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Equivalent availability index for the performance measurement of haul truck fleets

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Highlights

- This article presents a model of performance analysis for a truck fleet system.
- The algorithm considers heterogeneous fleets with individual characteristics.
- Equivalent Availability is a key indicator to determine the productive capacity.
- The methodology strengths are based on the capacity to define dynamic indicators.

Abstract

This article presents a model of performance analysis for a truck fleet system in an open-pit mine, considering special characteristics of haul fleets. In these systems, the expected availability of each piece of equipment and its operating capacity are the fundamental variables to construct a global fleet performance function. Our analytical algorithm considers heterogeneous fleets with known individual characteristics of transport capacity and failure and repair behavior. The results converge to a new indicator denominated "Equivalent Availability" (EA), which arises from the need to evaluate the capacity of the truck fleet to operate at a lower payload than required using different combinations of equipment to achieve an availability goal. EA is a key indicator to determine the productive capacity of a process, and for selecting equipment and their combinations to achieve production objectives. To exemplify the potentialities of the EA, a case study is implemented in a Chilean copper truck fleet mining process.

Keywords

performance assessment, reliability engineering, production management, availability.

Sets, parameters and variables

Sets	Description
E	set of equipment
nE	total number of equipment
i	index of equipment $i \in \{1,...,n_E\}$
S	set of operating states of the system (fleet)
nS	total number of possible operating states of the system
j	index of operating states of the equipments $j \in \{1,...,n_S\}$
Parameters	**Description**
C_S^R	system required capacity (tons)
H_{year}	operational planned time in a year (hr / year)
$MTTR$	Mean Time to Repair (hr)
$MTTF$	Mean Time to Failure (hr)
Variables	**Description**
A	Physical Availability $\in (0...1)$
C^{max_i}	Maximum individual capacity
C^{MAX}	Maximum capacity of the system
C^A	Available capacity (tons)
C^O	Operating capacity (tons)
P^A	Availability-based probability $\in (0...1)$
I	Impact $\in (0...1)$
δ	Matrix of possible combinations of operating states $\in 0,1\}$
PL_{syst}	System Production Level (tons / hr)
ω_j	Overcapacity indicator $\in \{0,1\}$

1. Introduction

In industrial processes, greater flexibility means better productivity, efficiency, and general results [12]. In this context, modelling systems in dynamic conditions have great importance in productive processes modelling, especially in those with multi-products, multi-configurations, and fleets [11, 24, 30] A system is considered dynamic when its characteristics and logical or capacity configuration change over time [9]. An emblematic case of these systems are fleets, in which several

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configurations may satisfy the same production goal; thus, the reliability calculation for these fleets is different than the calculation for a conventional system [27]. Specifically, for mining projects, transportation processes represent between 50% and 60% of operational costs [2, 5, 32]. A small improvement in transportation costs or efficiency percentage can produce meaningful savings. The latter motivates the development of analytical proposals that are capable of defining and quantifying the performance of a fleet, without losing sight of its complex characteristics.

Regarding reliability, current modelling methods include the Reliability Block Diagram (RBD) or Failure Tree (FT) [18]. However, Birolini [3] possesses limitations in representing dynamic systems. On one side, RBD presents several restrictions regarding dependencies in large complex systems [28, 31]. There are some proposals for a special analysis for an RBD, which gives the chance to adjust the analysis dynamic structure [19]. The new RBD version, which is referred to as the Dynamic Block Diagram (DRBD), was re-introduced by Xu et al. [31] in a more developed version that highlights the simplicity of its implementation. Distefano and Puliafito [8] contribute to the progress and application of the DRBD by constructing 3 case studies using the Open-SESAME software to validate the results. Nevertheless, it was not possible to introduce several characteristics from the model to the software, which causes a pending challenge for the software's development. On the other hand, He et al. [13] develops a model with a reliability analysis method for a multi-state system based on a triangular fuzzy method for Bayesian networks.

Furthermore, several methods have been developed to represent complex systems. One of the first approaches was the proposal of Akhtar [1], which makes an interesting contribution by considering the analysis of identical equipment. The author suggests that some failures cannot be repaired perfectly (imperfect repairing), which can be resolved by using Markov models. Shengdao and Fengquan [25] use a Markov chain to resolve availability problems regarding shared load systems. Particularly, the authors calculate the availability of shared load systems with variable failure rates over time by solving differential equations that require a large number of algebraic operations that are unmanageable for large systems. Jenab and Dhillon [14] employ a Markov chain to analyse the availability and reliability for K of n reversible multi-state systems for identical and independent component conditions. Che et al. [6] develops a comprehensive analysis of degradation rates due to component failures and surviving components for increasing workloads; the analysis considers load sharing characteristics [6]. Misra [21] proposes a solution to reliability analysis using Markov chains with the condition that the maximum number of components of a system must be sixteen due to its time resolution scaling.

Alternatives for solving the problem of dynamic systems reliability calculation [26] and their respective restrictions are described as follows:

1. Markov chains: Common with a maximum number of analysed equipment as a restriction.
2. Petri nets: Frequently employed to model redundancy and shared load [29] but have ineffective development for many elements.
3. DRBD: Considering the previously mentioned characteristics, this method does not have the ability to solve problems for shared load systems with dynamic conditions.
4. Simulations: Where any kind of distribution can be modelled, the Monte Carlo technique is one of the most explored techniques in diverse fields [15, 23]. However, depending on the accuracy of the modelling, obtained results may vary with respect to reality, which is a real challenge for complex systems.

As the discussed alternatives are not capable of solving complex dynamic systems (or fleets) with a shared load, we present a proposal to calculate the reliability of systems with characteristics using a novel analytical model. This calculation is performed by a numeric approach that analyses the system that is based on the equipment that composes it, analysing the possible configurations and estimating the system availability index [10]. The determination of the mentioned scenarios depends to a large extent on the context of the system, as a set of variables to complete the decision-making process. The analytical algorithm considers heterogeneous fleets [4] with previously known individual characteristics of transport capacity and failure and repair behaviours.

Given these antecedents, this paper's contribution is to show a new methodology for measuring the performance of a fleet of equipment by the calculation of the equivalent availability (EA) index, which dynamically includes the effect of redundancy and system requirements by the individual calculation of the elements that comprise the system. This methodology consists of a matrix evaluation of the state that each item may have by combining the state of all the elements of the system. The limitations of the existing techniques are overcome by the proposed methodology since it can be applied to different configuration settings that do not have a unique way of fulfilling a systemic EA.

This paper is presented as follows: First, the introduction and background describe the problem and contextualise the state of the art. The system description establishes the context of the proposal; the modelling and key performance design presents the model and its characteristics, scope, and assumptions. The proposed methodology defines the activities necessary for the application and evaluation of the model. A case study is introduced to present the characteristics and variables to be implemented with a sensitivity analysis, and the global conclusions of the model and the case study are also presented.

2. System description

Generally, transportation systems are characterised by their flexibility, large amount of equipment, and dynamism, which gives them a condition of overcapacity that is rarely the bottleneck of a process [17]. In addition, the particularity of sharing the load allows the calculation of a required capacity based on the sum of available equipment, which can even operate at a lower load than required. The condition of overcapacity is characterised by showing an installed capacity larger than required; hence, there are a series of combinations of equipment in use, which will be able to satisfy the same requirement. It is necessary that the equipment operates at different load levels. Consequently, the impact of equipment is variable and depends on the required load, its reliability and maintainability, as well as the characteristics of each equipment and subsystems that comprise the system, which surpasses the serial and redundancy logics considered in the RBD.

With this information, it can be observed that the EA is a complex process to perform [20]. Due to this complexity, we propose a methodology to generate an indicator for the availability and level of production for this type of system. The proposed methodology is then validated by its subsequent application in a case study, where the EA and the optimal fleet size is determined.

To contextualise the analysis of the availability in fleets, Figure 1 (from left to right) shows how the capacity of a system changes over time. The maximum capacity (C^{MAX}), which corresponds to the availability of the entire fleet of equipment or vehicles, is altered by the occurrence of failures. During failure, the available capacity (C^{A}) suffers a reduction until the moment of the repair, when the available and maximum capacity are equivalent ($C^{MAX}= C^{A}$). For the specific case of vehicle fleets, the required capacity (C_S^R) is generally below the available capacity (C^{A}). This finding means that the system is generally overcapacity, even in times of increased demand. In this way, the required capacity can be fulfilled using different and equivalent configurations of equipment. A graphic representation of the capacity of the entire fleet is shown on the right part of Figure 1. The graphic shows the sum of the capacity of all the vehicles (C^{MAX}), where each box and its size represent the specific capacity of a vehicle. There is

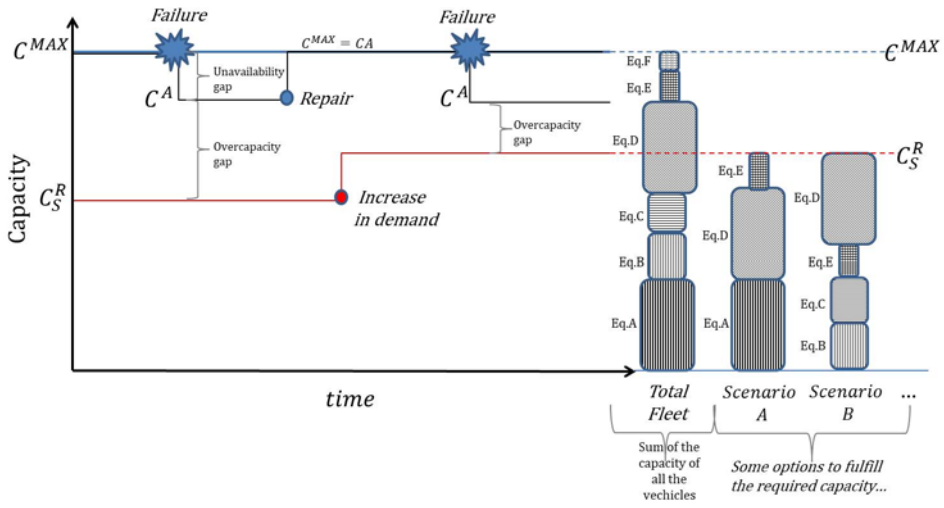

Fig. 1. Context of operation of a fleet regarding its capacity

the representation of two possible scenarios (A and B) that exemplify two different ways of achieving the required capacity, using different combinations of vehicles according to the availability or other circumstances. From these conditions arises the transcendence of calculating the EA Index.

3. Modelling and key performance design

The modelling of the equipment fleet for the load-sharing configuration is a complex task given the size of the analysis that can be achieved when considering many pieces of equipment. The design of the EA indicator for the system or fleet is generated from the need to evaluate the results obtained by different configurations/assignments of equipment related to the productive capacity of the process. This evaluation is performed with the foundation that consists of the availability of the elements that comprise the fleet and the capacity it has to respond to the failure of one or more elements.

The model is based on three fundamental principles, which are expressed via assumptions. These assumptions are indispensable for defining the scope and achievement of the desired results. For this case, the first assumption defines the two possible states of an element, that is, whether it is available or unavailable. The second assumption defines the maximum capacity for each scenario and safeguards the possible states of each element and the capacity required by the system. This assumption is utilised to evaluate if it can be satisfied, or alternatively, be operated at a lower capacity considering the unfulfilled load, as a partial availability of the system. In this way, the impact of each element is calculated depending on its state. The last assumption relates the calculation of the probability based on the availability of each state to the weighted impact for each piece of equipment, and the availability of the system and its production level (PL) are determined [16].

Assumption 1:

All equipment in the systems have two possible operating statuses: (1) available and (0) not available. With this assumption, the first step is to obtain all the possible combinations of operating states, given the total amount of equipment in the system. Since the operating states are binary, the total amount of operating states of the system is 2^{nE}.

Considering the set of n_E number of equipment that compose the fleet and a combination of the operative states $\in \{1, ..., 2^{nE}\}$ of the system, the correspondent binary variables used to visualise the operative status of each equipment item are defined as follows:

$$\delta_{ij} = \begin{cases} 1 & \text{If equipment i is in operative status} \\ 0 & \text{If equipment i is inoperative} \end{cases} \quad \forall j \in \left\{1,...,2^{n_E}\right\} \quad (1)$$

The available capacity for each combination of operative states can be obtained from matrix δ. This analysis is extensive for the equipment n_E, so it is necessary to apply the additive function from 1 to n_E:

$$C_j^A = \sum_{i=1}^{n_E} \Sigma \delta_{ij} \times C^{max_i} \quad \forall j \in \left\{1,...,2^{n_E}\right\} \quad (2)$$

The implementation of this assumption presents a great challenge due to the size of the generated matrix. Therefore, it is necessary in each implementation to analyse and pre-process the input data to group the elements, considering the reliability behaviour, size, and/or model. This approach avoids the redundant calculation of repeated states with a different order but equal impact.

Assumption 2:

In terms of modelling, in an expected scenario, given the operative state j of the system, it is assumed that the proportion between the operation capacity of the correspondent equipment C_{ij}^O and its maximum capacity C_i^{max} are equivalent for all equipment. Note that the operation capacity C_S^R refers to the real capacity that is applied, which can even be a fraction of the nominal capacity of the equipment. To determine the final impact of each piece of equipment, it is necessary to identify the operative states j from the systems, so the available capacity of the equipment is lower or equivalent to the required system capacity. Otherwise, the impact will be defined as 0, as the system can satisfy the capacity requirements. The ω_j binary variable is defined as follows:

$$\omega_j = \begin{cases} 1 & C^A{}_j \geq C^R{}_S \\ 0 & any\ other \end{cases} \quad \forall j \in \left\{1,...,2^{n_E}\right\} \quad (3)$$

The operative capacity COij of the equipment, therefore, will be:

$$C_{ij}^O = \frac{\left(\omega_j \times C_S^R + \left(1-\omega_j\right) \times C_j^A\right) \times \delta_{ij} \times C_i^{max}}{C_i^{max} + \sum_{k=1 \wedge k \neq i}^{n_E} \delta_{kj} \times C_k^{max}} \forall i \in \{1,...,n_E\}, j \in \left\{1,...,2^{n_E}\right\} \quad (4)$$

When calculating the impacts is applicable ($C_S^R > C_j^a$), the operation state of the system (j = 1) is considered as the state of reference for all the equipment. In this state, the available capacity is lower than the required capacity, and there is a loss of capacity. Conversely, when the available capacity is higher than the required capacity, the system can operate without capacity, and the impact is zero for each element of the system. The aim is to determine the loss of capacity

that the unavailable equipment exerts on the system, depending on the operational capacity that the system would have if this equipment were operating. Therefore, the formulation of the impact will be:

$$I_{ij}=\begin{cases}\dfrac{\left(C^{R}{}_{S}-C^{A}{}_{j}\right)\times\left(1-\delta_{ij}\right)\times C^{O}{}_{i1}}{C^{R}{}_{S}\times\sum_{k=1}^{n_E}\left(1-\delta_{kj}\right)\times C^{O}{}_{i1}} & C^{R}{}_{S}>C^{A}{}_{j}\\ 0 & C^{R}{}_{S}\le C^{A}{}_{j}\end{cases}\quad \forall i\in\{2,\ldots,n_E\}, j\in\left\{2,\ldots,2^{n_E}\right\} \tag{5}$$

Formula 5 is a key step of the methodology. This expression determines the specific impact of a failure of each element over the system. This objective is necessary to develop an assessment of each scenario, since there are scenarios without impact (overcapacity allows us to obtain the required capacity) and other scenarios where the failure impacts of the system capacity produce a loss (group of elements fail).

Assumption 3:

Considering the operating state of the system (j=1), the required capacity will always be satisfied. As a result, the probability based on the availability of each operating state of the system will be defined as follows:

$$P_j{}^{A}=\prod_{i=1}^{n_E}A^{\delta_{ij}}{}_{i}\times\left(1-A_j\right)^{\left(1-\delta_{ij}\right)}\quad \forall j\in\left\{1,\ldots,2^{n_E}\right\} \tag{6}$$

The weighted impact of the equipment, considering all the possible combinations for the operating state of the system, is:

$$I_i^{W}=\sum_{j=1}^{2^{n_E}}P_j{}^{A}\times I_{ij}\quad \forall i\in\{1,\ldots,n_E\} \tag{7}$$

The availability of load-sharing systems and overcapacity are calculated as follows:

$$A_{syst}=\sum_{i=1}^{n_E}A_i\times I_i^{W}\quad \forall i\in\{1,\ldots,n\} \tag{8}$$

The PL is determined with the following equation:

$$PL_{syst}=A_{syst}xC^{O}\ x\ H_{year} \tag{9}$$

Before presenting the methodology diagram, it is relevant to analyse the effect of determining the weighted impact introduced in Equation 7 as an equivalent indicator. Considering the formulation of problems for a load-sharing configuration, it is easy to consider the case of a transport fleet. A key request from the operations manager is, for example, to define the capacity of the fleet, which refers to the number of units or volume transported along a certain period. The equivalence is based on the availability and level of production. For example, regarding the number of units transported in a period, it could be equivalent to 60% availability and 100% PL or 80% availability and PL 75% for one month. Figure 2 shows the equivalent impact effect. This analysis only considers the effect of corrective maintenance detentions, given that considering the idle capacity of the fleet, it is possible to minimise the effect of preventive maintenance and operational stops.

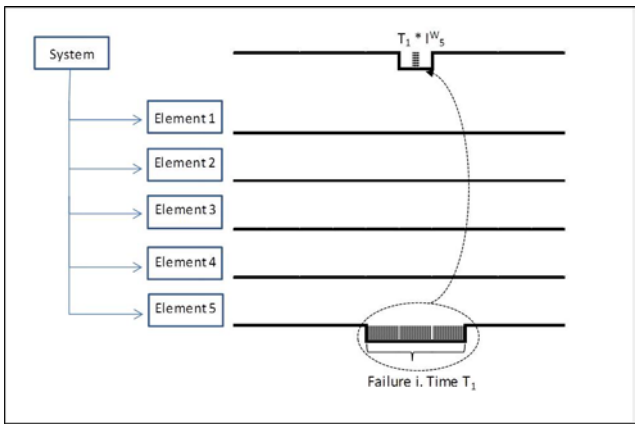

Fig. 2. Equivalent Impact Effect

4. Proposed methodology

With the previous assumptions under consideration, the steps to follow in the proposed methodology are shown in Figure 3, where

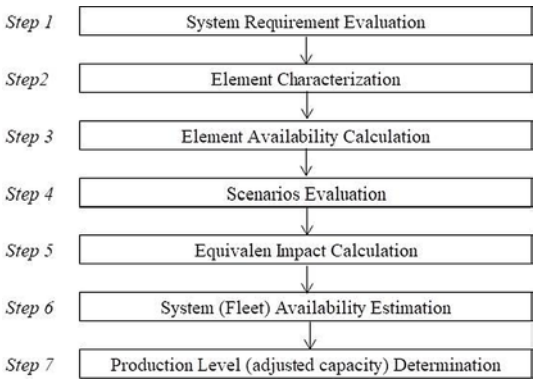

Fig. 3. Proposed methodology

these stages or steps are explained and justified for the evaluation of the Equivalent Availability in complex load-sharing systems:

Step 1: System characterisation is required in terms of the required and installed capacity, as well as its specifications. It is fundamental that the process can operate at a lower load than required, considering the corresponding loss. There are processes in which the operation must be stopped in case the required capacity level is not accomplished, i.e., food plants. Certainly, this model is not applied to them. Conversely, there are transportation systems in which, although there is a required capacity, due to failure to comply, it is convenient to operate at a lower load rather than take a full stop on the operation.

Step 2: Each element (equipment) must be evaluated independently and according to the characteristics of the process. The fundamental aspects to consider are reliability, maintainability, and capacity.

Step 3: After Step 2, the expected physical availability of each element is calculated. This step allows the modelling of states for the element and renders the combination between capacity and availability possible.

Step 4: Once the elements have been characterised, all the possible scenarios must be evaluated. For this task, equations 1, 2, and 3 must be applied. The difficulty that characterises this step is that the total number of scenarios has an exponential relationship with the number of elements, which is why a total of 2^{nE} scenarios are obtained for the evaluation.

Step 5: The calculation of impacts for each element is the characteristic and differentiating factor of this methodology. For this step, the application of equations 4, 5, 6, and 7 is needed. This calculation is performed in the evaluation of the scenarios by analysing the system's available capacity in each case and assigning the potential losses (failure to satisfy the required capacity) to items that were not available in the scenario study. As previously discussed, the impact of the equipment is dynamic since it depends on their rates and the rates of each of the other elements. In scenarios of overcapacity, the impact of equipment is not the ratio between its capacity and the required capacity, as commonly evaluated.

Step 6: After completing these steps, the equivalent system availability can be calculated by assessing the availability and weighted impact of each of the elements (equation 8). This availability establishes the level of productive capacity of the system, corrected by the probability of meeting with itself. The concept of equivalence is the result of the evaluation of scenarios, in which it operates at a lower required load, which could be treated as "partial availability".

Step 7: Since the EA is determined, the PL is evaluated based on an adjusted capacity analysis (equation 9). Note that each of the previously described steps is essential for the application of the methodology, which should be applied rigorously. In the next section, we outline the application of the various stages of our proposed methodology.

5. Case study

The case study is based on the analysis of a truck fleet in a copper mining process. The fleet includes 170 trucks that are classified in six classes, including the manufacturer, the model, and age of each element. The overall performance of the fleet is evaluated based on the availability and capacity of each element. The analysis focuses on the evaluation of each element's impact on the process. In addition, different scenarios of equipment use are evaluated to assess the impacts and results caused by changes in the allocation of the trucks for specific activities and differentiate the characteristics of capacity and availability. The specific aspects related to the routing and scheduling of the vehicles and their performances [22] are estimated within an expected capacity per truck.

The first section of the case study describes the context and study scenario (steps 1 and 2). The second section outlines the availability calculations per item (step 3). The third section carries out the system modelling, where the EA and PL of the fleet are calculated (steps 4, 5, 6, and 7). The fourth section corresponds to a sensitivity analysis where, once the model is implemented, it is possible to evaluate the impact of including more equipment, which complies with higher production targets.

5.1. Description of the production process and data collection

Step 1:

The mine is located in northern Chile and has an annual production of approximately 1,200,000 metric tons of copper. The applied case study is developed on the transport system of material from the mine to the concentrator plant. This material has a bill that exceeds 1.25% copper, and more than one million metric tons of material composed of mineral and ballast in a ratio of 3:1 is transported daily. The last aspect is relevant for understanding the importance of examining the system of trucks that perform this work. The site is located at an altitude that exceeds 3,000 meters above sea level. Once the material is extracted, it is loaded onto the trucks by blades with a capacity of 40 tons. The process has a capacity time greater than 42,000 tons, which are transported by trucks to a hopper for distribution in the milling process. The truck subsystem consists of 170 trucks of six different types, whose capacity ranges from 240 to 360 tons.

Step 2:

In this case, we analyse the behaviours of each of the 170 trucks in the mining facility. In the first instance, it is possible to group the trucks into six classes according to their age, model, manufacturer, and capacity (Table 1). This task has a very positive result for Assumption 1, considering the fleet size and total scenarios generated by the 170 trucks: reduction in processing time by pre-processing the raw data to avoid redundant equipment state configurations.

Table 1. Truck classification

Class	Quantity	Payload (ton)
A	20	240
B	80	360
C	10	320
D	25	240
E	15	360
F	20	240

5.2. Calculating and obtaining indicators

Step 3:

A particular analysis was performed for each truck i, via its reliability indicator (Mean Time To Failures (MTTF)) and maintainability (Mean Time To Repair (MTTR)) to calculate its physical availability indicator (A_i) [7] as follows:

$$A_i = \frac{MTTF_i}{MTTF_i + MTTR_i} \tag{10}$$

The result of this equation (and other equations) may vary over time. Nevertheless, their use has been simplified in the presented case to avoid additional complexities. To illustrate this point, an extract of the obtained information for trucks is shown (Table 2). This table considers only trucks from class A (same model and date of fabrication but different operational age).

Table 2. Truck indicator extract

Truck	MTTF (hours)	MTTR (hours)	A
A1	55.34	12.87	81.13%
A2	55.54	9.74	85.08%
A3	48.66	9.36	83.86%
A4	49.11	16.27	75.11%
A5	50.74	13.29	79.24%
A6	49.45	7.24	87.23%
A7	53.58	6.86	88.65%
A8	51.20	9.15	84.84%
A9	54.16	15.26	78.01%
A10	56.21	9.53	85.50%
.....			

An interesting analysis can be obtained when analysing the different rates of reliability, maintainability and availability for each truck, since it is possible to establish different patterns of variability and trends between different classes due to equipment age (Figure 4).

The graph in Figure 4 clearly shows that the trucks in classes A and B have a higher MTTF and MTTR with lower variability, which is explained by the lower accumulated operating time, since they correspond to the newest fleets. This analysis highlights the low variability of the index for the trucks from class B (highest number). This finding is justified due to the high volume of total procedures performed, which allows a better understanding of the equipment, and thus, standardisation of maintenance processes. Table 3 shows a summary of the characterisation of the equipment for each class obtained from the original data.

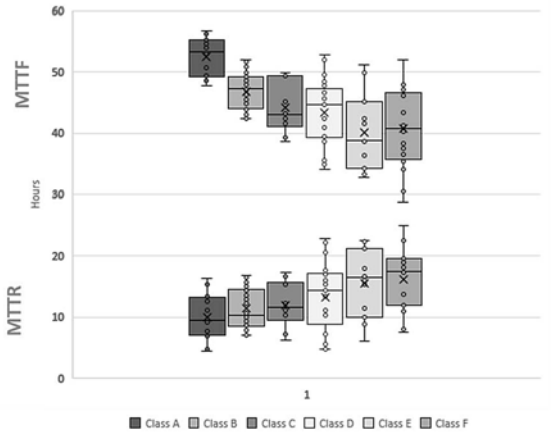

Fig. 4. Trucks MTTF and MTTR distribution graph by class

Table 3. MTTF and MTTR indicator for each truck classification

Class	Average MTTF (hours)	Variance MTTF	Average MTTR (hours)	Variance MTTR
A	52.55	8.97	9.90	15.46
B	46.88	8.20	11.32	9.46
C	44.23	17.12	11.87	13.84
D	43.40	27.79	13.15	29.51
E	40.08	36.45	15.43	28.45
F	40.74	40.98	16.04	28.98

In step 3, consolidated results on availability Ai for each truck are presented (Figure 5). As expected, the trucks from classes A and B present the highest rates. Class A trucks, which are smaller, more reliable and more maintainable trucks, stand out. Similar to the previous indicators in terms of average and variability, Table 4 shows the results.

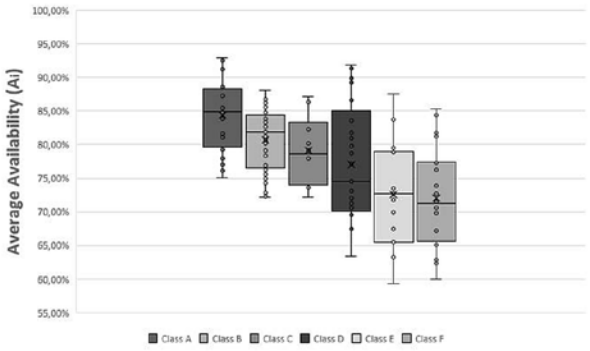

Fig. 5. Availability (Ai) indicator by class

Table 4. Availability (Ai) indicator for each truck classification

Class	Average A_i	Variance A_i
A	84.4%	0.31%
B	80.7%	0.20%
C	79.1%	0.26%
D	77.0%	0.76%
E	72.5%	0.65%
F	72.0%	0.58%

5.3 System modelling and obtaining EA

Step 4:

As mentioned in Section 3.1, transport of (C_S^R) 42,000 tons/h on average throughput is needed. Considering the capability of the total truck fleet, on average, 135 available trucks are needed for the activity at 100% capacity. Obviously, this number is dynamic and varies according to the specific capacities of the trucks, which are considered as well as the distances of each transfer. First, it is established that the required capacity C_S^R is 42,000 tons and the maximum capacity (installed capacity) C^{max_i} of the 170 trucks fleet is 53,000 tons.

Step 5:

Regarding the methodology, Step 5 allows us to calculate the impact of each of the equipment on the process. I_i is calculated with equation (5), which graphically shows the impacts Ii obtained for each truck in Figure 6. This impact Ii arises from the result of the existing effect between C_S^R and C^{MAX}, which implies the existence of overcapacity; therefore, the effect of the unavailability of a truck will be less than the ratio of their ability and capacity required , since it is corrected by the overcapacity factor. By analysing the information in the chart in Figure 7, it can be seen that the trucks of Classes A, D and F have the same impact; the same occurs with the trucks of class B and E. Since this impact is based on the capacities of the trucks, which are identical in these cases, this circumstance has the same result as I_i.

The weighted impact for each truck I_i^W is calculated, according to the equation (7). Note that unlike I_i, every I_i^W depends on the reliability, maintainability, and therefore, the capacity of each truck. This weighted impact is separately calculated from the analysis of each of the scenarios associated with each truck. This calculation is performed by evaluating the likelihood of each scenario and estimating the effect of the unavailability of a truck on the system, which is associated with the state of the other trucks. The impacts for each truck are shown in Figure 6 as a family of trucks for each class. For example, if truck A1 is unavailable and all other trucks are available, the impact of truck A1 is 0% since the capacity required C_S^R is achieved. This scenario has the probability calculated with equation (6) of 2.62 * 10-19. In this way, the same situation occurs with any combination in which the sum of the available trucks is equal to or exceeds the required capacity. The opposite is true when the same truck A1 is not available and all the other trucks from classes A and B are unavailable. In this case, the available fleet capacity will be 19,400 tons, which indicates a loss of production of 22,600 tons. Consequently, the impact of truck A1 will be 0.38%. This scenario has a probability of 2.90 * 10-84.

As shown in Figure 6, class A trucks are the trucks with the lowest impact since they have a high availability and their capacity is the lowest. Conversely, class E trucks are the trucks with the highest im-

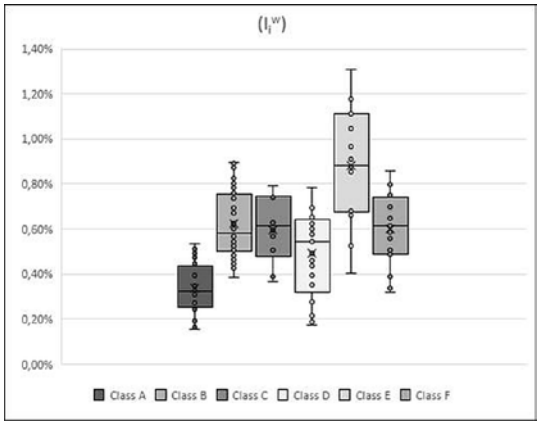

Fig. 6. Truck I_i^w impact graph by class

pact since their availability is low (class F trucks have the lowest availability) and their capacity is the highest. Specifically, the lowest impact is observed in truck A18 (truck 18), which has an expected availability of 92.89% and a capacity of 240 tons, which leads to an impact of 0.1527%. On the other hand, the highest impact is observed in truck E12 (truck 147), which has an availability of 59.32%, a capacity of 360 tons, and an impact of 1.3097%.

Table 5. Average Class I_i Impact

Class	Average I_i
A	0.34%
B	0.62%
C	0.60%
D	0.49%
E	0.88%
F	0.60%

According to Table 5, it is expected that the lowest Ii average is from class A, since its Ai is the highest and its capacity is the lowest. The effect of Ai can be verified by comparing its Ii with classes D and F, which have the same capacity; however, given their age, their availability is lower. The same result can be obtained by comparing the rates of class B versus those of class E.

Step 6:

In these conditions, the analysis can be concluded by calculating the expected EA from the truck fleet, which reaches a value of 88.49%. This calculation corresponds to the evaluation performed on each truck and its Ii, a procedure that follows Equation (8). As observed, this value is higher than the average availability of trucks that, in a weighted value by their capacity, would be 78.90%. This result is due to the overcapacity of the fleet (53,000 tons versus 42,000 required), which is one of the strengths of our model. In the case of including new equipment, independent of their Ai, the availability of the fleet will always increase. A sensitivity analysis is performed to evaluate various scenarios, such as the capacity increases versus increased availability.

Step 7:

Using the PL formula expressed as Equation 9, it is possible to determine that the PL, with an adjusted capacity based on EA, will reach 325 million of tons in one year, considering a continuous process. This estimation is based on the expected EA (88.49%), required capacity (42,000 tons per hour) and planned operational time for the year (8,760 hours). As detailed in equation 9, the multiplication of these three factors determines the annual production level forecast.

5.4. Sensitivity analysis

Once the model is implemented, a sensitivity analysis can be performed in two ways. The first way (Figure 7) shows the impact on the total availability (Y axis) of increasing 1, 2, 3, and 4 to 5% availability for a certain class of vehicle (in X axis). This analysis is developed in ceteris paribus conditions for the original fleet. The increased availability must be generated by an improvement in reliability and/or maintainability. As shown in Figure 7, it is clear that a marginal increase in the availability of class B vehicles is highly relevant for increasing the availability of the fleet. This effect is mainly given by the capacity of the vehicles in class B (in tons). For the remaining classes, there are no relevant differences.

A second sensitivity analysis (Figure 8) evaluates the impact of including more equipment to satisfy higher production targets by an increase in the expected availability of the transport system. Trucks are added from the different classes to the original fleet. This analysis is

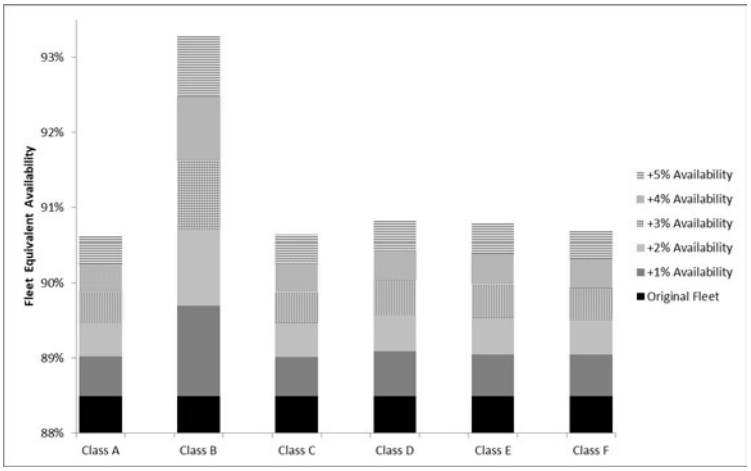

Fig. 7. Impact on the total availability of increasing availability of each class

developed in *ceteris paribus* conditions for the original fleet. As it can be seen in the graph in Figure 8, in terms of availability, the result of incorporating trucks (represented by the X-axis) from class A, is higher than the result obtained for trucks from other classes. For example, the second highest result was obtained by adding class B trucks. The base case considers the original 170 trucks, and in the testing cases, the numbers 5, 10, 15, 20, 25, and 30 represent the additional trucks. This result has a higher impact on class A, which is explained mainly by the high individual availability of type A vehicles versus type B vehicles, and even more than the proper capacity (tons) of each vehicle. The low capacity of class A trucks compared to class B trucks, for example, is overcompensated by their high individual availability. Every step of the simulation involves an increase of 1,200 tons for classes A, D, and F, an increase of 1,800 tons for class B and E, and an increase of 1,600 tons for class C related to the index C^{MAX}.

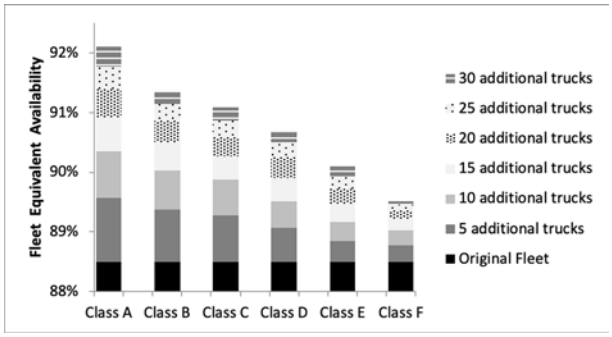

Fig. 8. Impact on the total availability of including more equipment to the fleet

Additionally, Figure 9 shows a direct contrast between the availability calculated via the traditional method, K-out-of-n and our proposed methodology. This finding clearly presents how the proposed

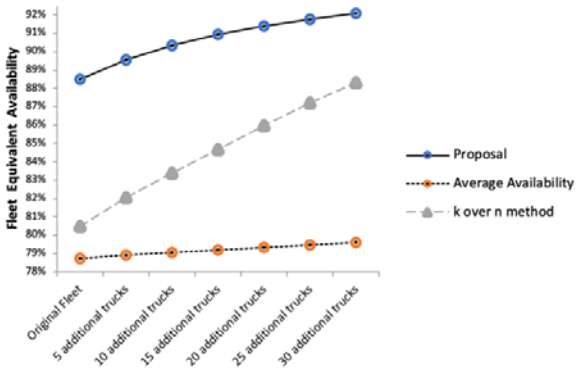

Fig. 9. Availability calculation comparison for class A equipment

methodology, compared with the other methods, gives higher availability values for any of the fleet configurations. The average method rises slowly due to the fact that Class A equipment are more available, but the overcapacity effect is not considered in its calculation conception. On the other hand, K-out-of-n obtains a higher estimation than the average method, but it is still less than our proposal in terms of fleet availability, as scenarios where the required capacity is not reached were not considered. The difference in the gap between K-out-of-n and the proposal methodology are reduced as more trucks are incorporated due to the redundancy degree of the fleet, and thus, its ability and probability to achieve the performance goal. Thus, it is easy to appreciate the notion that our proposal has the ability to resolve the problem of underestimating the fleet availability, which is a useful input to be employed for fleet design and control.

6. Conclusions

We present a new methodology for evaluating the availability and production level of complex systems, which represents load-sharing configurations with overcapacity and flexible work levels. We develop this methodology for systems that operate at less loads than required, which has not been previously addressed. We applied this methodology to a case study that makes understanding and application easier and presents significance, since it allows systems dimensioning, including the EA Index as a key variable. This innovation consists of expressing an EA and its production level related to their capacity to adequately represent the load sharing modelling, measuring the contribution of each element to the system's production level capacity. The employment of the EA Index prevents the exhaustive use of the Event Space Method, using for example the Binomial Distribution, to list all possible combinations of states of trucks that lead to success (reach the required capacity), and then calculating their probability of occurrence. Our proposed procedure can be applied to different industrial contexts, especially transport activities that work with equipment fleets, and eventually in modelling tasks for project design and dimensioning fleet size. The methodology is direct and transparent; however, its usage with systems consisting of many elements requires the support from specialised tools. Additionally, the methodology strengths are based on the capacity to define dynamic indicators for its application to determine the real work capacity for a period (day, way, month) adjusting the value by reliability, maintainability, and availability, measuring the effect of detention and idle time. In this case, the use of remote-control systems will have a great contribution. It is essential to compare our results with the application of the methodology in relation to current practice, based on indicators without a systemic vision, which prevents the optimisation of processes and which are based mainly on average and unadjusted indicators. For this, it is necessary to remark the calculation of the weighted impacts of each element, which consider their evaluation in every one of the scenarios, according to their probabilities. It is important to highlight that the methodology is applied in haul trucks fleet, but is possible to extend this application in many industrial sectors as supply chain, transportation, and public transport. As a matter of fact, in the processes where a fleet is developed and implemented, the EA index could be modelled and studied to analyse the performance indicators. Finally, the compliance of the objectives in this investigation is expressed, stressing the importance of its application in a case study, and its results.

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