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Optimization of locomotive allocation in railway transport flows using mixed-integer linear programming

Otimização de alocação de locomotivas em fluxos de transporte ferroviário com programação linear inteira mista

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ABSTRACT
Traditional methods for planning the sizing and allocation of railway locomotives are, at best, based on heuristics that lack reproducibility and standardization, often resulting in inefficient use of company resources. This study aims to develop a decision support system for locomotive operation planning using mixed-integer linear programming, incorporating the metrics of Overall Rolling Stock Effectiveness (ORSE) and Energy Efficiency (EE). Applied to MRS Logística S/A, the research relied on 24 months of historical and operational data (Jan/2017–Dec/2018), performance indicator analysis, and the development of a mathematical model implemented in LINGO® for planning operations in 2020. The results demonstrated improvements in fleet utilization, availability, and energy efficiency, as well as a reduction in the number of locomotives required to meet transport demand. The model reduced fuel consumption by 0.6% and increased overall asset effectiveness by up to 1.8% compared to heuristics, while also ensuring greater reliability, flexibility, and efficiency in the operational planning process itself.

RESUMO
Os métodos tradicionais de planejamento de dimensionamento e alocação de locomotivas ferroviárias são, no melhor dos casos, baseados em heurísticas que, além de carecerem de reprodutibilidade e padronização, resultam em ineficiência no emprego de recursos das empresas. Este estudo visa desenvolver um sistema de apoio à tomada de decisão para o planejamento da operação de locomotivas baseado em otimização com programação linear inteira mista, envolvendo as métricas de Efetividade Global de Material Rodante (EGMR) e Eficiência Energética (EE). Aplicada à MRS Logística S/A, a pesquisa utilizou dados históricos e operacionais de 24 meses (jan/17 a dez/18), análise de indicadores de desempenho, e desenvolvimento de um modelo matemático programado em LINGO®, para planejamento da operação de 2020. Os resultados demonstraram melhorias na utilização, disponibilidade e eficiência energética da frota, além de uma redução no número de locomotivas necessárias para atender à demanda de transporte. O modelo reduziu o consumo de combustível em 0,6% e aumentou a efetividade global dos ativos em até 1,8%, comparado às heurísticas, assegurando ainda maior confiabilidade, flexibilidade e eficiência no próprio processo de planejamento da operação.

1. Introduction

The railway sector is a key pillar in the logistics of agricultural commodities, iron ore, bauxite, containers, steel products, cement and other goods essential to the global economy. This is primarily due to its economic efficiency compared to other modes, especially when cargo loads exceed 40 tons, regardless of the distance traveled (CNT, 2013).

The competitiveness of this sector and the production chains in which it participates directly depends on productivity levels (Slack & Lewis, 2009), high asset utilization, an optimized ratio between production (train × km × load) and costs, railway energy efficiency, and adherence to global speed standards.

The growing pressure for operational efficiency has made the adoption of more robust decision-making practices increasingly imperative, grounded in the use of data and analytical models. The application of optimization techniques in railway planning is a promising alternative to overcome the limitations of traditional and empirical methods, such as the lack of standardization, predictability, and reproducibility of results of such processes.

Studies such as Beck *et al.* (2013) show that this reality is not exclusive to Brazil, highlighting opportunities for optimizing asset effectiveness also in the context of European freight operations. The absence of robust benchmarks and the heterogeneity of practices and metrics in railway performance management reinforce the urgency of developing analytical tools that enable decisions based on objective metrics and aligned with the organizational strategic objectives.

This research aims to develop a model for optimizing locomotive sizing and allocation decisions in railway logistics flows, through optimization to maximize overall asset effectiveness and energy efficiency, thereby ensuring better return on company investments and meeting customer production requirements. This outcome is grounded in the Overall Rolling Stock Effectiveness (ORSE) indicator developed by Domiciano (2020), and in the energy efficiency metric already consolidated and widely employed in the management of Brazilian railway operations (Albuquerque, 2006).

The application and validation of this research were conducted at MRS Logística S/A, one of the largest Brazilian railway operators, responsible for 1,634 km of railway and nearly 20% of all Brazilian exports, equivalent to almost one-third of the total freight transported by rail in the country. Its rolling stock fleet, the focus of this study, comprised more than 18,000 wagons and 700 locomotives in 2022.

2. Methodology

This is applied research in nature, as it seeks to solve specific and practical problems faced daily by railway operation planning areas. It is characterized as exploratory research, as it assesses the state of the art in optimization methods applied to locomotive sizing and allocation worldwide. Finally, this study employs a quantitative approach, using asset management and locomotive operational performance metrics in railway logistics flows within a mathematical decision-making model. Although applied to a Brazilian railway, the proposed framework is designed to be applicable to railway systems worldwide. The framework in Figure 1 summarizes the research methodology that was employed.

In the first phase, scientific publications that reflect the state of the art regarding methods for evaluating railway asset performance and their applications, energy efficiency, and locomotive allocation optimization techniques in freight railway transport flows worldwide are consulted. Next, the developed optimization model is presented in detail, and finally, the results of asset sizing and operational performance are compared when obtained through traditional heuristics and when obtained through mixed-integer linear programming optimization.

This comparison is based on the application of both methods to operational planning, using maintenance and operation databases provided by the railway concessionaire sponsoring this study,

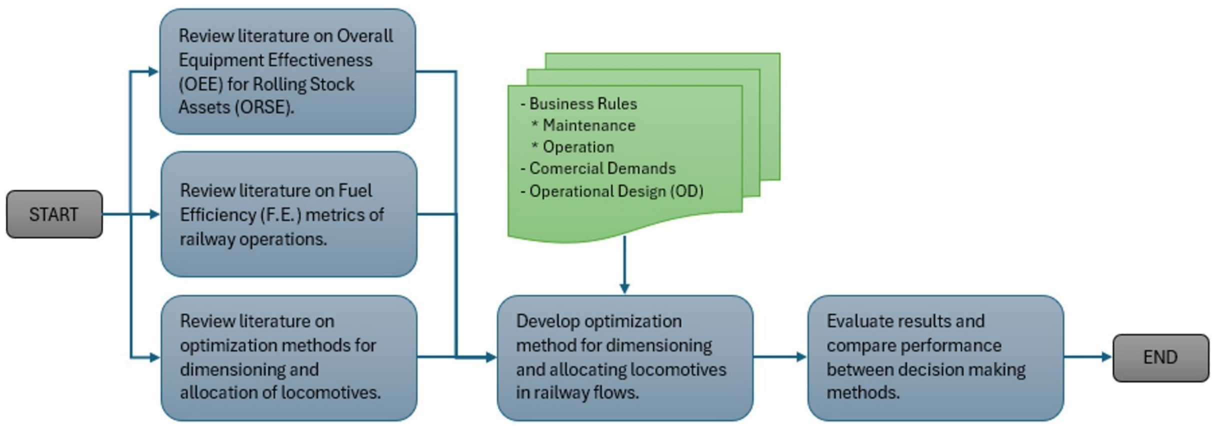

Figure 1 • Framework for developing and validation of locomotive allocation optimization (Domiciano, 2020)

spanning a 24-month period from Jan/2017 to Dec/2018, and for planning the operations of the 12 months of 2020. The optimization is carried out through mixed-integer linear programming, implemented in LINGO® software from LINDO Systems, licensed by the company itself.

3. Literature review

3.1. Definitions

For a better understanding of the developments carried out through this research, it is necessary to define terms considered basic in the context of railway operations, which may vary slightly between railways:

1) *Railway transport flow*: the definition of a specific cargo between a given origin and destination (Barra, 2008);
2) *Wagon consist (Wagon set)*: the group of wagons that serves a specific transport flow (Barra, 2008);
3) *Locomotive block*: the arrangement of locomotives (which may consist of one or more locomotives) required for hauling a wagon set (Barra, 2008);
4) *Train Consist (Composition)*: a wagon set attached to a locomotive block, intended to serve a railway transport flow (Cassemiro & Costa, 2015);
5) *Fuel (Energy) Efficiency* (F.E.): the fuel consumption required for the transportation of each 1,000 × TKU. Its importance is linked to the fact that fuel represents the largest share of a railway's operating costs (Rodrigues, 2018; Abreu & Lopes, 2017).

Once the main concepts in the railway operation context are understood, the necessary foundation is established to develop the review of the remaining principles of the optimization model proposed in this research.

3.2. Operational efficiency and overall asset effectiveness metrics

To achieve the previously stated objective of developing a model for optimal sizing and allocation of locomotives in railway logistics flows, it is essential that the optimization model incorporates performance indicators that capture all the key and most relevant aspects of railway operations. This is the basic purpose of overall asset effectiveness indicators, originally created in industrial environments and later adapted to diverse productive contexts worldwide (Hansen, 2002).

The railway context, especially concerning rolling stock, lacked specific metrics to measure the overall effectiveness of its assets. Silva & Leal Jr. (2015) analyzed operational efficiency indicators in Brazilian and international railway companies, noting that although all of them monitored energy efficiency, few tracked wagon productivity or the average cycle time of train consists, and none included an overall effectiveness indicator. Leal Jr. *et al.* (2010) also investigated the performance of Brazilian railway concessionaires, using indicators such as profit, revenue, and accidents, but did not address availability, asset utilization, or overall effectiveness. Waqas *et al.* (2015) suggest that while this metric is recognized, it is still rarely applied in the context of mobile equipment.

However, Domiciano (2020) developed the Overall Rolling Stock Effectiveness ($ORSE$) metric, based on the concepts of OEE (Overall Equipment Effectiveness) from industrial settings and on the propositions of Muñoz-Villamizar *et al.* (2018) in the context of road freight transport. Overall Rolling Stock Effectiveness ($ORSE$) in Equation 4 is a function of Physical Availability (PA) from Equation 1, Utilization (UTL) from Equation 2, and Productivity (PRD) of each locomotive block (b) for each logistics flow (f), from Equation 3:

$$PA(f,b) = \frac{\text{Hours of } (b) \text{ available in } (f)}{\text{Hours of } (b) \text{ allocated in } (f)} \tag{1}$$

$$UTL(f,b) = \frac{\text{Hours of } (b) \text{ used in } (f)}{\text{Hours of } (b) \text{ available in } (f)} \tag{2}$$

$$PRD(f,b)' = \frac{\text{Tractive effort requirement, in kgf, of } (f)}{\text{Tractive effort capacity, in kgf, of } (f)} \tag{3}$$

$$ORSE(f,b) = PA(f,b) \times UTL(f,b) \times PROD \times PROD(f,b)' \tag{4}$$

Considering that none of the individual components can exceed one (100%), will necessarily be less than or equal to one (100%). Figure 2 depicts the measurement method for locomotive overall effectiveness for the purpose of optimizing their allocation in railway transport flows.

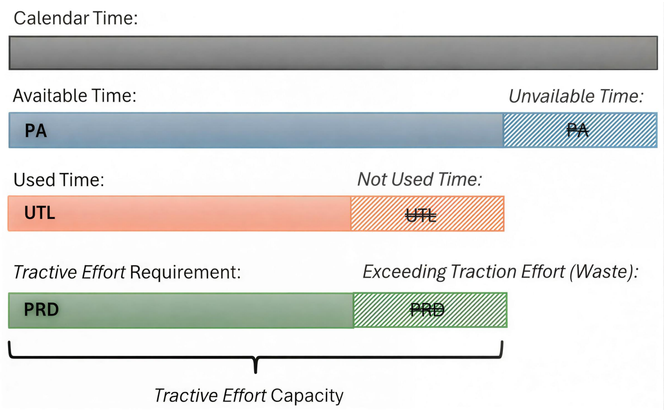

Figure 2 • Conceptual framework of Overall Rolling Stock Effectiveness ($ORSE$)

The metric proposed by Domiciano (2020) and employed in the locomotive allocation optimization model of this research, is currently adapted and used by MRS Logística S/A, including in the corporate scorecard of the company's operations and maintenance directorates. It has demonstrated excellent performance in capturing the company's operational performance both in aggregate and in disaggregated variables. Once the $ORSE$ metric is understood, the following section presents the treatment of the energy efficiency metric required for the optimization model of this study.

3.3. Fuel efficiency metric (*FE*)

The most commonly used energy (fuel) efficiency indicator is a function of the number of liters consumed for transporting a given volume of GTK (gross tonne kilometer), where the lower the value, the more efficient the railway or transport flow is (these are called negative-notation indicators, whose value improves as it decreases). Its formula is proposed by Abreu & Lopes (2017) as:

$$FE\ (\%) = \frac{\text{liters of fuel consumed}}{1,000 \times GTK} \tag{5}$$

Forecasting the fuel efficiency (FE) of a locomotive in different railway transport flows is particularly important, since not all locomotives necessarily have a utilization history across all production flows. It is therefore necessary to predict the locomotive's energy efficiency in these flows. The model developed by Abreu & Lopes (2017) for this estimation reached a determination coefficient (R^2) of 0.99, demonstrating the feasibility of reliably predicting the energy efficiency of a railway company. The results of this prediction method are used in the present study to establish the energy efficiency assumptions of each locomotive model in each railway operation flow.

4. Solutions for locomotive sizing and allocation

Sizing the assets required to ensure the service level of railway transport operations and allocating them across different logistics flows are decisions considered critical for the performance and competitiveness of railways. Currently, Brazilian railways make such decisions based, at best, on heuristics that reflect a set of rules, constraints, and operational particularities that must be considered. One of these particularities is the purpose of the operation, which can be classified as follows:

- *Transport*: the core objective of the railway, through which it adds value to the production chain and generates revenue;
- *Assistance*: required at ramp sections of the railway where the locomotives responsible for transport are not sufficient to haul the load. In these cases, one or more locomotives are attached to the train to provide traction along this segment, assisting the train's locomotives, and are then detached and regrouped into a block of locomotives that returns to the point of origin of the assistance;
- *Yard Service*: locomotives allocated at loading and unloading terminals, and in maintenance yards, whose purpose is to maneuver consists, locomotives, and wagon consists (sets);
- Infrastructure Maintenance: locomotives assigned to haul wagons carrying rails, ballast, sleepers, and special equipment for railway track maintenance;
- *Special*: locomotives with specific demands, such as electric locomotives operating on the rack railway for the Serra do Mar crossing between Piaçaguera and Santos in São Paulo.

In addition to the purpose of railway operations, the frequency of train formation also influences asset sizing and allocation, which can be:

- *On-demand*: where the train is formed with the number of wagons and frequency required by the client(s), depending on the existence of cargo to be transported; or
- *Scheduled*: where the train is scheduled to run between a standard origin and destination at a fixed frequency, regardless of cargo availability (commonly applied to container flows where service level is essential for railway competitiveness compared to road transport).

The sizing of locomotives for on-demand freight transport depends on: (1) the weight to be transported (in NT, net tonnes) in each period (weeks, months, or years, depending on the intended planning horizon); (2) the type of cargo, which determines the selection of the most suitable wagon for its transport; and (3) the expected circulation time of the train from its origin to its destination and back to the starting point, i.e., its cycle time.

The calculation of how many locomotives are required for scheduled freight transport is more straightforward, depending on the scheduled timetable for train circulation in a given period. Conversely, the number of locomotives allocated to assistance flows is directly proportional to the number of trains sized for the transport flows that require assistance. The model and quantity of locomotives used for assistance are also fixed. For this reason, the allocation of these locomotives is not the object of optimization in this research.

Locomotives for yard service are allocated according to shunting operations in loading/unloading yards and maintenance workshops, on a fixed basis, meaning their allocation is also not subject to optimization in this research.

Locomotives for track maintenance are sized similarly to transport trains, with their sizing defined by the maintenance department, considering their characteristics. However, the allocation of which locomotives can serve this purpose is subject to optimization and will be addressed in this study. Finally, locomotives with special purposes are sized and allocated on a case-by-case basis and are not the focus of the proposed optimization. The process and variables used for locomotive sizing through heuristics and through optimization are described in Figure 3.

Locomotive sizing and allocation based on heuristic relies, as shown in Figure 3, on the following variables:

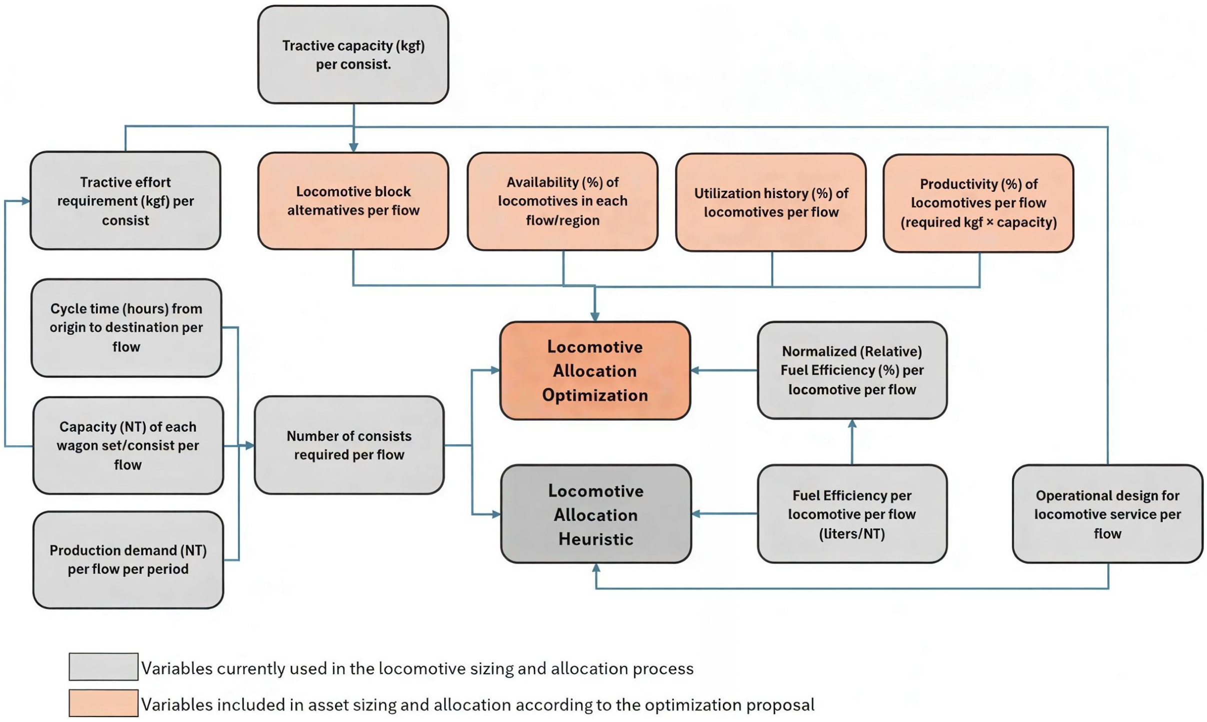

Figure 3 • Variable mapping for locomotive sizing and allocation via heuristics and via optimization methods

- Operational design (O.D.), which includes the profile of gradients between origin and destination, gross tonnage (GT) of each consist, tractive effort requirement for each train (in kgf), maximum speed of each section, among other data that determine which locomotive combinations are qualified to serve each flow. The O.D. is used both in the traditional allocation method and in the optimization proposed in this study.
- Cycle time (in hours), the load capacity (in NT) of each wagon set, and the transport demand (in NT) for each flow in each period, which directly influence the determination of how many consists will be formed.
- Fuel efficiency (FE), which is the variable traditionally used as the basis for locomotive allocation (in liters/NT). The optimization of allocation uses fuel efficiency variable in percentage terms, to compare the FE of each block qualified to serve a given flow with the best possible FE for that flow.

The optimization method for asset sizing and allocation, in addition to the variables used in heuristics, also considers:

- Tractive effort requirement per consist (in kgf), which, together with the O.D., influences the identification of which locomotive combinations (blocks), among several possible ones, are qualified to serve a given flow; and
- Physical Availability (PA) of locomotives in each flow (the fraction of time a locomotive is available for operation), the expected Utilization (UTL) of each block in each flow (which may be based either on historical usage or on the operating design itself), and the Productivity (PRD) of each block in each flow (representing the relationship between the tractive effort requirement of the flow and the tractive capacity of the locomotive block).

To understand the improvements and results of the optimization-based locomotive allocation method compared to traditional methods, the following section provides a brief overview of the heuristic traditionally employed in this process.

4.1. Locomotive allocation using the traditional method

For locomotive allocation in meeting freight railway flows transportation demands, the following variables are considered:

$PERIOD(p)$: represents the month in which locomotive allocation is performed;
$FLOW(f)$: indicates the flow for which there is production (transportation) demand;
$MODEL(a)$: indicates the type of locomotive available for operation;
$DISP(a,p)$: indicates the number of locomotives of model (a) available for operation;
$DEM(f,p)$: indicates the number of consists required (demand) to serve the flow (f) in the period (p), after calculations based on cycle time, cargo demand, and wagon set profile;
$REQ(a,f)$: indicates how many locomotives of model (a) are required to haul each train consist of flow (f);
$OD(a,f)$: indicates, from the operational design, whether a given locomotive model (a) can serve flow (f) – “YES” if it can, and “NO” if it cannot; and
$ALLOC(a,f,p)$: is the decision variable, on how many available locomotives of model (a) are allocated to flow (f) in period (p).

For distributing locomotives among flows, $DISP(a,p)$, the number of locomotives available by model in each period, is ordered from the model with the highest fuel efficiency to the model with the lowest. Similarly, $DEM(f,p)$, the number of consists required per flow in each period, is ordered from the flow with the largest projected load to the one with the smallest, measured in NT.

Based on this ordering, the allocation rule was structured in pseudocode, as shown in the algorithm:

```
For each PERIOD (p):
    For each FLOW (f):
        For each MODEL (a):
            If OD (a,f) = “YES” then
                If DEM (f,p) * REQ (a,f) <= DISP (a,p) then
                    ALLOC (a,f,p) = DEM (f,p) * REQ (a,f)
                    DEM (f,p) = 0
                    DISP (a,p) = DISP (a,p) - [DEM (f,p) * REQ (a,f)]
                Else
                    ALOC (a,f,p) = DISP (a,p)
                    DEM (f,p) = DEM (f,p) - [DISP (a,p) / REQ (a,f)]
                    DISP (a,p) = 0
                End If
            End If
        Next a
    Next f
Next p
```

This algorithm can be classified as a greedy sequential allocation heuristic, analogous to classical greedy resource allocation methods widely discussed in combinatorial optimization problems (Cormen *et al.*, 2009; Martello & Toth, 1990). Moreover, the structure of meeting partial or total demands depending on available capacity resembles simplified formulations of the Capacitated Assignment Problem and Network Flow Problems, where resources are sequentially distributed until capacity is saturated (Ahuja *et al.*, 1993; Hillier & Lieberman, 2021).

The main weakness of this approach lies in its validity only for locomotives allocated for freight transport purposes, making it inapplicable, for example, to track maintenance locomotives, where different rules apply. As a result, inefficiencies may occur, as will be demonstrated in the comparison between the performance of the heuristic and the optimization.

4.2. Asset scheduling methods in railway transport flows

The optimization of locomotive allocation in railway transport flows generally aims to determine at which freight loading terminals each locomotive model should be allocated, in order to optimize a specific objective—traditionally associated with the fuel efficiency of assets—while meeting the transport needs of the company's clients.

Bacelar (2005) developed a model to increase locomotive productivity and reduce the fleet of the Vitória-Minas Railway (EFVM), achieving a theoretical reduction of 18.8% by eliminating older and less efficient locomotives. Tazoniero (2007) applied computational intelligence and fuzzy sets to optimize real-time train circulation, minimizing stops and maximizing fleet utilization while respecting crossing and overtaking rules.

Barra (2008) created a locomotive allocation model focused on cost reduction, using the Dual Simplex method and prioritizing locomotive power. Similarly, Camargo (2010) expanded the approach by including optimization and simulation to maximize productivity in the transport of agricultural freight on EFVM and FCA.

Oliveira & Alves (2014) modeled locomotive allocation in FCA using linear programming to reduce fuel consumption, achieving significant savings when applying the model to three operational flows. In a very similar manner, Cassemiro & Costa (2015) proposed a model that reduced fuel consumption and improved fuel efficiency, considering variables such as transported volume, forecasted consumption, and available types of wagons and locomotives.

The study presented by Vasconcelos (2016) optimized locomotive allocation by considering logistical constraints and movements between corridors, reducing fuel consumption by 2.46% through simultaneous allocation planning over 12 months. Finally, Muñoz-Villamizar *et al.* (2018), in a way very similar to the approach proposed in this study, used mixed-integer linear programming and the OEE metric to optimize road transport networks, considering availability, productivity, and quality. Despite the focus on urban transport, the approach closely aligns with the goal of this work, which is to optimize locomotive allocation in railway flows, maximizing fuel efficiency and overall effectiveness.

4.3. Optimization model for locomotive sizing and allocation in railway logistics flows

The optimization of locomotive allocation in freight railway transport flows is proposed with the objective of ensuring maximum performance in terms of fuel efficiency (FE) and overall asset effectiveness—particularly for locomotives in this study. To this end, we employ the previously discussed Overall Rolling Stock Effectiveness ($ORSE$) metric. The Fuel Efficiency metric presented earlier (Equation 5) must be normalized into a relative indicator, here denoted $FEr(f,b)$, for each locomotive block (b) in each logistics flow (f), as shown in Equation 6:

$$FEr(f,b) = \frac{FE_{\min}(f)}{FE(f,b)}, \tag{6}$$

where $FEr(f,b)$ refers to the best (lowest) fuel consumption per unit of transport work known for any locomotive combination (b) in flow (f); $FE(f,b)$ represents the historical or estimated fuel efficiency for combination (b) in flow (f).

The FEr in Equation 6 will be used together with $ORSE$ in the optimization model for allocating locomotives to railway logistics flows.

The variables and parameters of the proposed optimization model are:

- p: period for which locomotive allocation is being planned;
- a: locomotive type that may compose one or more blocks;
- b: locomotive block (combination) eligible to serve a given flow;
- f: set of railway transport flows comparable to one another;
- FEr_{fb}: relative fuel efficiency for block (b) in flow (f), $FEr(f,b)$;
- PA_{fb}: physical availability percentage for block (b) in flow (f), $PA(f,b)$;

UTL_{fb}: utilization percentage (historical or estimated) of block (b) in flow (f), $UTL(f,b)$;
PRD_{fb}: traction productivity percentage of block (b) in flow (f), $PA(f,b)$;
OD_{fb}: operational design feasibility of block (b) to serve flow (f), as a binary parameter;
$CONV_{ab}$: number of locomotives of model (a) that compose block (b);
FA_{ap}: operational (active) locomotives of model (a) in period (p);
DEM_{fp}: number of blocks required in flow (f) in period (p);
w_{fe}: weight for fuel efficiency in the objective function;
w_{OE}: weight for overall effectiveness (ORSE) in the objective function;
w_{PA}: weight for physical availability in the objective function;
w_{UT}: weight for utilization in the objective function;
w_{PR}: weight for productivity in the objective function;
x_{fpb}: number of blocks (b) allocated in period (p) to flow (f) — decision variable.

The optimization model for locomotive sizing and allocation is detailed in Equations 7 to 10. The indices denote: p for the period; a for the locomotive type; b for the locomotive block; and f for the railway flow.

$$\text{MAX } Z = \sum_F \sum_P \sum_B x_{fpb} \left\{ (w_{FE}\, EER_{fb}) + \left[w_{OE} \left(w_{PA}\, PA_{fb} + w_{UT}\, UTL_{fb} + w_{PR}\, PRD_{fb} \right) \right] \right\} \quad (7)$$

subject to

$$\sum_F \sum_B \frac{(x_{fpb}\, CONV_{ab})}{PA_{fb}} \leq FAT_{ap} \qquad \forall a,\ \forall p \qquad (8)$$

$$\sum_B x_{fpb}\, OD_{fb} = DEM_{fp} \qquad \forall f,\ \forall p \qquad (9)$$

$$x_{fpb} \in \mathbb{Z}^+ \qquad \forall f,\ \forall p,\ \forall b \qquad (10)$$

The objective (Equation 7) maximizes locomotive overall effectiveness and fuel efficiency in selecting the blocks serving each flow in each period. Constraint (8) limits allocations to the available fleet by locomotive type and period. Constraint (9) ensures all block demands for the planned production are met across flows and periods. Constraint (10) enforces nonnegativity and integrality of the block allocations.

The data used for solving the model are as follows:

- The variable (p) represents the 12 periods (months) of the year 2020, numbered from 1 to 12.
- Each type (a) of locomotive consists of a set of locomotive models that are interchangeable for all allocation purposes considered in this optimization, based on characteristics such as tractive capacity, traction technology, axle load, onboard equipment for communication with the operations control center, the existence of radio-based locomotive pairing systems (Locotrol), among others. Based on these criteria, seven locomotive types were considered, named Type 1 through Type 7.
- Locomotive blocks (b) are combinations of locomotive types (a) employed to haul trains. In this study, 18 possible locomotive blocks were mapped for train hauling. The blocks were coded as a sequence of seven digits, each digit representing the number of locomotives of each type (1 through 7) included in the block. For instance, for example, block 0030101 is composed of three Type 3 locomotives, one Type 5 locomotive, and one Type 7 locomotive, whereas block 0110000 is composed of one Type 2 locomotive and one Type 3 locomotive.
- The hundreds of products, origins, and destinations that make up the railway transport network of the operator under study were grouped into flows (f) based on similarities between wagon and locomotive consists that serve these demands, among other characteristics. Nineteen transport flows were identified, covering agricultural commodities, ore, containers, steel products, track maintenance, and several other demands.

- The FEr for each block in each flow was calculated based on 24 months of operational history and, in some cases, on expert analysis for estimating expected fuel efficiency.
- Availability and utilization considered for each block in each flow result from weighting the historical maintenance and operational performance of each locomotive type composing the block in the region where the flow occurs, over a 24-month horizon. Since the maintenance workshop responsible for locomotive repairs varies by region, availability outcomes may differ accordingly.
- Productivity of each block in the flows was calculated from the tractive capacity provided by each block and the tractive effort requirement calculated in the operational design of each flow studied. In cases where the block's tractive capacity does not equal or exceed the flow's tractive requirement, productivity was considered to be 0%.
- The operational design specifies which blocks are eligible to serve each railway transport flow.
- The demand for locomotive blocks (trains) to meet transport requirements is considered for each of the twelve planning periods, as well as the total number of locomotives of each type employed in each block and the number of locomotives of each type eligible to operate (active) in each period.

Finally, the weights of each component in the optimization objective function (w_{FE}, w_{OE}, w_{PA}, w_{UT} and w_{PR}) were defined as a baseline solution based on consultation with railway experts.

5. Results and critical analysis

To obtain the solution of the proposed optimization with the mathematical model presented earlier, the LINGO® software from LINDO Systems was used. The results of locomotive allocation were evaluated for both the traditional heuristic and the mixed-integer linear programming optimization, considering weighted values of availability (PA), utilization (UTL), productivity (PRD), and normalized fuel efficiency (FEr) for the entire allocated fleet, as well as the total number of locomotives required for the company's operations.

The scenario presented below considers equal weights for all variables in the mathematical model's objective function (w_{FE}, w_{OE}, w_{PA}, w_{UT} and w_{PR}). The results qualitatively demonstrated that, as expected, the greater the need for locomotives in a given period, the higher the use of machines with inferior performance, mainly in terms of availability and fuel efficiency, since they are older and equipped with less advanced technology.

The performance difference between the methods, however, can be observed in the month-by-month comparison of results: the best period across all indicators is $P1$, where the weighted average fleet availability was 87.2% for the heuristic and 87.4% for the optimization; for utilization, the weighted average was 63.9% for the heuristic and 65.9% for the optimization; in terms of productivity, the heuristic achieved 79.3% compared to 77.2% for the optimization; consequently, the fleet's overall effectiveness was 42.9% under the heuristic and 43.7% under the optimization; finally, the weighted fleet fuel efficiency was 87.3% of the ideal in the heuristic case, and 87.9% in the optimization case.

When comparing average results across all periods, improvements with optimization were found in every indicator except fleet productivity, which remained constant, as illustrated in Figure 4.

In practice, these results can be summarized as follows:

- Asset sizing for production requirements: the optimization employed six fewer locomotives than the heuristic, representing an operational cost reduction by avoiding the use of older machines that entail high maintenance costs and low performance, for example.
- Reduction in fleet fuel consumption: for the same demand, the optimization improved fleet fuel efficiency by 0.6%, representing an additional cost reduction in transport operations.

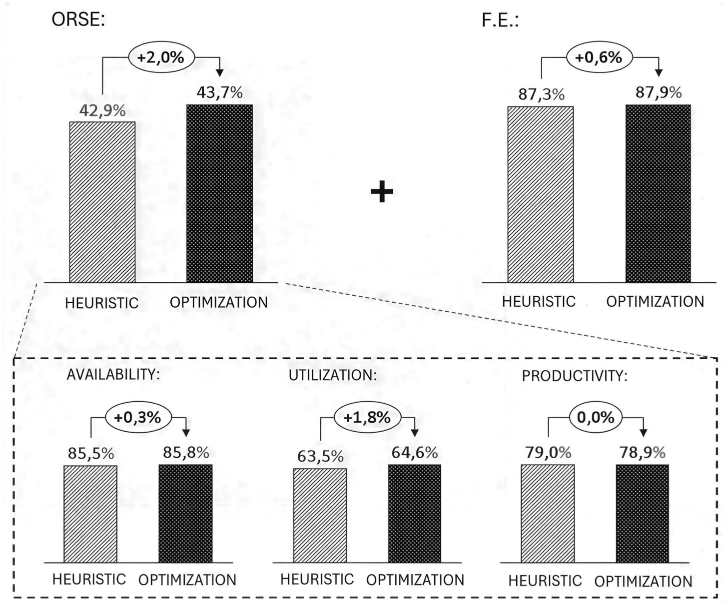

Figure 4 • Fleet performance comparison: heuristic and optimization approaches (Domiciano, 2020)

Indirectly, the use of optimization enabled faster generation of locomotive allocation results for different scenarios and parameter settings compared to the heuristic; enhanced reproducibility of results regardless of the specialist responsible for fleet sizing, which strengthens the proposed methodology; assurance of allocation quality, since all qualitative and technical constraints are observed in the process; and increased solution flexibility to accommodate new requirements, such as the creation or exclusion of flows, extension of the number of planning periods, acquisition of new locomotive models, among other variables.

6. Conclusion

This research set out to apply an optimization method to the sizing and allocation of assets required for railway operations, based on the Overall Rolling Stock Effectiveness ($ORSE$) metric combined with the traditional Fuel Efficiency (FE) metric.

The feasibility of using linear programming to obtain optimal locomotive allocation results was demonstrated, with the aim of maximizing asset availability, utilization, and productivity, in addition to the operation's fuel efficiency. The proposed optimization results evidenced improvements in fleet availability, utilization, and weighted productivity levels of up to 1.8% compared to solutions obtained with the traditionally employed heuristic, while also ensuring improvements of up to 0.6% in weighted fuel efficiency indicators – which already represented the basic criterion used in locomotive allocation.

The $ORSE$ metric employed in this research is suitable both for assessing railway transport performance globally, identifying opportunities in maintenance, operations, and maintenance engineering, as well as for optimizing the sizing and allocation of locomotives across different railway flows.

Given that Brazilian railway transport is essential for the development of numerous strategic production chains in the country, initiatives such as this, capable of improving the efficiency of rolling stock fleet operations, are critical to increasing Brazil's competitiveness in global consumer markets.

Therefore, future enhancements and developments to locomotive sizing and allocation optimization may aim at maximizing organizational profit by incorporating maintenance cost data by asset type and operation, along with tariffs per NT-km in each flow. Another direction for further research lies in wagon sizing to meet railway transport demand, encompassing the sizing and allocation of the entire rolling stock fleet, which, although differentiated by function and not always interchangeable, also represents opportunities for performance improvement.

CRediT authorship contribution statement

Luiz Carlos Domiciano: conceptualization, resources, data curation, formal analysis, investigation, visualization, methodology, writing – original draft. Renato Cesar Sato: validation, visualization, methodology, writing – review & editing. Luís Alberto Duncan Rangel: supervision, validation, visualization, methodology, writing – original draft.

Use of artificial intelligence-assisted technology

The authors state that artificial intelligence was used only for reviewing the translation of the final version from Portuguese to English. This was essential for making sure all specialized terms used in the paper were correctly defined in English. The authors have revised the text and take full responsibility for content generated with the aid of the artificial intelligence translation tool.

Competing interests statement

The authors declare that there is no conflict of interest.

Data availability statement

The data supporting the results of this study are not publicly available due to being confidential data originating from events, drawings and operational arrangements of locomotives owned by MRS Logística S/A.

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