The impact of payload truck factor use in mine performance reports for an open pit copper mine in Brazil

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Abstract

This article aims to evaluate the use of a truck factor for off-highway trucks in open pit mine operations, thus reducing error on material movement and mine production data entry. This method is current for a copper mine located in South East Pará, Brazil. With a dispatch system, the truck factor is calculated using three data inputs called measured t, dump t and excavator load time. This dispatch system, designed to upload real time data from each truck, acquires measured load information by a truck weightometer and provides the basis for long-term, medium-term and mainly short-term planning. Due to the significant impacts toward mine planning, through data error, a payload truck factor system provides data assurances in place of potential failure of onboard weighing. However, when using a system that is reliant on actual data, caution must be applied when replacing information with assumed fixed figures, thus forming the discussion on which this article attempts to review by providing overview on both the positive and negative impacts of implementing a truck factor system to an open pit mining using a dispatch system.

Keywords: truck factor, average load, production.

1. Introduction

A database that attains information from several sources, such as Production Data Acquisition Systems or Manufacturing Execution Systems, is inclined to have inaccuracies and inconsistencies (Reuter, 2016). Production reports that are date/time stamped or entail production volume data are susceptible to error through mechanical defects or human fault through manual reporting. The use of Key Performance Indicator and a continuous improvement program is widely used in the mineral industry (CROSER, 2005; NADER *et al.*, 2012). However, the increased need for quality data becomes even more crucial for manufacturing companies to improve efficiency and competitiveness, as it is an important prerequisite for intelligent factories, in which Cybernetic systems will operate autonomously based on accurate and consistent database reporting.

Hardy (2003) emphasizes the importance of the transport fleet, since it corresponds to 38% of the operational cost in open pit mines. It also addresses the accuracy of data from the truck weightometer: manufacturers warrant an error of 5%±, although the production reconciliation data point to larger errors.

One of the sources widely used for the control and monitoring of production is the datasets from Fleet Management Systems (FMS).

Most of the scientific articles focus on the automation and optimization of the truck dispatch rules (CHOI, *et al.*, 2009; ZHANG *et al.*, 2015; DINDARLOO *et al.*, 2015; CHAOWASAKOO *et al.*, 2017; MORADI AFRAPOLI and ASKARI-NASAB, 2017). The most practical subject with changes in the operation is the exchange of shifts (BASTOS, 2013).

The main objective of this article is to demonstrate the importance of the analysis of the database and to look for the operational causes of discrepancies. In literature, the closest theme is HSU (2015), which analyzes two FMS datasets that indicate data corruption (software / hardware issues) or human error (operator input issues). However, the author does not seek the correlations between the database and the mining operation.

Truck factors are a widely used methodology, which allows small operations to replace the need for the truck-mounted weightometer and large operations to minimize reporting error due to truck weightometer defect. This case study considerers the timing in which the truck factor is applied to a dispatch system report, whereby, if the load measured by the truck weightometer, in real time, is lower than the weight of the average load, it marks the point where the truck factor is then implemented into the production data. A percentage of the average load defines the current truck factor number to be applied in any such case and is reviewed to get as close as possible to the actual loads realized in the operation. The dispatch system saves both records in the database - the original, measured by the weightometer and the newly created record (average payload set), although, for performance reports the new values are set as the official.

Furthermore and specifically, for the mine in this case study, the quarterly data set of the measured payload is reviewed every three months with data categorized into three areas: transport fleet, excavation fleet and material classification. An illustrative scheme, Figure 1, exemplifies this methodology.

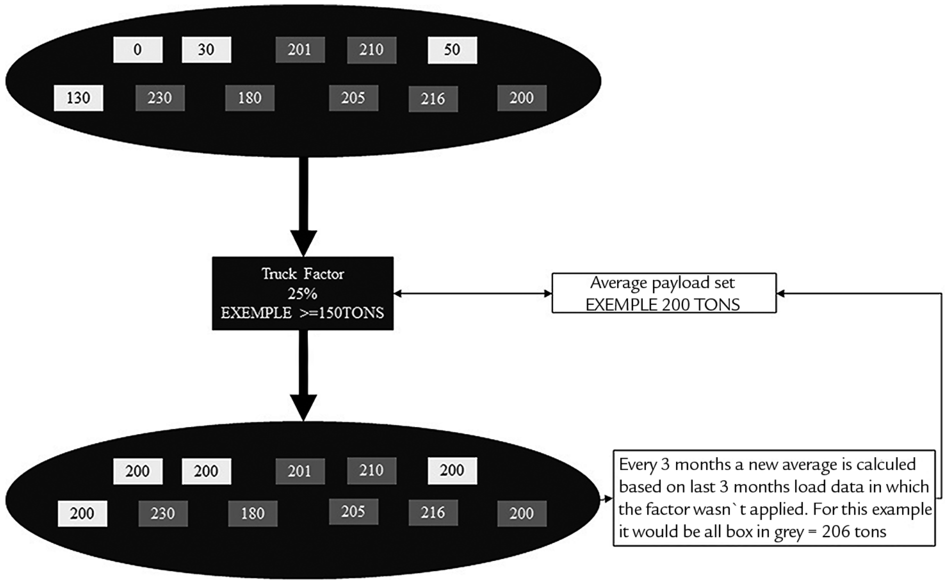


Figure 1
Truck factor exemple,
payload records in white are modify.

The example above considered a 25% truck factor and the average payload set is 200 t. Defining a 25% truck factor means that every time the weightometer measures a load lower than 25% of the average set, the dispatch system will automatically create a new record in which the average is the value and it becomes then the official load. For example, considering a 220 t average payload set in the system, every time the weightometer measures a load lower than 165 t (75% of 220 t), the official load would be 220 t and no longer 165 t. The average payload set is the average of the values of the last quarter that were not modified.

In the Figure 1 example, the factor was applied in four records - lower than 150 t and then these records now get a new value, which had been the average previously set as 200 t. The average payload set for the next quarter is 206 t, average of values to which the truck factor was not applied. In theory, values greater than 125% of the average payload set are modified, but in practice these values do not occur, so in this work we only treat the lower limit.

As previously mentioned, the methodology purposes to mitigate errors in performance reports caused by mechanical weightometer defect, which would otherwise generate data with lower production than actually executed. However, after analyzing data in this study, it is possible to state that if not regularly verified and updated, this methodology has the potential of increasing production that could affect production KPI's, such as costs, productivity, and affect mine planning and equipment sizing. In addition, Renström (2010) shows in his work that there is another economic factor related to the filling of the load of the truck, in which the more complete the truck load, the lower the fuel consumption, considering the unit l / kt.km.

2. Methodology

The methodology used in this case study is composed by data collection, processing and analysis.

Data collecting: All data below were collected from dispatch database within a period of one year: loads measured by the weightometer; truck factor loads; excavators cycle time; excavator productivity; production and mass transported.

Data processing: All datasets were extracted from the dispatch system, then analyzed and treated - outliers and small truck fleet data were not considered in the population. As aforementioned, in this case study, the average payload set is reviewed every quarter and updated in the system. In order to evaluate impacts, it was necessary to dispose the data in the same base for comparison – an average payload set for one of the periods was chosen and applied on all datasets. An index was created for data analysis – known as percentage of the truck factor application (%TF) and it is calculated as the total truck factor load divided by the total of loads.

Data analysis: after processing the data, we generate graphs in several periods to find correlations of shifts, crew, fleet and operator. In addition, a test was performed by altering T.F.

3. Results

In this section, we present the analysis of the use of TF. The index represents the amount of changed data, e.g. TF = 30% means 30% of the measured masses were changed to the mean value because the measurements in the system were wrong. The value of the variable is binary: mass changed or unchanged. Figure 2 compares the %T.F from January, 2014 to December, 2015. It clearly shows that the use of the %T.F has increased in the second semester of 2015.

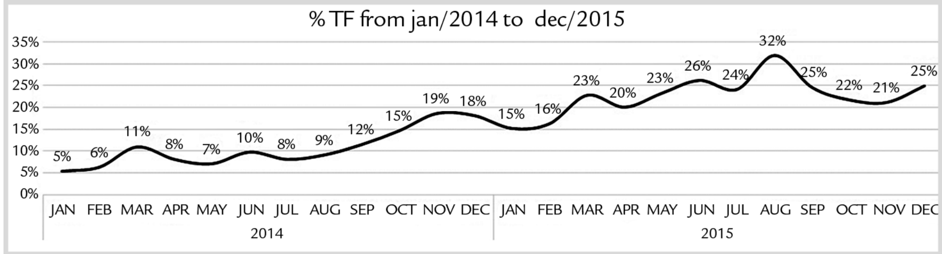


Figure 2
Truck factor use by time.

The fleets are analyzed in Figure 3, %TF is much higher in CAT793 fleet than CAT785, although for both fleets the index substantially increase during the second semester in 2015.

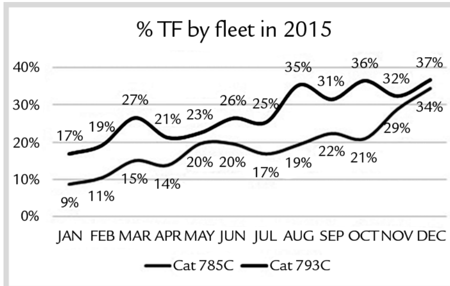


Figure 3
Truck factor use for fleet by time.

In order to compare the index in other bases, data was separated by excavation, crew and shift (Figure 4 – Figure 6). The data is whole dataset population from 2015:

• Excavator: It's possible to notice a trending %TF for each excavation fleet, which was not expected as trucks are not fixed in one excavator cycle.

• Crew: there is a high variance among the crews that shows that even with existing maintenance issues in trucks weightometers, there is also an evident operational behavior effect.

• Shift: A slight increase in %TF is observed for night shifts.

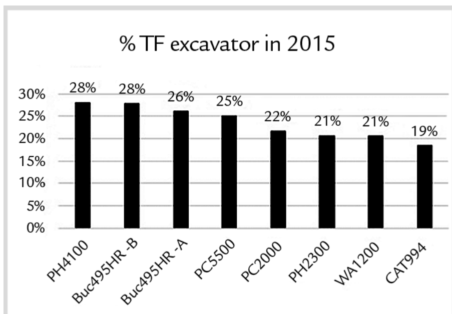


Figure 4
Truck factor use by excavator.

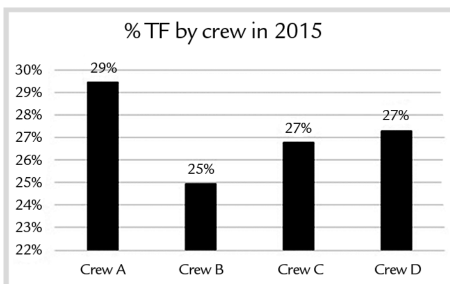


Figure 5
Truck factor use by crew.

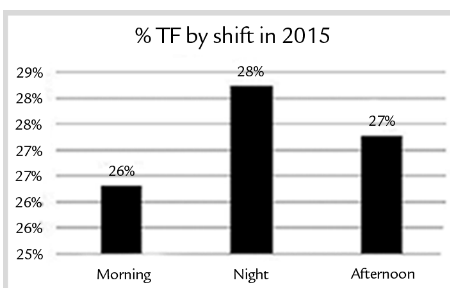


Figure 6
Truck factor use by shift.

The analysis shown in Figure 7 was better-detailed to clear up any trending behavior. The high rates found for crew A are even more evident after stratifying data by shift, in which it is possible to notice that %TF is higher during night shifts.

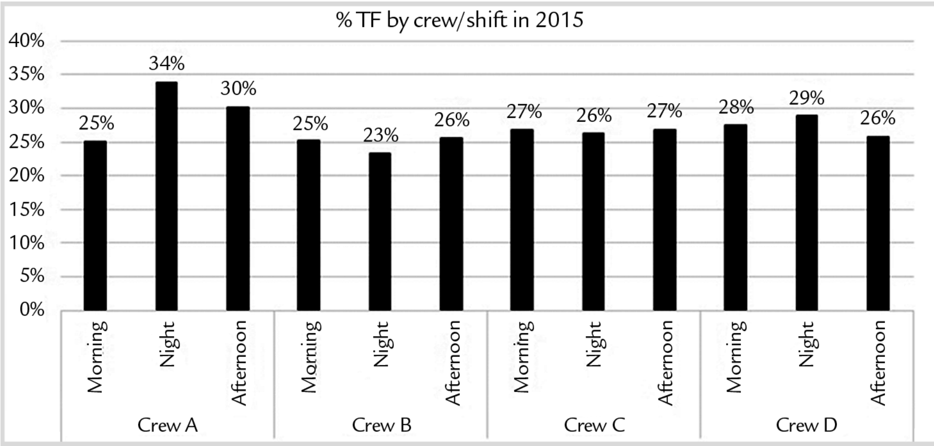


Figure 7
Truck factor use by crew/shift.

During the study, it was observed that the month of August, 2015 was the most critical (Figure 2: 32% use of T.F.), so additional analyses were performed for this month. The load factor modified 11.066 registers; half of the loads measured (5516 registers) are zero, probably due to a communication failure between the weightometer and the dispatch system. Despite the high number of zero values, the load factor was used many times, indicating a possible operational deviation. Detailed analyzes were performed to investigate the possibility of operational deviation.

For a better understanding of the whole process, the %TF was analyzed in comparison to loading time for one specific excavator and CAT793 fleet. The results in Figure 8 show that during the night (00h-06h) and afternoon (15h-00h) shifts, the %T.F is remarkably higher and loading time lower than the morning shift (06h-15h), which is expected, as the morning shift coincides with the administrative work time and all leaders are on site.

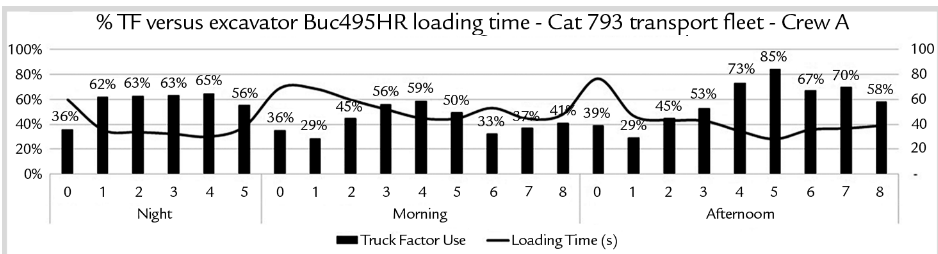


Figure 8
Truck factor use for specific excavator and truck fleet by shift – August/2015.

Figure 9 shows the quantity of measured loads for two different operators with different crews but during the same period of the day, as well as same excavator and same transport fleet. It is possible to identify very distinct behaviors: until the load of 110 t, the behavior is the same (probably problems with the weightometer); from this point on there are operational differences, operator B loads less material than A. Operator A concentrates 53% of the loads whereby he realized greater than 200 t and operator B realized only 12% of all loads around this tonnage. Operator B concentrates most of the loads around 150 t (30% lower than the average payload set – 220 t), in other words, the truck factor was applied in all those loads, showing a total production higher than that which was executed.

The most expressive result for this analysis is for operator's productivity by excavator. Operator A performed 3.562 t/worked hours, and operator B achieves 5.573 t/worked hours. Although the productivity for the operator B is rather high, it is also not real for most truck factor loads. Another method to evaluate operator's performance is by analyzing average loading time: for operator A, the average is 430 seconds and for operator B is 284 seconds, which endorses the fact that to reach this high performance, one needs to load less mass than the truck capacity, evidenced by short loading time.

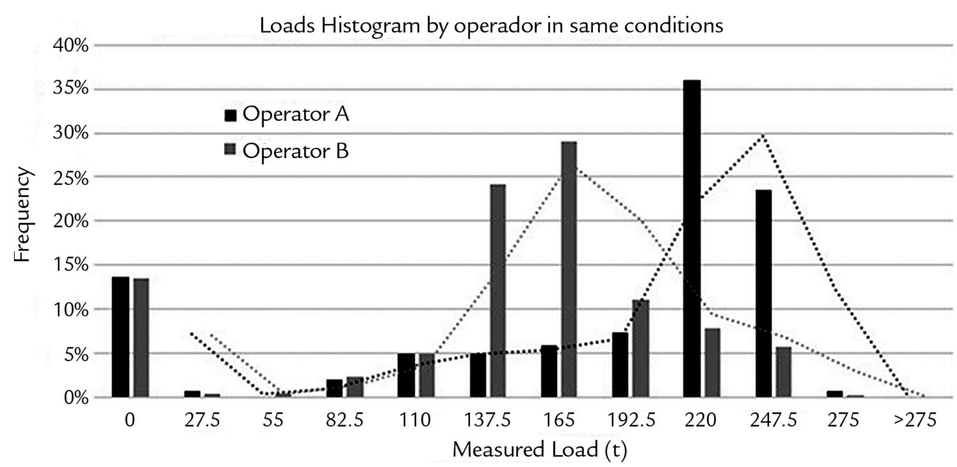


Figure 9
Truck factor use by excavator operator.

For analysis purposes, all the measured loads were calculated as a fraction of the average previously mentioned (Equation 1).

$$Load\ Mass\ Fraction\ (LMF) = \frac{Average\ Payload\ Set\text{-}Load\ Mass}{Average\ Payload\ Set} \quad \text{Equation 1}$$

Where LMF (Load Mass Fraction) equals 1, means the load measured was zero. In this case, the truck factor set is 25%. Therefore when the LMF is less than or equal to 0.25 means that the load has not been modified, since it is lower than the TF. In order to facilitate the visualization of the data, the zero load mass (LMF=1) was excluded from this analysis. The result is shown in the Figure 10.

For 97% of the loads (5393 registers), the value measured was between 0.25 and 0.7 of the average payload set. In this case the loads are possibly low due to loading issues and not weightometer defects. In other words, the TF should apply for loads 70% lower than the average and this study's results show a probable inappropriate application of the T.F.

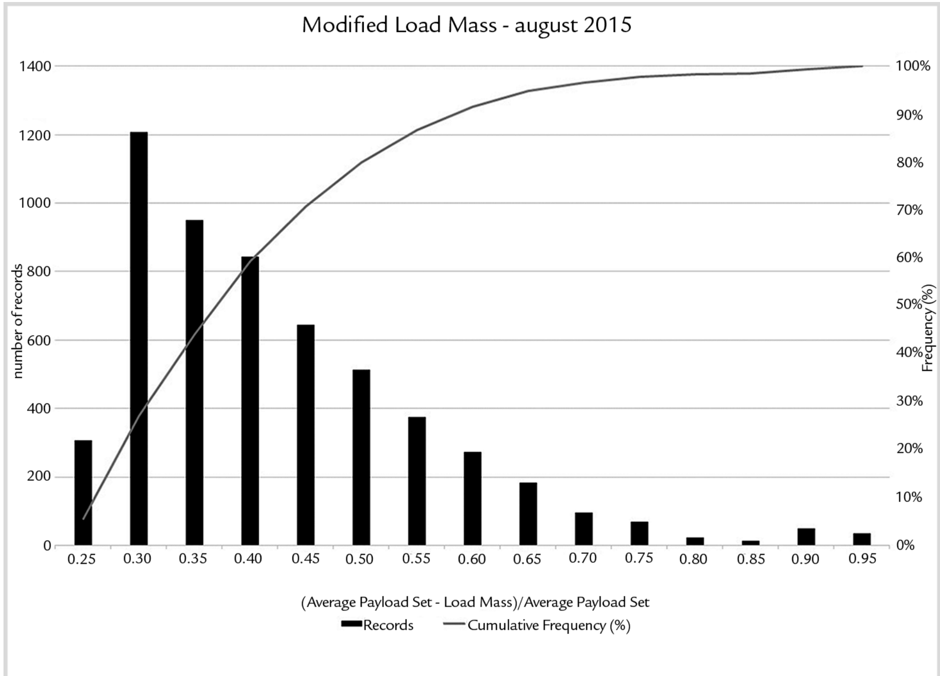


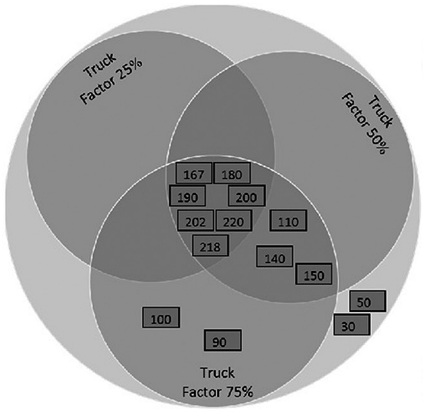
Figure 10
Modified Load Mass
as a fraction of the average payload set.

Using the previous dataset, a production test was made considering T.F as 70% instead of 25%. The results show a production 6% lower than the official increase mining costs, as shown below:

Fuel (R$)	6,000,000.00
Personnel (R$)	500,000.00
Tyres (R$)	4,000,000.00
TOTAL (R$)	10,500,000.00
Material moved official (t)	6853183.23
Cost per ton (R$/t)	**1.53**
Material moved test (t)	6422413.33
Cost per ton simulated (R$/t)	**1.63**

Table 1
Impact of material moved in KPI cost/ton.

An important topic to highlight is the zeroed loads measured by the weightometer as being in accordance with off-highway truck provider because it could be caused by connectivity failure in the management system web. A secondary impact from the currently used truck factor methodology is its influence on the average payload set. When modifying the factor to 25%, 50%, 75%, etc. it expressively affects the average load calculated. Taking a 220 t load as example and simulating the truck factor as 25%, 50% and 75%, the inferior limit would be 165, 110 and 55 t respectively. In other words, any loads measured under these limits would not be part of dataset for average calculation (Figure 11).



Truck Factor	25%		50%		75%	
Load	Measured	Official	Measured	Official	Measured	Official
Data Base	30	220	30	220	30	220
	50	220	50	220	50	220
	90	220	90	220	90	90
	100	220	100	220	100	100
	110	220	110	110	110	110
	140	220	140	140	140	140
	150	220	150	150	150	150
	167	167	167	167	167	167
	180	180	180	180	180	180
	190	190	190	190	190	190
	200	200	200	200	200	200
	202	202	202	202	202	202
	220	220	220	220	220	220
	218	218	218	218	218	218
Average	197		178		164	
Official Mass		2,917		2,657		2,407

Figure 11
Analyze of different truck factor, the payload values in grey are used for average calculated.

4. Conclusion

Truck factor must be assessed and updated often to identify any changes of statistical data behavior. Each mine has individualities in its operations, therefore, it is suggested that each operation be calculated for its own factor and define average payloads by taking loading fleet, transport fleet, operators behavior, type of material mined, etc. into account. It is also very important to compare production data to the mine survey, as it can supply information in regards to the actual production and indicates the necessity of index review.

As the definition of average payload is affected by the truck factor set, it is also suggested to compare the new index calculated to the previous one set in the system, analyze the values calculated and treat it to minimize expressive impacts on performance reports. The quantity of zeroed loads in database should be monitored, as it could be caused by communication web failures and not necessarily by weightometer issues and might outcome in integrity data loss.

Using a very high T.F., such as 70% suggested means that a 220 t truck may be carrying 66 t, an unacceptable fact. However, the use of T.F. should be monitored to ensure that the data represent the operation, without disguising operational deviations.

The analysis between the two operators demonstrates the case of operational deviation. In the information modified by the T.F., the operator B produces more than the operator A. However, in the measured loads the mass under the same conditions is lower, the productivity is extremely high and the loading time operationally very low. This comparison suggests that operator B load less mass to have a higher productivity. This artifice is possible because low loads are corrected by T.F.

In short, the use of T.F. is important to correct measurement errors, but its use must be controlled to be of pre-established parameters. When using T.F., a cause-and-effect analysis should be performed.

This study might be applied in other operations under due adaptations for tracking inconsistencies on database purposes, which could permit better error management and sensitively minimize impacts over mine performance and production reports, KPI's, costs, operation technical parameters, mine planning, equipment sizing, etc.

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