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Availability forecast of mining equipment

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Abstract
Purpose – The purpose of this paper is to present a methodology for forecasting the availability off-highway trucks used in a fleet for large transport operations of ore and sterile rock from an open pit mine.
Design/methodology/approach – This methodology enables the estimation of the number of hours of preventive and corrective maintenance required, which are used to predict truck availability. The authors used historical data for the maintenance strategy based on the hours of operation.
Findings – These data are statistically analyzed to obtain the key quantities and statistical models required to project availability and to develop equipment replacement plans.
Originality/value – A methodology for forecasting availability to assets in open pit mining industry was implemented.
Keywords Simulation, Forecasting, Maintenance, Availability, Off-highway trucks, Statistic model
Paper type Research paper

1. Introduction
Preventive maintenance requires numerous related data collection, analysis, and forecasting steps to define the optimal intervals between maintenance practices. The maintenance intervals can be defined in terms of elapsed hours (days, months, years) or operation hours. Key performance indicators (*KPIs*) for maintenance such as availability (*A*), mean time between failures (*MTBF*), and mean time to recovery (*MTTR*) are greatly influenced by these intervals. Conversely, operational time-based preventive equipment maintenance also requires efficient management of *KPIs*.

The availability of a fleet is a key management parameter to be predicted and controlled. Kothamasu *et al.* (2006) state that the only way to ensure minimum maintenance costs and a minimal probability of failure is to routinely monitor equipment condition and failures, and to make predictions on the basis of current conditions and historical equipment maintenance and operations.

Availability forecasting enables the anticipation of necessary corrective actions while providing strategic information to the client about the use of the fleet during production. The availability forecast is a key step in the maintenance management process, whereby costs are anticipated and actions can be taken to maintain and improve the reliability of the fleet.

The level of availability affects directly the planning of production process capacity. According to Lustosa *et al.* (2008) the process of production capacity can be quantified by the amount that can be produced. Thus, the availability establishes a direct relationship with the production capacity since it is a measure of time in which the equipment will be available for production operations.

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Computationally implemented mathematical models can help overcome challenges that arise in the forecast process. These models can also help overcome the challenges related to analysis. Several issues arise when analyses and forecasts are supported solely by employee input regarding maintenance processes, without the benefit of appropriate computational tools. Difficulties arise where the number of sensors and the volume of operating data are high. Faced with complex problems, with a wide range of variables, people tend to simplify the decision-making process and important variables can be discarded. This can lead to choices that may appear locally correct, but are not globally optimal (Iyer *et al.*, 2006). In many cases, maintenance professionals cannot identify incipient faults in the system, especially when several parameters are correlated with the failure (Kothamasu *et al.*, 2006). Neither can they suggest actions to prevent reductions in availability, all of which lead to significant impacts on production.

In large open pit mines, where the number and size of assets in operation are often high, forecasting equipment availability is a fundamental step in any effective management process. This ability assists in the prediction of maintenance costs and the actions required to ensure asset reliability. It is also critical for production planning and asset management.

2. Availability(A)

To Katukoori, the definition of availability is very flexible and based largely on the interruptions occurring during analytical operations. Some useful definitions relating to the difficulties that arise in forecasting availability are given below.

Lavraia (2001) defines availability $A(t)$ as a probability measure of the equipment being in working condition at time t. Katukoori further characterizes availability as a performance parameter that takes into account both the reliability and maintainability of a component or system.

2.1 Point availability (A_p)

In mathematical terms, availability represents the probability of an item being operational at time t. This value will depend on the probability that the item will not fail until the instant $t = t_0$ (reliability) and that the item can be recovered at time $u < t$, if a fault has occurred previously (maintainability). These two conditions, reliability and maintainability, competes with respect to a component or system being in operating condition at time t. We refer to the probability of a system's reliability, $R(t)$, when it is operating between 0 and t. When a system failure is recovered at instant u, where $0 < u < t$, we refer to the probability of the system's maintainability, $M(t)$, given by Equation (1), where $m(u)$ is the recovery density function (Katukoori, 1995):

$$M(t) = \int_0^t R(t-u)m(u)dt \tag{1}$$

thus the instantaneous or point availability, $A_p(t)$, is given by Equation (2):

$$A_p(t) = R(t) + \int_0^t R(t-u)m(u)dt \tag{2}$$

2.2 Inherent (A_i), achievable (A_a), and operational (A_o) availabilities

In the study and analysis of availability, there are three useful definitions, as described below.

2.2.1 Inherent availability (A_i). Inherent availability considers only those features estimated in the design phase for calculating reliability and maintainability. Inherent availability can be calculated using estimated values of $MTBF$ (reliability) and $MTTR$ (maintainability), respectively, during the equipment design phase, as shown in Equation (3):

$$A_i = \frac{MTBF}{MTBF + MTTR} \tag{3}$$

Inherent availability does not generally include administrative inherent time delays or logistics that are beyond the control of the designer; nor are the preventive maintenance times considered.

2.2.2 Achievable availability (A_a). Achievable availability considers the corrective and preventive maintenance times. It is the expected availability of the equipment, following the advanced design of the equipment and facilities. It assumes an environment in which there is optimal support and all necessary spare parts, tools, and manpower are available without delay (Keeter). Achievable availability is specifically geared to the equipment characteristics and does not consider operational or logistical factors.

Equation (4) may be used to calculate achievable availability:

$$A_a = \frac{OT}{OT + MCT + MPT} \tag{4}$$

OT (operational time) is the time period during which the equipment is available, *MCT* (maintenance corrective time) is the time required for performing corrective maintenance, excluding inspections before or after maintenance, administrative time, or delays in the delivery of parts, and *MPT* (maintenance preventive time) is the total time required for performing preventive maintenance.

The achievable availability curve determines the optimum level that is possible with respect to availability. It is important to consider location and the nature of this curve so that maintenance and operations managers do not inadvertently overspend or overcharge maintenance resources while attempting to achieve performance beyond what is actually possible (Katukoori, 1995).

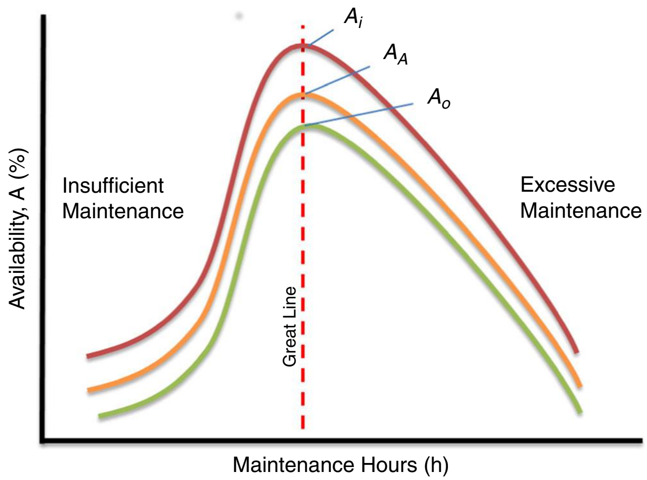
2.2.3 Operational availability (A_o). With operational availability, all times are considered, including the times required for corrective and preventive maintenance, administrative functions, and logistical delays. This value is more realistic than the previous two and is the availability that the customer actually experiences. It is generally defined by the following equation:

$$A_o = \frac{CH - MH}{CH} \tag{5}$$

where *CH* (calendar hours) is the total time and *MH* (maintenance hours) is time in hours in which the equipment is in maintenance.

As noted by Katukoori, operational availability is essentially a posteriori availability based on real system events, while the previous availability estimates are based on a priori models and probability distributions of system maintenance time failures.

Since, in this study, we are interested in forecasting availability for an actual operation, we use operational availability. Figure 1 shows schematic curves of inherent, reachable, and operational availability.



Source: Adapted from Keeter

Figure 1. Schematic curves of inherent, reachable, and operational availability

2.3 Maintenance hours (MHs)
Historical data include records of *MHs* from previous years.

The time values regarding maintenance incidents recorded in the data sources may be classified into two groups, as described below.

2.3.1 Hours of corrective maintenance (HCM). These hours are those accrued owing to the maintenance or repair of equipment returned to operation after unexpected failures, including repair times, administrative delays, and the preparation and logistics associated with this type of failure. Failures related to the hours spent in corrective maintenance are generally seen by the user (Dhillon, 2002) and negatively impact planning.

2.3.2 Hours of non-corrective maintenance (HNCM). *HNCM* values include all instances of maintenance that were planned in advance. These include preventive and predictive maintenance, administrative delays, and the preparation and logistics associated with this type of maintenance.

Preventive maintenance includes all actions performed in a planned manner and at defined intervals to keep items or equipment in working condition through a process involving the inspection, replacement, and reconditioning of components. Predictive maintenance uses modern methods of measurement and signal processing to accurately diagnose the condition of equipment during operation (Dhillon, 2002).

In this study, we make no distinction between the hours of preventive maintenance and those of predictive maintenance.

2.4 Service hours (HORs)
In this study, we report the availability, hours, and maintenance parameters obtained for the lifetime of the assets considered. Asset lifetime is given in hours of engine operation, typically referred to as *HORs*.

3. Historical data

We accessed available historical *HOR* records (see Subsection 2.4) for 99 large mining off-highway trucks (240 tons).

We also obtained maintenance records for the occurrence of corrective and non-corrective *MHs* (see Subsections 2.3.1 and 2.3.2) for the range in years from 2010 to 2013.

3.1 Treatment of historical data

3.1.1 Processing of HORs. We generated a time series using values from the *HOR* records, with one day of rest for each asset. For the days when records were unavailable, we made a linear interpolation of the values to generate sets for the time series. As readings typically occurred at less than 24 h intervals, these interpolations did not significantly affect the data.

Since the registration information of several assets was shown to have inconsistent *HORs*, we processed the data to eliminate errors. We also found various database inconsistencies due to the following reasons:

(1) entry errors in the recorded *HOR* readings;

(2) procedural inconsistencies and incorrect *HOR* records; and

(3) loss of early historical data for the equipment.

Thus, these records provided an active log of *HORs* for the analysis period. The graph in Figure 2 shows data records from an available asset, for which inconsistent data were excluded using a Hampel filter (Pearson), and the subsequently generated time series (blue line).

Using these historical time series of the *HORs* for all assets of the fleet, we constructed a graph of the average daily variation of *HORs*. To reduce the number of calculations required, we ranked the data by the daily average variation, at 100 h intervals, in the lifetime of each asset. We then obtained log variation values for the average *HORs* for the 100 h lifetime range of each of the fleet assets, with the results shown in Figure 3.

From our analysis results, we observed at least four distinct phases in the lifetime of an asset:

(1) the first phase shows a high degree of variation in the recorded *HORs*-approximately 20 h/day, from 0 to 10,000 h of asset lifetime;

(2) in the second phase, there is a sharp drop in the daily variation (approximately 19-15 h/day) from 10,000 to 20,000 h in the *HOR* records;

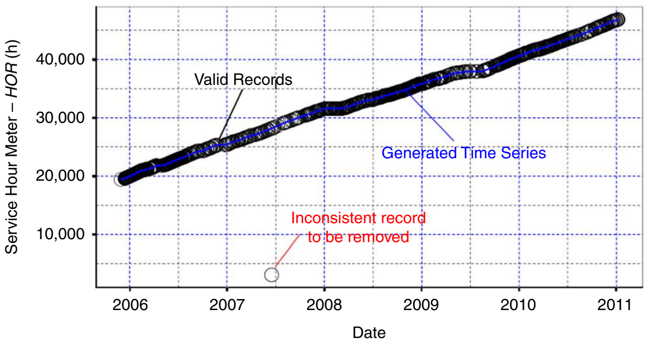


Figure 2.
Time series, with one-day time intervals, based on historical service hour records

(3) in the third phase, the variations show a smaller drop (approximately 15-14 h/day) from 20,000 to 35,000 h of asset lifetime; and

(4) in the fourth phase, the variation increases again after 35,000 h of asset lifetime.

Each of these phases is strongly characterized by the data's variability, with the last phase showing even higher variability. In this study, we separated these asset lifetime stages using a clustering algorithm, and considered the mean values of each phase and all their associated variabilities.

We also note that the changes represent a record of the *HORs* of engine operation. This measure reflects the efficiency of assets and takes into account both their operational availability and use. Utilization (U) is the percentage of time that the asset is available and stays in operation. The values of U are not modeled in this study since this external variable was unavailable, being controlled only by the user.

3.1.2 Hours of maintenance treatment. The points in the graph of Figure 4 compose a sample of the durations of the fleet's daily occurrences of corrective maintenance between 2010 and 2013. We reduced the amount of data required using an average of 100 h track of lifetime each asset, as was followed for the *HORs*, to obtain the graph shown in Figure 5.

The Figure 6 graph shows the sample time durations of non-corrective maintenance. The Figure 7 graph shows the daily average values for each group at 100 h intervals of asset lifetime.

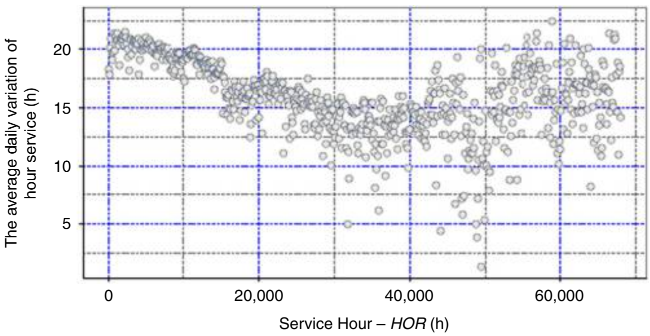


Figure 3. Calculated average service hour variations for all fleet equipment at 100 h intervals over the lifetime of the assets

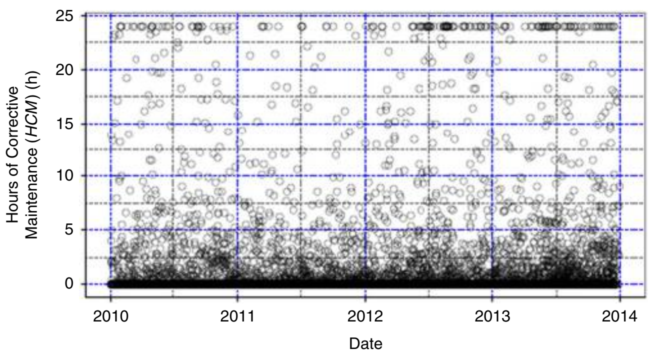


Figure 4. Daily history of corrective maintenance hours

As expected in the early lifetime of the assets, values for *HCM* and *HNCM* are smaller, and those at the end of asset lifetime are higher. The variability follows the same trend as the daily variation of recorded *HORs*.

3.1.3 52-weeks map. A common practice in maintenance management is to establish a plan for preventive maintenance based on operating hours (*HORs*). In this case, stoppages for reviews, recovery, and replacement of components are established at regular intervals, and the duration of these stoppages are known and may be estimated as the hours spent in preventive maintenance. For example, in the maintenance plan held in off-highway trucks at every 250 *HORs*, the standard time for preventive

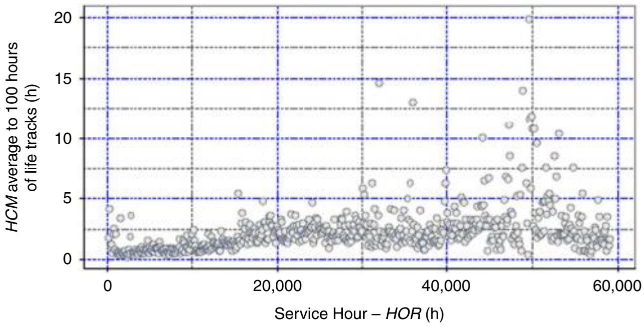


Figure 5. Averaged hours of corrective maintenance for all equipment in the fleet at 100 h intervals of asset lifetime

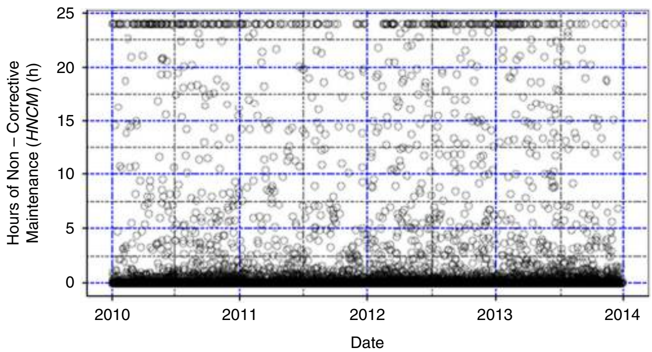


Figure 6. Historical daily hours of non-corrective maintenance

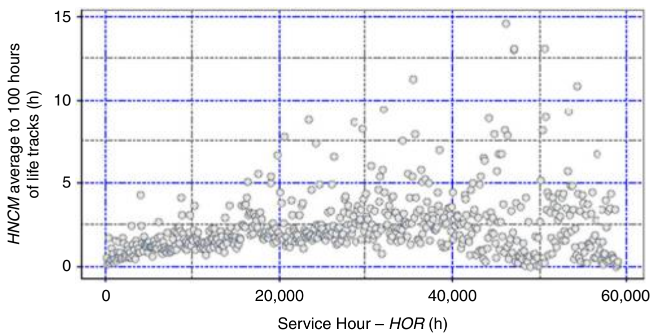


Figure 7. Averaged daily hours of non-corrective maintenance for all fleet equipment at 100 h intervals of asset lifetime

maintenance established by manufacturer and maintenance team is four hours, being carried out tasks as component inspections, exchange, and filter cleaning, safety items testing and collects of fluids of engine and hydraulic systems for analysis.

These plans, known as 52-weeks maps, refer to scheduled stoppages over the year. While they often do not record the associated administrative and logistical delays, they are often used to predict times during which there are no corrective shutdowns.

Figure 8 shows a sample 52-weeks map for the review of a planned asset for the year 2016. Figure 9 shows a 52-weeks map regarding the exchange of components planned for the entire fleet of assets. The two maps indicate the duration periods anticipated for the revision and replacement of components, and may be used to estimate the times required for non-corrective maintenance.

4. Forecast models

The availability forecast methodology includes the projection of *HORs* and the hours required for corrective and not-corrective maintenance. The flowchart in Figure 10 shows the sequence of simulations performed to obtain a projection of the daily availability.

The models used in this study directly predict *MHs* for availability forecasting. Another common alternative prediction methodology is the use of indirect parameters such as the failure rates, *MTBF*, and *MTTR*. However, as discussed by Smith (2011), the hypothesized repeatability of parameters such as the failure rate for systems is questionable. This is because even when assuming no variability in operating conditions and the environment, the variability can be actually high, as observed in the available historical data. Smith (2011) also concludes that complex models can result in misunderstandings and economic losses.

In this study, we use statistical models of relatively low complexity, which can be implemented computationally and can also take into account the variability of data through well-known function distributions.

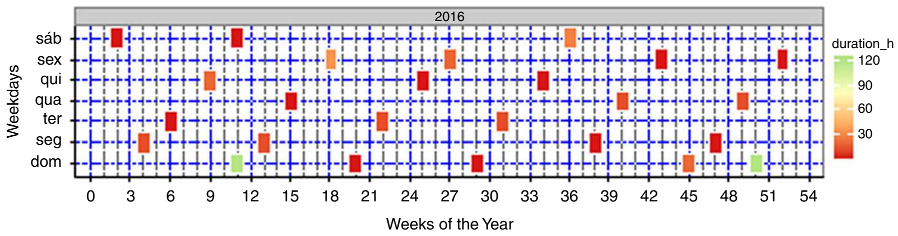


Figure 8.
Example of a 52-weeks map for planned revisions of an asset

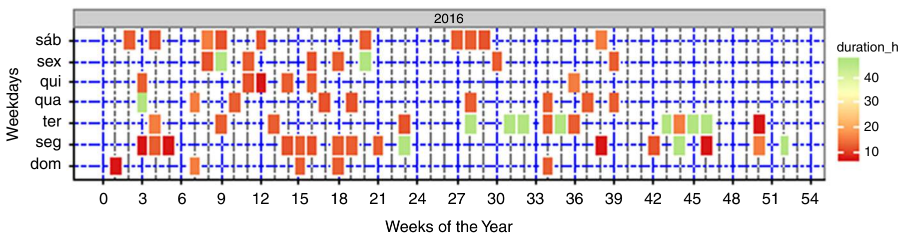


Figure 9.
A 52-weeks map for the replacement of components in fleet assets

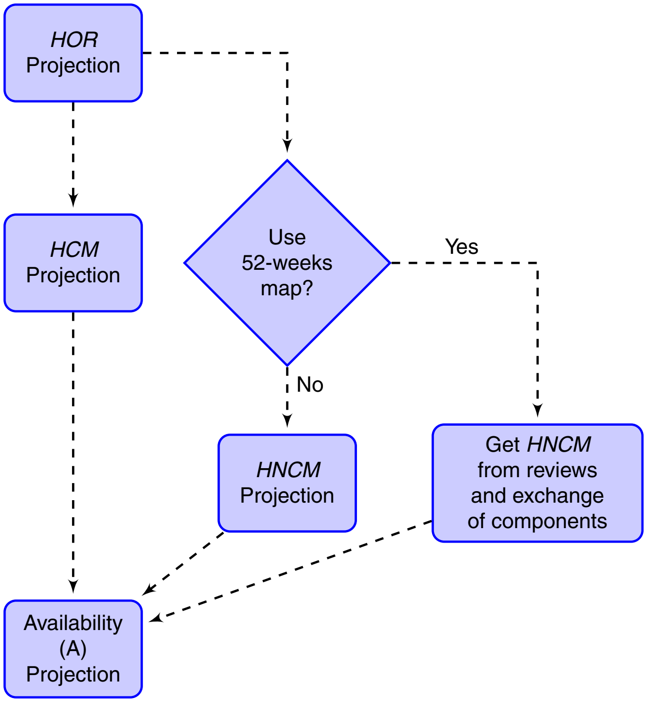


Figure 10.
Flowchart of the methodology used

4.1 HOR forecast model

The Figure 11 histogram shows the distribution of the daily variations in *HORs*. It is clear that there are two sets of data-days when the variation of recorded *HORs* is 0 and days when the variation behaves according to a statistical distribution.

We use a binomial distribution as statistical model to providing the option of choosing whether the variation in the *HORs* is 0, and a Weibull distribution to simulate the variation in the registered *HORs* on days when the variation was greater than 0.

Using a Weibull distribution to model the variation in daily *HORs*, we improved the accuracy of the models. The data of *HORs* variation are separating into clusters obtained from a k-means (Jain, 2010; Hartigan and Wong, 1979) algorithm. Then, we generated the statistical model (Weibull 2p) for each cluster, which allowed us to project the average

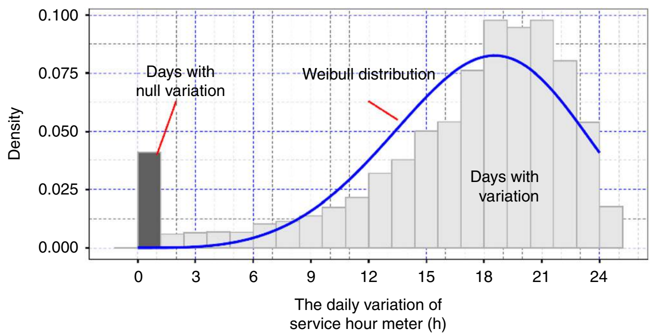


Figure 11.
Histogram of day-to-day service hour variations in fleet assets

values and simulate dispersions in the mean changes. The graph in Figure 12 shows the Weibull curves for each cluster.

Thus, for an asset in the range 0-3,500 recorded *HORs*, the average daily variation in *HORs* is 20.5 h, the first quartile is 19.9 h and the third quartile is 20.9 h. In the range 49,200-51,800 *HORs*, we obtained daily variation values of 10, 12.9, and 15.9 *h* for the first quartile, the average, and the third quartile, respectively.

4.2 *HCM forecast model*

The Figure 13 histogram shows the distribution time for corrective maintenance.

Then the variations of *HORs* were clustered, we established a statistical model to *HCM* for each cluster. We then adopted an exponential distribution to this *HCM* in which the simulation takes into account the average values and the dispersion of this distribution in each cluster. The plots in Figure 14 shows the clusters and the *HCM* exponential data models adopted for each one.

4.3 *HNCM forecast model*

We performed the *HNCM* forecast using two methods for comparing their performances. In the first, we obtained the hours from the 52-weeks map, and in the second, we used statistics from the *HNCM* and *HOR* models.

4.3.1 52-weeks map. We obtained the *HNCM* values by observing the dates for which revisions and replacements of components were provided in the 52-weeks map. Tables I and II show some examples of the time durations considered. See Figures 8 and 9.

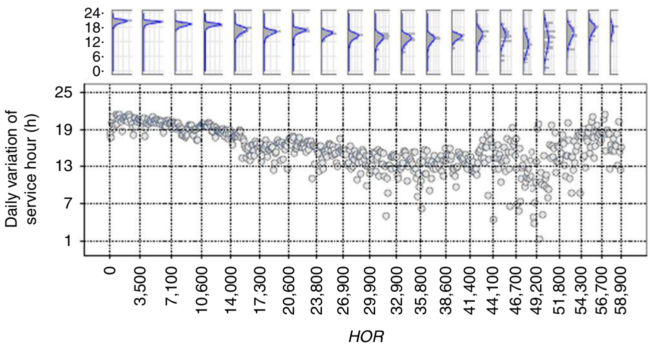


Figure 12. Statistical model for the daily rate of service hour's variation

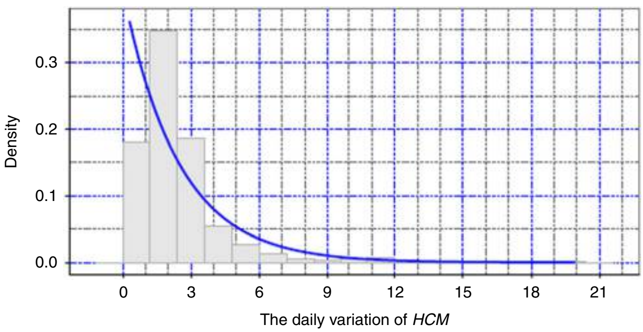


Figure 13. Histogram of *HCM* records for fleet assets

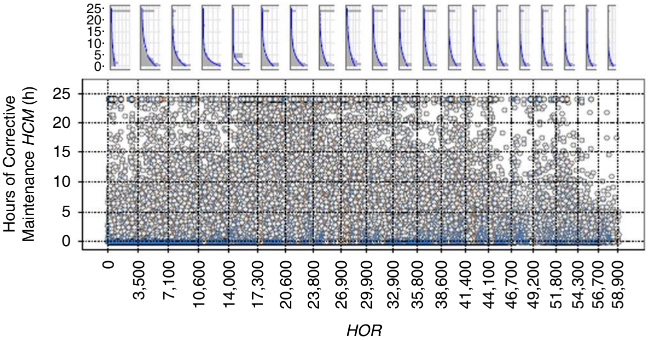


Figure 14.
HCM statistical model

Table I.
52-weeks map example of revision time data for an asset

Asset	Date	Revision	Duration
CM18	2015-06-09	250	4
CM18	2015-06-13	500	15
CM18	2015-07-18	250	4
CM18	2015-07-24	1,000	21
CM18	2015-09-16	250	4
CM18	2015-09-27	500	15
CM18	2015-10-11	250	4
CM18	2015-10-21	6,000	35

Table II.
52-weeks map example of asset component replacement times

Asset	Component	Date	Duration
CM35	Final drive left side	2017-03-24	15
CM35	Final drive right side	2018-12-11	15
CM35	Torque converter	2017-11-14	18
CM35	Diesel motor	2017-11-14	47
CM35	Transmission	2018-05-02	10
CM35	Differential	2018-06-30	13

4.3.2 HNCM model. The second method for obtaining the *HNCM* follows the same procedures as those for obtaining the variations of *HOR* and *HCM*. The histogram of Figure 15 shows the time distribution for *HNCM* and Figure 16 shows the graph of the statistical model. We used exponential distribution curve models.

5. Simulations and results

The procedure begins with simulation calculations of the daily variations registered with respect to the *HOR* clusters shown in Figure 12. This allows the machine to predict the *HORs* at a specified future date. Then, we simulated the time for *HCM* according to the clusters' statistical models shown in Figure 14. Finally, we simulated the durations of *HNCM*, which can be obtained using the projections of the 52-weeks map (see Figures 8 and 9) or the statistical models shown in Figure 16.

With time, we can estimate the operational availability of a given day using Equation (5), where $HM = HCM + HCNM$, and provide a monthly average for an operating fleet within a specified confidence interval.

Figure 17 shows the averaged results of a simulation at 100 h intervals of the operation of fleet assets until they reach 50,000 h of operation. We simulated *HNCM* using the history in Figure 16.

Table III shows numerical prediction results for an active truck for the year 2014. The table columns show, respectively, the month of the forecast, the expected *HORs*, and the prediction of *A*, considering the *HCM* and *HNCM* based on historical data, with an 85 percent (A_{HL}, bottom of the range), 50 percent (A_H, average), or 15 percent certainty

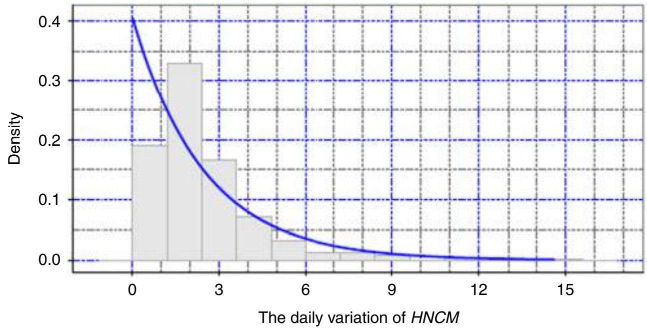


Figure 15. Histogram of the day-to-day *HNCM* records for fleet assets

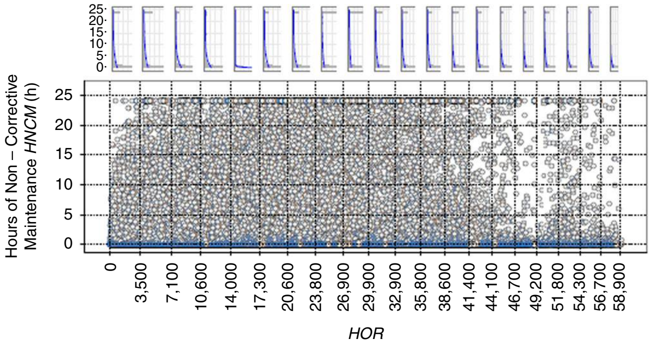


Figure 16. Statistical model for *HNCM*

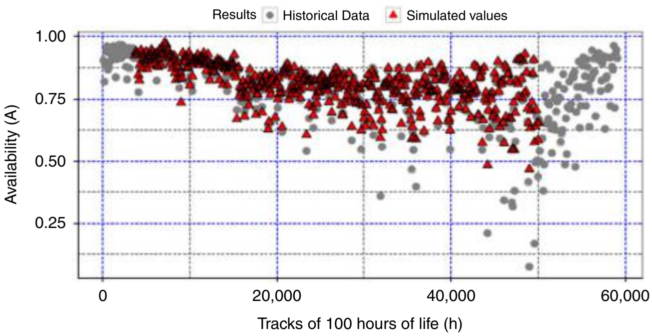


Figure 17. Comparison of availability obtained by simulation over assets lifetimes with that obtained from historical data for 100 h of service

	Ativo CM99						
	HOR	A_{HL} (%) 85%	A_H (%) 50%	A_{HH} (%) 15%	A_{ML} (%) 85%	A_M (%) 50%	A_{MH} (%) 15%
jan/14	11,968	89.25	90.50	91.54	84.32	88.66	93.16
fev/14	12,502	88.19	89.43	90.60	90.61	92.58	95.03
mar/14	13,088	82.90	84.83	86.95	85.44	88.72	91.32
abr/14	13,545	87.39	88.59	90.20	66.04	73.37	81.41
mai/14	14,088	82.96	84.41	86.71	81.57	85.98	90.77
jun/14	14,589	88.14	89.31	90.40	90.12	92.48	94.40
jul/14	15,096	90.00	90.99	92.34	90.46	93.23	96.31
ago/14	15,619	78.29	81.02	84.28	81.58	84.72	88.28
set/14	16,086	79.40	81.53	83.36	79.07	84.44	88.26
out/14	16,588	73.83	77.59	80.66	85.63	88.12	90.80
nov/14	17,062	83.12	84.74	86.78	85.90	89.41	92.23
dez/14	17,458	76.32	78.86	80.76	57.59	64.99	72.39
2014	17,458	83.32	85.15	87.05	81.53	85.56	89.53

Table III.
Table of simulation results for truck CM99

levels (A_{HH}, upper limit of the range). Next we based the prediction of A on the *HCM* from historical data and on the *HNCM* hours from the 52-weeks map, obtaining 85 percent (A_{ML}, bottom of the range), 50 percent (A_M, average), and 15 percent certainty levels (A_{MH}, upper limit of the range). Table IV shows the values obtained for an entire fleet of 99 trucks.

This range of certainty allows managers to make choices that are more conservative (85 percent), typical (50 percent), or challenging (15 percent).

The 52-weeks map could not predict administrative and logistical time delays (inefficiencies maintenance planning). Therefore, the resulting *HNCM* schedules based on 52-weeks map were underestimated in the simulation and the values in Tables III and IV to 52-weeks map are higher.

The data in the two tables above are for fleets with no assets replacements, so the average age of the fleet increased. Figure 18 shows the projection curve for the next five years for a fleet making no assets replacements, considering the *HNCM* predicted from

	Frota						
	HOR	A_{HL} (%) 85%	A_H (%) 50%	A_{HH} (%) 15%	A_{ML} (%) 85%	A_M (%) 50%	A_{MH} (%) 15%
jan/14	28,450	75.04	78.10	81.24	81.82	85.45	89.01
fev/14	28,831	75.34	78.31	81.40	81.27	84.99	88.73
mar/14	29,266	74.83	77.89	80.81	79.76	83.61	87.54
abr/14	29,690	76.20	78.99	81.82	80.15	84.09	87.93
mai/14	30,121	74.34	77.42	80.49	79.49	83.41	87.26
jun/14	30,288	75.64	78.56	81.47	80.29	84.01	87.81
jul/14	30,715	74.94	77.87	80.86	79.10	83.10	87.03
ago/14	31,139	74.73	77.83	80.96	79.02	83.19	87.26
set/14	31,548	74.04	77.21	80.49	79.47	83.37	87.51
out/14	31,949	74.96	78.01	81.07	75.63	80.46	85.19
nov/14	32,348	73.30	76.51	79.65	78.45	82.48	86.48
dez/14	32,532	72.14	75.43	78.80	78.76	82.65	86.70
2014	32,532	74.62	77.68	80.75	79.43	83.40	87.37

Table IV.
Table of simulation results for entire fleet

historical data. The curve of the recorded *HORs* shows a growth of over 16,000 h and the availability curves for the provided fleet. The upper curve indicates the challenging case, the intermediate curve the typical case, and the bottom curve the conservative case.

Figure 19 shows projection curves for the next five years for the fleet with assets replacement for the *HNCM* predicted from historical values.

The operational availability values in the first two months of 2014 were 74.50 and 76.33 percent in the region close to that considered conservative. Figure 20 shows the expected curves of the challenging, typical, and conservative values for the first two months of 2014.

6. Conclusion

The availability forecasting should be done with great care and a thorough conceptual knowledge of the various methods for determining the optimal time to be spent on maintenance. An appropriate choice is to use the definition of operational availability that includes the customer's perspective regarding service maintenance.

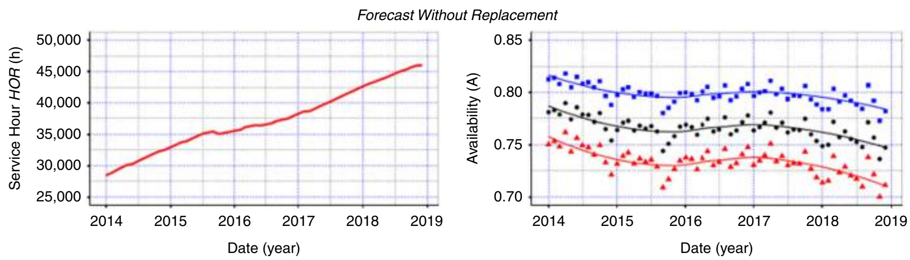


Figure 18. Result for five-year simulation for assets with no assets replacements when they reach 50,000 h of operation

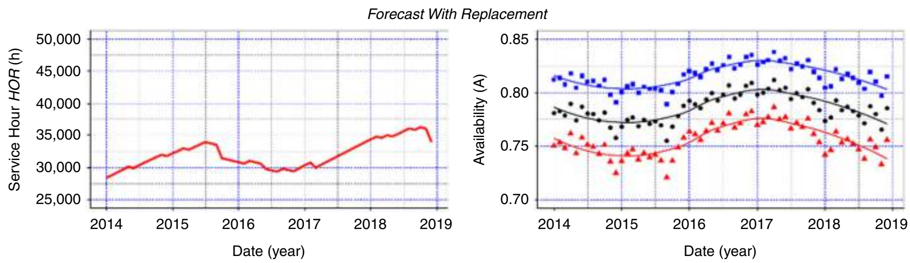


Figure 19. Results for five-year simulation where assets are written off and replaced when they reach 50,000 h of operation

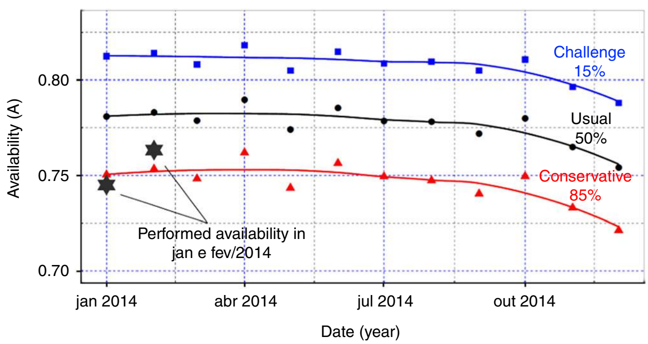


Figure 20. Operation availability check for January and February of 2014

Seemingly accurate models of prediction parameters may be incompatible with highly variable historical data. This variability is a relevant factor in decision making based on operational availability forecasting. Simulations allow us to consider availability average *A* values, and the associated variability, which can provide a broader and more useful scope regarding asset predictions.

We note that historical estimates based on hours of corrective and non-corrective maintenance models are more consistent with reality because they consider the current state of the maintenance process. Models based on 52-weeks maps, usually incomplete because they cannot map the logistical and administrative delay times, can provide overestimated availability predictions.

The case study values for the first two months of 2014 (74.50 and 76.33 percent) indicate that projection results using this methodology are appropriate since they indicated with 85 percent certainty that the monthly operational availabilities were down 75.34 percent in the first two months.

The results and analysis indicate that this methodology can also be used for treating data and performing the simulations necessary for predicting the expected lifetime and availability of fleet assets.

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