (mutation and crossover) to evolve the solutions in order to find the best one(s) (Azadeh et al., 2011).

In the 1990s, Storn and Price (1977) developed the evolution strategy named differential evolution (DE). The DE algorithm is particularly well-suited to find the global optimum of a real-valued function in a wide variety of fields, including operation research. The members of successive generations are more likely to represent the global minimum of the objective function, the optimization process (Ardia et al., 2011a). The DE algorithm performs well with variables with distinct distributions and demands a considerable but manageable processing time. The implementation of DE using R uses the DEoptim package, first published by Ardia in 2005[1] (Ardia et al., 2016).

Each generation transforms the initial population. DE disturbs the current population members $x_{1,g}$ with a mutant, a trial parameter vector $v_{i,g}$, by choosing randomly three members of the population $x_{r0,g}$,$x_{r1,g}$and$x_{r2,g}$, which are the ones more likely to minimize the given objective function.

$$v_{i,g} = x_{r0,g} + F\cdot(x_{r1,g} - x_{r2,g}) \tag{8}$$

where

i indexes the vectors that make up the population and *g* indexes the generation
F is a scale factor, typically less than 1.

Mutations continue until all population members have been mutated or $rand > CR$, where *rand* is the random number from μ (0,1) and *CR* is a crossover probability $CR \in [0,1]$, the fraction of the parameter values that are copied from the mutant. The objective function value associated with v (children) is calculated. If a trial vector $v_{i,g}$ has equal or lower objective function value than vector $x_{i,g}$, $v_{i,g}$ replaces $x_{i,g}$ in the population, otherwise $x_{i,g}$ remains. The algorithm stops after a set number of generations or after the objective function value has been reduced below some threshold (Ardia et al., 2011a).

The use of a genetic algorithm to determine the weights of the TOPSIS model, simulating optimized scenarios of a production system based on the performance of its subparts, is an innovative approach of this research. Subsection 4.3 presents the pseudo-code with the application of the genetic algorithm.

3.3. Tobit model

The stochastic model proposed by Tobin (1958) describes the relationship between a non-negative latent variable and the independent variable (vector). The latent variable $y_t$is linearly dependent on x_t via a parameter β. The error term $u_t$captures the random influences from the relationship.

$$y_t = x_t\beta + u_t, \quad \text{if} x_t\beta + u_t > 0 \tag{9}$$

$$y_t = 0, \quad \text{if} x_t\beta + u_t \leq 0 \tag{10}$$

$$\mathrm{t} = 1,\ 2,\ \cdots, \mathrm{N} \quad u_t\ \mathrm{N}(0, \sigma^2)$$

where N is the number of observations, y_t is the dependent variable, x_t is the vector of independent variables, β is the vector of unknown coefficients, and u_t is the error term with normal distribution N (0, σ^2).

Because of its left censored characteristic, the Tobit model is well adequate for TOPSIS scores as the dependent variable of the regression. In the second stage, the censored regression is applied to evaluate the sign and significance of the contextual variables on the performance scores and is an additional contribution of this research.

4. Database, results, and discussion

4.1. Exploratory analysis

There were 7,351 railway sections selected from 2013 to 2016. The database comes from the Network Statement drawn up every

[1] The results presented were obtained with the R software version 3.3.4 available at cran (https://cran.r-project.org/).

Table 2
Data statistics.

variable	unit	type	min	Median	mean	Max	sd
rail section length	[km]	–	0.11	12.37	15.49	225.00	13.88
predominant gauge	[m]	p	1.00	1.00	–	1.60	0.26
minimum curve radius	[m]	p	0.00	225.00	326.80	5,292.00	350.85
# operational days per year	[days]	p	0.00	365.00	360.70	365.00	26.24
installed capacity	[trains/day]	p	0.70	9.10	15.81	223.20	19.63
linked capacity	[trains/day]	p	0.00	2.50	6.96	72.50	11.36
idleness	[trains/day]	n	−2.00	5.30	8.85	176.50	11.93
bottleneck	[trains/day]	p	0.00	34.90	39.32	200.00	30.58
linked capacity.rail section length	[trains.km/day]	p	0.00	36.29	87.01	4,650.75	230.86
increasing ramp tax	[%]	n	0.00	1.00	0.97	10.00	0.81
auxiliary power	[hp]	n	0.00	0.00	525.40	12,202.00	1,944.03
percentage of idleness	[%]	n	−100.00	65.10	60.68	100.00	30.58

p = positive; n = negative; idleness = [installed capacity - linked capacity]; bottleneck = [linked capacity/installed capacity*100]; percentage of idleness = [(1- linked capacity/installed capacity)*100]; # rail sections = 7,351 (2013–2016); negative values for idleness means over utilization of the rail section.

year by BRCS' concessionaires and disclosed by ANTT (ANTT, 2018). The errors (railway sections with a length or installed capacity equal to zero) and the missing data that disqualify the railway section for the purposes of the study (installed capacity, minimum curve radius, ramp, dangerous cargo, embedded equipment, type of traffic control, number of operational days per year, or linked capacity not informed) were excluded. Railway sections with a linked capacity equal to zero were considered to be one hundred percent idle. Table 2 presents the descriptive statistics of the quantitative variables that characterize BRCS's railway sections. The positive and negative variables used in the TOPSIS model are highlighted.

Figs. 2 and 3 show the behaviour of the idleness of the railway sections for each BRCS operator. Fig. 2 presents the idleness boxplot while Fig. 3, in a complementary way, represents the profile of the railway network's idleness for each concessionaire, whether small, medium, or high. Railway sections with idleness less than or equal to 10% are considered low idleness, idleness above 10% and less than or equal to 50% are considered medium idleness, and idleness above 50% are considered high idleness. It is easy to observe that the average idleness of the BRCS is high and greater than 60% (Fig. 2) and that the railway sections used the most (low idleness) do not exceed 10% of the length of the network of each concessionaire, except for the concessionaires EFC and MRS (Fig. 3). The concessionaires with their railway network less than 50% idle are EFC, MN, EFVM, and MRS, which not surprisingly are the most efficient ones (Marchetti and Wanke, 2017) (Fig. 3).

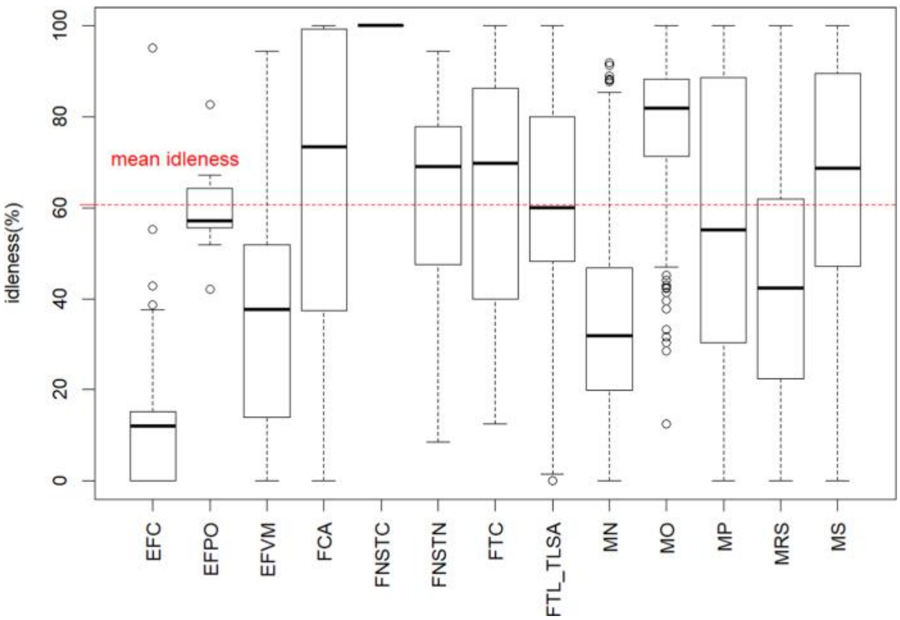

Fig. 2. Boxplot of rail section idleness by concessionaire.

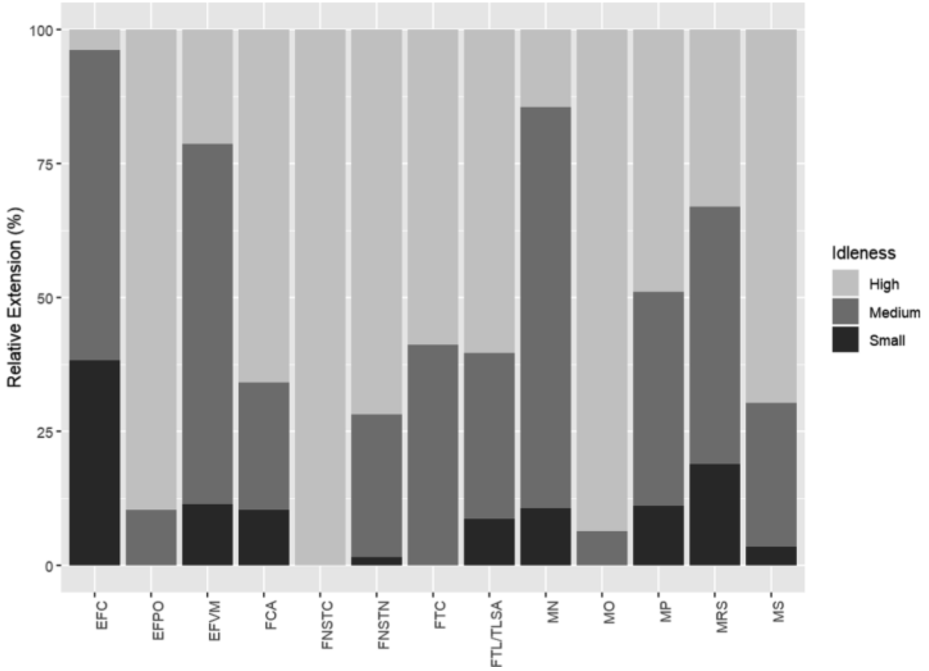

Fig. 3. Relative extension of the railway network according to idleness profile by concessionaire.

4.2. TOPSIS scores

Positive and negative variables of the TOPSIS model are presented in Table 1. When the value of the positive variables increases, it is approaching the ideal solution, and the inverse occurs with the value of the negative variables. Fig. 4 shows the histogram of the scores of the railway sections obtained from the TOPSIS model considering the positive and negative variables with equivalent weights and equal to 1 (medium scenario). The median of the scores is low (0.38) due to the high idleness of the BRCS.

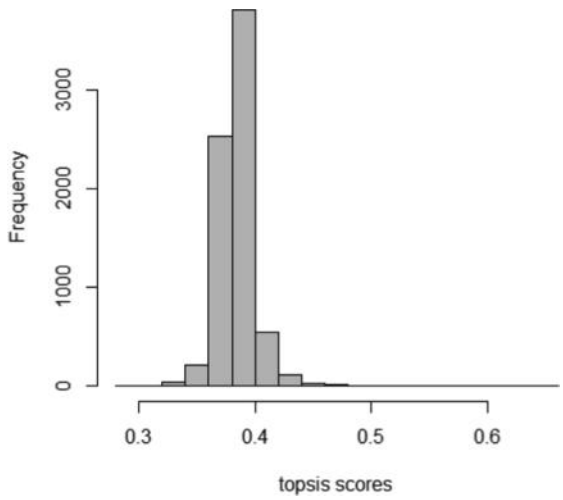

Fig. 4. Histogram of the TOPSIS scores of the railway sections in the medium performance scenario.

The TOPSIS scores of the railway sections in the medium performance scenario were separated by deciles, making it possible to interpret the frequency distribution profile of the sections by concessionaire according to the scores. The first decile is the set of the 10% least efficient railway sections (medium scenario qt 10) and the last decile is the set of the 10% most efficient railway sections (medium scenario qt 90).

Fig. 5 shows the boxplot and histogram of the TOPSIS scores of the railway sections per concessionaire considering three different situations in the medium performance scenario. On the left, the graph represents the first decile (medium scenario qt 10), the low performers, while on the right the graph represents the last decile (medium scenario qt 90), the high performers, and the integral medium scenario is in the centre. The highest histograms on the left show the largest amount of railway sections with the lowest scores, which are located in concessionaires MO, MP, MRS, and MS. To the right, the concessionaire MRS also holds the highest amount of sections with the best scores, showing heterogeneity. The railway sections of concessionaires EFC and EFVM, the most efficient ones, present the best scores and are concentrated in the last decile, as shown in the medium scenario qt 90 boxplot in the centre.

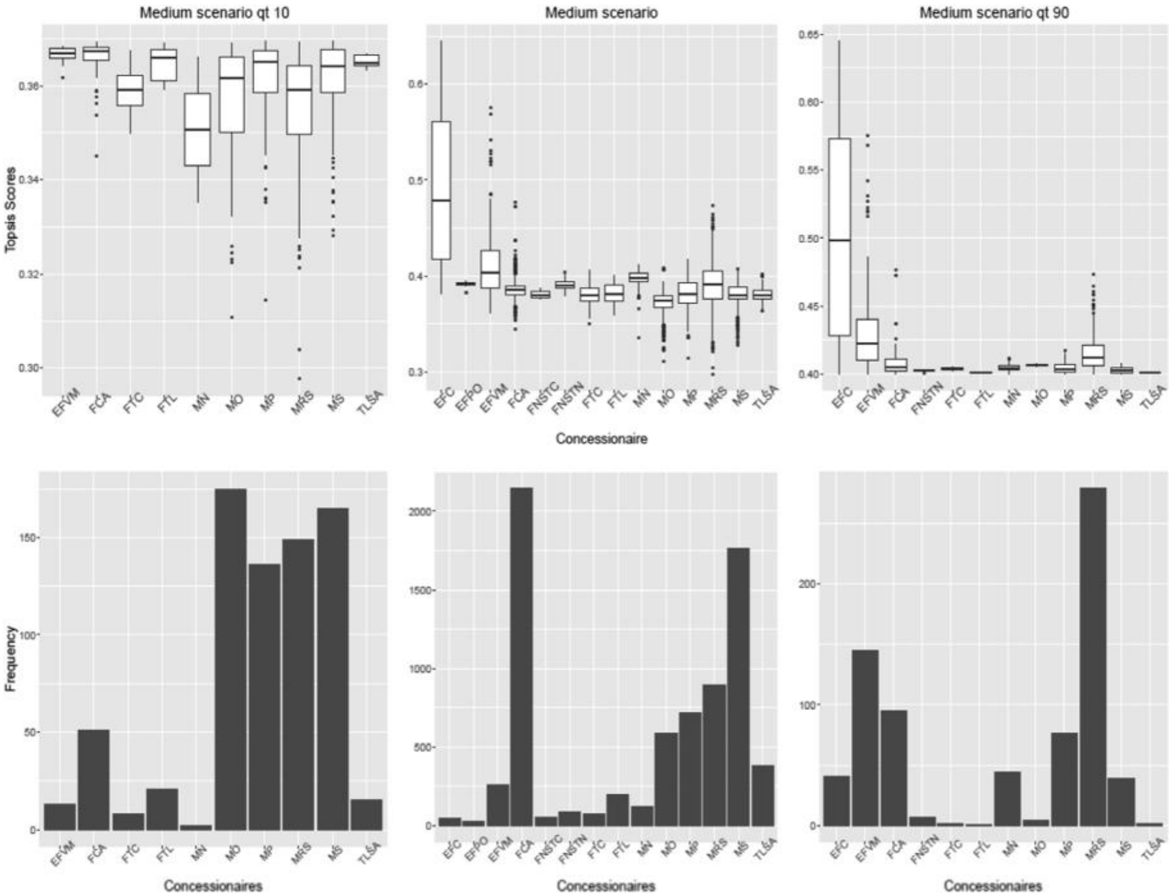

Fig. 5. Boxplot and histogram of the TOPSIS scores of the railway sections in three different conditions in the medium performance scenario.

4.3. Optimization scenarios

As commented in Section 3, a genetic algorithm was used to modify in an evolutionary way the weights applied to each one of the positive and negative variables of the TOPSIS model, creating new generations of values for the scores, and finally, after a limited interaction number, obtaining optimized scenarios (low and high performance). The objective function was the median of the scores. The reason for using the Differential Evolution Optimization (DEOptim) algorithm (Ardia et al., 2011a, 2011b) is due to the fact that it works well with variables of different distributions and because its processing time is manageable.

The optimization process took place in accordance with the pseudo code from Table 3. First, a random drawing was done without replacement of eight railway sections from each concessionaire in order to represent the heterogeneous profile of the BRCS. The sample size was defined considering a population of 7,351 railway sections, a confidence interval of 95%, and an error lower than 10%. Next, the highest and lowest median value of the TOPSIS scores from the sample was determined through a maximization (high performance) and minimization (low performance) process by applying the differential evolution algorithm, saving the vector of weights assigned to the sample's variables. A bootstrapping was implemented, generating 100 new samples. At the end of the processing, the average weights of each scenario were determined. Finally, the TOPSIS scores of the railway section population was calculated considering the optimized weights in the high and low performance scenarios. The objective of building extreme scenarios was to gather evidences that characterize these scenarios, making feasible this way to point out the planning guidelines needed to increase BRCS' efficiency.

Table 3
Pseudo code.

1. Random sort of 8 railway sections per operator without replacement (s = 112, N = 7,351; CI = 95%; error = 10%)
   2. Optimize the objective function value with the DE algorithm considering the high (maximization) and the low (minimization) scenarios for each sort, saving the results (weights)
3. Execute bootstrapping (n = 100)
   4. Determine the mean of the weights applied to each positive and negative variable for the high and low scenarios (n = 100)
   5. Calculate the TOPSIS scores with the optimized weights for the high and low scenarios considering all railway sections. End of process.

s = sample size; N = number of railway sections; CI = confidence interval; n = number of bootstrapping repetitions.

Table 4 summarises the optimized weights in the low and high performance scenarios resulting from the optimal solutions found.

Table 4
Weights applied to the TOPSIS variables in the optimized scenarios.

variable	high performance scenario	low performance scenario
predominant gauge	0.20824	0.22204
minimum curve radius	0.02875	0.07779
# operational days per year	1.01578	0.20191
installed capacity	0.01852	0.15048
linked capacity	0.02165	0.24341
idleness	0.16800	0.01491
bottleneck	0.05880	0.06297
linked capacity.rail section extension	0.01114	1.82255
increasing ramp tax	0.08802	0.03055
auxiliary power	1.83682	0.01126
percentage of idleness	0.06463	0.08182

Fig. 6 illustrates the density plot showing the distribution of the TOPSIS scores according to the low, medium, and high performance scenarios. The x-axis shows the score values and the y-axis presents the probability density function (kernel density estimation). One can note that the frequency distribution behaviour of the optimized scores is consistent with the pseudo-code's strategy (Table 3).

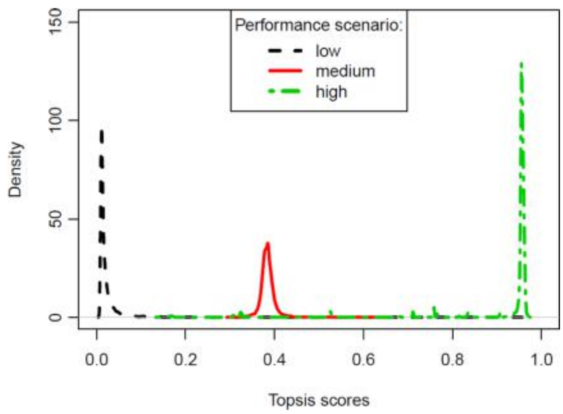

Fig. 6. TOPSIS score density according to low, medium, and high performance scenarios.

4.4. Tobit model results

The Tobit model shows the effect of the contextual variables selected on the scores in different scenarios (dependent variable). The independent variables selected were the relative performance of the operators in relation to benchmarking (EFC), the technologies employed in the railroad operation (hazardous cargo, embedded equipment, and track control), the type of cargo transported (agricultural and general cargo), and the type of regulation regarding the use of the railway track (restrictive or open). Table 5 presents the results, including coefficient estimates and the significance of the variables according to low, medium, and high performance scenarios. It is worth noting that the transport of all type of cargo, the centralized control of the operation, and the sharing of the rail track are significant for high performance.

Table 5
Tobit regression results.

type of variable	variable	Scenarios					
		low performance		medium performance		high performance	
		Estimate	Signif	estimate	Signif	estimate	signif
	(Intercept)	0.29584	***	0.46931	***	0.99672	***
Brazilian railway operators	EFPO	−0.33434	***	−0.09776	***	0.01007	
	EFVM	−0.23545	***	−0.07398	***	0.02904	
	FCA	−0.33585	***	−0.10265	***	−0.01549	
	FNSTC	−0.33604	***	−0.10588	***	−0.02864	
	FNSTN	−0.32834	***	−0.09727	***	0.00025	
	FTC	−0.32816	***	−0.10291	***	0.01366	
	FTL_TLSA	−0.33214	***	−0.10271	***	−0.06615	**
	MN	−0.30021	***	−0.09137	***	−0.01819	
	MO	−0.33380	***	−0.11197	***	−0.11573	***
	MP	−0.32328	***	−0.10242	***	−0.08669	***
	MRS	−0.29884	***	−0.09276	***	−0.09912	***
	MS	−0.33384	***	−0.10741	***	−0.02187	
diverse characteristics	hazardous_cargo (y = 1/n = 0)	0.00472	**	0.00243	**	−0.03032	***
	embedded_equipment (y = 1/n = 0)	0.03971	***	0.00786	***	−0.07184	***
	track_control (CCO = 1/local = 0)	0.01065	***	0.00614	***	0.01544	*
cargo type	agricultural	0.00138		0.00320	.	0.05397	***
	general_cargo	−0.00382		−0.00172		0.08217	***
legislation type	restricted	0.00155		−0.00032		−0.03781	***

Signif codes: 0 |***|; 0.001 |**|; 0.01 | * | ; 0.5 | · |; 1 | |
EFC = Estrada de Ferro Carajás S.A; EFPO = Estrada de Ferro Paraná Oeste S.A; EFVM = Estrada de Ferro Vitória a Minas S.A; FCA = Estrada de Ferro Centro-Atlântica S.A.; FNSTC = Ferrovia Norte Sul Tramo Central; FNSTN = Ferrovia Norte Sul Tramo Norte; FTC = Ferrovia Tereza Cristina S.A.; FTL = Ferrovia Transnordestina Logística S.A.; MN = Rumo Malha Norte S.A.; MO = Rumo Malha Oeste S.A.; MP = Rumo Malha Paulista S.A.; MRS = MRS Logística S.A.; MS = Rumo Malha Sul S.A.; TLSA = Transnordestina Logística S.A.; TLSA (2013–2014), FTL (2015–2016).
CCO = centralized control of the operation

Fig. 7 illustrates the evolution of the behaviour of the coefficients of the Brazilian railway operators, the diverse characteristics employed, the main cargo type transported, and the legislation type according to the low, medium, and high performance scenarios, facilitating the interpretation of the results.

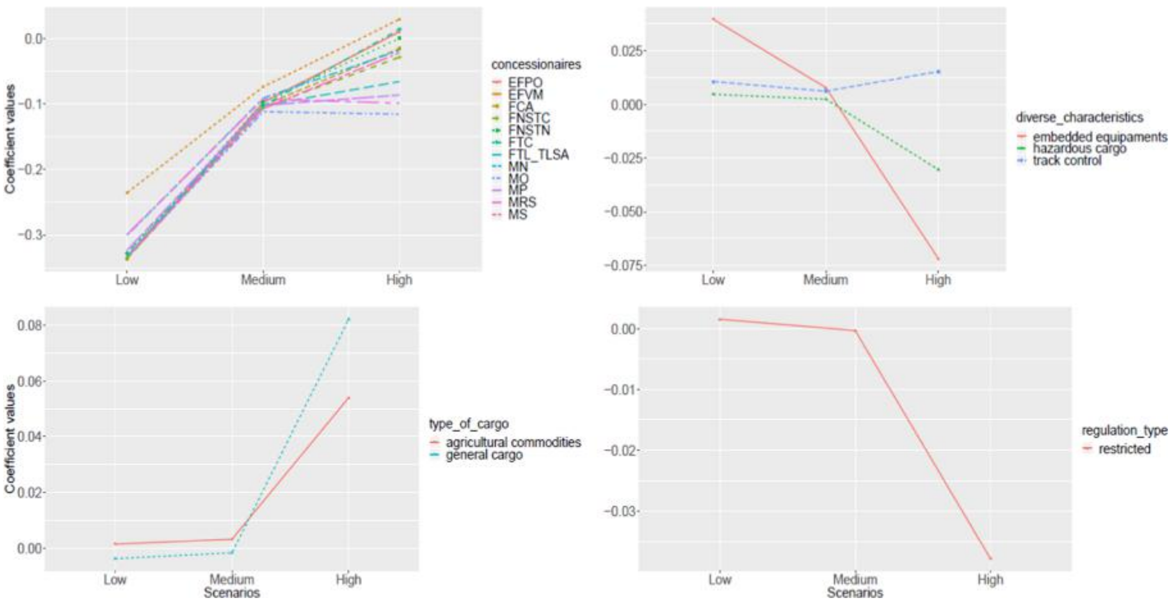

Fig. 7. Coefficients behaviour of contextual variables according to the scenario.

Considering the upper-left graph of Fig. 7, one can note that the performance of the concessionaires in low and medium performance scenarios is heterogeneous and significantly distant from the benchmark (negative coefficients). In the high performance scenario, however, there is evolution and convergence in the values of the coefficients showing much less dispersion, indicating improvement in BRCS's overall performance. The concessionaires that transport general and agricultural cargo (EFPO and FNSTN) showed a reversal in their coefficients signal (negative to positive). Considering the upper-right graph of Fig. 7, one can observe that the use of control centre of operations (CCO), thus bringing more safety to the railway's operation, remained significant in all scenarios, making it the most significant technology to be employed to increase BRCS's efficiency. Considering the lower-left graph of Fig. 7, one can note that, differently from the low and medium performance scenarios, the transportation of agricultural cargo and general cargo is significant in a high performance scenario. The transport of all types of cargo is significant for high performance. The reversal of the signal found in the coefficients of the concessionaires transporting agricultural and general cargo (EFPO and FNSTN) brings robustness to the evidence. Finally, considering the lower-right graph of Fig. 7, one can observe that the restrictive regulation presents significantly negative coefficients in the high performance scenario, meaning that the regulations that encourage competition between operators through sharing the use of railway sections (open access) contributes significantly to the scores.

4.5. Analysis of the percentiles of the optimized scenarios

The TOPSIS scores of the railway sections in the low and high performance scenarios were separated by deciles, making it possible to interpret the frequency distribution profile of the sections by concessionaire according to the scores. The first decile is the set of the 10% least efficient railway sections (low scenario qt 10 and high scenario qt 10), the low performers, and the last decile is the set of the 10% most efficient railway sections (low scenario qt 90 and high scenario qt 90), the high performers. They assist in understanding the extremes, where the critical railway sections are found, requiring greater attention from administrators for purposes of efficiency gains and possible references.

Fig. 8 shows the boxplot and the histogram of TOPSIS scores of the railway sections from three different situations considering the low performance scenario.

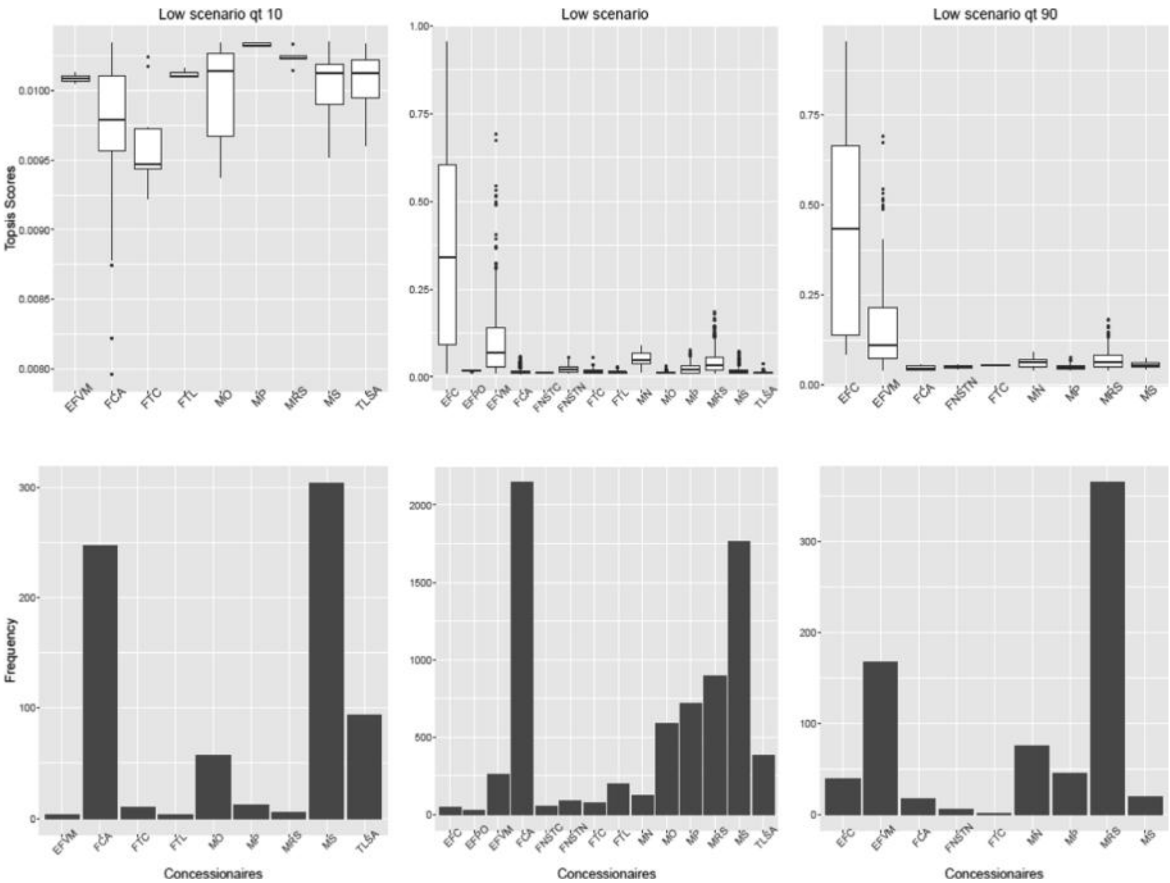

Fig. 8. Boxplot and histogram of the TOPSIS scores of the railway sections in three different conditions in the low performance scenario.

Some aspects should catch the attention of administrators and those responsible for public policies. On the left, the higher histograms of concessionaires FCA and MS represent the largest quantity of low performing railway sections. To the right, the high histogram of concessionaire MRS represents the largest amount of high performing railway sections. In the centre, considering all the sections, the boxplots of the benchmark concessionaires EFC and EFVM show that they have the railway sections with the highest scores and best operational conditions.

Fig. 9 plots the same graphs of Fig. 8, now considering the high performance scenario.

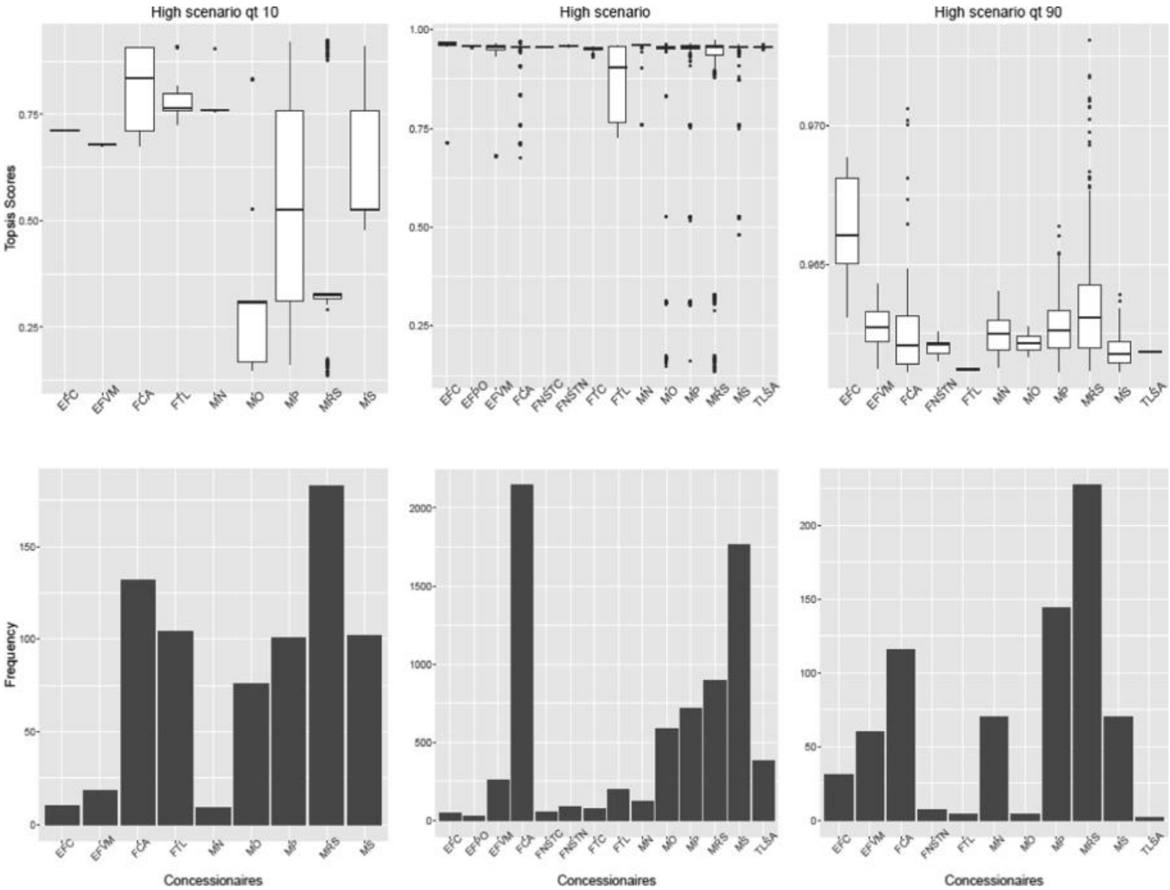

Fig. 9. Boxplot and histogram of the TOPSIS scores of the railway sections in three different conditions in the high performance scenario.

To the left, the boxplots of concessionaires MO, MRS, MP, and MS show that they hold the lowest performing critical railway sections. On the right, the boxplots of concessionaire EFC and the outlier sections of concessionaires MRS and FCA point out the best railway condition. At the centre, considering all the railway sections, the boxplot of concessionaire FTL shows the worst profile among all operators.

Fig. 10 shows the scatterplot of the cumulative extension of the railway sections (x-axis) by the number of sections (y-axis) per concessionaire. The heterogeneity (higher dispersion) of the low performance scenario in the first decile (low scenario qt 10) and in the last decile (low scenario qt 90) is replaced by the greater homogeneity (lower dispersion) of the high performance scenario in the first decile (high scenario qt 10) and in the last decile (high scenario qt 90). In the high performance scenario, the performance of the operators is much more homogeneous between the percentiles, confirming the results of the regression.

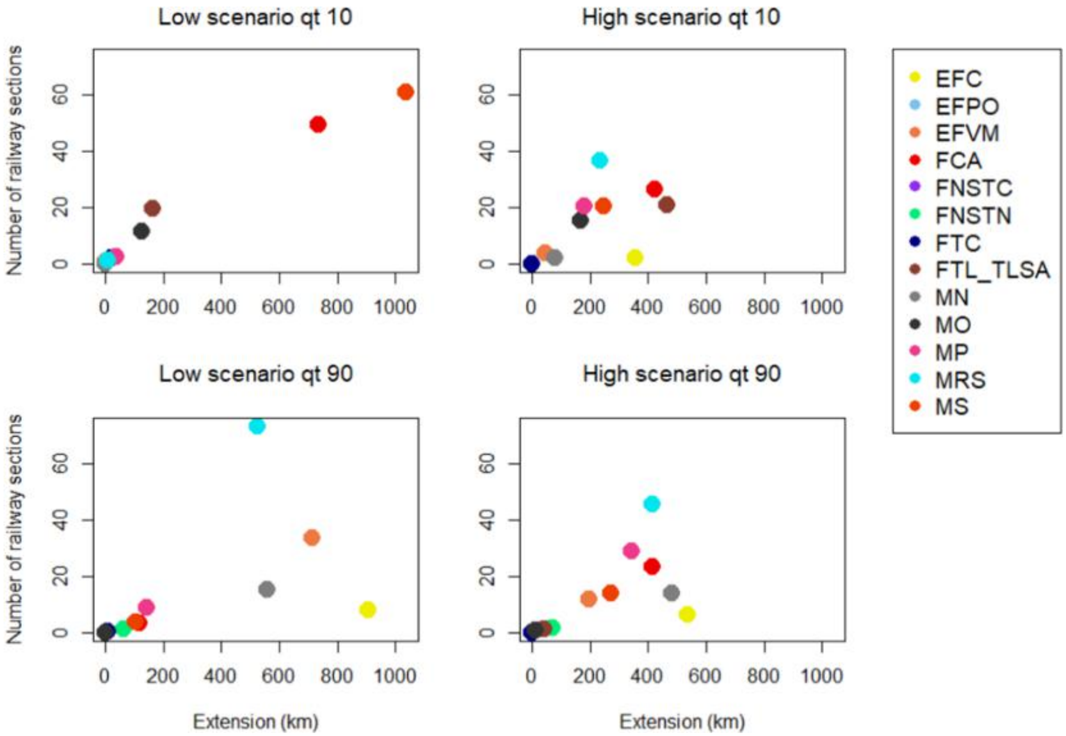

Fig. 10. Plot of the number of railway sections × cumulative extension (km) per concessionaire, according to the extreme scenarios.

4.6. Statistical tests between scenarios

Table 6 provides the results of two statistical tests applied into the variables used in the TOPSIS model (upper part) and one statistical test applied into contextual variables used in the Tobit model (lower part). It shows the statistical results found between the low and high performance scenarios according to low performers (left part) and high performers (right part) quartiles.

The Komolgorov-Smirnov test was used (two sample K-S test) to compare the distribution found in the median of the (positive and negative) variables used in the TOPSIS model between the low and high performance scenarios according to the low and high performers quartiles. The distributions are significantly different between the scenarios except for the variables ‘predominant gauge' and 'number of operational days per year' for the high performers, whose basic hypothesis (same distribution) was not rejected. The results of the Willcox Test, the difference between the medians, follow the results found in the K-S test except with the significance of the 'predominant gauge' for the high performers.

The proportion test (prop test) compared the proportion of existing railway sections between the low and high performance scenarios according to the low and high performers quartiles. It suggests that there is a significant difference between the scenarios, but mostly with the low performers. Considering the railway sections part of quartile 10, the basic hypothesis (same proportion) was not rejected for two concessionaires (FTL-TLSA, MO), the Mid-West region (MW), and all the technologies tested (transportation of hazardous material, embedded equipment, and CCO). As for the quartile 90, the basic hypothesis was not rejected for five concessionaires (EFC, FNSTN, FTC, MN, and MO), the North and Mid-West regions (N and MW), the CCO technology, and the restrictive regulation. Table 6 presents the results.

Table 6
Statistical tests between the low and high performance scenarios.

TOPSIS model variables	Description	low performers (10th percentile) (n = 735)		ks.test (p-value) (H_0 same distrib)	willcox.test p-value (H_0 same medians)	high performers (90th percentile) (n = 735)		ks.test (p-value) (H_0 same distrib)	willcox.test p-value (H_0 same medians)
		low perf scenario	high perf scenario			low perf scenario	high perf scenario		
TOPSIS positive criteria (median)	predominant gauge	1.000	1.000	**0.000**	**0.000**	1.600	1.600	0.058	**0.004**
	min curve radius	143.000	143.000	**0.000**	**0.000**	254.000	600.000	**0.000**	**0.000**
	operational days/year	365.000	365.000	**0.000**	**0.000**	365.000	365.000	0.989	0.326
	installed capacity	5.800	13.400	**0.000**	**0.000**	52.500	12.620	**0.000**	**0.000**
	linked capacity	0.200	5.800	**0.000**	**0.000**	38.700	10.000	**0.000**	**0.000**
	bottleneck	3.840	50.150	**0.000**	**0.000**	73.270	86.630	**0.000**	**0.000**
	linked capacity*length	1.600	66.300	**0.000**	**0.000**	287.840	148.800	**0.000**	**0.000**
TOPSIS negative criteria (median)	increasing ramp tax	1.700	1.000	**0.000**	**0.000**	0.700	0.600	**0.000**	**0.039**
	auxiliary power	0.000	3,600.000	**0.000**	**0.000**	0.000	0.000	**0.000**	**0.000**
	idleness	5.400	6.460	**0.000**	**0.003**	11.200	1.990	**0.000**	**0.000**
	idleness percentage	96.160	49.850	**0.000**	**0.000**	26.730	13.370	**0.000**	**0.000**

Tobit model variables	Description	Yes	no	yes	No	prop.test (p-value) (H_0 same prop)	yes	no	yes	no	prop.test (p-value) (H_0 same prop)
railway operator	EFC	0	735	10	725	**0.004**	39	696	31	704	0.391
	EFPO	0	735	0	735	na	0	735	0	735	na
	EFVM	3	732	18	717	**0.002**	168	567	60	675	**0.000**
	FCA	247	488	132	603	**0.000**	17	718	116	619	**0.000**
	FNSTC	0	735	0	735	na	0	735	0	735	na
	FNSTN	0	735	0	735	na	6	729	7	728	1.000
	FTC	10	725	0	735	**0.004**	1	734	0	735	1.000
	FTL_TLSA	97	638	104	631	0.649	0	735	6	729	**0.041**
	MN	0	735	9	726	**0.007**	75	660	70	665	0.726
	MO	57	678	76	659	0.102	0	735	4	731	0.133
	MP	12	723	101	634	**0.000**	45	690	144	591	**0.000**
	MRS	5	730	183	552	**0.000**	365	370	227	508	**0.000**
	MS	304	431	102	633	**0.000**	19	716	70	665	**0.000**
location (region)	MW	60	675	47	688	0.228	75	660	74	661	1.000
	N	0	735	10	725	**0.004**	45	690	38	697	0.498
	NE	144	591	104	631	**0.006**	0	735	6	729	**0.041**
	SE	217	518	472	263	**0.000**	595	140	547	188	**0.003**
	S	314	421	102	633	**0.000**	20	715	70	665	**0.000**
diverse characteristics of the railway operation	hazardous cargo	659	76	661	74	0.931	588	147	662	73	**0.000**
	embedded equipment	730	5	726	9	0.420	728	7	696	39	**0.000**
	CCO	686	49	700	35	0.144	726	9	721	14	0.401
cargo type	agricultural	504	231	257	478	**0.000**	122	613	268	467	**0.000**
	general cargo	213	522	284	451	**0.000**	53	682	205	530	**0.000**
	mineral	18	717	194	541	**0.000**	560	175	262	473	**0.000**
regulation type	restricted	49	686	216	519	**0.000**	138	597	139	596	1.000

MW = Mid-West; N = North, NE = Northeast; SE = Southeast; S = South

4.7. Public and management policies

Evidences for public and management policies were obtained in two ways. First from the significance of the variables selected in the railway section scores from each performance scenario. The results suggest that, in view of the common objective of increased efficiency, the regulator authority should pursue a competitive regulatory structure by removing restrictions or barriers to enter and exit and should encourage sharing the railway section among operators. In the high performance scenario, concessionaires transport any kind of cargo and have a homogeneous operating performance, reducing the differences among the operators as observed today (evidence from the low and medium performance scenarios). The use of CCO technology for increasing the railway operation safety also contributes to high performance.

The second set of evidences is the availability for identifying the efficiency of the railway sections of each concessionaire. They can be classified in an ascending/descending order according to the score in each scenario and identify which sections are part of quartile 10 (low performers) and quartile 90 (high performers), facilitating the managerial actions for improvement. This is useful for both managing the railway track as well as for the regulating and inspecting bodies. It highlights what each operator should emphasize or reference to increase efficiency. Greater homogeneity on the network should be pursued. Tables 7 and 8 in the supplement present a list of high (low) performing railway sections of each concessionaire in the high (low) performance scenario, indicating length, region, idleness, predominant type of cargo, and TOPSIS score.

5. Conclusions

This paper analyses the efficiency of BRCS's railway sections in the period 2013–2016 using a hybrid method and the significance of the variables selected in the optimized scenarios. The hybrid methodology used applied a differential evolution genetic algorithm to obtain the weights of the variables selected in the TOPSIS model, building optimized extreme scenarios. The methodology proposed differs from studies already done in the literature with the application of hybrid models with a genetic algorithm for a multi-objective optimization and TOPSIS to rank the optimal solutions.

The database of railway sections made it possible to link performance to physical and operational characteristics, transportation capacity, idleness, and type of regulation of the sections of each concessionaire, allowing findings that contribute significantly to answering the research question.

The contributions of this paper are twofold. As to the best of our knowledge, a simulation of the extreme scenarios in a (railway) system based on the characteristics of its network subparts (the rail sections) using a genetic algorithm to optimize the performance of the entire system according to the TOPSIS scores of the subparts is an innovative contribution of the research. The methodology proposed can be applied to different economic sectors treated as a network such as passenger and cargo railway systems and energy or telecommunication transmission lines.

In the second stage, the significant determinants to achieve high performance of BRCS were revealed. In the high performance scenario, the performance of the concessionaires is more homogeneous, different from the low and medium performance scenarios where there is dispersion in the operating performance. The transportation of general cargo is significant for the results, different from the low and medium performance scenarios whose transport is concentrated in bulk mineral and agricultural products for export. The market structure in a monopoly format is inefficient because it can inhibit the rise of new services that contribute to reducing the idleness of the assets. CCO technology is significant for high performance because it allows for a dense railway operation with trains coming from different regions and destinations operated by several concessionaire in an environment of greater integration and complementarity. The high performance scenario suggests a market structure where there is neither restriction of access to the railway track nor barriers to the entry and exit of new operators and services.

The implication of the paper is to determine new guidelines for BRCS's long-term strategic planning in order to increase the system's average performance. Public managers should push the companies toward transporting any type of cargo, service diversification, a centralized control of the operation, and sharing the railway track. Competition and diversification are key elements for high performance.

The secondary data from the railway sections was a limiting factor in the research. Obtaining data of total and linked capacity of BRCS's railroad segments with selected origin and destination may allow new findings and be the object of future research to expand the knowledge of the Brazilian rail cargo system's efficiency frontier.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article on request https://doi.org/10.1016/j.tre.2020.101858.

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