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Original Article

Improving Payload Efficiency in Open-Pit Mining: An Integrated Model using Six Sigma and Artificial Intelligence

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Abstract *- Increasing the payload efficiency in open-pit mining is paramount for productivity, costs, and process variability. In this paper, an integrated methodological approach that combines Six Sigma, the PDCA cycle, and artificial intelligence is proposed to optimise the loading process in a copper mining operation. The goal is to reduce variability and increase control on the loading operation by knowing the variables that relate to the operator training, the adherence to preventive maintenance, and the monitoring of the operation. The proposed methodology was tested on an industrial case involving three truck models and used process capability indicators based on predictive analytics to assess their performance. Results indicate measurable gains in payload efficiency that range from 2.22% to 5.25% for three of the four truck models, despite the presence of a high-performance level already. Availability increased from 88% to 94%, and null payloads dropped, which improved the data reliability when making decisions. Overall, the findings demonstrate that the integration of established process improvement methodologies with artificial intelsligence provides for more rigorous and repeatable control of the loading operation than the two on their own. Although mined at a single site, the proposed framework lends itself to scalability and can also be implemented in other mines. This research contributes to the advancement of data-driven process optimization in mining by providing a robust and transferable model for enhancing payload efficiency and operational performance.*

Keywords *- Six Sigma, PDCA cycle, Artificial Intelligence, Payload efficiency, Open-pit mining, Process optimization.*

1. Introduction

1.1. Mining Sector

Mining exports in Peru represent more than 60% of the country's total exports, mainly driven by copper and gold production, highlighting the strategic relevance of the sector within the national economy. Mining activities contribute approximately 10% of Peru's gross domestic product and account for nearly 11% of private investment, reflecting the sustained interest of domestic and international stakeholders in this industry [1]. Supported by a favourable geological structure and significant mineral reserves, Peru has positioned itself among the leading global producers of copper and gold, reinforcing mining as a key driver of economic growth and regional development.

Despite its economic importance, the Peruvian mining sector operates in an increasingly complex environment characterized by operational, social, and economic constraints. Global disruptions caused by the COVID-19 pandemic, geopolitical tensions arising from the conflict between Russia and Ukraine, and the intensification of climate-related events have exerted considerable pressure on mining operations. Additionally, socio-environmental conflicts have emerged as a critical challenge affecting the sector's sustainability. Currently, 65.9% of the 132 socio-environmental conflicts registered nationwide are linked to mining activities, revealing persistent tensions between mining companies and local communities [2]. These conflicts have resulted in operational interruptions, financial losses exceeding S/1.5 billion, and reduced investor confidence, further aggravated by political instability and delays in large-scale mining projects.

Although mineral production declined during the pandemic period, recent indicators suggest a gradual recovery. Copper production recorded a 0.4% increase during the January–April 2024 period compared to the same timeframe of the previous year, driven by the initiation of new mining projects and improvements in operational efficiency [3]. Nevertheless, these improvements remain insufficient to fully offset structural inefficiencies observed in material handling and transportation processes, which continue to constrain productivity across the sector.

1.2. Problem Statement and Research Motivation

In recent years, the case study mining company has faced challenges related to the efficiency of its operational processes, especially in the material transportation and loading phases associated with copper production. Inefficiencies in these stages have caused operation costs to increase and productivity to decrease. Mining expenditures rose to US$32.3 million in 2021, due to the need for higher material throughput and growing maintenance costs. Copper extraction reached 290,097 tons in 2022, a 7% decline compared to levels seen in 2020 [4].

This drop reflects better summarized inefficiency patterns affecting not only our studied company, but also the Peruvian mining sector, with more than 200 active mining operations [5]. Loading and transport inefficiencies have become more severe in situations of social and environmental disputes, disrupting normal operations, highlighting the need for more resilient and effective operational strategies that enhance productivity while curbing cost overruns and keeping performance less variable. The presented study aims to tackle those operational challenges, proposing reductions in production costs of the order of 5%, improving material loading phase performance, and achieving payload targets of different vehicle types, thus contributing to the overall productivity [6].

In methodical terms, again, studies conducting mining operations optimization reviews tend to either focus only on some optimization technique or descriptive analysis, with notions of an integrated analytical framework combining process improvement methodology and predictive capabilities, for instance, rarer, revealing a research line towards specific model developments trying to accomplish both at the same time. Proposed approach aims to fill such a gap through the combination of techniques for minimization of variability on material transportation processes, inspired in Six Sigma [7] as technique to improve reliability and means of data analysis from big data for decision making, through its integration with AI techniques, predicting operational performance through analysis of influence of critical variables like operator training level, preventive maintenance or operational monitoring, being able to provide prediction capabilities of each one of them and in a combined way.

As a consequence, an analytical model is reached in order to evaluate process performance impact and support performance continuous improvement initiatives. Using capacity analysis combined with artificial intelligence yields energetic operational insights, enhances organizational learning, and enables informed decision-making about such critical drivers for effectiveness. The proposed methodology is expected not only to help the case study company but also to be transferable to other mining operations, enhancing payload efficiency and profitability in similar situations.

This article is organized as follows: in Section 1, we motivate the context and definition of the problem. In Section 2, we review the state of the art in relation to mining process optimizations and analytical tools. In Section 3, we outline the proposed methodology and point out its novel aspects. In Section 4, we explain the validation of results and the main outcomes we reached. And finally, in Section 5, we draw the conclusions and indicate future work.

2. Materials and Methods

This section introduced the description of the methodological design to regulate and improve (possibly) loading and extraction processes in open-pit mining operations.

Their methodology aimed to assist operators in optimizing the payload per truck type and limiting the operational variability of the transportation chain. Next, they defined the variables involved in loading performance and measurement reliability, designed and executed the improvement actions at different levels of intensity relying on PDCA and Six Sigma principles, and finally the artificial component, aimed to model the relationship between the selected variables and performance, allowing evaluation of the relative importance in loading performance of training, preventive maintenance compliance and operationaling monitoring.

As a result, they defined a set of subprocesses to (i) identify and regulate the most influential variables, (ii) perform the actions, and (iii) determine the most effective operational conditions.

2.1. Propose Methodology Overview

The model comprises PDCA as a cycle of continuous improvement to structure the application of the actions, and Six Sigma (DMAIC) to quantify and reduce the variability of the process concerning loading performance. These two supported the identification of critical factors in payload efficiency and the stabilization of the loading process through measurable improvement actions.

An AI-based predictive component is also described to estimate the performance of the process under different operating conditions and the contribution of the selected variables (training level, preventive maintenance compliance, and operational monitoring) to the loading outcome Figure 1.

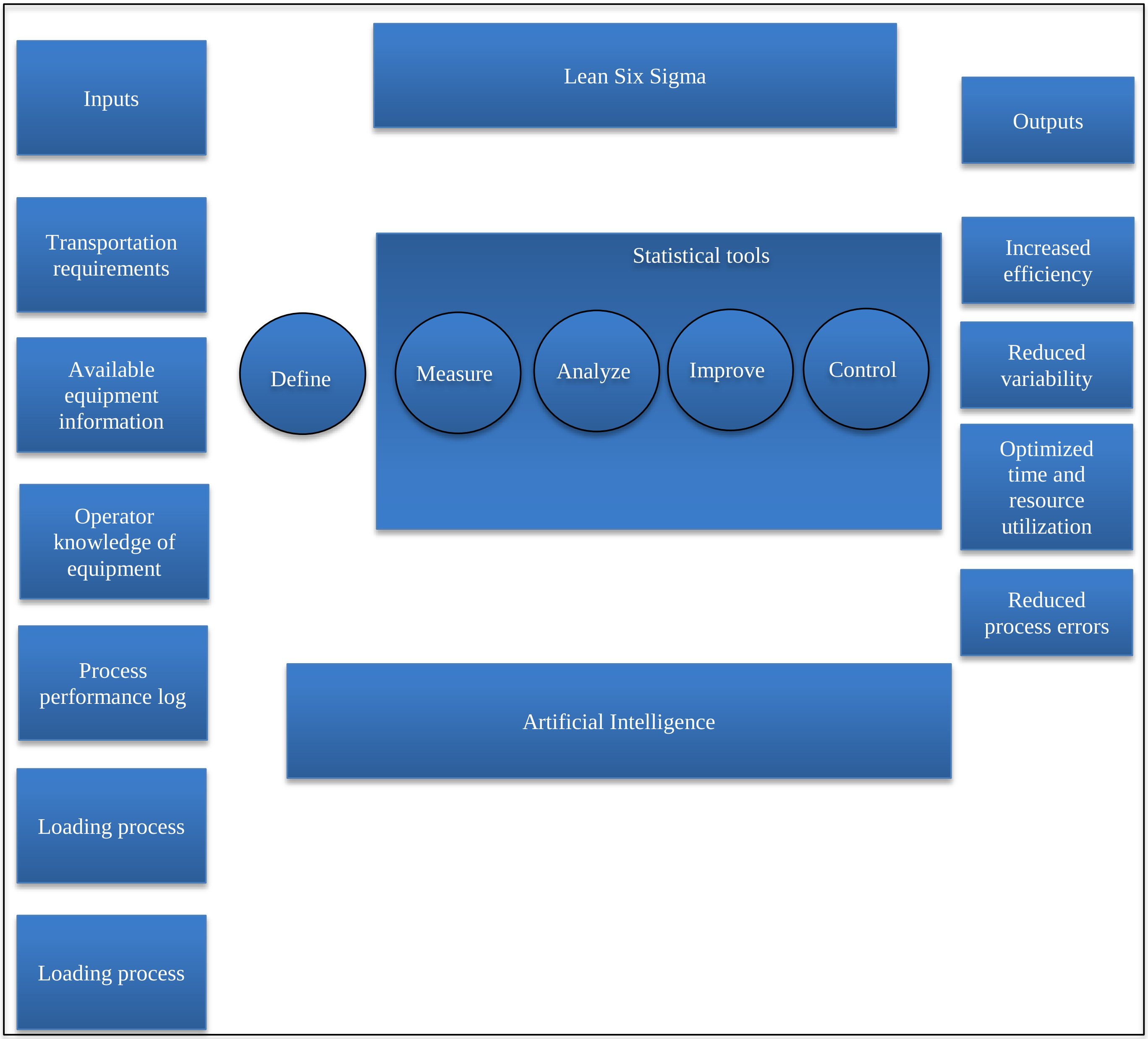

Fig. 1 Overview

2.2. Detailed View

This proposed methodology aims to execute some of the processes seen in Figure 2 to improve the efficiency of material transport at the mines, which will, in turn, yield increased production and profit. The goal of this model is to improve the loading of these valuable materials for copper concentrate delivery and to favour exports to enhance profitability. Our proposed methodology consists of five stages.

Stage 1. Blast Zone

The process starts in the explosion zone, where the material will be extracted from. Inspection of the material occurs, as well as the preparation of the extraction site from the premises.

Stage 2. Command Centre

Then, with the Command centre to set the departure times for vehicle movement and shovel operators, and to deploy personnel by shift report regarding the assigned operator. In this phase, the training hours of each employee are analysed to confirm that performance is in keeping with the organisation's approval procedures for work procedure objectives.

Stage 3. Zone of Extraction

In the extraction zone, vehicles are received, and material loading commences. The tonnage is proven before taking it to the pulverizing area. Here, a reliability study of the load control equipment is applied, and the cargo handled by each of the operators is entered into a database. For the realisation of an effective Control process, reference needs to be given to the effect that preventive maintenance has on the equipment in maintaining process control and keeping the maintenance programme up to date all the time. An analysis has been made with regard to the effect supervision has on the process attended, with the result that the extraction activity is carried out through two work shifts generally, a greater degree of supervision being assigned to the first shift than to the second.

Stage 4. Crusher Zone

This stage will entail a procedure to verify that the condition of other PLMs (Payload Meters), located on each truck, to log the tonnage loaded per vehicle and operator, is effective in its optimum state. The mined material is tipped, and the tonnage handled by each of the shovel operators will be ascertained.

Stage 5. Vehicle Storage Area

The trucks now proceed to the truck yard to begin their journey to the site of extraction. Each operator was supervised regarding his work output and checked that the tonnage loaded on each truck was in accordance with the specified quantities. That the process performance Value was found at this stage by the use of Artificial Intelligence and loading results analysis, and that further attention was given to the same variables - Training, Supervisors Levy, and preventive maintenance compliance - and modifications to these for loading conditions according to any of the variables was made, where deemed necessary, in continuing with the study, are recognised as adding value to the lessons learnt from having so many variables to consider in process performance at this point.

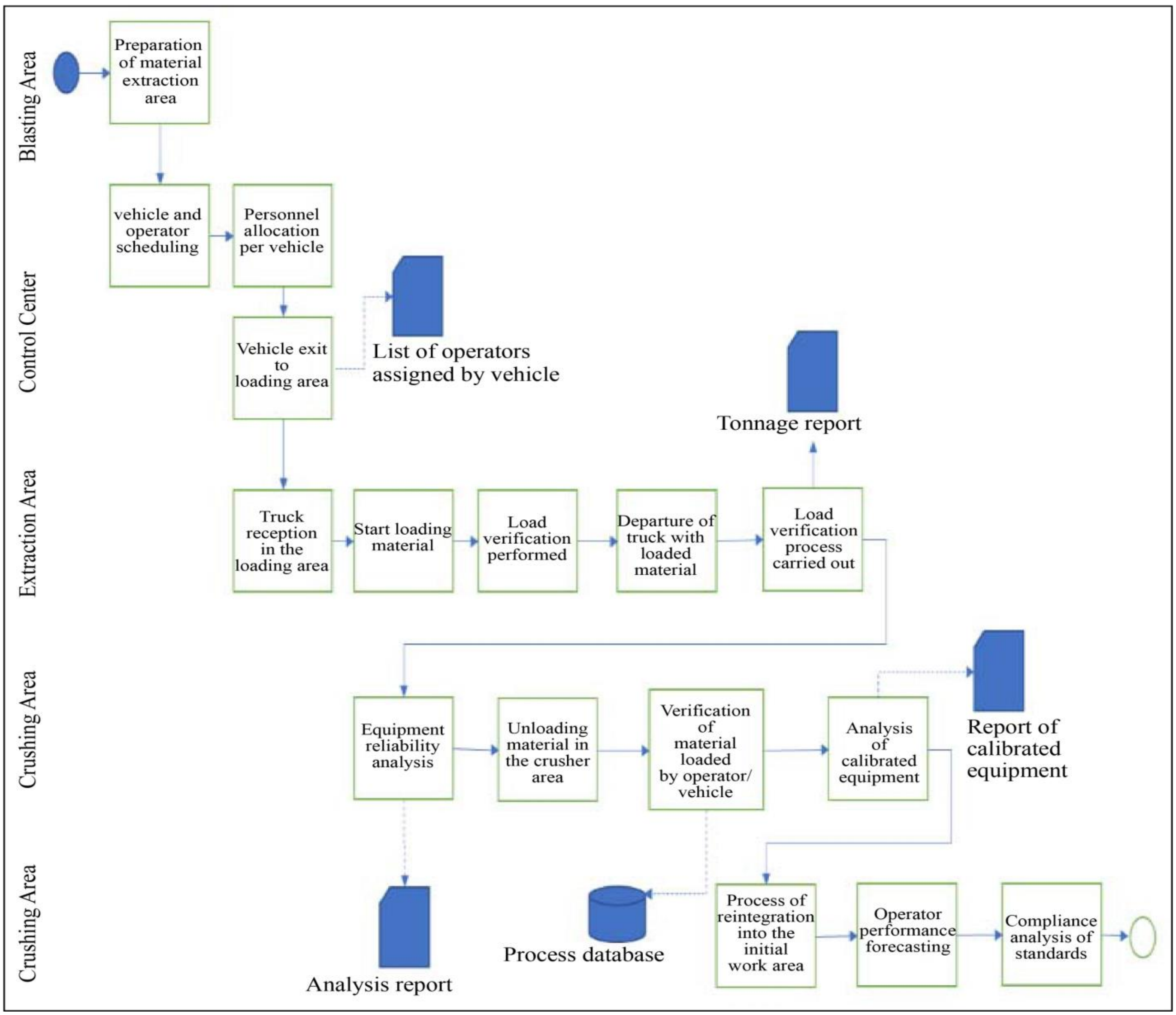

Fig. 2 Detailed view

2.3. Proposed Process Overview

2.3.1. Calibration Process

The calibration procedure for the zone of the PLM sensor trucks to measure the cargo of the trucks begins as follows:

- The calibration zone is prepared, and the truck must be free of any burden. If there is cargo, it will be discharged only in this area.
- The PLM systems will be checked to know if calibration will require inclinometer calibration or structural check calibration.

An improvement has been established corresponding to preventive equipment maintenance and calibration verification, which will be adjusted or verified and prepared in a report. The intention is to keep a history of load values, to maintain compliance with an established preventive maintenance, and to report with a load report the load carried by each vehicle and operator, as well as to evaluate the contributions of each operator. This is one of the variables that predict the performance of the process of transporting material by vehicular transport, and whose improvement was achieved with PDCA and DMAIC techniques. The intention is to know compliance with preventive maintenance, and to evaluate its influence on the operational process of transporting material by vehicle.

Finally, all the calibrations done are filed in a report for tracing in the future (See Figure 3).

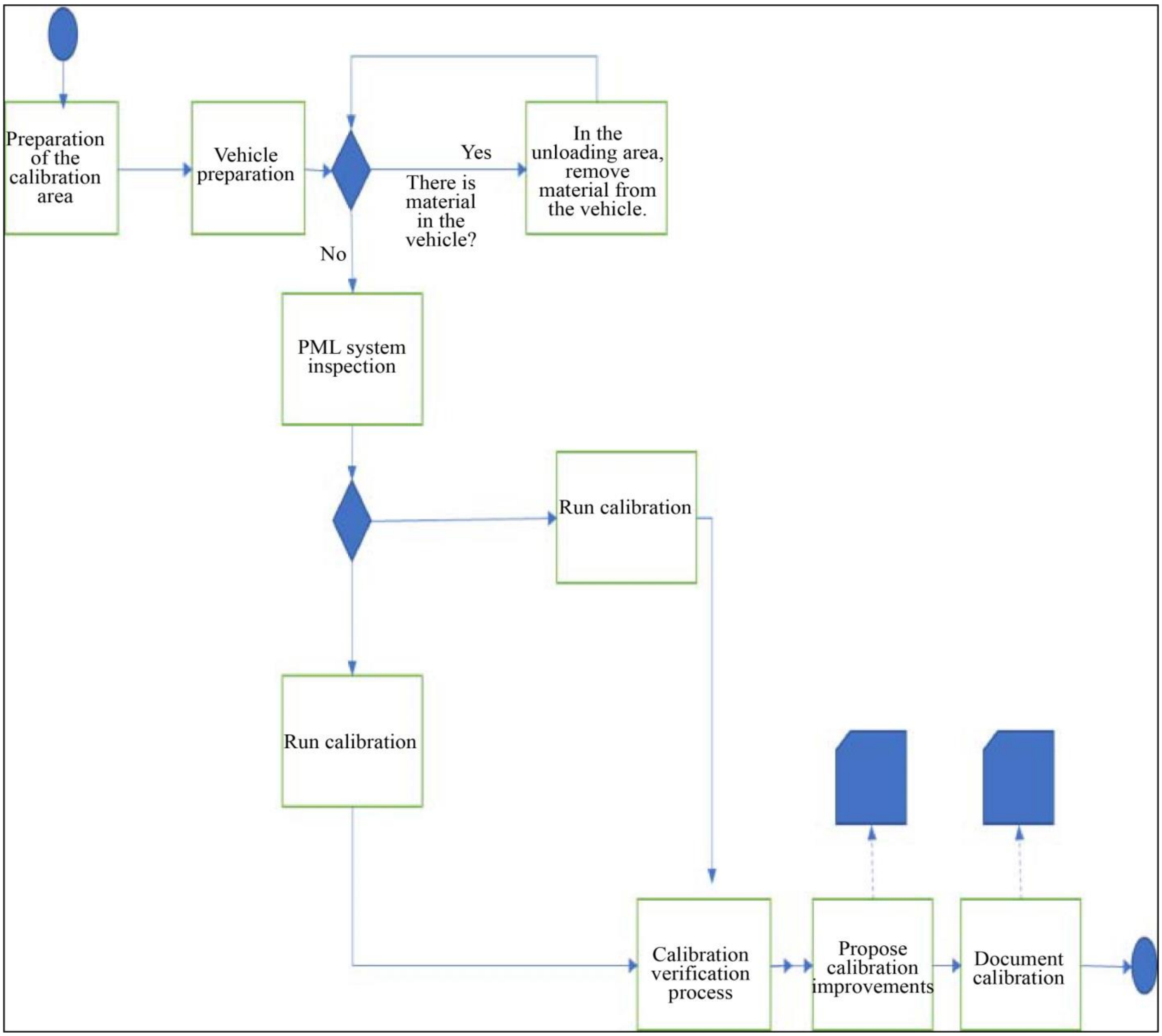

Fig. 3 Calibration process

2.3.2. Maintenance Process

The maintenance form begins in the operations department with the maintenance schedule report with respect to the PLM measuring equipment. This is the apparatus that registers the weight of material conveyed into each vehicle for delivery to the processing side. If maintenance is required and external vendors are required, the necessary spare part will be quoted accordingly, or if internal maintenance is undertaken, personnel will be assigned to carry out the appropriate maintenance action.

But the vital part involves scheduling and keeping to a preventive maintenance scheme for each separate piece of gear. The scheme involves determining from time to time the date of maintenance to be carried out, dependent upon hours of operation, hours worked, the calibration of measuring equipment thereon, etc., and in so doing retaining objective data as to the efficiency of the loading of each vehicle, and of the operator concerned. The details of what occurs on each occasion are to be recorded in a database. In the event of malfunctioning of the equipment, the particulars concerning the incident to be investigated, and improvements to be made in consequence thereof, in accordance with the report, which, if the malfunctioning continues, will be the subject of a report to the operations department for approval. If necessary, a report may be presented for specialized maintenance, or, alternatively, a quotation for replacement equipment if desired, in both cases being considered with the operations department, as in Figure 4.

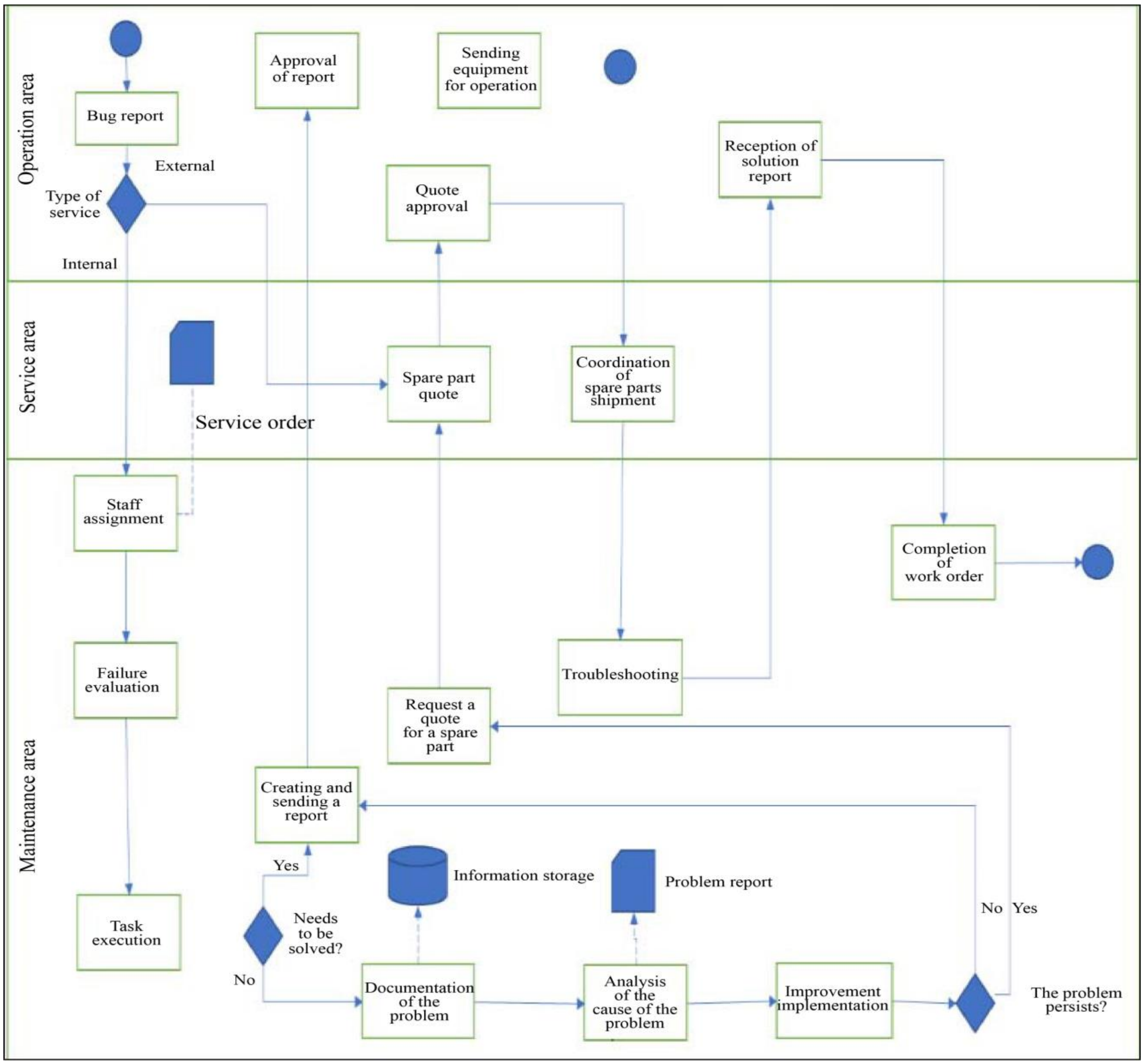

Fig. 4 Maintenance process

2.3.3. Training Process

The human resources and community relations training program is targeted for local recruitment (for surrounding communities), as well as external recruitment (other departments). Once personnel have been selected, they are trained in an adaptation module. Those who complete will follow on with specialized training for the machines they will operate, otherwise called an adaptation program. Individuals who fail to pass this training will be excluded from the process.

An enhancement process has been put in place that includes the use of machinery to aid in the transfer of mine material into vehicles. This defines the training hours, loading equipment usage, material handling, and placement within cubic space, thereby allowing for the maximum occupation of cars for use in the operational phase. This training mimics the operating conditions for filling with mine material in cars. There will be some supervision of the operation of the machine.

The training report verifies training hours and progression for each employee, and the employee's progress over time. The use of KPIs would prove to be important in producing information as to how to increase the training hours for each employee until the target outcomes are reached at this stage, prior to moving into the production process. Employees scoring way above optimal would be moved into the company, while those failing to meet standards would be trained until they are passed or withdrawn from the supervisory process (Figure 5).

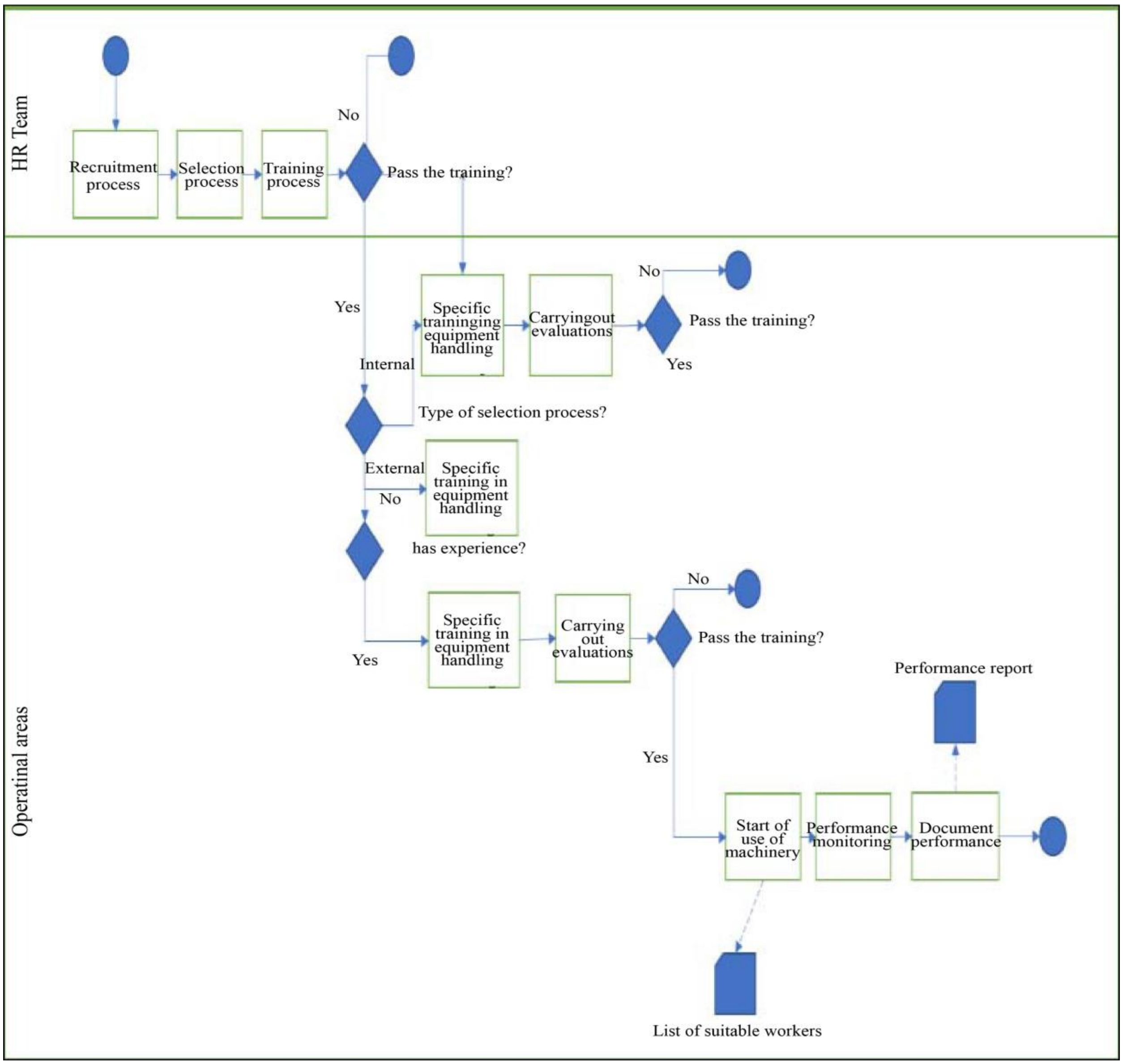

Fig. 5 Training process

2.3.4. Data Analysis Process

The procedure for data analysis using AI includes:

- Collection of data: performance for each vehicle will be recorded. The data we actually intend to analyse will not come from a sample but will actually consist of information on the whole population (vehicle ID, cargo load, driver name, recharge schedule). The data will be verified for completeness and quality. In order for the data we have collected to be suitable for analysis, the two processes mentioned that we built our procedure on, the maintenance process and calibration process, need to actually be carried out, thus making the re-design of the procedures having a great deal of importance.
- Analysis of data: The integrity of data will be assessed, verified, and normalized to make it most usable. Explore: A model using descriptive statistics and graphical visualization will be built to analyse patterns, outliers, and trends in the data. The earlier correlation process, where variables from various sections were correlated, should again occur. Identification of key variables: the example used here is CP and CPk for the analysis of the Six Sigma process.

The model suggested here is that we are going to analyse these three variables: training hours, adherence to preventive maintenance, and operational oversight. These are not the only variables to consider; the proposal is to add more variables and see what effect they have on the loading process, and show each variable has a vehicle loading outcome, thereby indicating this variable's effect on the process.

Model Structure and Definition

How the variables are defined, and the way these are combined in the model to study the results obtained, and how the change of these results affects the general performance of the process, provides the organization with a learning process. For this reason, since this is a learning process, we will be able to determine the correct number of variables to employ and the magnitude of each.

Model Formalization

Training the model: The cleaned and standardized dataset was used to train predictive algorithms (regression-based models and tree-based models) to estimate CP performance levels as a function of the selected operational variables. The modelling task was to predict process performance under various combinations of training hours devoted to this, compliance with preventive maintenance, and operational supervision.

Validation and Testing

To ensure generalizability, the data were randomly split into training and testing subsets, and cross-validation was employed during training to mitigate overfitting. The performance of the models was measured using standard regression metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). These metrics acted as an objective baseline for comparing alternative models, and also to verify that these variables explained some of the "signal" variation in process performance.

Conduct and Forecasting

Usage Efficiency: The model will be used to tell us levels of CP and CPk of the process by vehicle, carrier, and schedule, taking into account training or "practice" hours, maintenance of the measuring equipment, and the monitoring process of loading hard materials on vehicles.

Suggesting Actions: Based on this outcome, the subsequent model will generate the actions these two must carry out to enhance around these resources, including maintenance, supervision, and even changing the process to include as part of the process we now design sufficiently many hours of the personnel loading the hard material on motor cars.

Monitoring Loop: The system and with it the daily performance will be noted, for purposes of examining how this acts upon these three variables and for purposes of updating the system with newer data, thus closing the cycle (Figure 6).

Indicator Overview

The following indicators were defined to monitor implementation performance, and their calculation formulas are presented in Eqs. (1) – (3).

Loading Process Efficiency (LPE)

To optimize the use of truck capacity, a daily KPI has been established to measure the efficiency of the loading process. This indicator is adjusted according to the type of truck, as each has a maximum and minimum load limit that must be reached.

$$EPC = \frac{Tons\ transported\ per\ trips}{Value\ established\ in\ theoretical\ tons\ to\ be\ transported\ per\ vehicle)} \quad (1)$$

Null Value Reading Rate (NVR)

To minimize the number of null readings, the Null Value Reading Rate indicator has been created and will be evaluated daily. The goal is to ensure that this indicator does not exceed 0.5%.

$$VN = \frac{\text{Number of readings with null value}}{\text{Number of daily readings}}\, x\ 100 \quad (2)$$

Measurement Equipment Availability (MEA)

To maximize the use of measurement equipment, a KPI has been established. This indicator achieves excellent performance when equipment availability is between 91% and 100%.

$$DEM = \frac{\text{Number of teams available}}{\text{Number of total teams}}\, x\ 100 \quad (3)$$

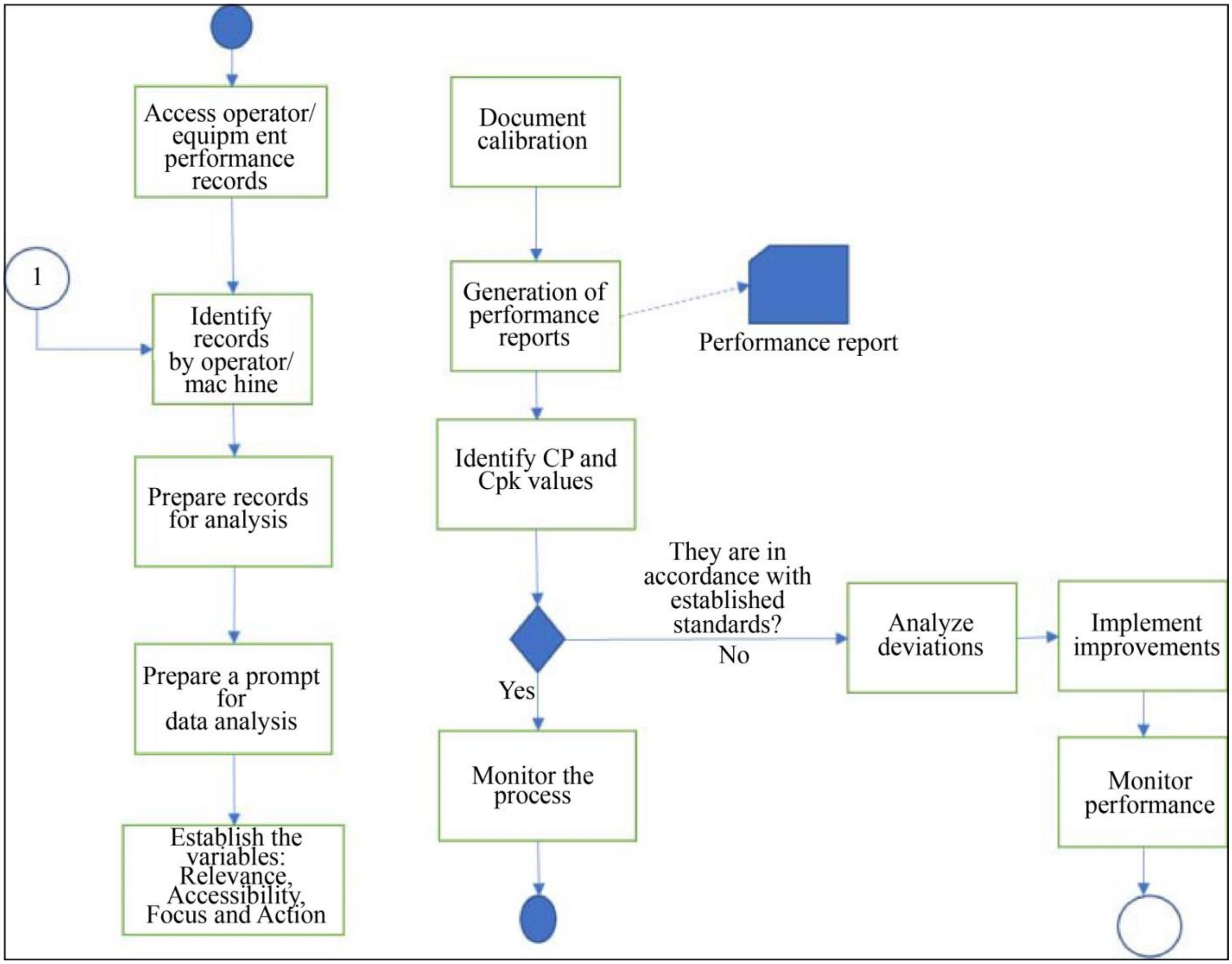

Fig. 6 Data analysis process

3. Results

3.1. DMAIC State of the Art

3.1.1. Six Sigma

Six Sigma is a continuous improvement methodology that aims to reduce process variation. Its aim is to increase quality by reducing defects and optimizing processes. Response to increasing competitive pressure from foreign manufacturers prompted Motorola to use this methodology around 1987, but in enhancement projects. A number of enhancement projects were run by Motorola engineers using the project MAIC. Later, the methodology developed into the DMAIC by the addition of Modify, where the D for Define was added by General Electric (GE) in the 1980s [6].

Six Sigma is a data-driven methodology that uses a variety of statistical tools to minimize the variability of a system's controllable variables. Six Sigma processes aim at improving consistency or reducing errors to no more than 3.4 per million opportunities. Because of its clear, organized, and rigorously scientific approach, Six Sigma has become one of the most widely used methodologies for ongoing improvement in a wide variety of industries, such as manufacturing, as varied as financial services and information technology [7].

There are many benefits to be gained from implementing Six Sigma in an organization. In its pursuit of improved efficiency and quality, Six Sigma focuses on reducing variation in processes. By reducing variability, organizations can ensure that a high-quality product and service are delivered consistently, leading to increased customer satisfaction.

Additionally, because Six Sigma efforts reduce errors, they help lower operating costs by stopping errors before they occur by addressing the root cause of errors wherever possible [8].

The DMAIC Cycle

The DMAIC cycle is a step-by-step framework that helps teams spot, examine, and fix shortcomings in current workflows, leading to lasting gains in speed, output, and quality.

a. Define
b. Measure.
c. Analyze.
d. Improve.
e. Control.

Inside the DMAIC Cycle, a set of supportive tools helps move phases along and keep them on course:

a) The Gantt chart lays out tasks on a timeline, so schedules, people, costs, and risks stay in step.
b) Failure Mode and Effects Analysis, or FMEA, scans for failure points, scores their risk, and flags actions by priority.
c) Measurement Systems Analysis, known as MSA, studies how much trust can be placed in data gathered by instruments and operators alike.
d) Hypothesis testing uses proven statistics to confirm whether a change really drives improvement or whether the gain is simply chance.
e) Analysis of Variance (ANOVA) tests whether meaningful differences exist among two or more groups of data, thus revealing where variation originates and helping managers make choices grounded in numbers [9].
f) Regression analysis examines how variables interact, pinpoints the key drivers behind a process, and guides tuning of its settings so that results become more consistent or more productive.
g) A Design Of Experiments (DOE) study deliberately varies factors to map cause and effect, then uses that map to adjust settings toward peak output, quality, or efficiency.
h) Statistical Process Control (SPC) refers to a set of charts and rules that keep watch over a process while it runs, signalling trouble before defects or delays multiply.
i) Control charts plot data in time so operators can see patterns, notice when points stray out of expected bands, and react quickly rather than after a batch is ruined.
j) Capability analysis measures how well a process naturally fits within its specification limits, using indices such as Cp, Cpk, and Ppk to compare the machine's design potential with actual output quality.
k) The SIPOC tool-suppliers, inputs, process, outputs, and customers give a clear overview of every facet of a process as it exists today [10].

Six Sigma has already found a home in Peru's mining industry, where firms sought to cut equipment downtime. At Canta Mine, practitioners turned to the DMAIC cycle to streamline mineral hauling and transport, spot chances for gains, and put into practice changes that enhance day-to-day operations [11].

3.1.2. PDCA

The Plan, Do, Check, Act (PDCA) methodology has provided a foundation for continual process improvement across different industries, and such fundamental concepts have been employed globally, but particularly in Japan after World War II, following World War II. This portrayal results from statistician W. Edwards Deming teaching Japanese leaders how to use quality control tools and how to resolve challenges systematically. The PDCA cycle allows organizations to improve their production efficiency and effectiveness, resulting in great improvements in the quality of their goods and services [12].

The PDCA cycle, also known as the Deming cycle, is a four-phase cycle for promoting continuous improvement, which is commonly used for improvement in quality and for process improvement across various organizations. This approach is based on a logical four-phase cycle of Plan, Do, Check, and Act. Each step of this cycle serves an important purpose and supports systematic process improvement [13].

3.1.3. PDCA Cycle Tools

To assist in its use and implementation, and to make sure the changes it produces actually have a lasting effect, the PDCA cycle uses a number of different Specific instruments: • Stratification: In this approach, data is broken into segments that create deeper insight into the causes of a given problem. This causes the surfacing of patterns or trends that might otherwise be obscured in global data. • Cause and Effect Diagrams: also known as Ishikawa diagrams. Graphical tools that assist in surfacing possible causes of problems and indicate areas where action may be appropriate. • Control Charts: As this tool is used to observe and study variation in the process over time, the team is able to catch deviations early and make informed decisions regarding process control. • Pareto Analysis: Based on the Pareto principle, 80% of problems stem from 20% of the causes. This allows a focus for development on the vital few causes with the most impact [14, 15].

3.2. Artificial Intelligence State of the Art

Recently, the increased use of computer systems to execute functions of human behaviour and cognition has resulted in a massive proliferation and revolution of our common society and modes of production, including education [16].

The mining sector is no exception. Numerous have been the applications in which AI has proven to be of great help. Such applications are at every stage from exploration, through exploitation, all the way to recovery. It is precisely in those processes where data analysis for informing decisions comes as an aid in improving the performance of the process. The use of AI in mining operations and management decisions makes possible the analysis of the mining industry's impact on the environment and sustainability, particularly with regard to the refining of its quarry [17].

3.2.1. Investigation

The first stage in which artificial intelligence has been of help is the exploratory stage. We start with knowing roughly where we have to look for our mining deposit, then we have to know its features that will allow us to evaluate and project its productivity and economic yield [18].

So that the AI-powered analyses help and inform cost/benefit studies, enabling assessment of the profitability of the activity given a number of market conditions, and for making investment decisions with the two most widely used methods of extraction: open pit or underground [19].

Thus, results that artificial intelligence has been used for mine design, tunnel construction, for example, and excavation underground, to enhance yield and profit [20]. But their applications for predicting surface vibrations and possible landslides resulting from explosions or simply mining [21].

3.2.2. Extraction

A major issue of concern at this point is the workers who do the work. Given work with that nature, many times it is required to go underground, operate in closed spaces and little light, be exposed to dangerous substances and vapours, and even amidst refuse. During drilling and blasting, a lot of heavy machinery is used, and people can get seriously injured that way. This is where artificial intelligence can lessen the time workers are in dangerous places [22].

Other applications have to do with truckloads being offered to make operations more efficient and utilise them in such a manner. Opening times can be shortened, for example, and efficiently scheduling the trip loads has resulted in slightly better operating costs of 15% [23].

Another field is that of strength and durability tests, vein quality, and miscellaneous hazardous substances monitoring [23]. Making use of their data to help decisions, to inform on the mines in terms of locations to gather, and inferring relevant data from the work done.

On the safety side, using robots or sensors that take up spaces of danger for labourers once certain conditions come up, and such [24].

3.3. Case Study

To validate the model described above, it was implemented in a mining company located in the Apurimac region of Peru. This company has been operating since July 2016 and specializes in the export of copper concentrate. Its main clients include companies in South Korea, Japan, and Chile.

3.3.1. Diagnosis

The company under study has been facing a significant decrease in the payload of mining material destined for copper concentrate production. This reduction directly impacts the trucks that transport the ore to the crushing area, resulting in a 3.29% decrease in profitability. The associated causes and their implications are detailed below.

a) The operators of the material-loading equipment are not meeting the established targets for the payloads of the truck models, directly affecting the ton of material transported by each truck, thus impacting the loading target established for each truck. Which are shown below:

Table 1. Payload compliance per truck model

Truck Model	Average Load per Trip (Tons)	Target Load (Tons)	Compliance Percentage
CAT 797F	379	397	95.47 %
KOM 930 E-4SE	308	315	97.78 %
KOM 980 E	377	387	97.42

b) The availability of Payload Meter (PLM) measuring equipment has decreased by 12%, affecting material loading accuracy. Furthermore, reports have been received of inadequate maintenance of this equipment, further exacerbating the problem.

c) The quality plan for calibrating Payload Meter equipment is deficient, resulting in null values in measurements. This impairs the accurate capture of the weight of the loaded material and causes problems in actual load measurement. The total percentages of null values for the CAT 797F, Komatsu 930E, and Komatsu 980E trucks are 3.93%, 2.15%, and 2.17%, respectively.

3.3.2. Results

To validate the proposed model, a process analysis was conducted for each stage. The proposed model was subsequently implemented, and the final results were analyzed. Likewise, the Six Sigma capacity analysis tool t is used in each truck model, these being the models: CAT 797F, KOM 930 4SE, and KOM 980 E, Minitab statistical software to implement improvements and evaluate the effectiveness of the methodology applied in the company's loading process. The steps followed for the analysis in Minitab are shown below:

1. Define the problem and prepare the data.
2. Identify the output measurement, in this case, weight in tons.
3. Define the LSL (Lower Specification Limit) and USL (Upper Specification Limit), in this case, the maximum load weight of each vehicle.
4. Verify that the data are reasonably stable and representative of the process.

5. In Minitab, the data were organized in one column (Y), and the study variables were organized in another column: supervision compliance per shift, training hours, and preventive maintenance performed.
6. The stability and variability of the process (data set) were verified.
7. Control charts were created:
   Route: Stat > Control Charts > Variables > Xbar-S.
   The Y column and the Subgroup column were inserted.
   The graphs and tests were created:
   Graphs: Graph > Histogram, Graph > Normality Plot, or Andamento (normal probability).
   Normality tests: Stat > Basic Statistics > Normality Test (e.g., Anderson–Darling).
   The capability analysis was performed:
   Path: Stat > Quality Tools > Capability Analysis > Normal.
   In "Samples in one column" (or similar), select the Y column.

   Enter LSL and USL and add the subgroup column so that Minitab can account for variability between subgroups.
   7. Pp and Ppk: Production-level capability versions (using the entire data set) rather than variability within subgroups. Useful if they already have a large data set and need a general overview.
   Typical interpretation:
   Cpk ≥ 1.00: The process is generally acceptable, with reasonable capability.
   Cpk ≥ 1.33: Good capability (level close to the 6-sigma target).
   Cpk ≥ 1.50: Typical target in Six Sigma (based on the idea of a 1.5 sigma shift).
   Cpk < 1.00: Insufficient capability; investigating the causes and improving the process is recommended.
   Sigma Note: A common rule of thumb is Sigma ≈ 3 × Cpk when the process is centered, and the distribution is normal, and with the Six Sigma interpretation, a target of Cpk ≈ 1.5 is often taken to achieve operation with adequate slack versus specifications.
   Diagnosis and Next Steps
   If Cpk is low:
   Investigate causes of bias (centering) and variability. If Cp is high but Cpk is low:
   The problem is bias (centering). Address the process, centering on bringing it closer to the target.
   If the process is stable but does not meet specifications, consider improved process capability or specification revision (sometimes tolerances are too tight).
8. "OK" was entered to obtain Cp, Cpk, CPU, CPL, Pp, and Ppk (as appropriate).
   The results (main indices) were interpreted.
   Cp: Process capability, assuming it is centered within the specification range. High Cp indicates that there is room for variability within the specification. Cp does not consider bias relative to the target.
   Cpk: Actual capability, considering the location of the process relative to the limits. Cpk = min (Cpu, Cpl). This is the key index for Six Sigma because it incorporates process displacement.
   For the case presented, the process capacity (Pp and Ppk) and its evolution were analyzed as management and maintenance variables were added:
   V3: Shift supervision (Day 96%, Night 56%).
   V2: Training compliance.
   V1: Preventive maintenance compliance (proxy for technical availability).

Table 2 below presents the results of each variable applied by type of truck and the results obtained.

Table 2. Results of each variable applied by type of truck

Truck model	Variables used	Ppk	ΔPpk_ abs	ΔPpk_%	Pp	ΔPp_ abs	ΔPp_%
CAT 797F	V3 (supervision)	1.421	NaN	NaN	1.722	NaN	NaN
CAT 797F	V3 (supervision)+ V2 (training)	1.465	0.044	3.093	1.776	0.053	3.09
CAT 797F	V3 (supervision)+ V2 (training)+V1 (preventive maintenance)	1.495	0.03	2.041	1.809	0.034	1.88
KOM 930E-4SE	V3 (supervision)	1.19	NaN	NaN	1.308	NaN	NaN
KOM 930E-4SE	V3 (supervision)+ V2 (training)	1.227	0.037	3.093	1.348	0.04	3.09
KOM 930E-4SE	V3 (supervision)+ V2 (training)+V1 (preventive maintenance)	1.252	0.025	2.041	1.376	0.028	2.04
KOM 980E	V3 (supervision)	1.361	NaN	NaN	1.75	NaN	NaN

KOM 980E	V3 (supervision)+ V2 (training)	1.403	0.042	3.093	1.804	0.054	3.093
KOM 980E	V3 (supervision)+ V2 (training)+V1 (preventive maintenance)	1.432	0.029	2.041	1.838	0.034	1.906

As can be seen, the Ppk and Pp values increased for each truck type as variables were added.

This allows us to identify which variables are associated with process improvements and to determine the extent to which training, supervision, and the percentage of maintenance to be implemented can be increased.

All Pp and Ppk metrics remain < 2, consistent with operational mining.
- V3 (monitoring) produces the largest initial jump (control and σ reduction).
- V1 (training) and V2 (maintenance) add up to improvements of around 2–3% per stage.
- Zero loads are integrated as V4 (zero t rate), penalizing σ, without deleting data.
- The use of LSL/USL = target ±3% makes the requirements more stringent and the results more credible.

Below is the analysis by truck, analyzing the initial and final values considering the variables applied in the study.
1.- Type of truck CAT 797 F and the results obtained, see Table 3

Table 3. Truck model CAT 797F

Capacity	Initial Value	Final value considering a variable	Final value considering two variables	Final value considering three variables
Pp	1.3	1.722	1.776	1.809
Ppk	0.09	1.421	1.465	1.495

The PPk and PP values increased significantly as learning to improve the variables occurred.

Figure 7 shows the behavior of the load values, which shows that the values obtained are more constrained to the center, reducing process dispersion while maintaining control.

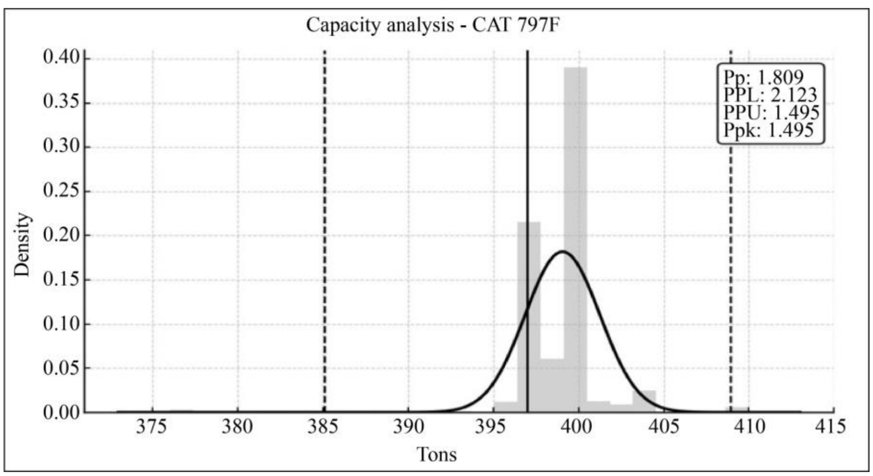

Fig. 7 Capacity Analysis Truck model CAT 797 F

2.- Type of truck KOM 930E-4SE and the results obtained; see Table 4.

Table 4. Truck model KOM 930E-4SE

Capacity	Initial Value	Final value considering a variable	Final value considering two variables	Final value considering three variables
Pp	0.87	1.308	1.348	1.376
Ppk	0.5	1.190	1.227	1.252

The PPk and PP values increased significantly as learning to improve the variables occurred.

Figure 8 shows the behaviour of the load values, which shows that the values obtained are more constrained to the center, reducing process dispersion while maintaining control.

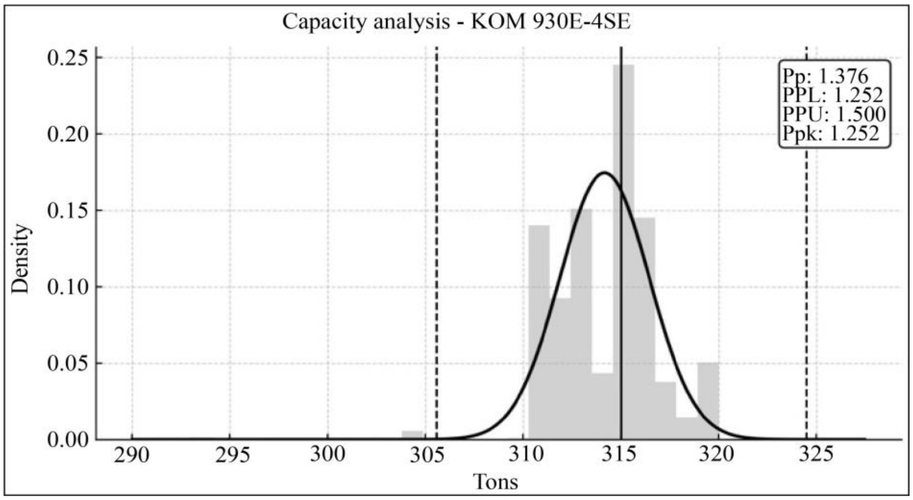

Fig. 8 Capacity analysis Truck model KOM 930E-4SE

3.- Type of truck KOM 980E and the results obtained, see Table 5.

Table 5. Truck Model KOM 980E

Capacity	Initial Value	Final value considering a variable	Final value considering two variables	Final value considering three variables
Pp	1.12	1.750	1.804	1.838
Ppk	0.7	1.361	1.403	1.432

The PPk and PP values increased significantly as learning to improve the variables occurred.

Figure 9 shows the behavior of the load values, which shows that the values obtained are more constrained to the center, reducing process dispersion while maintaining control.

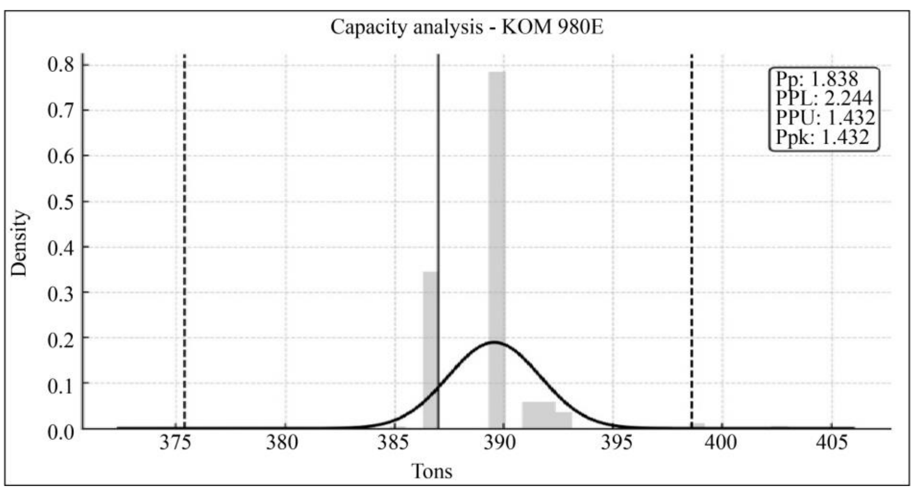

Fig. 9 Capacity analysis Truck model KOM 930E-4SE

It can be concluded that the application of process improvement through the Six Sigma methodology and through AI to make decisions on the performance of variables to be implemented, taking advantage of learning and favouring decision-making, has allowed for improved process performance.

4. Discussion

4.1. Results Interpretation

The findings of this research confirm the effectiveness of integrating Six Sigma and PDCA methodologies, complemented by artificial intelligence, to optimize payload processes in open-pit mining. Achieving payload efficiency levels of up to 100% across the three evaluated vehicle models demonstrates a substantial reduction in operational variability and enhanced process stability. While previous studies have reported performance improvements through the isolated application of Six Sigma or PDCA tools, the results obtained in this study indicate that their structured integration with artificial intelligence enables more consistent and data-driven control of loading operations.

The observed efficiency improvements are consistent with the ranges reported by Solanki and Desai, even though the initial performance baseline in this case was already high. As stated, a reduction in null readings is also consistent with the approach of Mittal et al. on data quality measures, while the 7% improvement in equipment availability is aligned with Nguyen et al.'s findings based on PDCA iterative interventions. Overall, the proposed integrated approach engenders some of the best practices on the reduction of variability, predictive approaches, and operational control with an integrated methodology for prospecting the mining industry.

Regardless of the beneficial results, there are certain caveats in implementing the approach. To start, the notion that all the data is fit for prediction implies that the data used in determining capacity analysis shares an identical bell-shaped curve. Any deviation would meddle with the Pp and Ppk indices. A high initial efficiency threshold from the fleet of trucks also means that improvement may not yield such an attractive payback period. An opportunity exists for other loading applications with lower threshold requirements. Only in one context does implementation occur, in this case study, a copper-producing company in Peru; thus, for now, clear external validity is hard to spot. Even the power of artificial intelligence used relies ultimately upon calibration of operationally and how well the metric operates.

Insights presented have an impact on practice for mining operations. First, addressing the demand of adherence to an optimal payload leads to improved turnover and reduces costs in the process, thus allowing more scale with less risk for mining executives. Improving availability for the PLM thus allows for hard data to inform more on-demand decisions. Better approaches to null readings improve data quality, thus allowing executives to manage better resources and make more reliable plans. Improved operator knowledge does lead to better cultural awareness and to better improvements in practices. Profit + resilience for such a volatile industry is witnessed presently here.

4.2. Limitations

The limitations exposed hereby also share the traits of adequate opportunities to expand upon and validate the proposed model in future efforts: integrating predictive maintenance systems featured with real time monitoring could render equipment availability and reliability even better, the combination of this approach coupled with geospatial information could lead to truck dispatching optimisation and enhanced safety; another avenue may be to cope environmental performance indicators to value how the model goes towards sustainable mining; finally perhaps more sophisticated AI algorhythms, deep learning techniques in particular, could increase the model predictive power.

5. Scientific Contribution

This work is pertinent to the scientific literature of mining processes improvement in that it proposes an integrated methodology (that combines Six Sigma, PDCA, and artificial intelligence) to improve payload efficiency of open pit mining operations. The originality of the contribution rests on the integrated way this work combines the use of process improvement methodologies with predictive analytics to methodically evaluate which operational variables could improve the efficiency of a process and how. Unlike methodologies that use these tools separately, we show a structured way for linking variability reduction (Six Sigma), performance prediction (PDCA), and control of the operation, as well as the clear traceability of methodological steps and guidance of decision making.

6. Perspectives and Future Work

Future work should seek to apply the model to other mining environments (underground or polymetallic mining, for example), while assessing whether the model scales appropriately both in terms of its mappings and in terms of the precision of its outputs. Integration with predictive maintenance systems and/or real-time geospatial data could, in turn, assist in further refinement of the model and optimization of resource allocation and risk. Alternatively, merging this approach with environmental performance indicators might allow the impact of the model to be applied in the context of sustainability and ensure this green metric of 'economy of the mind' is encouraging sustainable behaviour in mining.

7. Conclusion

This study demonstrates that the mix of Six Sigma and PDCA methodology combined with AI is a smart solution for optimizing the operational performance of the payload process of an open-pit miner. The results of the implementation of the model represented an average improvement of the payload efficiency of a truck model between 2.22% and 5.25%. This is important feedback considering, as shown in the results, the performance is quite high, so the optimization potential is limited. The progress in the analysis of the process capacity indicators is significant according to the objectives set by the company, and the P-value index increases as variables that affect process performance are included in the study. In this case, training, compliance with preventive maintenance, and improvements in monitoring processes are included, with an improvement of 30%. At the same time that null readings of the payload take-up decreased from 39.75% to 13.82%, operating integrity is improved. The availability of the equipment improved from 88% to 94% taking advantage of our calibration and maintenance protocols. The training system for wheel loader operators integrates staff performance and positively impacts the sustainability of outpatient process improvements. In conclusion, the model is considered effective in serving as a comprehensive basis for the continuous improvement methodology provided in this work. Its modular structure, based on data management and monitoring, serves as a leap-off point for other mining or industrial processes that may face similar challenges.

Author Contributions

J.L.V.V., S.A.P.L.R., and J.A.R.G. collected and analyzed the data. J.L.V.V. and S.A.P.L.R. prepared the first draft of the manuscript. J.C.Q.F. supervised the research process and contributed to the writing, revision, and final approval of the manuscript. S.N. provided methodological support and guidance in model validation. All authors reviewed and approved the final manuscript.

Data Availability Statement

The dataset supporting the findings of this study is publicly available in the Mendeley Data repository. The data can be accessed at: Quiroz Flores, Juan Carlos (2025). Improving Payload Efficiency in Open-Pit Mining: An Integrated Model Using Six Sigma and Artificial Intelligence. Mendeley Data, V1.
DOI: https://doi.org/10.17632/v3pv2ys3rz.1

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