



Evaluating the Operational Impact of Drive-by Loading on Spotting Time and Excavator Productivity in Open-Pit Mining

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ABSTRACT

Loading and hauling operations strongly influence equipment utilization, production efficiency, and operating cost in open-pit mining. Although simulation, dispatch optimization, truck-shovel allocation, and Double Side Loading (DSL) have improved fleet performance, field evidence for Drive-by Loading (DBL) a continuous forward truck-approach strategy that targets the positioning micro-cycle at the loading point remains limited. This study evaluates DBL in an open-pit coal mine in South Kalimantan, Indonesia, using a quantitative before-and-after design involving two excavator classes and 100–110-ton rigid dump trucks. The screened dataset comprised 1,440 valid loading cycles (720 per condition). Cycle-level records were used for descriptive analysis and aggregated into 28 matched shift-level analysis blocks for inferential testing. Matching considered excavator–truck configuration, operator team and shift type, haul-distance category, material domain, production target, and trafficable weather and road conditions. Records with incomplete or non-chronological event timestamps or externally interrupted cycles were excluded without imputation. Average spotting time decreased from 30 s to 17 s (–43.3%), loading cycle time decreased from 167 s to 152 s (–9.0%), and excavator productivity increased from 859 BCM/h to 1,120 BCM/h (+30.4%). Paired tests on the 28 matched blocks produced $df = 27$ and confirmed significant improvements in spotting time and productivity ($p < 0.001$). The scientific contribution is field-based, statistically validated evidence linking a redesigned truck-approach sequence to both micro-cycle time and excavator productivity. DBL therefore offers a practical, low-capital operational option where mine geometry, traffic control, and safety conditions permit a continuous forward approach.

1. Introduction

The increasing demand for minerals, coupled with rising operational costs, stricter environmental regulations, and growing expectations for sustainable mining practices, has intensified the need to improve operational efficiency in open-pit mining operations (Igogo et al., 2021; Fadillah et al., 2026). Efficient resource utilization has become a strategic priority for mining companies, as operational improvements not only enhance production performance but also reduce fuel consumption, greenhouse gas emissions, and overall operating costs (Wang et al., 2024). Among the major production activities in open-pit mining, the loading–hauling system plays a dominant role in determining operational performance because it accounts for more than half of total mining operating costs while representing one of the largest

sources of energy consumption and carbon emissions associated with mobile mining equipment (Wang et al., 2024). Consequently, improving the efficiency of loading and hauling operations has become one of the most effective approaches for increasing equipment utilization, minimizing operational losses, and supporting sustainable mine production (Awuah-Offei, 2024).

Within the loading–hauling system, overall operational performance is strongly influenced by the efficiency of individual loading cycle components, including truck maneuvering, spotting, loading, and hauling activities. Among these components, truck spotting time defined as the time required for a haul truck to position itself correctly before loading begins represents one of the most critical sources of non-productive time in open-pit mining operations (Barbosa et al., 2021). Excessive spotting time interrupts the continuity



of excavator loading cycles, increases equipment idle time, prolongs truck queuing, and reduces excavator utilization, ultimately leading to lower production rates and higher operating costs (Awuah-Offei, 2024; Manyele, 2017). Because spotting activities occur repeatedly throughout every production shift, even relatively small reductions in truck positioning time can generate substantial improvements in loading efficiency, equipment productivity, and overall fleet performance without requiring additional capital investment (Aguayo et al., 2021; Mnzool et al., 2024).

Previous loading-hauling research can be grouped into three principal approaches. First, simulation and mathematical allocation studies optimize fleet size, truck-shovel assignment, or loading strategy at the system level; surge-loader and dispatch studies have reported higher shovel utilization, shorter waiting time, and improved fleet productivity (Aguayo et al., 2021; Zhang et al., 2022; Tapia et al., 2021). Second, digital approaches use Fleet Management Systems, Internet of Things data, machine learning, or real-time dispatching to reduce assignment and traffic inefficiencies, but their benefits depend on data quality, communications infrastructure, and algorithm adoption (Zhang et al., 2022; Tapia et al., 2021). Third, loading-geometry interventions alter the physical interaction at the loading point. Front-geometry optimization has improved productivity by approximately 18–25% (Salam et al., 2025), while Double Side Loading (DSL) positions trucks on two sides of the excavator to maintain loading continuity and has reduced queuing, hanging, and cycle time under field conditions (Sudarwanto et al., 2022). Collectively, these studies demonstrate that both system-level allocation and loading-point geometry can improve production performance.

A specific gap nevertheless remains at the truck-positioning micro-cycle. Dispatch optimization determines which truck should travel to which loading unit, but it does not prescribe the final approach and spotting maneuver. DSL maintains two loading positions around the excavator and therefore requires sufficient working width, compatible traffic circulation, and coordinated dual-side truck access. DBL is operationally distinct: it replaces stop-reverse-reposition movements with a predefined continuous forward approach, one truck at a time, to reduce maneuvering and spotting losses immediately before loading. Published evidence has rarely isolated this mechanism under active mine production, distinguished it explicitly from dispatch and DSL, or linked its effect on spotting time to loading-cycle performance and excavator productivity using matched field observations and inferential statistics.

Accordingly, this study contributes: (i) a field-tested definition and operational sequence for DBL; (ii) a controlled before-and-after evaluation based on 1,440 valid cycles and 28 matched shift-level analysis blocks; (iii) statistical evidence for changes in spotting time and excavator productivity, together with correlation and regression analysis of their relationship; and (iv) an assessment of implementation boundaries and economic implications. The contribution is therefore not merely the implementation of a

new procedure, but a reproducible empirical evaluation of how a micro-cycle redesign affects loading performance under actual operating conditions.

2. Research Methods

2.1 Research Framework

This study employed a quantitative before-and-after comparative approach to evaluate the operational impact of the DBL method on the performance of a truck-shovel loading system in an open-pit coal mine. The research framework was developed to systematically assess operational improvements resulting from the implementation of DBL under actual production conditions. The framework integrates field observations with statistical analysis to quantify changes in operational performance before and after implementation. Fig. 1 illustrates the overall research framework adopted in this study. The framework begins with identifying operational problems and establishing baseline operational conditions under the conventional loading system. DBL was subsequently prepared and implemented as the engineering intervention through truck maneuver redesign and operational standardization. The resulting operational datasets were validated and statistically analyzed to quantify the impact of DBL on loading performance. The effectiveness of the proposed method was evaluated based on changes in spotting time, loading cycle time, truck waiting time, excavator productivity, and excavator utilization.

Fig. 2 also illustrates that the expected benefits of DBL are achieved through a cascading operational mechanism rather than through a direct increase in equipment capacity. Under the conventional loading method, haul trucks frequently perform stopping, reversing, and repositioning maneuvers before reaching the loading point, creating additional maneuvering time and increasing spotting delays. DBL addresses these inefficiencies by introducing a standardized continuous forward approach supported by predefined travel paths and truck-positioning procedures. As a result, truck arrival at the loading point becomes more predictable, interruptions to excavator loading continuity are reduced, and idle periods between successive loading cycles can be minimized.

The framework therefore assumes that improvements in excavator utilization and productivity occur as secondary effects of reducing non-productive positioning activities, making spotting time an important intermediate variable linking truck movement efficiency to overall loading performance.



Figure 1. Field-based Drive-by Loading evaluation framework

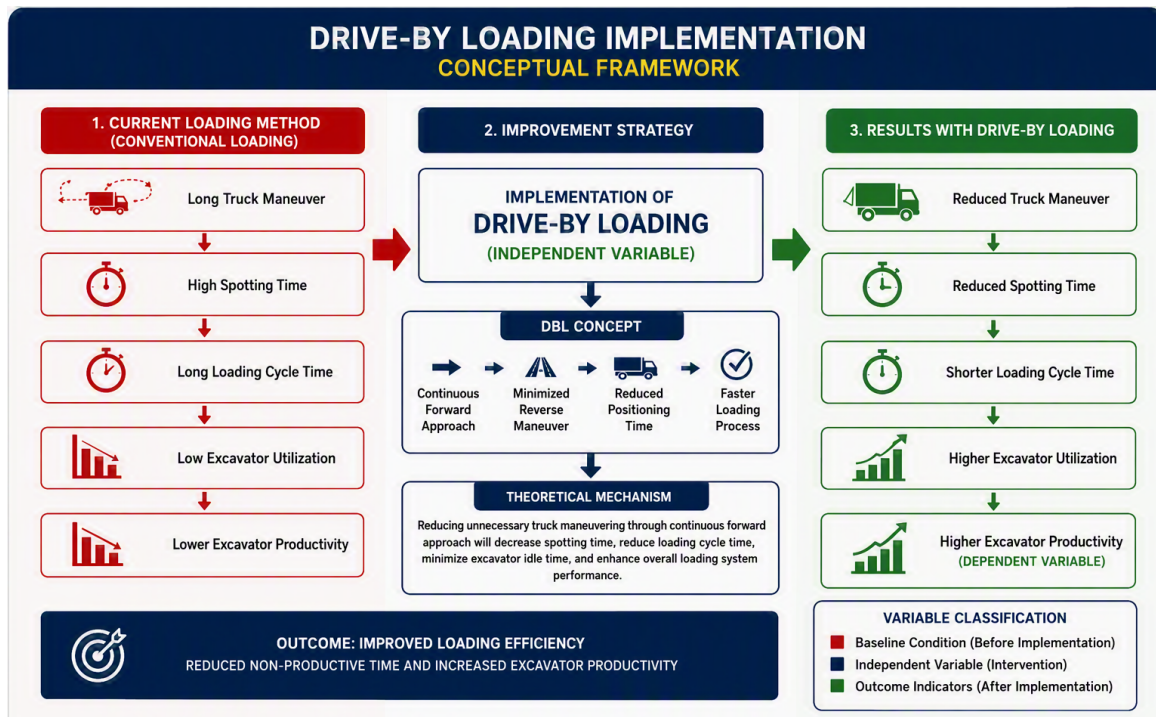


Figure 2. Conceptual mechanism linking DBL to loading performance

The study area, operational characteristics, and data acquisition process adopted in this research are described in the following section.

2.2 Study Area and Data Collection

This study was conducted at a large-scale open-pit coal mining operation in South Kalimantan, Indonesia, employing a conventional truck–shovel mining system consisting of hydraulic excavators and rigid dump trucks. The mining operation has implemented various operational improvement initiatives to enhance loading efficiency and fleet productivity, providing a suitable environment for evaluating the effectiveness of the DBL method under actual production conditions.

Operational observations focused on two hydraulic excavators representing different production classes, namely a Liebherr R9250 (approximately 250-ton class) and a Komatsu PC2000 (approximately 200-ton class), operating with 100–110-ton rigid dump trucks. To reduce confounding, before and after records were matched by excavator–truck configuration, operator team, day/night shift type, haul-distance category, loading area and material domain, production target, and dispatch rule. Only periods with trafficable haul roads and no active rain closure, major road maintenance, blasting interruption, refueling, or equipment breakdown were retained. The same primary operator teams were represented in both conditions; where an exact operator match was unavailable, the record was matched at team and shift-type level and was not paired if the remaining operating conditions differed materially.

The field campaign covered 14 production days and included repeated day and night observations, both excavator classes, and recurring operator teams. After screening, 1,440 valid loading cycles were retained, comprising 720 cycles under conventional loading and 720 cycles after DBL implementation. This duration was considered adequate for the short-term field evaluation because it captured repeated operating rotations and a large cycle-level dataset under both conditions; however, it does not represent seasonal variability, which is acknowledged as a limitation. Raw cycles were used to describe the distribution of operating performance. Because cycles collected within the same shift are not statistically independent, inferential testing did not treat the 1,440 cycles as 1,440 pairs. Instead, cycle records were aggregated into 28 matched shift-level analysis blocks. Each before–after block was matched on the control factors described above, and the block mean was used as the paired observation. Thus, the paired t-test used $n = 28$ pairs and $df = n - 1 = 27$.

Data quality screening was completed before aggregation. FMS event sequences were checked for complete timestamps, correct chronological order, duplicate records, and consistency with field and production logs. Records were removed when an essential timestamp was missing, the event sequence was impossible, or the cycle included an externally caused interruption unrelated to the loading method. No missing value was imputed, and no extreme but operationally valid observation was deleted solely because it was statistically unusual. The reported 720 cycles per condition therefore represent complete, valid cycles after screening.

Table 1. Summary of Data Collection and Observation Characteristics

Parameter	Description
Operation	Open-pit coal mining.
Location	South Kalimantan, Indonesia.
Mining Method	Truck–shovel operation.
Geological Setting	Tertiary sedimentary coal deposits.
Excavators	Liebherr R9250; Komatsu PC2000.
Haul Truck	Rigid dump trucks (100 Tonnes payload).
Study Design	Before-and-after comparative.
Observation Period	14 production days covering repeated day and night observations.
Statistical Unit	28 matched shift-level analysis blocks (n = 28 pairs).
Sampling Method	Purposive operational matching.
Observed Cycles	1,440 valid cycles (720 before; 720 after).
Primary Data	Field observations.
Secondary Data	Production reports; equipment performance records.
Operational Variables	Excavator productivity, spotting time, loading cycle time, truck maneuvering time, truck waiting time, excavator utilization, production achievement.

Based on the study area and operational dataset described above, the implementation procedure of the DBL method is presented in the following section.

2.3 DBL Method

The DBL method was implemented as an operational improvement strategy to reduce non-productive truck maneuvering activities during the loading process. Unlike the conventional loading method, where haul trucks are required to stop and perform reverse maneuvers before reaching the loading position, DBL allows trucks to approach the excavator using a continuous forward movement. This operational modification minimizes unnecessary maneuvering time, shortens truck positioning activities, and enables smoother interaction between the haul truck and excavator throughout the loading cycle.

As illustrated in Fig. 3, the DBL sequence consists of a continuous truck approach, positioning, loading, and departure without excessive reversing movements. During the approach phase, the haul truck follows a predefined travel path toward the loading point while the excavator continues its digging cycle. Once the truck reaches the designated loading position, material loading begins immediately without requiring additional repositioning. After loading is completed, the truck exits the loading area through a forward movement, allowing the next truck to enter the loading zone with minimal interruption to excavator operation.

By reducing truck maneuvering activities and eliminating unnecessary positioning delays, DBL is expected to decrease spotting time, shorten loading cycle time, reduce excavator idle periods, and improve overall loading efficiency. Consequently, improvements in these operational parameters are anticipated to increase excavator productivity and utilization while maintaining a smooth and continuous loading sequence under actual production conditions.

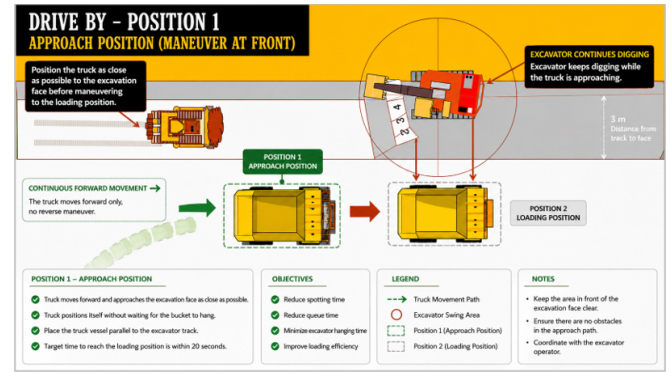


Figure 3. Operational sequence of the DBL method

The operational performance indicators used to evaluate DBL are presented in the following section.

2.4 Operational Performance Evaluation

The operational impact of DBL was evaluated through a set of performance indicators covering truck maneuvering, spotting, loading-cycle efficiency, equipment utilization, and productivity. These indicators were selected to capture both the immediate effects of the intervention and the resulting changes in overall loading-system performance.

Each indicator evaluates a specific stage of the loading–hauling process. Truck maneuvering time and spotting time were used to assess the immediate operational impact of DBL on truck positioning efficiency. Loading cycle time and truck waiting time were subsequently evaluated to quantify improvements in loading performance. Finally, excavator utilization, excavator productivity, and production achievement were used as overall operational performance indicators reflecting the effectiveness of the implemented loading method. Collectively, these indicators provide a comprehensive assessment of the operational benefits achieved through DBL implementation.

Table 2. Operational Performance Indicators Used in This Study

Indicator	Unit	Description
Truck Maneuvering Time	s	Time required for truck positioning before loading begins.
Spotting Time	s	Time required for a truck to reach the designated loading position.
Truck Waiting Time	s	Time during which the truck waits before loading commences.
Loading Cycle Time	s	Total time required to complete one loading cycle.
Excavator Utilization	%	Ratio of effective operating time to available operating time.
Excavator Productivity	BCM/h	Volume of material loaded per effective operating hour.
Production Achievement	BCM	Total production achieved during the observation period.

The operational performance indicators described above formed the basis for the subsequent statistical analyses used to quantify the effectiveness of DBL. The statistical procedures adopted in this study are presented in the following section.

2.5 Statistical Analysis

Statistical analyses were performed at two levels to avoid pseudoreplication. Cycle-level data (720 observations per condition) were summarized using descriptive statistics to characterize the operating distributions. Inferential analyses used the 28 matched shift-level block means described in Section 2.2. Paired observations were selected because each before block had a corresponding after block with comparable equipment, operator-team, shift, material, haul-distance, weather/road, and production conditions. Pearson correlation and simple linear regression were then used to examine the association between spotting time and excavator productivity in the aggregated analytical dataset (Montgomery et al., 2019; Montgomery et al., 2021).

Normality was assessed on the 28 paired differences, rather than on all individual loading cycles, using the Shapiro–Wilk test. Paired sample t-tests were applied at $\alpha = 0.05$; with $n = 28$ matched pairs, the test degrees of freedom were $df = 27$. Effect size was reported using Cohen's d for paired observations. Pearson correlation quantified the direction and strength of the spotting-time–productivity relationship, and simple linear regression estimated the change in excavator productivity associated with a one-second change in spotting time. Analyses were performed using Minitab® Statistical Software Version 17. This hierarchy preserves the descriptive information in the cycle-level data while maintaining an appropriate independent unit for hypothesis testing.

The statistical methods described above relied on operational performance indicators derived from field observations. The mathematical formulations used to calculate these indicators are presented in the following section to ensure consistency and transparency in the evaluation process.

Table 3. Statistical Methods Applied in This Study

Analysis	Purpose
Descriptive Statistics	Summarize operational performance characteristics before and after DBL implementation.
Shapiro–Wilk Normality Test	Assess whether the datasets satisfy the normality assumption.
Paired Sample t-test	Evaluate significant differences between operational performance before and after DBL implementation.
Pearson Correlation	Examine the relationship between spotting time and excavator productivity.
Simple Linear Regression	Quantify the influence of spotting time on excavator productivity.

2.6 Mathematical Formulation

The operational performance indicators evaluated in this study were calculated using standard equations commonly applied in loading–hauling performance analysis. These formulations provide a consistent basis for quantifying operational performance before and after DBL implementation, thereby ensuring that the subsequent statistical analyses were performed using comparable performance metrics (Manyele et al., 2017).

The first indicator evaluated was truck maneuvering time, which represents the duration required for a haul truck to position itself before reaching the designated loading point. Since this parameter was directly obtained from the Fleet Management System (FMS) event timestamps, it was calculated as the difference between the start and end timestamps of the maneuvering activity:

$$T_m = t_2 - t_1 \quad (1)$$

where T_m is truck maneuvering time (s), t_1 is the timestamp at the start of maneuvering, and t_2 is the timestamp at completion of the maneuver.

Following the maneuvering process, the spotting time was calculated as the time required for the truck to move from the final maneuvering position to the designated loading position. This parameter reflects the effectiveness of truck positioning before loading begins and was determined using:

$$ST = t_4 - t_3 \quad (2)$$

where ST is spotting time (s), t_3 is the timestamp when the truck begins its final approach after maneuvering, and t_4 is the timestamp when the designated loading position is reached.

The efficiency of the loading operation was subsequently evaluated using the loading cycle time, which represents the total duration required to complete one loading cycle. It was calculated as:

$$LCT = t_6 - t_5 \quad (3)$$

where LCT is loading cycle time (s), t_5 is the timestamp at the beginning of the loading cycle, and t_6 is the timestamp at completion of the loading cycle.

To evaluate queuing performance, the truck waiting time was calculated as the duration between truck arrival at the loading area and the commencement of loading. This indicator is expressed as:

$$WT = t_L - t_A \quad (4)$$

where WT is truck waiting time (s), t_A is the truck-arrival timestamp at the loading area, and t_L is the timestamp when loading commences.

The overall effectiveness of excavator operation was evaluated using excavator utilization, which represents the proportion of productive operating time relative to the total available operating time. Excavator utilization was calculated using:

$$EU = \frac{T_o}{T_a} \times 100\% \quad (5)$$

where EU is excavator utilization (%), T_o is effective operating time (h), and T_a is total available operating time (h).

To quantify production performance, excavator productivity was calculated as the volume of material loaded during the effective operating period:

$$EP = \frac{Q}{T_o} \quad (6)$$

where EP is excavator productivity (BCM/h), Q is total material loaded (BCM), and T_o is effective operating time (h).

Finally, the overall production output during each observation period was represented by production achievement, which was determined by summing the total material loaded throughout the observation period:

$$PA = \sum_{i=1}^n Q_i \quad (7)$$

where PA is production achievement (BCM), Q_i is the material volume loaded during the i -th cycle, and n is the number of valid loading cycles.

The operational performance indicators calculated using the above formulations served as the quantitative basis for comparing loading performance before and after DBL implementation. The resulting values were subsequently subjected to the statistical analyses described in Section 2.5 to evaluate the effectiveness of the proposed loading method.

3. Results

This section presents the results of the field implementation of the Drive-by Loading (DBL) method and discusses its impact on loading-hauling performance. The analysis begins with an evaluation of the baseline operational condition under the conventional loading method, followed by the implementation of DBL and the resulting changes in operational performance. The effectiveness of the proposed method is subsequently assessed through comparative and statistical analyses, including descriptive statistics, hypothesis testing, and correlation and regression analyses, to quantify the relationship between truck positioning efficiency and excavator productivity.

3.1 Baseline Operational Performance

Prior to implementing DBL, the operational performance of the conventional loading system was evaluated to establish the baseline condition against which subsequent improvements could be assessed. The evaluation focused on excavator productivity and truck spotting time because these parameters directly represent the efficiency of truck positioning and loading continuity during production operations.

Table 4 summarizes the baseline operational performance under the conventional loading method. The results indicate that the existing loading operation had not yet achieved the expected production performance. The average excavator productivity reached 859 BCM/h for the Liebherr R9250 and 535 BCM/h for the Komatsu PC2000, both remaining below the company's production targets.

Table 4. Baseline Operational Performance Under the Conventional Loading Method

Performance Indicator	Value	Operational Target	Observation
Excavator Productivity (Liebherr R9250)	859 BCM/h	1000 BCM/h	Below target
Excavator Productivity (Komatsu PC2000)	535 BCM/h	800 BCM/h	Below target
Average Spotting Time	30 s	20 s	Above target
Minimum Spotting Time	26 s	–	–
Maximum Spotting Time	36 s	–	–

In addition, the average truck spotting time was 30 s, ranging from 26 s to 36 s, exceeding the operational target of 20 s. These findings indicate that truck positioning activities constituted a significant source of non-productive time within the loading cycle.

Field observations further revealed that haul trucks frequently performed multiple steering corrections and reverse movements before reaching the designated loading position. These maneuvering activities interrupted loading continuity and reduced the effective utilization of the excavator by increasing idle periods between successive loading cycles. Consequently, the loading process became less efficient, limiting the achievable production rate despite the availability of sufficient excavator capacity. Similar operational constraints have also been reported in previous loading-hauling studies, where excessive truck maneuvering contributed to longer cycle times and lower equipment productivity.

The baseline assessment therefore confirmed that truck positioning represented a critical operational bottleneck requiring improvement. Based on these observations, DBL was introduced as an engineering intervention designed to simplify truck maneuvering and improve loading continuity, as discussed in the following section.

3.2 Implementation of the Drive-by Loading Method

Based on the baseline evaluation, DBL was implemented as an operational intervention to improve truck positioning efficiency and loading continuity. Unlike the conventional loading configuration, which required multiple steering corrections and reverse movements before loading, the proposed method enabled haul trucks to approach the excavator using a continuous forward movement. This operational modification was intended to reduce unnecessary maneuvering, shorten spotting time, and increase the proportion of productive excavator operating time without requiring additional equipment or infrastructure.

Fig. 4 illustrates the operational differences between the conventional loading method and the proposed DBL configuration. Under the conventional loading system, haul trucks approached the excavator through a combination of forward and reverse movements, often requiring multiple steering adjustments before reaching the designated loading position.



Figure 4. Comparison of loading methods: (a) conventional loading; (b) Drive-by Loading

In contrast, the DBL method allowed trucks to enter the loading area using a continuous forward approach, thereby eliminating unnecessary reverse maneuvering and reducing truck positioning time prior to loading.

To ensure successful implementation, DBL was introduced through a structured operational improvement program consisting of loading pattern redesign, operator coaching, supervisor briefing, field monitoring, and continuous performance evaluation. Operators were instructed to follow the standardized truck approach route, while supervisors monitored field compliance and provided immediate corrective actions whenever deviations from the prescribed loading procedure were observed. This implementation strategy ensured that the operational improvements were consistently applied throughout the observation period.

Unlike capital-intensive productivity improvement initiatives, the implementation of DBL primarily involved modifications to operational procedures rather than physical infrastructure or equipment replacement. Consequently, the proposed method represents a low-cost operational improvement strategy that can be implemented within existing truck–shovel systems while maintaining production continuity. By simplifying truck positioning, the method reduces non-productive activities that do not contribute directly to material movement, thereby creating greater opportunities for productive excavator utilization.

3.3 Comparative Performance Analysis

Following the implementation of DBL, the operational performance of the loading system was re-evaluated under comparable production conditions to quantify the effectiveness of the proposed loading method. The comparative assessment focused on excavator productivity and truck spotting time, as these indicators directly reflect improvements in truck positioning efficiency and loading continuity. Unless otherwise stated, productivity values reported in the comparative analysis represent aggregated matched-block observations pooled across the monitored excavator fleet rather than a single excavator class. Fig. 5 illustrates the distribution of excavator productivity before and after the implementation of DBL.

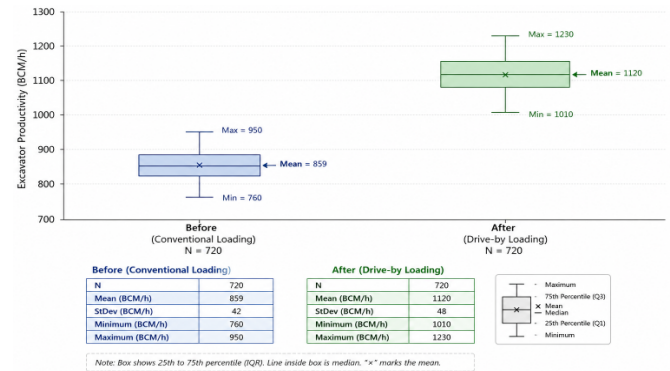


Figure 5. Excavator productivity before and after DBL implementation

The average excavator productivity increased from 859 BCM/h under the conventional loading method to 1,120 BCM/h following DBL implementation, representing an improvement of approximately 30.4%. In addition to the higher average productivity, the post-implementation observations exhibited a narrower distribution, indicating that loading operations became more stable and consistent throughout the observation period.

The improvement in excavator productivity can be primarily attributed to the reduction in non-productive activities associated with truck positioning. Under the conventional loading method, excavators frequently experienced idle periods while waiting for haul trucks to complete maneuvering before loading. By enabling a continuous forward truck approach, DBL reduced these interruptions, allowing excavators to perform productive loading activities more continuously. Consequently, a greater proportion of the available operating time was converted into effective material loading, resulting in higher overall productivity.

Fig. 6 presents the distribution of truck spotting time before and after DBL implementation. Average spotting time decreased from 30 s to 17 s (–43.3%), and the post-implementation distribution was narrower, indicating more consistent truck positioning during the observed loading operations.

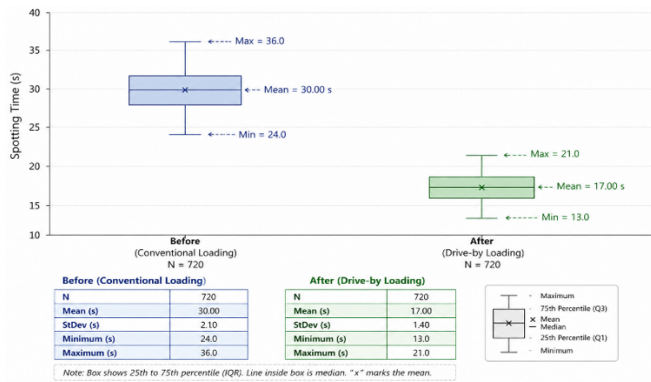


Figure 6. Truck spotting time before and after DBL implementation

The substantial reduction in spotting time demonstrates that the primary operational objective of DBL was successfully achieved. The elimination of unnecessary reverse maneuvering and steering corrections simplified truck positioning, thereby reducing delays before loading commenced. Although the reduction in spotting time appears relatively small in absolute terms (13s per cycle), the cumulative effect across hundreds of loading cycles per production shift resulted in a considerable increase in effective loading time and excavator utilization. This finding highlights that small improvements in repetitive operational activities can generate substantial productivity gains over prolonged production periods.

Table 5 summarizes the overall operational improvements achieved following DBL implementation. The results clearly demonstrate that simplifying truck maneuvering substantially reduced spotting time while simultaneously increasing excavator productivity. The inverse relationship between these two performance indicators suggests that improvements in truck positioning efficiency directly contributed to enhanced loading performance.

The observed operational improvements are consistent with previous studies reporting that reducing truck positioning delays and improving loading continuity contribute directly to higher productivity. However, unlike many previous investigations that primarily relied on simulation models or analytical optimization, the present study demonstrates the effectiveness of DBL through full-scale field implementation under actual production conditions. This practical validation confirms that relatively simple operational modifications can generate measurable productivity improvements without requiring additional capital investment.

Table 5. Comparative Operational Performance Before and After DBL Implementation

Indicator	Before	After	Improvement
Truck Maneuvering Time (s)	18.5	8.9	-51.9%
Spotting Time (s)	30.0	17.0	-43.3%
Loading Cycle Time (s)	167	152	-9.0%
Excavator Productivity (BCM/h)	859	1,120	+30.4%

While the comparative results indicate substantial operational improvements following DBL implementation, statistical analyses are required to determine whether these observed differences are statistically significant rather than resulting from normal operational variability. The statistical validation of the observed performance improvements is presented in the following section.

3.4 Statistical Validation of DBL Performance

Statistical validation followed the two-level data structure defined in Section 2.5. Descriptive statistics used all 720 valid cycles per condition, while the Shapiro–Wilk test and paired t-tests used 28 matched shift-level block differences. This distinction prevents repeated cycles from the same shift from being treated as independent experimental units. Correlation and regression analyses were conducted on the aggregated analytical data to examine the relationship between spotting time and excavator productivity.

Descriptive statistics were first used to summarize the characteristics of the operational datasets before and after DBL implementation. The analysis included the mean, standard deviation, minimum value, and maximum value for each operational performance indicator to provide an overall representation of loading system performance.

Table 6 summarizes the operational variables evaluated in this study. The implementation of DBL substantially improved overall loading performance. The average truck maneuvering time decreased from 18.5 ± 2.6 s to 8.9 ± 1.8 s, while the average spotting time decreased from 30.0 ± 2.1 s to 17.0 ± 1.4 s. Similarly, the average loading cycle time was reduced from 167 ± 7 s to 152 ± 6 s. These operational improvements were accompanied by an increase in average excavator productivity from 859 ± 42 BCM/h to $1,120 \pm 48$ BCM/h. In addition to the changes in mean values, the lower standard deviations observed after implementation indicate that the loading process became more consistent and less variable under the DBL configuration.

Before hypothesis testing, the distribution of the 28 paired shift-level differences was examined. The Shapiro–Wilk test was selected because it is appropriate for assessing normality in moderate samples and directly tests the distributional assumption required for the paired t-test.

Table 6. Cycle-Level Descriptive Statistics (720 Valid Cycles)

Variable	Condition	Mean	SD	Min	Max
Truck Maneuvering Time (s)	Before	18.5	2.6	13	25
	After	8.9	1.8	5	13
Spotting Time (s)	Before	30.0	2.1	24	36
	After	17.0	1.4	13	21
Loading Cycle Time (s)	Before	167	7	152	184
	After	152	6	140	165
Excavator Productivity (BCM/h)	Before	859	42	760	950
	After	1120	48	1010	1230

As shown in Table 7, the paired differences for spotting time and excavator productivity produced p-values greater than 0.05. Normality therefore could not be rejected, supporting the use of paired parametric tests. These p-values refer to the 28 matched analysis-block differences, not to the 720 cycle-level observations per condition.

Following confirmation of data normality, paired sample t-tests were conducted to evaluate whether the observed differences in operational performance before and after DBL implementation were statistically significant. Table 8 shows statistically significant improvements following DBL implementation. Mean spotting time decreased by 13.0 s ($t = -14.32$, $df = 27$, $p < 0.001$), while excavator productivity increased by 261 BCM/h ($t = 9.87$, $df = 27$, $p < 0.001$). The value $df = 27$ follows directly from the 28 paired shift-level analysis blocks ($df = n - 1$), whereas the 1,440 raw cycles were used for descriptive characterization. Cohen's d values of 2.71 and 1.87 indicate very large effects within the observed matched operating conditions.

To investigate the relationship between truck positioning and excavator performance, Pearson correlation was applied to the aggregated analytical observations. Spotting time was strongly and negatively associated with excavator productivity ($r = -0.91$, $p < 0.001$), indicating that shorter spotting times coincided with higher productivity under the matched operating conditions. Because the study is a controlled before-and-after field evaluation rather than a randomized experiment, this relationship is interpreted as strong intervention-associated evidence rather than proof that spotting time is the only causal factor. To quantify the magnitude of this relationship, a simple linear regression analysis was subsequently performed using spotting time as the independent variable and excavator productivity as the dependent variable.

Table 7. Shapiro–Wilk Normality Tests for 28 Paired Block Differences

Variable	W Statistic	p-value	Decision
Paired difference: spotting time	0.978	0.612	Normal
Paired difference: excavator productivity	0.969	0.428	Normal

Table 8. Paired Sample T-Test Results ($n = 28$ Matched Blocks; $df = 27$)

Variable	Mean diff.	95% CI	t	df	p	Cohen's d
Spotting Time (s)	-13	-14.90 to -11.10	-14.32	27	<0.001	2.71
Excavator Productivity (BCM/h)	+261	198.40 to 323.60	9.87	27	<0.001	1.87

Table 9. Pearson Correlation Between Spotting Time and Excavator Productivity

Variable Relationship	Pearson r	p-value	Interpretation
Spotting Time vs Excavator Productivity	-0.91	<0.001	Strong negative correlation

Table 10. Simple Linear Regression Results

Predictor	Coefficient (β)	t-value	p-value	Interpretation
Constant	1,720.35	18.42	<0.001	Significant
Spotting Time	-28.95	-9.64	<0.001	Significant negative effect

Table 11. Regression Model Summary

R	R ²	Adjusted R ²	F-value	p-value
0.91	0.83	0.82	92.93	<0.001

The regression analysis confirmed that spotting time had a statistically significant negative effect on excavator productivity. The regression coefficient indicates that each one-second increase in spotting time was associated with an estimated decrease of approximately 28.95 BCM/h in excavator productivity. Furthermore, the regression model explained approximately 83% of the observed variability in productivity ($R^2 = 0.83$), demonstrating that truck positioning efficiency is one of the dominant factors influencing loading performance under the observed operating conditions. Nevertheless, approximately 17% of the remaining variability may be attributed to other operational factors, including operator performance, bucket fill factor, truck arrival sequence, and short-term production interruptions that were not explicitly evaluated in this study.

From an operational perspective, the findings demonstrate that relatively simple improvements in truck positioning procedures can generate substantial gains in loading performance without requiring additional equipment or infrastructure investment. The observed reduction in spotting time enabled excavators to spend a greater proportion of their available operating time performing productive loading activities, thereby increasing overall production efficiency. These findings are consistent with previous studies reporting that improvements in loading configurations and truck–shovel interactions enhance equipment productivity and reduce operational delays. However, unlike many earlier investigations that primarily relied on simulation-based analyses or optimization models, the present study provides quantitative evidence from full-scale field implementation under actual mining production conditions. Although the proposed method proved effective under the observed operating environment, further validation across different mine sites, fleet compositions, and geological conditions is recommended to improve the generalizability of the proposed approach.

Overall, the statistical analyses consistently demonstrate that the operational improvements achieved following DBL implementation were both statistically significant and operationally meaningful. The combination of large effect sizes, a strong negative correlation, and a regression model with high explanatory power provides robust quantitative evidence that reducing truck maneuvering and spotting time contributes directly to improved excavator productivity. Collectively, these findings confirm the effectiveness of DBL

as a practical operational improvement strategy for enhancing loading–hauling performance in open-pit mining operations.

4. Discussion

The results demonstrate that DBL provides statistically significant improvements in loading performance by reducing truck maneuvering and spotting time while increasing excavator productivity. Beyond the observed operational improvements, the findings provide several important implications for truck–shovel system optimization in open-pit mining operations. These implications are discussed in terms of comparison with previous studies, practical applications, scientific contributions, and future research opportunities.

First, the operational improvements observed in this study are generally consistent with previous investigations reporting that optimizing truck–shovel interactions contributes directly to higher equipment productivity and loading efficiency. (Aguayo et al., 2021) reported that improvements in loading configuration increased shovel utilization by approximately 11% and overall productivity by 13%, whereas (Salam et al., 2025) demonstrated productivity improvements of approximately 18–25% through loading geometry optimization. Similarly, the present study achieved a 43.3% reduction in spotting time and a 30.4% increase in excavator productivity following the implementation of DBL. Unlike many previous studies that primarily relied on simulation models or analytical optimization techniques, the present study provides quantitative evidence obtained through full-scale field implementation under actual mining production conditions. This distinction demonstrates that relatively simple operational modifications can generate measurable productivity improvements without requiring major changes to equipment configuration or mine infrastructure.

Second, DBL has practical economic potential because it reduces recurring non-productive time without requiring another excavator or haul truck. Across the 720 post-implementation cycle-equivalents, the observed 13-s spotting reduction corresponds to 9,360 s, or 2.6 h, of positioning-related delay avoided. For an annual cycle count N , the corresponding avoided delay can be estimated as $13N/3,600$ h; potential fuel and operating-cost benefits can then be calculated by multiplying those hours by the measured idle-fuel rate and the applicable equipment hourly cost. In addition, the increase from 859 to 1,120 BCM/h implies a theoretical 23.3% reduction in excavator operating hours for a fixed material volume, provided that downstream hauling, dumping, and production constraints do not become limiting. Implementation costs are largely limited to layout preparation, route marking, training, supervision, and compliance monitoring. Site fuel-burn, maintenance, labor, and cost-rate data were unavailable, so a monetary saving is not claimed; the equations above provide a transparent basis for a future site-specific business case.

Third, this study contributes to the existing body of knowledge by providing statistically validated field evidence of the relationship between truck positioning efficiency and

excavator productivity. The combination of descriptive analysis, hypothesis testing, correlation analysis, and regression modeling demonstrates that operational improvements achieved through DBL are both statistically significant and operationally meaningful. Furthermore, the regression model explains approximately 83% of the observed variability in excavator productivity, highlighting truck spotting time as one of the dominant operational factors influencing loading performance. These findings strengthen the empirical foundation for future studies investigating operational optimization within truck–shovel systems.

Despite the encouraging results, the internal and external validity of the study has boundaries. It was conducted at one open-pit coal mine over a 14-day field window using specific excavator and 100–110-ton truck configurations. Operational matching reduced variation in operator team, shift type, material domain, haul-distance category, weather/road condition, and production target, but a before-and-after field design cannot eliminate all time-varying confounding. The study also did not directly quantify fuel burn, equipment cost, maintenance effects, operator fatigue, or safety exposure. The results should therefore be interpreted as short-term performance effects under the matched conditions rather than universal values for all mines or seasons.

DBL applicability is also constrained by mine layout and traffic conditions. A continuous forward approach requires adequate bench and loading-floor width, stable ground, clear operator sightlines, a protected truck path, and an unobstructed exit. Benefits may diminish in narrow or irregular loading areas, soft or wet floors, high traffic density, mixed fleets with large differences in truck dimensions or acceleration, short dumping intervals that create downstream queues, or configurations in which multiple loading units share the same approach. In such settings, interaction risk and traffic interference may offset the spotting-time benefit. Implementation should therefore be preceded by a site-specific geometry and risk assessment, traffic simulation or controlled trial where appropriate, operator competency verification, and clearly defined stop criteria.

Future research should extend the evaluation of DBL across multiple mining sites with different fleet compositions, geological conditions, and operational characteristics to improve the generalizability of the proposed approach. In addition, the integration of DBL with digital mining technologies, including Fleet Management Systems (FMS) (Hazrathosseini et al., 2024; Wang et al., 2023) Internet of Things (IoT)-based equipment monitoring (Anand et al., 2023; Fadillah et al., 2025) and machine learning-driven dispatch optimization (Choudhury et al., 2022; Farahpoor et al., 2024) offers promising opportunities to support adaptive and autonomous loading operations through real-time operational data. From a sustainability perspective, future studies should also investigate the integration of DBL with energy-efficient mining practices (de Carvalho et al., 2022) and renewable energy-powered mining systems (Zolotov et al., 2024) to reduce fuel consumption, greenhouse gas emissions, and overall environmental impacts. Furthermore,

comprehensive assessments incorporating economic performance (Bodziony et al., 2024; Fadillah et al., 2026) equipment lifecycle analysis (Rojas et al., 2025), maintenance strategies (Bodziony et al., 2024), and carbon emission evaluation would provide a more holistic framework for sustainable and intelligent loading–hauling operations in open-pit mining.

5. Conclusion

This study provides field-based evidence that Drive-by Loading can improve truck–shovel performance by redesigning the final truck-approach and spotting micro-cycle. Under matched short-term operating conditions, spotting time decreased from 30 s to 17 s, loading cycle time decreased from 167 s to 152 s, and excavator productivity increased from 859 to 1,120 BCM/h. The 1,440 valid cycles supported descriptive characterization, while inferential testing correctly used 28 matched shift-level analysis blocks ($df = 27$). The scientific contribution is the explicit distinction of DBL from dispatch optimization and DSL, together with a statistically validated link between a continuous forward approach, reduced positioning loss, and improved excavator performance. DBL is a low-capital option, but its transferability depends on loading-area geometry, traffic density, fleet compatibility, road condition, operator control, and safety requirements. Multi-site and longer-duration studies should quantify fuel, cost, maintenance, and safety outcomes before the observed effects are generalized or converted into a full economic claim.

Disclosure Statement

The authors declare that this manuscript has no conflict of interest and has been prepared in accordance with the journal's policies and ethical standards.

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