Vol. 11, No. 1, 2026, pp. 745-758
DOI: https://doi.org/10.29210/30036932000

Contents lists available at Journal ELORA

JRTI (Jurnal Riset Tindakan Indonesia)
ISSN: 2502-079X (Print) ISSN: 2503-1619 (Electronic)

Journal homepage: https://jrti.eloracenter.org/jrti

Adapted overall equipment effectiveness for evaluating loading and hauling equipment performance in open-pit coal overburden removal

Raihan Mhd Indrawan, Riam Marlina*), Jukepsa Andas, Rizto Salia Zakri
Universitas Negeri Padang, Indonesia

Article Info

Article history:

Received Jun 9th, 2026
Revised Aug 10th, 2026
Accepted Aug 16th, 2026

Keywords:

Overall equipment effectiveness
Overburden removal
Open-pit coal mining
Utilization factor
Bucket fill factor

ABSTRACT

Proper equipment functioning is essential to achieving overburden-removal targets in open-pit coal mining, yet independent assessments of Overall Equipment Effectiveness (OEE) for loading-hauling fleets at small Indonesian coal contractor operations remain scarce. This single-site, single-period descriptive case study quantified the productivity of one excavator and four dump trucks engaged in overburden-removal work at BBMM, Jambi, Indonesia, and simulated the potential productivity gain from raising OEE to the 85% world-class benchmark. Cycle times were sampled from ten independent field observations per hauling unit and four documented sub-phases per loading cycle, cross-checked against company production records. Primary data (cycle time, effective working hours) and secondary data (production targets, equipment records) collected in June 2025 were analyzed descriptively using an adapted OEE formulation (Availability × Utilization × Speed × Bucket Fill Factor) suited to BELT (belt-based excavating, loading, and transport) equipment, followed by scenario-based simulation at 85% OEE. Actual overburden production reached 213,566.96 BCM against a target of 216,036.00 BCM, a shortfall of 2,469.04 BCM (98.86% achievement). Adapted-OEE values across all units ranged from 71.2% to 75.2%, below the 85% benchmark, with utilization identified as the primary limiting factor. The 85% OEE scenario indicated potential productivity gains of up to 8,341 BCM/month for the excavator and 1,606–2,268 BCM/month for the dump trucks, corresponding to a 13–19% possible monthly production increase over current performance. Utilization losses, rather than mechanical unavailability, were found to be the main constraint on fleet efficiency, suggesting that targeted dispatching, reduced standby time, and effective-hour management offer greater production leverage than expanding maintenance staffing. This study offers a diagnostic approach applicable to similar small-fleet coal contractors facing overburden-removal shortfalls.

Corresponding Author:
Riam Marlina,
Universitas Negeri Padang
Email: riammarlina@ft.unp.ac.id

Introduction

Equipment productivity and good operational efficiency are main factors affecting cost competitiveness in open-pit mining where the loading and hauling operations take up a large portion of the operational costs. When production schedule is restricted and coal mines are operating at the thinner margins, obtaining maximum

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production with the present fleet of machines instead of getting the new ones is considered by the contractors and mine operators one of the strategic aims of this period. This preference for equipment-utilization strategies over new capital acquisition is consistent with broader reviews of surface-mining equipment-selection decisions (Burt & Caccetta, 2014). This emphasis on sweating existing assets rather than expanding fleet size is consistent with recent mining-productivity literature (Kumar & Ghorbani, 2023).

In the field, however, loading and hauling operations most often work below their theoretical potential. Equipment utilization can go down for many reasons: waiting time, standby time, unplanned delays, and adverse working conditions at the front. At the same time, factors such as haul road quality, rainfall, and inefficient dispatching make the entire job cycle longer. Dispatch inefficiency of this kind has long been recognized as a major source of truck-shovel productivity loss in open-pit operations (Alarie & Gamache, 2002; Zhang & Xia, 2015). Quite often such losses are so scattered and there is no direct cause-effect, which makes it very hard if not impossible to pinpoint what is causing problems, thus diagnosing and implementing fixes are both delayed. Consequently, it is essential to put in place a structured and component-based measurement toolset to clearly identify what part of the machine is ready (i. e. mechanically) and what usage is just under-employment of the machinery at the operational level, respectively.

Originally devised by Nakajima (1988) as a tool within Total Productive Maintenance (TPM), Overall Equipment Effectiveness (OEE) helps uncover sources of loss in equipment performance by breaking it down into separate factors, availability, performance efficiency, and quality for instance, which multiplied together indicate how efficiently a system is performing. While OEE initially applied only to discrete manufacturing equipment, it has become a commonly used method for diagnosing the performance of various types of mining equipment including drilling rigs (Gutiérrez-Diez et al., 2024), continuous mining systems (Pavloudakis et al., 2024), shovel-truck fleets (Toraman, 2024), and mining transport vehicles in general (Hia et al., 2022). Broader reviews of OEE's theoretical development and cross-industry adaptations (Muchiri & Pintelon, 2008; Ng Corrales et al., 2020) confirm that modifying the quality term is the most common strategy when OEE is transplanted outside discrete manufacturing, which supports the fill-factor substitution adopted in this study.

Several mining-focused papers have pointed out that the traditional availability-performance-quality decomposition does not accurately reflect the operating conditions of bucket-based excavating, loading, and transport (BELT) equipment where the notion of a measurable "quality" output like a manufactured part is not applicable. These authors have also suggested that the concept of bucket- or payload-fill-factor can be a substitute for the quality component (Hia et al., 2022; Ullah et al., 2023), whereas factors like cycle-time optimization (Mnzool et al., 2024), match-factor analysis (Mohtasham, 2025). These developments build directly on earlier mining-adapted OEE formulations for shovel and BELT equipment (Elevli & Elevli, 2010; Mohammadi et al., 2017), which first established that replacing the manufacturing quality term is necessary when OEE is applied to excavating and hauling operations. Weather-induced loss of productivity (Basar et al., 2024; Kuznetsov & Kosolapov, 2022) are considered as important covariates affecting utilization and speed rather than OEE components. Based on the findings of this stream of research, a mining-adapted OEE model is seen to be technically feasible as long as the changes and their implications are properly disclosed and not masked through a manufacturing-standard approach.

Taking into account all that progress, it is important to recognize that focused OEE assessments are still focused to the great extent on shovel-truck or continuous-mining at the major mines; similar data regarding small contractors' coal fleets, usually one or two excavators together with a few dump trucks which are prevalent in Sumatra & Kalimantan, cannot be considered to be that extensive. Small fleets are not immune to the pressures of utilization and dispatching the same as larger operations but they have a far greater risk of running out of spare capacity: a single underperforming unit can significantly impact monthly production. PT Bumi Bara Makmur Mandiri (BBMM), which is an open- pit contractor in Jambi, Indonesia, is a very good example of a small fleet that operates in this very situation. A single Caterpillar 330 GC excavator and four Mercedes-Benz Axor 2528 Euro 4 trucks were the vehicles of BBMM's Fleet 2. In the month of June 2025, this Fleet 3 had expected to complete 216, 036 BCM overburden removal target whereas they were able to achieve only 213, 566.96 BCM of that task.

This paper fills that gap by using a modified OEE model (Availability × Utilization × Speed × Bucket Fill Factor) on BBMM's Fleet 2, determining which component mostly limits effectiveness for one another, and turning diagnosis into simulations of world-class level productivity with OEE reaching 85%. While doing this, the paper adds value by: (a) presenting a methodologically clear analysis of why and how the OEE formula is adjusted for BELT equipment in juxtaposition with the classic Nakajima (1988) model; (b) unit-level data showing which OEE factor is a bottleneck in a small mixed loading-hauling fleet; and (c) a scenario-based, instead of a descriptive, production gain estimate that can provide a sound basis for, not an overstatement of, managerial decision-making. In doing so, the study extends recent unit-level and mining-adapted OEE applications (Rija & Anaperta, 2019; Toraman, 2024; Pavloudakis et al., 2024) to the previously unexamined case of a small, single-excavator contractor fleet, addressing a specific empirical and methodological gap rather than replicating an existing diagnostic approach.

The research study is basically a response to three queries: (1) At what rate were actual overburden productivity and production shortfall in Fleet 2 in June 2025? (2) How were the adapted-OEE values at the level of each loading and hauling unit, and which factor limited effectiveness the most? (3) What is the estimated productivity gain when OEE is increased to the 85% benchmark, and what are the managerial implications and limitations of that situation?

Literature Review and Research Gap

According to Nakajima (1988), OEE is the combined result of Availability, Performance of the machine, and Quality Rate, and it was also aligned with a Six Big losses diagnostic approach of TPM breakdown, changeover, idling/minor stoppage, reduced speed, defect, and rework providing the vocabulary for identification of loss sources. In its original manufacturing use, the system works well under the conditions where the output item is discrete and quality inspection can be carried out on it. The target 85% composite value is achieved at the component targets of around 90% availability, 95% performance, and 99% quality. But on average, manufacturing units usually operate between close to 60-70% (this was mentioned as a part of our thesis work with reference to Jain et al., 2017).Mining applications of OEE have grown substantially in the past five years as digital monitoring has made equipment-level time-use data more accessible. Gutiérrez-Diez et al. (2024) proposed an "Overall Mining

"Equipment Effectiveness" (OMEE) index for surface drilling rigs was studied by an investigator in two Spanish coal mines during ten years. The study concluded that availability and utilization are the diagnostic components of a maintenance management-policy performance rather than quality. Pavloudakis et al. (2024) also applied OEE to continuous mining systems of a Greek lignite mine and concluded that it is not the decrease in output quality but rather reduced availability due to hard-rock inclusions and reduced utilization due to face changes and staffing constraints that were mainly responsible for low OEE values. Toraman (2024) estimated a level of OEE for shovel and truck fleets at an open-pit lignite operation and similarly reported that categories of mining losses specific to operational conditions such as dust, lighting, and Truck-shovel matching were mainly responsible for the effectiveness outcome, more than any quality inspection aspect.

Another stream of research has suggested OEE formulas being changed to better suit mining industries. Hia et al. (2022), for instance, have developed an OEE-based metric known as "Overall Vehicle Effectiveness" for mining transportation with utilization-of-capacity losses that replace payload/quality-related losses. Ullah et al. (2023) have reviewed all OEE adaptations across the industry settings. They have emphasized that in the case of OEE transplantation into other fields aside from discrete manufacturing, it is the quality term that is being modified the most. Replacing the quality term with a bucket (or payload) fill factor for excavating, loading, and transport (BELT) equipment is in line with the adaptation logic described above: it describes the output loss resulting in a bucket not being filled to its rated capacity which is the closest to a manufacturing quality defect from the point of view of a miner.

Secondary documents discuss the operational covariates that affect utilization and speed losses in loading-hauling systems but without direct use of the OEE label. Mnzool et al. (2024) demonstrated that the three time-component factors of truck operation (loading, hauling, and placing) can be minimized through optimization so as to get the overall truck cycle time reduced in surface mining. Mohtasham (2025) and previous match-factor analyses reveal that an unmatched truck fleet with shovel/discharging equipment capabilities leads to chronic unproductive waiting time losses, which reduce utilization significantly while the availability of the equipment is still quite high. Both Basar et al. (2024) and Kuznetsov and Kosolapov (2022) were able to measure quantifying the increase of the cycle time and loss of production due to such events like heavy rains and bad climate on the activities of excavators as well as dump trucks in terms of front-preparation, slippery-condition, and standby losses reported by the coal companies in Indonesia. It is further shown through various contributions of Choi et al. (2022), Das et al. (2024), Khan and Asad (2023), and Kumar and Ghorbani (2023) that dispatch based upon machine-learning, selection of the best available haul route and minimization of utilization cost optimization have now emerged as the main methods for bridging the gap between the estimated and measured productivity of the fleets, and, as a result, utilization, rather mechanical condition, becomes the target of improvement in the case of most surface mining fleets.

At Indonesian contractor coal mining sites, OEE or closely related productivity methods have been prior work that has used to find out reasons behind similar production problems of miners. According to Rija and Anaperta (2019), the OEE at Bangko Barat overburden-removal operations of the whole fleet ranged from only 34 to 44%, due mainly to extensive machine down time and also the machine's operator waiting time. Octova

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and Mahesa (2021) described it that decreasing the loss time at a Batu Ampar excavator operation allowed a previously under-production-capacity fleet to surpass its production target, although the OEE level was still below the 85% level even after the enhancement. Applying OEE on the crushing plant at a certain location, Has et al. (2022) discovered that, unlike the case of excavator/truck production system, the main limitation from an OEE point of view had been quality-related losses not lack of machine hours (availability) or low machine speed (performance), showing thus that which of the constraints of the OEE concept becomes the limiting factor is extremely dependent on particular types of equipment and production processes being carried out. Using match factor with linear programming but not OEE per se, Erwanda et al. (2022) showed the possibility of a significant increase in the overburn output by fleet-composition adjustment. The main idea is that the matching of resources or utilization level is very likely to be a common factor in most of the studies with respect to the Indonesian miner case.

The combination of this literature shows two things: first, that OEE may be rightly used for BELT devices only when the quality parameter is exchanged with fill-factor, the change is clearly announced, and not made to resemble a manufacturing norm; second utilization (dependent on stand-by time, dispatching and weather) is consistently cited as a more stringent constraint on the equipment effectiveness in the mining industry than mere mechanical availability. Not many studies have looked into the component-specific OEE at the individual equipment level of small, single-excavator contractor fleets where the loss of one unit's effective hours heavily affects the monthly production, and fleet average data often hides which specific unit should be chosen for intervention. The authors of this paper fill that void by using BBMM's Fleet 2 and they present the work as an assessment of equipment effectiveness and productivity, particularly, at the individual-unit level of open-pit coal overburden removal equipment.

Methods

Research Design

This project is quantitative applied research (only observational and computational aspects, not experimental). Every real data value given in it is based on the basic source of a previous undergraduate thesis data set (Indrawan, 2026) made at PT Bumi Bara Makmur Mandiri. This study makes use of the primary data which are gathered by direct field observation and measurement and the other is secondary data, company operational records, and it computes via formulas the level of productivity, availability/utilization, and adapted-OEE indicators, and it runs a scenario-based simulation of productivity at an assumed 85% OEE target. The data in this study are of a single period that is descriptive. Therefore, no inferential statistical tests (e.g., regression, hypothesis testing, confidence intervals) has been done and it is compatible with it being descriptive, single-period dataset. The data collection-to-analysis sequence followed four stages: (1) field observation and timing of loading and hauling cycles, (2) extraction of secondary records from company archives, (3) computation of productivity, availability/utilization, and adapted-OEE indicators, and (4) scenario-based simulation of productivity at the 85% OEE benchmark.

Study Area and Mining Operation

PT Bumi Bara Makmur Mandiri (BBMM) is a coal mining services company performing operations on an exploration/production permit of 1, 945 hectares area located at Batin XXIV Sub-district, Batang Hari Regency, Jambi Province, Indonesia, within the stratigraphy coal-bearing South Sumatra basin (formed by Muaraenim and Air Benakat). This company is engaged in conventional surface (open-pit) mining operations. The source of data is Fleet No. 2 that were in overburden removing mode from June 2025 (30 calendar days, 300 planned hours) the company's monthly overburden target in this period was not fulfilled either.

Equipment Characteristics

Table 1 <Characteristics of Mining Equipment>

Unit code	Function	Model	Key specification
CAT 330 GC	Loading (excavator)	Caterpillar 330 GC	Bucket capacity 1.6 m³
DT-055	Hauling (dump truck)	Mercedes-Benz Axor 2528 Euro 4	Not reported in source thesis
DT-027	Hauling (dump truck)	Mercedes-Benz Axor 2528 Euro 4	Not reported in source thesis
DT-072	Hauling (dump truck)	Mercedes-Benz Axor 2528 Euro 4	Not reported in source thesis
DT-045	Hauling (dump truck)	Mercedes-Benz Axor 2528 Euro 4	Not reported in source thesis

Note. All four hauling units share the same make and model. Rated payload capacity, engine power, and tare weight for the Axor 2528 Euro 4 units were not reported in the extractable text of the source thesis and are marked accordingly rather than estimated.

Fleet 2 comprised one loading unit and four hauling units, summarized in Table 1. This omission is treated explicitly as a limitation on the external validity of unit-level productivity comparisons among the hauling units, rather than being filled by estimation (see Section 8, Limitations and Future Research).

Data Collection

Primary data, cycle time of loading and hauling units, actual working hours, and effective working-time efficiency were gathered primarily via field observation of each operation step, daily production-form recording, and informal interviews with the operators and field supervisors. For each haul unit cycle time was sampled based on ten independent readings per unit. The haul cycle was timed and broken up into six individual sub-phases (Ta1, Ta6 corresponding to maneuvering, loading-position approach, loading wait/queue, hauling, dumping, and return travel). Similarly, the loading unit cycle time was also measured as four separate phases: digging/loading, loaded swing dumping and empty swing swing. Secondary data such as IUP (mining permit) boundaries, topographic and geological maps, monthly production targets, and equipment data sheets were all extracted from the company archives. Field-recorded cycle times were cross-checked against the corresponding company daily production reports for consistency, and discrepant readings were re-verified with the field supervisor before being entered into the analysis dataset.

Productivity Calculation

To determine excavator productivity the following data was used: bucket capacity, bucket fill factor, swell factor, cycle time, and job efficiency; dump truck productivity was determined by means of the numbers of loading passes required to fill the vessel, cycle time and job efficiency, following standard mechanical earthmoving productivity procedures (Partanto Prodjosumarto, 1996). At Fleet 2 the loading material was clay. From field measurement and reference material-density tables in the source thesis, a bucket fill factor of 95 percent and a swell factor of 85 percent were decided to be the case for clay.

Equipment Availability and Utilization

Mechanical Availability (MA), Physical Availability (PA), Use of Availability (UA), and Effective Utilization (EU) are calculated from recorded working, standby, and repair hours by applying standard mechanical-availability formulas that are routinely applied in Indonesian engineering mining. These four indicators reflect the equipment readiness and time-use efficiency yet are different from and lead to the Availability and Utilization factors used in the modified-OEE formula described below.

Adapted OEE Calculation

Nakajima (1988) set out the classical OEE formulation. It runs like this:

OEE (%) = Availability (%) × Performance Efficiency (%) × Rate of Quality (%)

This way of doing it expects a clearly defined, countable manufacturing output and thus cannot really be used on excavator, loader, and truck (BELT) fleet where the output is a heap of the material without a clear quality-pass/fail indication. It aligns the mining-adapted OEE formulas that instead of quality use capacity-fill concept (Hia et al., 2022; Ullah et al., 2023), and the operational formulation of the source thesis, it was this way that the researcher carried out a study.

OEE (%) = Availability (A, %) × Utilization (U, %) × Speed (S, %) × Bucket Fill Factor (BFF, %)

Availability (A) = Available time + Total calendar time; Utilization (U)= Utilization time + Available time; and Speed(S) = Planned cycle time ÷ Actual cycle time. The Bucket Fill Factor is used to replace the classical Rate-of-Quality concept. It stands for the proportion of rated bucket/capacity vessel loading achievement. The change in terminology is handled as a methodological variation rather than just the OEE in the manufacturing context in the Discussion. The implications, and boundaries, of the change are spelled out explicitly in Sections 5.1 and 8.

Simulation of OEE Improvement

Productivities for the scenarios of OEE reaching the 85% world-class benchmark found in the TPM/OEE literature were estimated using bucket capacity, swell factor, and material characteristics as fixed. The simulation was a straight scaling of a given unit's monthly productivity by the factor between the target of 85% and its current OEE level to estimate its productivity under the benchmark of world class ($Productivity_{85}$= $Productivity_{aCTUaL}$x 85 / OEE_{aCTUaL}). It is possible production result under the benchmark of world class but it is not a forecasting or a guarantee, It is a theoretical projection based on existing data, It is not modeling any specific intervention, cost or implementation pathway.

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Data Analysis
Data analysis was based on description and comparison: it included mean cycle times, percentage achievement against target and the component-wise comparison of four different metrics (Availability, Utilization, Speed, and Bucket Fill Factor) across the five units. It may also surprise you to know that regression, correlation significance testing and confidence intervals were not considered at all. All that was presented were mere descriptions and comparisons. The dataset (n = 30 production days; n = 10 cycle-time observations per hauling unit; n = 5 pieces of equipment) simply does not allow for generalization and thus, any inferential claim of that nature would have been unjustified. The percentages differences referred to here are only simple arithmetic differences between two numbers and not the result of any statistical testing.

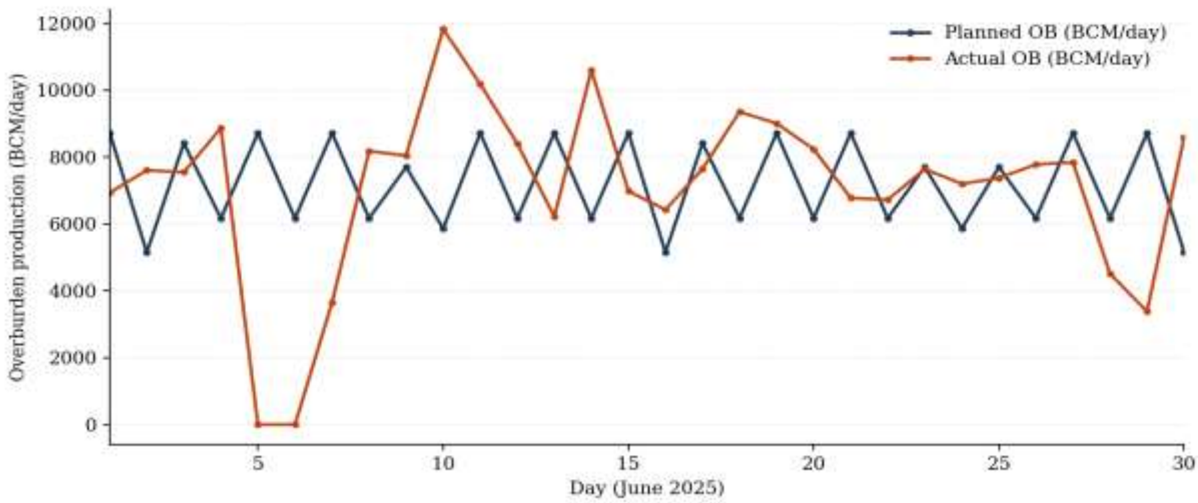
Results and Discussions

Production Performance
In June of 2025, Fleet 2 generated 213, 566.96 BCM of overburden production but its goal was 216, 036.00 BCM. It missed the target by 385.88 BCM (98.86% achievement). As per the data given in Table 2, the coal production achieved 1.28 times the target in this period. The figures (126.90 BCM actual vs 70.496.00 BCM planned) are indicative of the fact that the gap was due to overburden removal activities rather than an overall productivity issue with the fleet. This divergence reflects differing exposure during the reporting period: overburden removal was more directly affected by the front-preparation and standby losses detailed in Table 3, whereas coal loading proceeded largely uninterrupted once a face was exposed, allowing coal output to exceed target even as overburden lagged behind it.

Table 2 <Production Target and Actual Production, June 2025>

Material	Target (BCM/month)	Actual (BCM/month)	Achievement (%)
Overburden	216,036.00	213,566.96	98.86%
Coal	70,496.00	90,126.90	127.85%

Note. Values are as reported in the source thesis Daily Production Report (30 days of data, 1–30 June 2025). Overburden was not achieved on 14 of 30 working days; production was not carried out at all on 5–6 June 2025.



Note. Constructed from the source thesis's Daily Production Report. Zero-production days (5–6 June) correspond to a full-day production stoppage reported in the source data.

Figure 1 <Daily Overburden Production, Planned vs. Actual, June 2025>

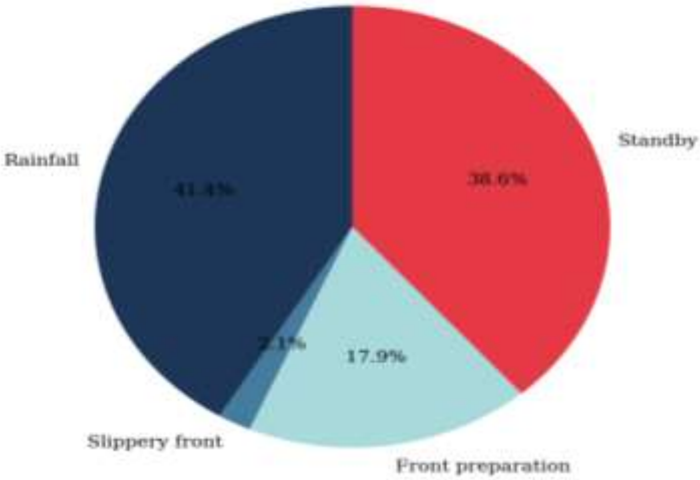
Figure 1, illustrates the variation in daily production which was around the planned line. The worst underperformance was concentrated on the last third of the month during 24, 29 June, when both the rainfall and standby episodes occurred (Section 4.2).

Effective Working Time and Operational Losses
Total achieved 231.34 fleet-EWH is equivalent to 93.78% of planned time (including overtime). A combination of 4 recorded sources contributed for the total loss of time rainfall, slippery front conditions, front-preparation delay, and standby time, as presented in Table 3.

Table 3 <Effective Working Time and Operational Losses, June 2025 (Month-to-Date)>

Component	Hours (MTD)	Share of total lost time
Scheduled working time	300.00	–
Additional (long-shift) time	15.00	–
Rainfall-related loss	0.76	2.3%
Slippery working-front loss	6.50	19.3%
Front-preparation loss	14.00	41.6%
Standby loss	12.40	36.8%
Effective Working Hour (EWH)	281.34	–
Cumulative rainfall	31.0 mm	–
Total lost time	**33.66**	**100%**

Note. Reconstructed from the source thesis's Effective Working Hour table (Table 4 of the original document). The narrative description in the source thesis reports these four loss categories in a different numerical order than its own tabulated month-to-date totals; this study reports the tabulated (arithmetically consistent, 0.76 + 6.50 + 14.00 + 12.40 = 33.66) figures and flags the discrepancy as a data-reporting limitation of the original document (see Section 8).



Note. Front-preparation delay and standby together account for over three-quarters of total recorded lost time, exceeding the contribution of rainfall and slippery-front conditions combined.

Figure 2 <Contribution of Operational Loss Categories to Total Lost Time, June 2025>

The major part of the lost time, according to Figure 2, was due to losses from the joint effect of front-preparation and standby losses. Rain This situation is parallel to a loss structure dominated by utilization reported for open-pit coal fleets in other parts of Indonesia by Basar et al., 2024, and also discussed in Section 5.2.

Cycle Time

The average cycle time of a CAT 330GC excavator was 22.03 seconds with digging taking 4.90 sec, the loaded swing 6.29 s, dumping 4.16 s, and the empty swing 6.68 s. So in order to fill one dump truck, about four bucket lifts were needed which took the excavator almost 88.12 seconds. The averaged hauling-unit cycle times based on ten observations for each were 366.78 s (DT-055), 357.74 s (DT-027), 356.55 s (DT-072), and 380.29 s (DT-045).

Equipment Productivity

By multiplying cycle, bucket, and swell factor, fill factor, and the job efficiency, the CAT 330 GC produced 179.46 BCM/hr (53, 838 BCM/month), while the four dump trucks operated anywhere from 39 to 41 BCM/hr (11, 700, 12, 327 BCM/month) as shown in Table 4.

Table 4 ***Cycle Time and Productivity of Loading and Hauling Equipment***

Unit	Mean cycle time (s)	Productivity (BCM/hour)	Productivity (BCM/day)	Productivity (BCM/month)
CAT 330 GC	22.03	179.46	1,794.60	53,838
DT-055	366.78	40.58	405.80	12,174
DT-027	357.74	39.00	390.00	11,700
DT-072	356.55	40.18	401.80	12,054
DT-045	380.29	41.09	410.90	12,327

Note. BCM = bank cubic meter. Monthly productivity assumes the recorded effective working hours reported in Table 3.

Availability and Utilization

For the 5 types of mining equipment tested (CAT 330 GC, DT-055, DT-027, DT-072, and DT-045), both MA and PA values were over 89% indicating mechanical systems were in good shape. MA was 97.0% and PA was 97.4% in CAT 330 GC; MA was 99.42% and PA was 99.53% in DT-055; MA was 99.12% and PA was 99.33% in DT-027; MA was 98.0% and PA was 98.5% in DT-072; and MA was 99.33% and PA was 99.43% in DT-045. On the other hand, the availability for use (UA) was considerably low while the actual usage rate (EU) varied from mine to mine for mining trucks and trucks of different sizes. The UA / EU values of the CAT 330 GC was UA 85.33 / EU 85.33; DT-055, UA 79.84 / EU 79.47; DT-027 the lowest in the fleet (UA / EU 75.77 / 75.27); DT-072 (UA 78.61 / EU 77.43); DT-045, being the dump truck with the highest UA and EU value of (UA 85.18 / EU 84.70). The study thus concluded that it was the inefficient utilization of time during working hours rather than inadequate preparation of the plant (mechanical readiness) that resulted in loss of productivity.

Adapted OEE Performance

Table 5 displays the breakdown of improved-OEE (Availability × Utilization × Speed ×Bucket Fill Factor) for each machine unit.

Table 5 *Availability, Utilization, Speed, Bucket Fill Factor, and Adapted OEE*

Unit	Availability (%)	Utilization (%)	Speed (%)	OEE (%)
CAT 330 GC	97.33	87.67	90.80	73.6
DT-055	99.53	79.84	97.20	73.3
DT-027	99.13	75.92	99.66	71.2
DT-072	98.50	78.61	100.00	73.6
DT-045	99.43	85.18	93.80	75.2

Note. Bucket Fill Factor = 95.00% for all units (uniform, clay material). World-class OEE benchmark = 85%. All five units fall 9.8–13.8 percentage points below this benchmark.

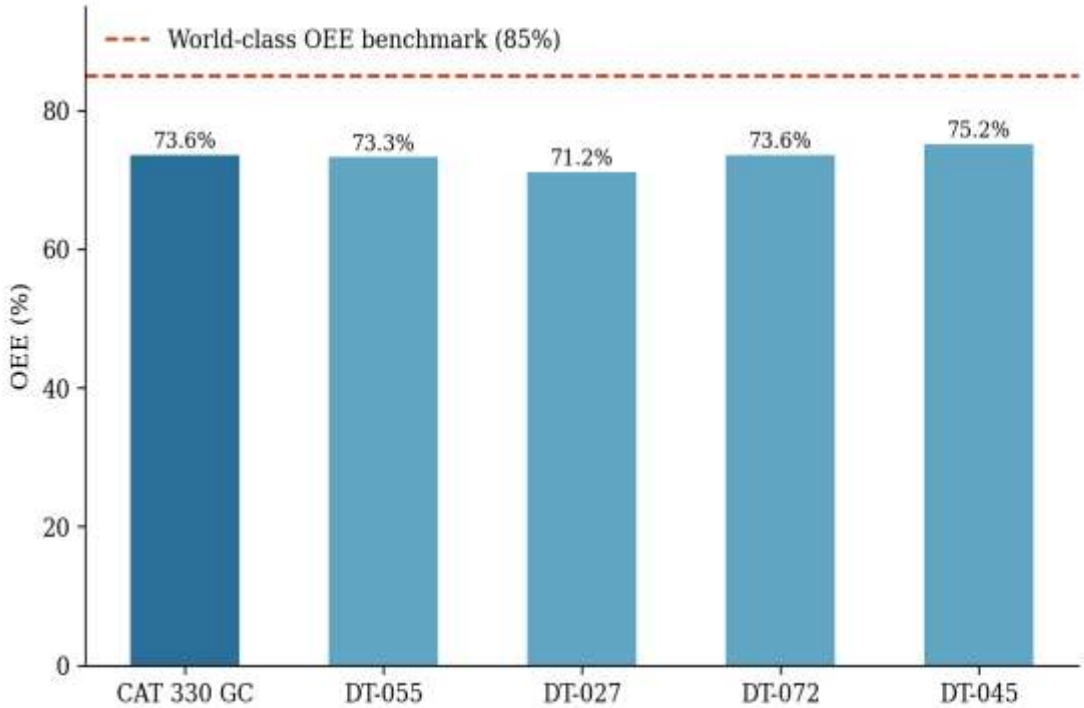
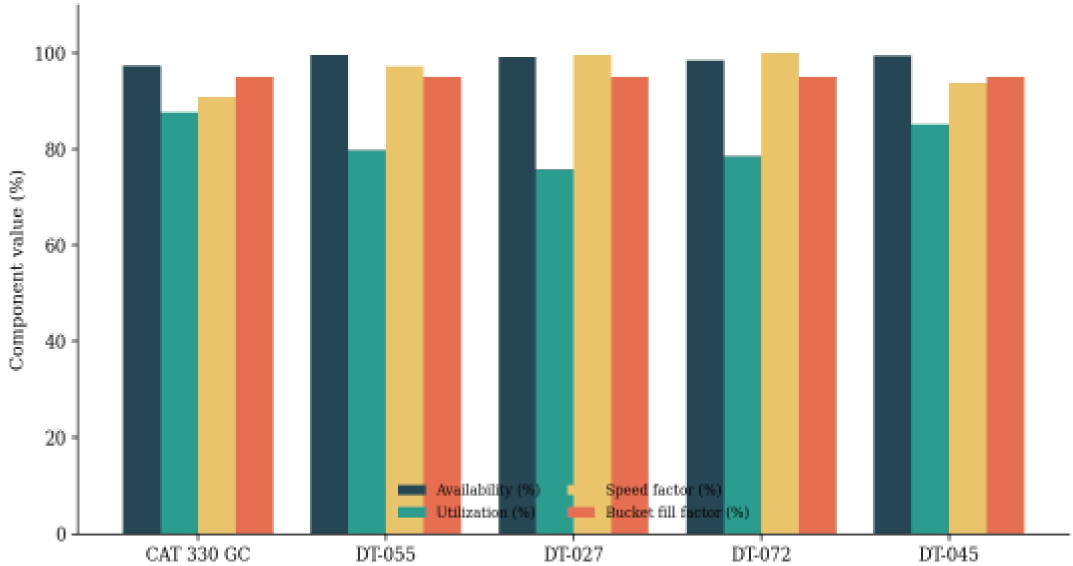


Figure 3 <Adapted-OEE Comparison Across Loading and Hauling Equipment Against the 85% World-Class Benchmark>

Referring back to the Table 5 and Figure 4 below availability levels and the fill factor of the machine's operating hours were constantly high and did not show much differences between units. Utilization, on the other hand, ranged between 75.92% (DT-027) at its minimum and 87.67% (CAT 330 GC) at max which is the biggest difference among all machine components; whereas speed ranged from 90.8% to 100% only. Such a regularity in the results suggests that the reason the overall productivity of the fleet falls short of the theoretical maximum is primarily related to how efficiently time was used and not to the technical failure of the machines or loss in the material-handling.



Note. Bucket fill factor is uniform across units (95%) because all units handled the same clay material at Fleet 2; availability and speed cluster near their upper bound, while utilization is visibly the most variable and lowest-scoring component.

Figure 4 <Availability, Utilization, Speed, and Bucket Fill Factor by Unit>

Simulation of OEE Improvement

The table below, Table 6, outlines simulated productivity at 85% OEE under a scenario approach, as explained in section 3.8. This productivity level shows a possible gain if OEE target becomes reality under that scenario, as opposed to showing how much is going to be produced.

Table 6 <Comparison of Actual Productivity and Simulated Productivity at 85% OEE>

Unit	Actual OEE (%)	Actual productivity (BCM/month)	Simulated productivity at 85% OEE (BCM/month)	Potential gain (BCM/month)
CAT 330 GC	73.6	53,838	62,179	8,341
DT-055	73.3	12,174	14,116	1,942
DT-027	71.2	11,700	13,968	2,268
DT-072	73.6	12,054	13,921	1,867
DT-045	75.2	12,327	13,933	1,606

Note. Simulated values represent a scenario-based potential productivity gain assuming OEE reaches the 85% world-class benchmark, holding equipment specification and material characteristics constant. Figures should not be interpreted as a guaranteed or forecast outcome of any specific intervention.

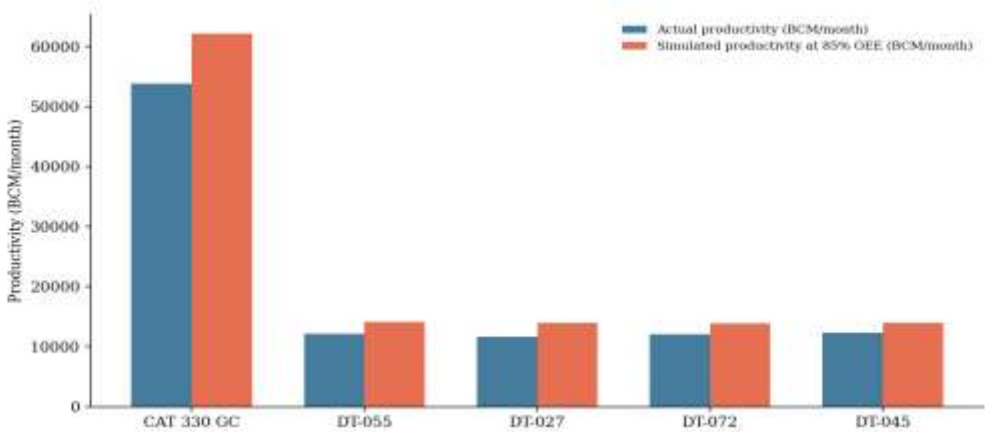


Figure 5 <Actual Productivity Versus Simulated Productivity at 85% OEE, by Unit>

As it can be seen from Figure 5 and Table 6, the excavator provides the highest absolute potential gain (which amounts to 8, 341 BCM per month) for two reasons: first, it is a continuous operation equipment with much larger productivity and, second, there aren't dump trucks that could even be compared with the performance of an excavator. Among the dump trucks, DT-027 that has the lowest actual OEE shows the highest potential gain (which is 2, 268 BCM per month), which is very consistent with the identification in Section 4.6 of the unit as the most utilization-constrained unit in the entire fleet.

Priority of Improvement

Table 7 arranges the five units in a list based on their OEE values (from the lowest to the highest) and highlights for each one that particular OEE part that is the furthest from the maximum value of practical OEE in the fleet. This is considered as the top indicator for management to turn the spotlight on the corresponding unit, it is not supposed to be interpreted as a formal statistical ranking.

Table 7 <Priority of Improvement Based on Equipment Performance>

Rank	Unit	OEE (%)	Gap to 85 (pp)	Dominant limiting component	Improvement priority
1	DT-027	71.2	13.8	Utilization (75.92%, lowest in fleet)	Highest
2	DT-055	73.3	11.7	Utilization (79.84%)	High
3	DT-072	73.6	11.4	Utilization (78.61%)	High
3	CAT 330 GC	73.6	11.4	Speed (90.8%) and utilization (87.67%) jointly	High
5	DT-045	75.2	9.8	Speed (93.8%); best-performing unit in fleet	Moderate

Note. pp = percentage points. Ranking is based on the magnitude of the actual-OEE gap to the 85% benchmark and is intended as a management-prioritization aid, not a statistically weighted index.

Discussion

Equipment Effectiveness in Overburden Removal Finding: All five units in Fleet 2 achieved adapted-OEE values ranging between 71.2% and 75.2%, which is clearly below the 85% world-class benchmark. Explanation: The shortfall was not because of mechanical readiness issues, the levels of Mechanical and Physical Availability were above 97% across the fleet (Section 4.5), but because of the joint influence of a relatively low utilization (75.9, 87.7%) and, in the case of the excavator especially, a speed factor below 91%. Comparison: This is the same trend found by Rija and Anaperta (2019) who noted even lower OEE (34, 44%) at an overburden mining project in the Jambi area similar to ours, which was mainly due to very long stoppages and waiting. Our findings are also in agreement with Toraman (2024) and Pavloudakis et al. (2024) who both singled out availability and utilization, and not a quality/fill-factor analog, as the most effective indicators of OEE results in mining. Implication: given the fact that BBMM's machines are already well-maintained, incremental improvements in OEE can mainly expect time-use efficiency and not more maintenance spending, one of the main topics in Section 5.6.

Dominant Factors Limiting Equipment Performance

Finding: Utilization was the most fluctuating OEE component, and at the same time, for four out of five, it turned out to be the lowest-scoring component. See the table with the lowest utilizations (dt-027 was only 75.92% fleet-level); Explanation: Front-preparation delay and standby time from the loss-time structure (Table 3 and Figure 2) contributed to the low utilization as the total loss due to both reasons came nearly to three-fourths of the total loss which is much bigger than the sum of loss from rainfall and from front slip; Comparison: Such usage-dominated pattern of OEE components is similar to what Erwanda et al., (2022) and Mohtasham (2025) pointed out that the shortage of resources was mainly due to inefficiencies in matching and dispatching the fleet and not because of weather or mechanical problems; Implication: Measures directed exclusively at rainfall avoidance or more mechanical maintenance are very unlikely to lead to a higher return in effectiveness per unit managerial input than efforts targeted at reducing standby time and optimising dispatch coordination.

Relationship Between Utilization, Waiting Time, and Productivity

Finding: DT-027 that had the least utilization (75.92%) and also the least Overall Equipment Effectiveness (OEE), 71.2% at the same time, turned out to also have the lowest actual monthly output among the four dump trucks (11, 700 BCM/month, Table 4); this is despite having an intermediate cycle time (357.74 s) even though it was a faster than DT-055 and DT-045. Explanation: this suggests the cycle-time inefficiency of a machine was not the reason DT-027 had the lowest productivity level; in fact, the total time-use loss captured by the utilization factor of that unit outweighed its somewhat favorable cycle time. Comparison: this divergence of the cycle time performance from the realized productivity is in agreement with Mnzool et al. (2024), who report that if cycle-time optimization is conducted without tackling simultaneously the queuing and positioning-related losses, the returns in productivity will be minimal. Also this is in line with literature on match-factor (Mohtasham, 2025) stating that fleet-matching losses can be even greater than efficiently timed individual units. Implication: interventions focused mainly on improving the cycle times (e.g., operator coaching on individual driving segments) would not likely eliminate the productivity disadvantage of DT-027; therefore, in addition, interventions should tackle the causes at the level of dispatch and at the front-level responsible for DT-027 standby and waiting time.

Comparison With Previous Studies

Observation: The overall fleet OEE of BBMM is around 72-75% which is better than the 34-44% as per Rija and Anaperta (2019) but not as good as the 49.29% of similarly machined but differently run plant-crushing-plant OEE as found by Has et al. (2022, referred in source thesis); Reason: it is likely that the reason for having a higher OEE at BBMM is that its fleet has been available almost all of the time (more than 97%) compared to Bangko Barat where it was really bad. Finding Similar to Other Works globally, Toraman (2024) and Gutiérrez-Diez et al. (2024) report an OEE in the range of a shovel-truck and drilling-rig fleet at a mature open-pit operation to be less than 85% which in fact is a common situation across all such classes of surface mining equipment. Shovel-level OEE-improvement studies report a comparable pattern, with utilization-related losses again identified as the leading constraint once mechanical availability is already high (Sharma et al., 2022). Therefore, the result at BBMM is pretty much in agreement with the wider body of literature instead of pointing out a really serious performance issue; Recommends: Comparing BBMM performance solely against a hypothetical 85% level might overdo the problem it is facing. So, instead of a mere comparison with such a very high figure, measuring the utilization level at its closest competitors, who also show up very few downtimes, would give a much more useful idea about how well or poorly BBMM is doing its job through its equipment usage. Theoretical mechanisms and measurement validity: the recurrence of utilization, rather than mechanical availability, as the dominant constraint across BBMM, Rija and Anaperta's (2019) Bangko Barat site, and the mature open-pit operations reported by Toraman (2024) and Gutiérrez-Diez et al. (2024) does not, on its own, establish a single causal mechanism. Competing explanations – constrained dispatch resources, maintenance doctrines that prioritize availability over active time-use, and site-specific operational-planning limits such as shift scheduling or front-preparation practice – could each independently produce a utilization-dominant OEE profile, and the present descriptive, single-period dataset cannot adjudicate between them. In addition, because the adapted-OEE formulation used here substitutes Bucket Fill Factor for the classical Rate-of-Quality term (Section 3.6), this study cannot rule out the possibility that the modification masks a genuine fill-related loss that a standard OEE formulation, if it were applicable to BELT equipment, might have captured separately from utilization; this is treated as an open methodological question for future comparative work (Section 8).

Implications for Mining Fleet Management

Fact: The fleet's 2, 469.04 BCM overload shortage (Table 2) is a smaller percentage (1.14% of the target) than the per unit reported OEE gap of 9.8, 13.8 percentage points (Table 7).Reasoning: This difference is due to the high output levels from the excavators compared to the dump trucks, therefore the monthly production is not affected as drastically as the unit-level OEE losses, so the fleet-level performance can hide unit-level underperformance, especially the one of the very lowperforming hauler units.Simmilarity: Such a "concealment" of the unit performance at the fleet level is indeed a point made in Gutiérrez-Diez et al. (2024) for the mining operations that instead of the mining fleet-averaged, should use the unit-level OEE. Action point: : Decisions to improve production of the small fleets, which is not very sensitive when considering fleet-level metrics, solely by comparing the monthly production aggregates, would lead missing DT-027's very low utilization level; in this study the monitoring of the individual OEE at the unit-level was shown to be an essential add- on to the production reporting for small fleets.

Practical Improvement Strategy

Finding: loss-time breakdown and also an OEE component decomposition both (Table 3 and Table 5) lead to a single interpretation which is utilization and not availability is the limiting factor of the fleet; Explanation: Front-preparation delay and standby time are two types of losses that can be controlled by management and dispatch, whereas such as weather-related losses (rainfall, slippery front) are largely out of operational control; Comparison: The difference is the same one made by the levels of intervention in the work of Choi et al. (2022) and Khan and Asad (2023), who have shown that data-driven dispatching and cost optimization focusing on utilization will produce larger increases in productivity than weather-adaptive scheduling alone; Implication: the priority for the BBMM's improvement strategy (1) dispatching coordination to reduce the front-preparation and standby delay, (2) periodic OEE monitoring at the individual-unit level to identify regularly under-performing machines such as DT-027, (3) continued preventive maintenance to sustain the fleet's strong availability and therefore not mainly to bring about OEE.

Conclusion

This research investigated PT Bumi Bara Makmur Mandiri's Fleet 2 real productivity and adapted-OEE performance in June 2025. At the same time, it simulated its productivity under an 85% OEE scenario. A real overburden mining output amounted to 213, 566.96 BCM vs. the target of 216, 036.00 BCM, which equates to a discrepancy of 2, 469.04 BCM. Adapted-OEE numbers 73.6% (CAT 330 GC), 73.3% (DT-055), 71.2% (DT-027), 73.6% (DT-072), 75.2% (DT-045) were still not reaching the target of 85%, with utilization being the biggest constraint across the fleet despite very high mechanical availability (> 97%). The 85% OEE scenario forecast that excavator productivity could increase by potential 8, 341 BCM/month and by 1, 606, 2, 268 BCM/month for the dump trucks as a whole. So, the total production could get improved approximately by 13, 19%. Such data confirms that utilizing-oriented measures better coordination of dispatching, elimination of stand-by time, and OEE of machines will be the better means of increasing the level of productivity in this fleet compared to the mechanical-maintenance enhancement investment.

Practical Implications

Building directly on the utilization-versus-maintenance finding above, the following practical implications translate this diagnostic conclusion into prioritized management actions. For coal mine contractors BBMM and others similar in business scope, these results highlight four important areas that they may be able to improve immediately. They are, based on the extent of evidence provided above: Shorten waiting and idling times through the deployment of more efficient dispatching and by coordinating better the work of loading and transporting units. Start with DT-027. Review how the front is prepared to make sure that a working surface is already there when equipment gets there. If this step is executed adequately it is likely to minimize the largest single category of lost time identified. In terms of the simulation results (based scenarios rather than forecasts) shown in Section 4, 7, it is a very logical choice to view setting 85% OEE level as the operational target for a medium-term period rather than as an immediate requirement.

The following paragraph is extracted from a technical report.This research work was based on the underlying dataset collected from one coal surface mining plant, resulting in the paper being constrained with several limitations from a single facility perspective. Firstly, the duration for the study was one month (June 2025), and a specific fleet, fleet 2, were chosen for data analysis, so one could not generalise the findings to another time, different period, or other fleets at the same mining operation. Because coal type, pit geometry, haul-road geology, and fleet composition differ across sites, generalization of the specific OEE and productivity figures reported here to other contractors or coal types should also be treated with caution; it is the diagnostic approach, rather than the point estimates themselves, that is intended to transfer.To begin by highlighting this aspect, the authors have pointed out quite clearly in what can be called a "shortcoming, " which may very well result in a misinterpretation by the readers of the work itself, the cycle-time for the loading and unloading units (hauling units) was based on ten observations per unit, so even though that number is adequate for calculating the descriptive productivity, it is too small to do statistical inferences, therefore, the generalisation to a population is not claimed.Thirdly, if the 85% OEE case of Section 4.7 is to be taken seriously, it is only a scenario-based simulation, not a verified forecast, because it hasn't been tested after any implemented strategy, so the author is not claiming to predict or forecast the actual change in productivity.Fourthly and finally among these shortcomings, the authors were quite clear in explaining the lack of technical specifications of the Mercedes, Benz, Axor 2528 Euro4 dump trucks since the data source only had the thesis text extract as reference, hence these features have not been estimated and the author is very responsible in marking it as missing data or not reported. This means the performance of the equipment can only be approximated based on other vehicles.Fifth, the authors' own Effective Working Hour table, that is Section 4.2, of the source thesis contains a discrepancy that the authors' text and narrative of loss-time explanation and the tabulated data are not aligned; for transparency, this study report internally consistent tabulated data only and highlights the underlying discrepancy as an issue without a solution.Sixth, there is nothing like the benchmarking of the modified-OEE equation (i.e., Availability × Utilization × Speed) used in the paper here with other mining-adapted OEE equations. For example, one could think of mining-specific OEE approaches such as OMEE that one of the mining experts, Gutiérrez-Diez et al. (2018), suggested so that it could be known if or how much the results of the OEE change with various formulations that were used.There is scope for future exploration. The first step is to widen the research observation timeframe by covering different months and seasons to capture variability due to rains. The next step is to compare different mining-adapted OEE formulas on the common dataset after their application. Finally, in case if an intervention is applied then the simulated productivity outcome should be verified against real-life post-intervention results.

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