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Impact factor improvement and maintenance schedule optimisation of mining shovels by remaining useful life and linear programming

The mining industry is slow in adopting digitisation compared to other industry segments. The companies are coping with operation cost pressures due to demand fluctuations and increased operations costs. The equipment maintenance costs aggregate around 10% to 30% of the direct mining operations costs due to different operating conditions. This article leverages the Cox regression machine learning (ML) model to determine the survival days of shovels. Subsequently, to increase the availability, a mathematical model is formulated to optimise the maintenance schedules of shovels to increase their availability. Finally, decision optimisation (DO) ILOG CPLEX and remaining useful life (RUL) is deployed to combine maintenance schedules of preventive maintenance (PM) and predictive maintenance (PdM). This ML led innovative model optimises maintenance schedule drives the data-driven actions to demonstrate the metrics of overall equipment effectiveness (OEE), overall throughput effectiveness (OTE) and impact factor (IF) computation. furthermore, the IF improvement is demonstrated through a case study of mining shovels. The IF improvement is also aligned with the productivity improvement of equipment as per the United Nations (UN) sustainable development goals (SDGs).

Keywords: OEE, sustainability, ML, cost optimisation, mining shovel, RUL

1.0 Introduction

Although the measurement of various operations is done as per the defined best practices key performance indicators (KPIs), it must measure the impact across multiple processes or activities. The structured context and a methodology framework are required so that the mining enterprises can define the metrics, measure, monitor, manage and report the performance. These KPIs can be achieved by framing a scorecard with the measurement insights, performance reporting, and associated innovation guidelines. Many maintenance policies have been studied and redefined over the years, focusing primarily on increasing equipment availability. Total productive maintenance (TPM) and OEE were introduced in the manufacturing industries, also adopted in the mining industries. The TPM was submitted during the 1980s in the automobile industry, and for its evaluation, OEE was proposed by Nakajima. TPM is calculated as the product of availability, performance, and quality (Nakajima 1988). Multiple research and publications have been done for OEE, which can be leveraged for mining shovels. The overall throughput effectiveness (OTE), an index with systemic vision, was proposed by (Muthiah and Huang 2007) in order to measure the productive performance of production lines taking into account the taxonomy of the equipment present in the system. This index considers the OEE of each piece of equipment and makes it possible to carry out factory level diagnostics, detect bottlenecks, and identify hidden capacities. OTE is developed based on comparing the actual throughput with respect to the maximum throughput achievable by the system (Muthiah and Huang 2007).

Earlier, the characteristics of OEE measurement did not consider external effectiveness, complexity, and innovation. The improvements in OEE can be achieved by the decentralised design of the organisation and address the challenges (Jonsson and Lesshammar 1999). The innovative OEE framework lays out the process for a state-of-the- art data collection system for improvement, and real-time visibility of total productivity (Jeong and Phillips 2001). Most industries measure OEE based on downtime losses and ignore the other losses. The information technology (IT) and operation technology (OT) integration provide measuring and monitoring of loss reasons which can be brought in the ambit of OEE measurement as the OEE was 55%. The insights from the study portray that majority of the losses were due to performance losses. These performance losses need to be revisited for improving the OEE (Ljungberg 1998).

Therefore, this challenge of productivity improvement was partially addressed by a study performed by calculating OEE using he TPM inputs (Samanta and Banerjee 2002). If we elaborate on OEE, it is a combination of six big losses

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defined to calculate the revenue loss. The six big losses comprise:

1. Breakdown loss of equipment
2. Set-up and adjustment time of equipment
3. Minor stoppages: idle time, marching time
4. Speed loss
5. Quality
6. Yield loss

These six losses contribute significantly to the calculation of OEE. Therefore, measuring and monitoring OEE is a paradigm for mining operations. As per the research performed in manufacturing industries, an improvement in OEE of more than 23% decreases the losses by more than 40% (Al-Najjar and Alsyouf 2004). Similarly, various types of time losses are significant parameters for the calculation of shovel OEE and can be derived either by calendar hours days or loading hours based. Further still, a lot of improvements needs to be executed to calculate the OEE of mining equipment which will address the integrities of the complex loading process in mining (Elevli and Elevli 2010). Even though OEE calculation is an effective key performance indicator (KPI), it can derail mining shovel effectiveness due to the intricate process. Various evolving OEE definitions have also come up in research and practice, coupled with their modified formulations based on the industry segment. The emerging digitally enabled platforms would create new economic value and be innovated by the innovators to develop and measure, which can be estimated to be about 70% of the new value (Herweijer, Celine 2019).

The objective of this article is to reduce "Breakdown loss" by cost optimisation and therefore improve the productivity of shovels demonstrated by IF in a structured method.

1. Optimise cost of PM and PdM
2. Reduce maintenance downtime "Breakdown Loss" for improved OEE, OTE and IF leveraging maintenance cost optimisation
3. Harness the future potential of exponential technologies in mining

To improve the availability of equipment survival days calculated based on the historical breakdown is utilized to determine the predictive maintenance. The combined maintenance strategy of preventive and predictive maintenance increases the availability to reduce shovel management costs and improve overall performance efficiency. This paper provides comprehensive characteristics of maintenance attributes to be strategised to ensure effective maintenance by the metrics of OEE, OTE and the IF.

The article structure is as follows: Section "Literature Review" illustrates the prevalent maintenance practices and justification of this innovative approach. Section "Methods" provides insights on methods and entails, step by step solution process flow, exploratory data analysis, Remaining Useful Life (RUL) modelling, mathematical modelling, and optimisation. Further, section "Results" narrates the results and section "Conclusions" concludes the discussions.

Literature Review

Mining, an intrinsic asset-based industry, and extreme operating conditions lead to numerous unplanned maintenances, resulting in prolonged downtime and becomes cost-intensive. These conditions lead to emergency repairs, and unbudgeted investments in equipment spare parts exceed the budget (Stahl et al. 2011) incurrence. These extensive running expenses for mining equipment fluctuates from 10% to 30% of the production operations cost. However, leading-edge maintenance strategies and practices can prolong the useful life of equipment with insignificant costs (Gölbacsi and Demirel 2017) and provides the way forward for "Integrated Asset Management (IAM) (Alaswad and Xiang 2017). Organisations' primary aim is to decrease unanticipated failures and to lower various cost constituents present the optimisation potential by assuring a precise PdM strategy (He et al. 2018). The mining operations' quintessential operating costs are the mining machinery and equipment, which varies from 20% to 35% (Dhillon 2008). Furthermore, the operation costs per hour of these shovels are on the scale of thousands of dollars, so it is pertinent to sustain a sound health profile of them to derive maximum gain (Alla et al. 2020). In their investigation, Vayenas and Wu assessed the inherent conditions of load-haul-dump (LHD) failures and performed mathematical analysis for its associated losses (Vayenas and Wu 2009). Mobley contemplated that reactive maintenance (fix it when required) is threefold more expensive than the scheduled maintenance. However, PM's expenses can be costly depending on consolidated costs of maintenance and production losses (Mobley 2002).

Salvatore Peralta et al. define resource degeneration and heterogeneous geologic conditions, increase the operations and equipment cost (Peralta et al. 2016). The extraordinary fuel consumption by diesel equipment contaminates the environment, and subsequently, the intention is to diminish the discharge of carbon and progress towards sustainable mining (Botin and Vergara 2015). The vitality utilisation impact of mining equipment maintenance was evaluated based on emanating substances. Subsequently, by limiting these impacts, they observed that costs would be restricted to approximately 75% (Peralta et al. 2016). The reduction in equipment reliability drives to risen operation cost due to high fuel consumption and Green House Gas (GHG) emissions (Katta et al. 2020). The fuel cost has a significant portion in equipment operations cost and is to be assessed for determining the reliability estimation of equipment in deliberation (Peralta et al. 2016).

Manuel Parente et al. illustrates the leverage of AI strategies to evaluate equipment operations profitability by multi-constrained resource allocation, leading to an increase in methodologies to reduce costs and work duration as per the research objective (Parente et al. 2016). Christina et al. targeted the primary cause of cost minimisation by selecting the equipment for mining operations while contemplating the age of mining equipment, historical performance, and fleet size after maintenance and overhaul. These selections of attributes play a fundamental part in optimising the cumulative cost of production operations (Burt and Caccetta 2018).

Topal and Ramazan explained how to minimise the maintenance cost of upkeep for the HEMM and presented an innovative approach dependent on Mixed Integer Programming (MIP) methods. The MIP model solutions principally focus on the production schedule and reduce the maintenance costs to the tune of 10% to 25% (Topal and Ramazan 2010). The PdM has emerged from a statistical model to transition to an ML model to monitor the equipment life-cycle and drive corrective actions appropriately as necessitated (Chen et al. 2020). The sole method to drive productivity improvement is by enhancing the economies of scale and introduce innovations to strategise and transform the mine operations (Nehring et al. 2018).

C. Dutoit explained that a nearly accurate PM schedule could accomplish failure prevention. Therefore, the increase and decrease of the PM schedule time intervals as per the specified tolerance can retain the equipment quality for its peak performance (Dutoit et al. 2018). Hemanth Reddy Alla et al. describes a relationship between the significant increase in job orders which is directly proportional to maintenance costs due to equipment ageing. The references of repetitious patterns in a disintegrated time-series of data present the metrics perspectives of maintenance costs to the job order numbers with impact due to seasonal variances (Alla et al. 2020).

There are several similar attributes in the maintenance scheduling of mine equipment to the automobile (Prytz et al. 2015), aircraft (Aremu et al. 2019), and manufacturing where the failure prediction is contemplated as leading and pro-active maintenance operations. F.S. Nowlan et al. concluded that the maintenance schedule frequency should be based on failure patterns and dynamic based on his predominant research in the airline industry. Reliability Centric Maintenance (RCM) is the best method to improve equipment availability. This research in the airline industry formed the basis of RCM based PdM and is universally acknowledged as the best practices of equipment maintenance across all industry segments (Nowlan and Heap 1978) (Chen et al. 2020).

The sustainable maintenance objectives are explicitly defined on how they affect the environment and its impact that can be minimised, the risks mitigated, the cost of non-productive operations, and waste. The balanced approach to reducing costs and digitisation of mining operations provides visibility to real-time operations. Recent technology interventions add the ability to predict and respond to operational disruptions. The availability and utilisation of mining equipment are lowest compared to most industries, for example, oil and gas, power, and manufacturing. Therefore, there is an immense improvement in equipment maintenance as it is aligned as per SDG 8 and SDG 9.

This productivity improvement and innovation objectives align with SDGs mentioned below for improved OEE through responsible production and consumption. The SDGs (Compact and others 2016) are:

1. SDG 8: Attain higher economic scales of productivity through a technological upgrade, diversification, and innovation, with a focus on the industry segments which demand intense labour and create high value.
2. SDG 9: By 2030, with improved resource efficiency and more comprehensive adoption of clean and environmentally reliable technologies and processes for sustainable development. Respective countries undertake actionable measures as per their capabilities with a single objective of reducing CO_2 emission per unit of value-added. Innovative solutions that boost productivity, enhance energy efficiency, improve the utilization of resources.
3. SDG 12: The SDG items 1 and 2 mentioned above are corroborated by the likely impact of such developments for innovative and responsible production operations. SDG 12 also provides a framework for consumption of natural resources, fossil fuel in this case. In the future, remote work arrangements, OEE and OTE will be key metrics for measurement.

The mining equipment needs to be effectively assigned to the maintenance repair workshops to optimise the maintenance costs. The impact to the production operations schedules is enormous if not effectively allocated which, results in production loss and increased operations cost (Sharma et al. 2019) (Botin and Vergara 2015). The cost pressure is impacting all the organisations at present, and the companies recognise that maintenance cost savings are the most sought for an avenue to reduce the overall impact (Ghosh and Roy 2009). The numerous studies conducted by researchers (Lister and others 2012) (Jantunen et al. 2011) and businesses for the computation of various maintenance activities concluded that the wrench time for the equipment maintenance is minimal compared to other actions combined. Wrench time, which is the actual work time, aggregates only 35 % to 40 % of the total maintenance time as demonstrated in Fig.1.

The intention to resolve the maintenance predicament continues the same even though numerous analytical

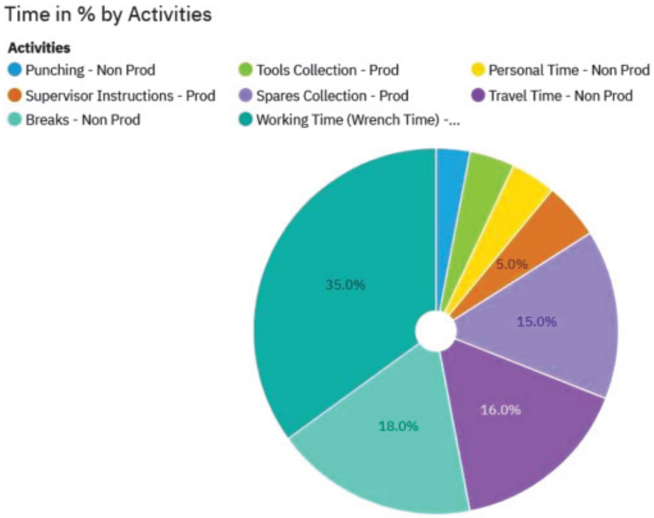

Fig.1: Maintenance activities in % of time

methods and approaches have deployed to decrease the significant impact of the maintenance costs (Mi et al. 2020) (Angeles and Kumral 2020). It is undeniable that in this era of the 4th industrial revolution, AI coupled with IIoT can improve the productivity of mining enterprises, which is comparable to the airline industry (Edwards et al. 2017). These exponential technologies and innovative practices would improve the OEE (Samatemba et al. 2020) by adapting the amalgam of technology, business rules and constraints.

Based on historical failure data, historical tasks, and maintenance data, Machine Learning (ML) (Susto et al. 2015) (Dalzochio et al. 2020) determines the shovels likelihood of failure. If the equipment maintenance operation is executed too late or too early, either way, it results in a more substantial loss due to production and unscheduled failure (Allah Bukhsh et al. 2019) (Gölbacsi and Demirel 2017). Furthermore, if the frequency of equipment maintenance is too short, it will result in more maintenance time and decrease equipment availability. Therefore, the novel combination of PdM and PM would decrease maintenance time and costs resulting in maximising production output.

Diverse researches have been conducted to optimise the PM schedule of equipment individually by employing survival analysis blended with linear optimisation. However, the organisations earlier did not implement the model that combines PdM and PM's maintenance schedule with many constraints to decrease the maintenance job time. The recommended model leverages equipment's survival analysis, blended with IBM's Ilog CPLEX's Decision Optimization (DO), to overcome the challenge of maintenance schedule with the objective of downtime reduction. Therefore, this research introduces an innovative novel combination of Cox regression and the DO model to overcome the prevalent challenges in maintenance operations. Moreover, this article explores the research gap of combining the PdM failure probability with the PM frequency incorporating specific constraints to reduce equipment's maintenance time, thus reducing the overall downtime. As an outcome, the recommended intelligent maintenance predictive model for mining shovels maintenance will provide significant cost savings in maintenance.

To deliver an optimal maintenance plan, DO consumes mining shovel data. The data contains production history, maintenance cost at various stages of shovel failure, production plan, probability of predicted failure, loss due to production, loss due to earlier maintenance before preventive schedule or earlier than shovel's Remaining Useful Life (RUL) resource constraints. However, prior PM schedules decreased the repair and maintenance costs, the value proposition of combined cost benefits by combining PdM and PM maintenance schedules were missing. In brief, the current study bridges the gap by proposing an optimisation model to increase mining equipment's availability and reduce cost pressures. Furthermore, an experiment with actual shovel data was performed to derive the core objective of maintenance time reduction by reinforcing the model.

Methods

Efficient integration of Information Technology (IT) and Operational Technology (OT) systems renders data in real-time or at a specific frequency harnessed to develop meaningful insights. For example, unique Independent Software Vendors (ISVs) systems Fleet Management produces and stores equipment health and performance data (Kruczek et al. 2019) (Mi et al. 2020). On the one hand, if the mining enterprise can get real-time sensor data, RUL calculation is more apparent if the company does not have rainbow fleets (Chen et al. 2020). On the other hand, the harnessing of historical data is simpler to determine the RUL. As per Wang et al.'s comprehensive and structured analysis of numerous statistical methods can be typically incorporated for the ML techniques development for survival analysis of equipment. These acumens and intelligence provide a framework for the selection of the statistical model for developing an approach for determining the survival days (Wang et al. 2019). The extensive usage of the semi-parametric model of Cox PHM and its variants in PdM is due to its applicability in modelling censored and uncensored data. The Cox PHM reveals the relationship between reliability and survival time. It further analyses the relationship between time-independent covariates and the hazard function (Chen et al. 2020). Researchers propose additional studies to leverage PHM variants for equipment RUL based on the data availability and applicable scenarios. These comprehensive insights lead to the selection of Cox regression to compute the equipment's data available for our equipment survival analysis.

Shovel data was collected for two years from India's coal mines to perform the analysis and modelling. The data comprises equipment id, hours of operations, equipment failures, payload, trips, marching hours, idles hours, utilisation, age, and availability shift-wise. The extent of 16000 records of equipment performance of ten equipment across three shifts was available for analysis. The model utilises this data to develop a predictive model and optimise five mining shovels of mean age 9056 days for RUL, OEE and OTE computation. The censored data is 58%, and the mean breakdown is 4.598 hours, mean work hours 1.567, mean march hours 0.461, mean idle hours 1.375, in a shift of 8 hours.

From these data, first, the survival function from the historical data is calculated. The shovel operation and failure hours data are analysed using IBM-SPSS Modeler 18.1 (statistical tool). The Cox regression is employed to determine the survival function of the equipment. Each shovel's survival function helps us predict the equipment failure in failure days with the desired confidence intervals. The Cox regression model is shown in Eq. 1.

$$h(t) = h_0(t)\ exp\ (\beta_1 X_1 + \beta_2 X_2 + \cdot \cdot \cdot + \beta_n X_n) \qquad ...\ (1)$$

where $h(t)$ is the expected hazard at time t, $h_0(t)$ portray the baseline hazard and represents the hazard when all the predictors (or independent variables) $X_1, X_2 \ldots X_n$ are equal to zero. The model estimates $\beta_1, \beta_2, \ldots, \beta_n$ based on the collected data. The baseline hazard $h_0(t)$ which is a generic function, and estimates the maximum likelihood was put forward by Breslow (Breslow 1975).

1. Variable(s) entered at step Number 1: March hour
2. Variable(s) entered at step Number 2: Breakdown hour
3. Variable(s) entered at step Number 3: loads/trips

From Table 1, we can interpret that as the significance value of breakdown hours, idle hour, and the trips/loads are less than 0.05. Therefore, these independent variables are significant in determining the survival days. Age is the most significant variable, followed by trips, and then followed by idle hours. Another uncomplicated way to decipher this is by using a confidence interval (CI). If both lower and upper bound have the same symbols (both positive in this case), it will be significantly distinct from zero. The closer the values of the two bounds, the more established the confidence interval can be, which is a desirable outcome. Currently, the three variables with high statistical significance emphasise that our baseline model has excellent predictive power. If we dissect a substantial sample size of shovels, it will improve the number of breakdown events and marginally increase the model and confidence interval bounds. The investigation symbolises a negative correlation of idle hours with failure, which is anticipated because the more unproductive a shovel's time, the less likely it is to fail.

Table 2 shows that the Chi-square is significant; we can conclude that the difference between the baseline and new models is also significant. Loads/trips contribution is higher than breakdown hours and march hours in making sure that the new model is better than the baseline model. However, the other two variables, breakdown hours and loads/trips, are increasing Chi-square values across steps and blocks, indicating that the model's accuracy will improve when we include these predictor variables. To summarize, the Chi-square value implies that the new model is good compared to the baseline model.

Fig.2 deciphers the shovels' survival days; RUL is defined as the duration left for the occurrence of breakdown based on the probability threshold of failure, i.e., after how many days the cumulative probability falls to 80%. This predictive failure day from survival data is utilised in combination with the PM frequency to optimize the maintenance schedule, to further minimizing the costs (van Nunen et al. 2018) (Civerchia et al. 2017). RUL is extensively used to derive the failure's occurrence from instating the appropriate action to calculate the equipment's reliability in mines. Fig.3 illustrates the age in days vs the survival days of shovels and it is inferred that throughout the useful life the breakdown and loads is a prime measure for failures. To minimize the cost of maintenance loss and production loss, the optimal maintenance day in a time

TABLE 1: VARIABLES IN THE EQUATION

Vars	β	SE	Wald	df	Sig.	Exp(β)	95% CI	Exp(β)
							Lower	Upper
Breakdown hrs.	-0.107	0.030	12.345	1	0.000	0.899	0.846	0.945
March hrs	-0.069	0.018	14.293	1	0.014	0.934	0.901	0.967
Loads/trips	0.003	0.001	5.161	1	0.023	1.003	1.000	1.005

TABLE 2: SIGNIFICANT VALUES OMNIBUS TESTS OF MODEL COEFFICIENTS

Step	-2LgLhd	Overall (score)			Chg. from pre-step			Chg. from pre-block		
		Chi-sq	df	Sig.	Chi-sq	df	Sig.	Chi-sq	df	Sig.
1a	8305.616	18.351	1	0.000	20.055	1	0.000	20.055	1	0.000
2a	8289.977	34.061	2	0.000	15.639	1	0.000	35.693	2	0.000
3c	8284.768	39.231	3	0.000	5.209	1	0.000	40.903	3	0.000

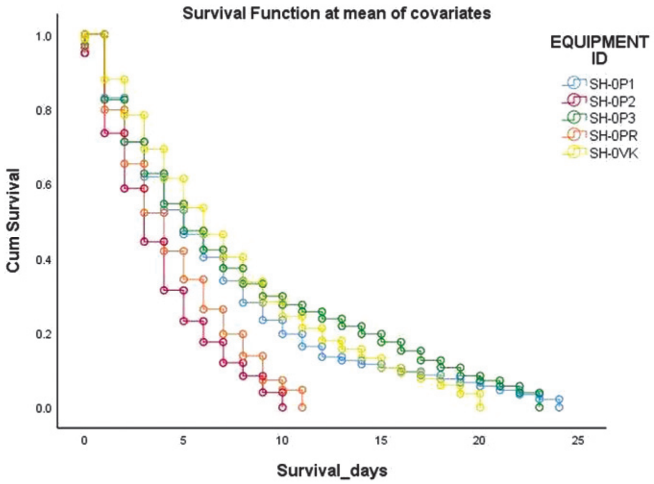

Fig.2: Plot of survival days vs survival prob. of shovels

horizon must be determined. The optimized schedule is generated based on the PM day and the predicted failure day based on the survival analysis. These schedules are governed by cost minimization metrics (PM cost, PdM cost, production loss) which meets the production and cost objectives coupled with constraints resources, workshop, and weather insights. This optimization generates an actionable maintenance plan based on these objectives and constraints and reduces the total maintenance downtime.

A mathematical formula for cost optimization is defined for shovels schedule optimisation. The notations employed for formulation are illustrated in Table 3. The objective of the problem is to minimize the total cost. The total cost TC considers the following costs:

- Cost of lost production if failure before the scheduled maintenance ... (2)

$$Cost\_PLM_{i,t} = Prodvalue\_unit_{i,t} \times prob\_break_{i,t} \times (Prod_{i,t} - Cap_i \times (l - RL_{i,t})),\ i \varepsilon I,\ t \varepsilon T$$

TABLE 3: NOTATIONS FOR OPTIMISATION FORMULATION

Sets	
T	Set of planning horizon
I	Set of shovel machines
Parameters	
$RL_{i,t}$	Repair loss in % for machine i in time t
$ML_{i,t}$	Maintenance loss in % for machine i in time t
$Capi$	Maximum production (prodn.) capacity of machine i
$Prod_{i,t}$	Actual prodn. by machine i in time t
$Cost\_PLM_{i,t}$	Cost of lost prod. (in \$) if failure before scheduled maintenance i in time t
$Cost\_PL_{i,t}$	Cost of lost production due to maint. (in \$) i in time t
$Cost\_EM_{i,t}$	Cost of maintenance too early (in \$)
$Prob\_break_{i,t}$	Probability of breakdown of machine i in time t based on OEM
$Prob\_rul_{i,t}$	Failure prob. of machine i in time t based on RUL
$Cost\_repair_i$	Cost per repair for machine (in \$) i
$Cost\_maintenance_i$	Cost per maintenance (in \$) for machine i
$Cost\_earlylife_i$	Cost of early replacement (in \$) for machine i
$Prodvalue\_unit_{i,t}$	Production value (in \$) per day of machine i in time t
$life_{i,t}$	Expected life of machine i in time t
W_t	If weather is favourable = 1 otherwise 0 in time t
F_i	No. of PMs during the planning horizon (in \$) for machine i
Decision variable	
$maintenance_{i,t}$	If maint. is performed on machine i at time t {0,1}

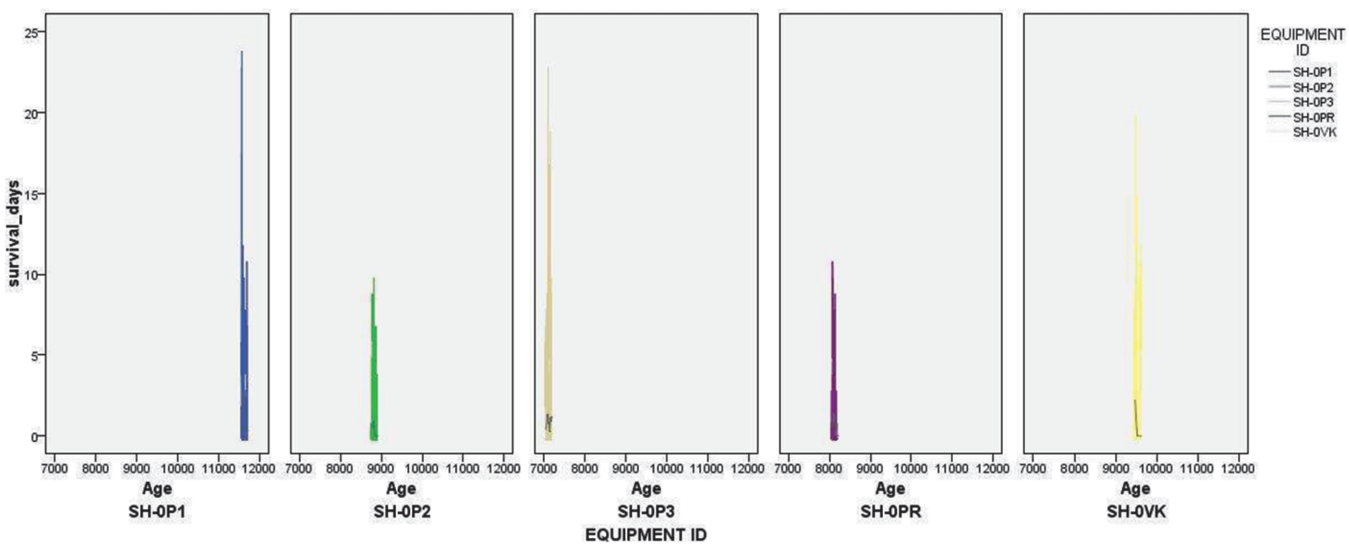

Fig.3: Plot of age vs survival days of shovels

- Cost of repair if breaking before maintenance ... (3)
  $Cost\_repair_{i,t} = Cost\_repair_i \times Prob\_rul_{i,t}, \; i\varepsilon I, \; t\varepsilon T$
- Cost of maintenance ... (4)
  $Cost\_maintenance_{i,t} = Cost\_maintenance_i \times (1– prob\_rul \times maintenance_{i,t}, \times i\varepsilon I, \; t\varepsilon T$
- Cost of lost production due to maintenance ... (5)
  $Cost\_PL_{i,t} = Prodvalue\_unit_{i,t} \times Prob\_break_{i,t} (Prod_{i,t} – Cap_i \times (1–ML_{i,t})), \; i\varepsilon I, \; t\varepsilon T$
- Cost of maintenance too early ... (6)
  $Cost\_EM_{i,t} = Cost\_earlylife_{i,t} \text{ x } \max \{life_{i,t} – t, 0\}, \; i\varepsilon I, \; t\varepsilon T$
- Objective minimum total cost ... (7)
  Objective : Min total cost =
  $$\sum_{t=1}^{i=1}\sum_{t=1}^{t=T}(Cost\_PLM_{i,t} + Cost\_repair_{i,t} + Cost\_maintenance_{i,t} + Cost\_PL_{i,t} + Cost\_EM_{i,t})$$
  Subject to the following constraints:
- Constraint 1: At a day only one equipment can be maintained: (8)
  $$\sum_{i=1}^{i=1} t\_maintenance_{i,t} \le \forall t\varepsilon T$$
- Constraint 2: An equipment should be maintained F = planning horizon (in days)/PM recommended in days ... (9)
  $$\sum_{t=1}^{t=T} maintenance_{i,t} = F_i \forall t\varepsilon T$$
- Constraint 3: An equipment should be maintained when weather is favourable (10)
  $$maintenance_{i,t} = W_{i,t} \forall i\varepsilon I, \; t\varepsilon T$$

For the model formulation, as in Fig.4 two types of maintenance are considered. The first maintenance type is PM as per the OEM recommendation. The second type of maintenance is PdM which is based on the probabilistic failure, which is the second type of maintenance. PdM is derived from the Cox regression model, which gives a survival probability distribution function.

The formulation of the problem is a MILP, which is developed and implemented in IBM ILOG CPLEX 12.10 using python. To demonstrate and implement the optimisation results, haul trucks data from Indian mines were ingested. The model for the expected output of "optimised Maintenance Schedule" (allocation of maintenance date for specific equipment id) is developed based on the constraints as mentioned in Eq.8, 9 and 10.

Fig.5 demonstrates the PM schedule recommended by OEM. For a piece of given equipment, we assume a probability distribution for PM. This solution brings flexibility to move around PM based on the availability of workshop or weather conditions; simultaneously if PM moves away from the target date, the system imposes a cost penalty to minimize the target PM's deviation. The PdM is based on the survival analysis shown in Fig.6, which depicts days of survival against survival probability. These results are derived based

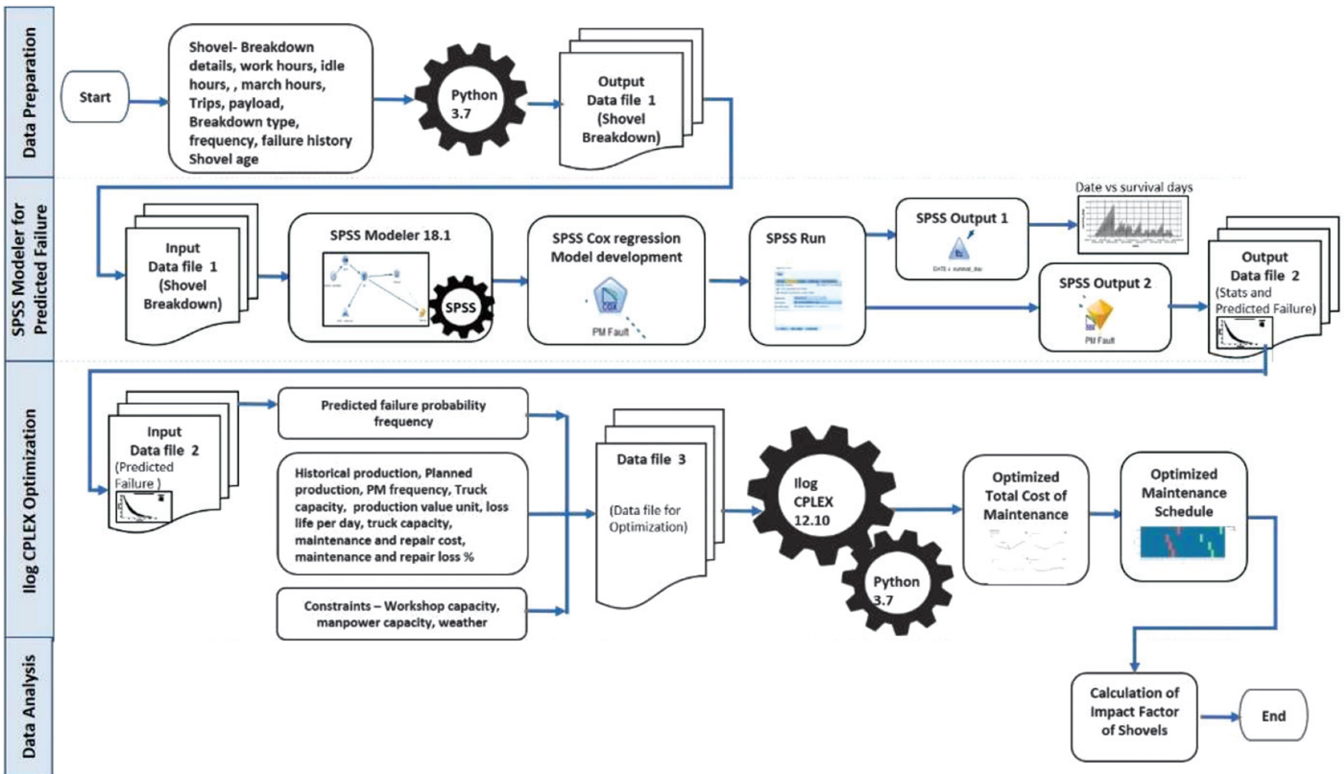

Fig.4: Step by step process flow of shovel optimisation and IF calculation

on the data collected and survival models of the four haul trucks. The cut-off probability of survival is 80% to 85%, used as one of the optimisation models'inputs. The range of 80% to 85% is determined based on the mining industry's current best practices. If we keep a high cut-off survival probability, then the mining enterprise ends up with intensive equipment damage, a costlier affair for maintenance. Additionally, when a low survival probability is considered for shovel maintenance, it results in production loss and the spare part's under-utilised life.

The shovel data is shown in Table 4. The Table 4 illustrates the daily production capacity (Tonnes/day), PM frequency (days), maintenance loss (%), maintenance cost ($), repair loss (%), repair cost ($), loss of life per day ($/Ton), production value ($)), planned PM time (in hours) and planned repair maintenance time (hours), which are the essential data for the optimization model. The repair cost and repair loss have a higher impact than maintenance cost and maintenance loss, which occurs due to predictive and PM. Further, unconstrained production based on historical production and planned production is ingested into the mathematical optimization model. Weather insights for the planning horizon are considered to capture any variability due to rain, storm, and fog. Additionally, the maintenance workshop can only accommodate one shovel per day. These sets of data have been used for the cost optimization of shovel's in combination with data of Figs.5 and 6.

Based on the objective function, the total cost of maintenance is minimized for a planning period of thirty days. Therefore, our objective function attempts to club both PM and PdM so that the impact of

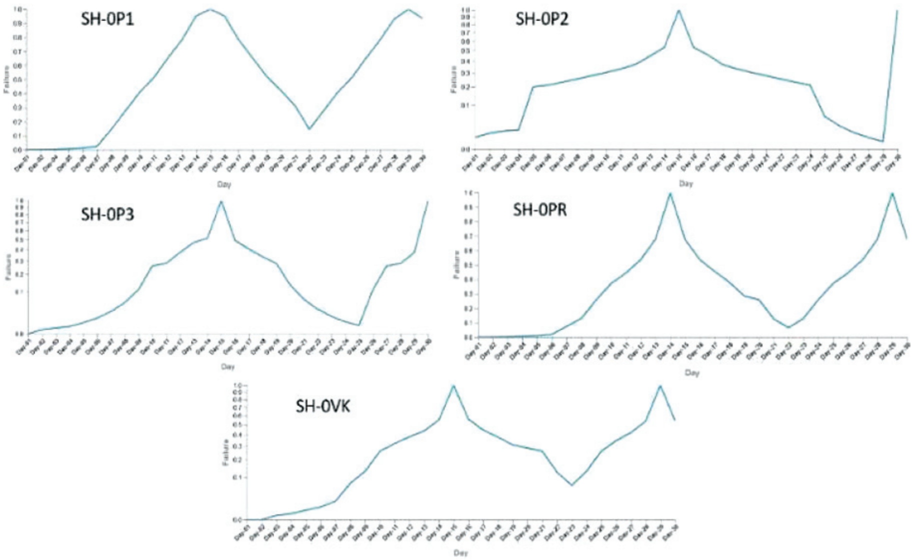

Fig.5: Preventive maintenance schedules of mining shovels

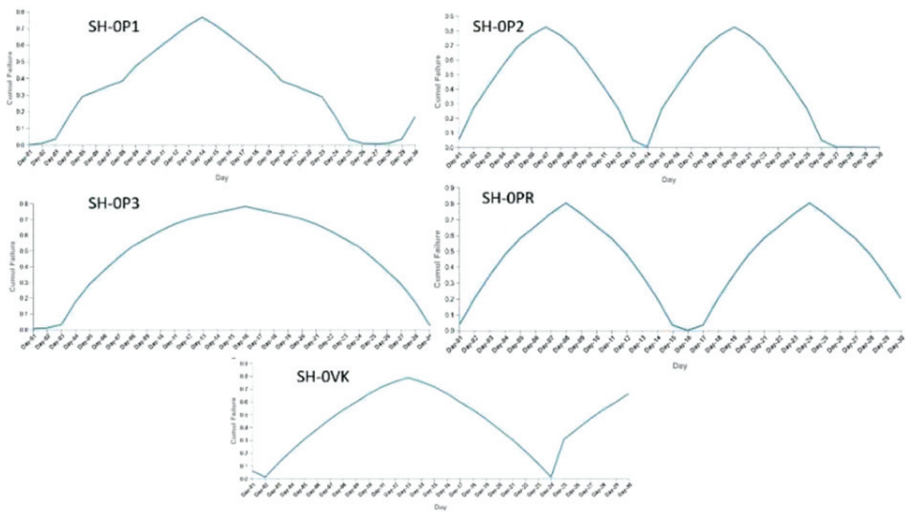

Fig.6: Predictive maintenance schedules of mining shovels

Table 4: Notations for optimisation formulation

Equipment (Shovel) Id	SH–	SH–	SH–	SH–	SH–
Capacity per day (tons)	6000	5800	5900	5950	4400
Prev. maint. freq. (days)	15	15	15	14	15
Prev maintenance loss (%)	15	15	15	15	15
Maintenance cost ($)	10	10	10	10	10
Repair loss (%)	21	21	21	21	21
Repair cost ($)	20	20	20	20	20
Loss per life day (tons)	6000	5800	5900	5950	4400
Production value unit	10	10	10	10	10
Prev. maint. time (hrs)	3.5	3.5	3.5	3.5	3.5
Pred. maint. time (hrs.)	5	5	5	5	5

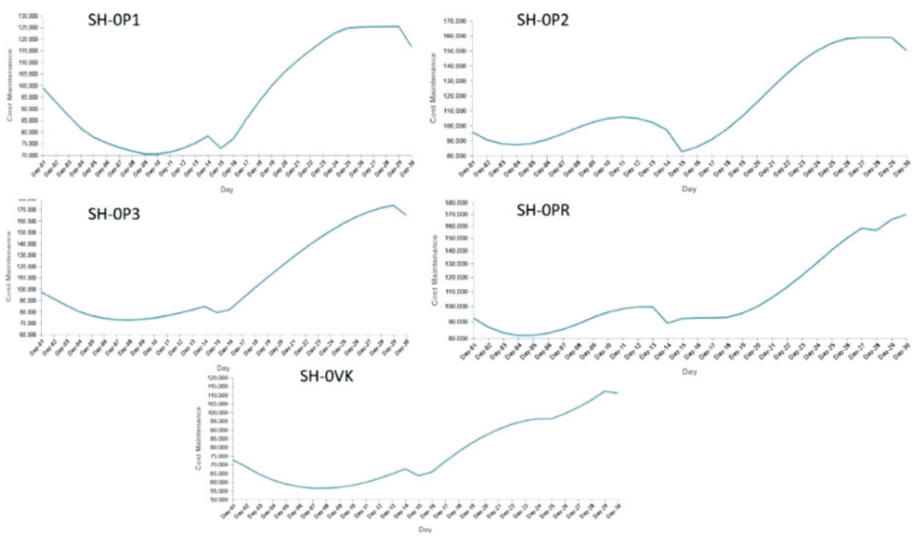

Fig.7: Total optimised maintenance cost of mining shovels

downtime (production loss) is minimized. Simultaneously, it penalizes any early PM because early PM (before the target date) has a higher total cost. Hence, the objective function finds a sweet spot (minimum cost) to accommodate both PdM and PM such that all the business constraints are satisfied.

Results

The optimised schedule is represented by the Fig.8 determining the equipment maintenance on 10th, 15th , 8th, 7th and 4th day respectively for shovels SH-0P1, SH-0P2, SH-0P3, SH-0PR and SH-0VK.The mathematical optimization generates output, an optimized maintenance schedule by solving formulation and ingesting data derived based on minimum total cost as shown in Eq.7. The total cost plot, as in Fig.7, signifies the behaviour of the objective function. It shows the total cost function of five shovels: SH-0P1, SH-0P2, SH- 0P3, SH-0PR and SH-0VK. The cost curve of individual shovel's illustrates the minimum optimized cost when the combined maintenance is scheduled to satisfy all the constraints and dependencies: resources, weather, production plan, maintenance loss, and repair loss.

TABLE 5: NOTATIONS FOR MINING EQUIPMENT OEE & OTE FORMULATION

Parameters

$TT_{i,t}$ = Total time of equipment i in time t

$TW_{i,t}$ = Total working time of equipment i in time t

$TB_{i,t}$ = Total unplanned breakdown downtime of equipment i in time t

$PMT_{i,t}$ = Total planned preventive schedule (PM) downtime of equipment i in time t

$PdT_{i,t}$ = Total planned predictive schedule (PdM) downtime of equipment i in time t

$TI_{i,t}$ = Total idle time of equipment i in time t

$TS_{i,t}$ = Total scheduled maintenance time for equipment i in time t

$TM_{i,t}$ = Total marching time for equipment i in time t

$TO_{i,t}$ = Total other time for equipment i in time t

$PPL_{i,t}$ = Planned loads for equipment i in time t

$APL_{i,t}$ = Actual loads for equipment i in time t

$AT_{i,t}$ = Availability of equipment i in time t

$P_{i,t}$ = Performance of equipment i in time t

$Q_{i,t}$ = Quality per formance of equipment i in time t

$OEE_{i,t}$ = OEE time based i in time t

$OTE_{i,t,max}$ = OTE time base d i in time t a fte r optimis ation

$OTE_{i,t,min}$ = OTE time based i in time t before optimisation

$IF_{i,t}$ = IF of shovels i in time t

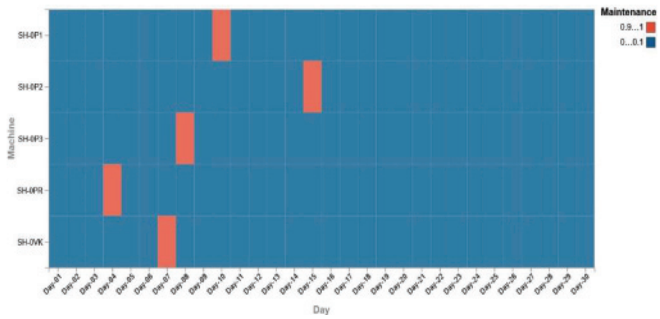

Fig.8: Optimised shovel maintenance schedule

The impact factor of OTE is calculated leveraging Eq. 11 to Eq. 27 and the notations as in Table 5. The formulations are represented as in the equations below.

- OTE of group of shovels based on operation time ... (11)

$$\sum_{i=1}^{i=1}\sum_{t=1}^{t=T}\left(\frac{OEE_{i,t}+APL_{i,t}}{APL_{i,t}}\right)$$

- Total scheduled planned downtime of equipment i in time t ... (12)

$$TS_{i,t} = PMT_{i,t} + PdT_{i,t}$$

- Availability of equipment i in time t ... (13)

$$AL_{i,t} = \frac{TT_{i,t} - TB_{i,t} - TS_{i,t} - TO_{i,t}}{TT_{i,t}}$$

- Load performance of shovel i in time t (14)

$$P_{i,t} = \frac{APL_{i,t}}{PPL_{i,t}}$$

- Net production time of equipment i in time t ... (15)

$$Q_{i,t} = \frac{AL_{i,t} - TM_{i,t} - TI_{i,t}}{AL_{i,t}}$$

- PM wrench time: 35% of $PTM_{i,t}$ time in hours, per maintenance $PMW_{i,t} = 0.35* PMT_{i,t}$ ... (16)

- PM other time: 65% 3of $PTM_{i,t}$ time in hours, per maintenance $PMO_{i,t} = 0.65* PMT_{i,t}$ ... (17)
- PdM wrench time: 35% of $PdM_{i,t}$ time in hours, per maintenance $PdW_{i,t} = 0.35* PdT_{i,t}$ ... (18)
- PdM other time: 65% of $PdM_{i,t}$ time in hours, per maintenance $PdO_{i,t} = 0.65* PdM_{i,t}$ ... (20)
- Combined other time hours (higher value of $PMO_{i,t}$ and $PdO_{i,t}$ per schedule $COT_{i,t} = PdO_{i,t}$ ... (21)

Table 6: Input parameters for OEE benefits calculation

Input parameters for calculations						
Notation	Eq/parameters	SH-OPl	SH-OP2	SH-OP3	SH-OPR	SH-OVK
Cap_i	Planned cap tonnes/day	6000	5800	5900	5950	4400
$TCap_{i,t}$	Total planned cap tonnes/30days	180000	174000	177000	178500	132000
$TT_{i,t}$	Total time 30 days (in hs.)	720	720	720	720	720
$TB_{i,t}$	Total BdM Hs. 30 days	346	430.94	335	430.98	484.8
$TM_{i,t}$	Mean march Hs.30 days	57.9	30.02	70	36.36	40.54
$TI_{i,t}$	Mean idle Hs. 30 days	153.2	89.58	146.94	79.48	122.18
$TW_{i,t}$	Mean work Hs. 30 days	154.4	160.96	159.56	164.68	63.98
$TO_{i,t}$	Mean other time Hs. 30	0	0	0	0	0
$PMT_{i,t}$	First PM Hs. 15 days	3.5	3.5	3.5	3.5	3.5
$PdM_{i,t}$	Total PdM Hs. 30 days	5	5	5	5	5
$TS_{i,t}$	Total planned maint. hrs.	8.5	8.5	8.5	8.5	8.5
$PMT2_{i,t}$	Second PM Hs. 15 days	3.5	3.5	3.5	3.5	3.5

Table 7: Calculated OEE and IF of mining shovels

Equipment - mining shovels						
Notation	Calculations for shovels	SH-OPl	SH-OP2	SH-OP3	SH-OPR	SH-OVK
$PMW_{i,t}$	PM wrench t 35%*$PMW_{i,t}$	1.225	1.225	1.225	1.225	1.225
$PMO_{i,t}$	PM other t 65%*$PMW_{i,t}$	2.275	2.275	2.275	2.275	2.275
$PdW_{i,t}$	PdM wrench t 35%*$PdM_{i,t}$	1.75	1.75	1.75	1.75	1.75
$PdO_{i,t}$	PdM other maint. t 65%*$PdM_{i,t}$	3.25	3.25	3.25	3.25	3.25
$COT_{i,t}$	Combined other t $PdO_{i,t}$	3.25	3.25	3.25	3.25	3.25
$TS_{i,t}$	Total planned maint. Hs.	8.5	8.5	8.5	8.5	8.5
$TSO_{i,t}$	Optimized planned maint. Hs.	6.225	6.225	6.225	6.225	6.225
$AWH_{i,t}$	Additional work Hs. per opt	2.275	2.275	2.275	2.275	2.275
$PP_{i,t}$	Production T per H.	869.702	632.747	624.987	745.567	1420.147
$PB_{i,t}$	Production in T bef opt.	134281.98	101847	99723	122780	90861
$PA_{i,t}$	Production in T aft opt.	136260.56	103286.5	101144.85	124476.17	94091.83
$AB_{i,t}$	Availability bef opt.	0.508	0.39	0.523	0.39	0.315
$PB_{i,t}$	Performance bef opt.	0.746	0.585	0.563	0.688	0.688
$QB_{i,t}$	Quality net t bef opt.	0.422	0.574	0.424	0.587	0.282
$AA_{i,t}$	Availability aft opt.	0.511	0.393	0.526	0.393	0.318
$PA_{i,t}$	Performance aft. opt.	0.757	0.594	0.571	0.697	0.713
$QA_{i,t}$	Quality net t aft opt.	0.426	0.577	0.427	0.59	0.289
$OEEB_{i,t}$	OEE bef opt.	0.16	0.131	0.125	0.157	0.061
$OEEA_{i,t}$	OEE aft opt.	0.165	0.135	0.128	0.162	0.066
$OEE_{i,t,\ inc}$	Min OEE % increase aft	2.969	2.847	2.872	2.782	7.238
IF %	IF Factor in percentage 49.28% computed as per Eq.27					

aft : after, bef: before, opt.: optimisation, Hs.: hours, H.: hour, t: time, T: tonnes, maint. Maintenance, %: percentage

- Total maintenance hours (sum of $PMT_{i,t}$, $PdM_{i,t}$ for 2 schedules of PM and 1 schedule of PdM in 30 days ... (22)
  $TS_{i,t} = 2^* PMT_{i,t} + PdM_{i,t}$
- Combined total maintenance hours (sum of $PdW_{i,t}$, $PMW_{i,t}$ and $PdO_{i,t}$) 1 combined schedule per optimisation ... (23)
  $TSO_{i,t} = PMO_{i,t} + PdM_{i,t} + COT_{i,t}$
- Total savings of maintenance hours per optimisation run $AWH_{i,t} = TS_{i,t} - TSO_{i,t}$ ... (24)
- OTE of group of shovels after optimisation (25)
  $$OTE_{i,\max,t} = \sum_{i=1}^{i=I} \sum_{t=1}^{t=T} (OEEA_{i,t})$$
- OTE of group of shovels before optimisation ... (26)
  $$OTE_{i,\min,t} = \sum_{i=1}^{i=I} \sum_{t=1}^{t=T} (OEEB_{i,t})$$
- IF group of shovels based on operation time due to optimisation ... (27)
  $$IF_{i,t} = \sum_{i=1}^{i=I} \sum_{t=1}^{t=T} (\tfrac{OTE_{i,\max,t} - OTE_{i,\min,t}}{OTE_{i,\max,t}})$$

OEE and IF calculation is calculated as defined as per the notations illustrated in Table 5 and data using Table 6 and the formulas from Eq.11 to Eq.27. The objective of the formulations is to represent various attributes of OEE and IF calculation for mining equipment, essentially shovels and is represented in Table 7.

The OEE is increased in the range of 2.7 % to 7.2 % which is quite significant in the mining industry. The all-inclusive IF has increased by 49 % for a month. These improvements are as per the objectives of productivity improvement.

Conclusions

This article's inherent objective was to maximise benefits by minimising maintenance time, reducing production and maintenance loss through optimisation. An innovative DO model achieved this objective by leveraging exponential technologies by combining preventive and predictive maintenance with constraints. The combined PM and PdM can be best utilised to reduce the maintenance time and improve the equipment's health score and extend its useful life which is demonstrated using OEE and IF improvements. The primary finding is that equipment age is the most significant variable, followed by trips, next by idle hours. The objective of maintenance time reduction by optimisation is achieved by the application DO model.

These optimised schedules can be further complemented by real-time integration with ERP and COTS systems to derive maximum benefits to address the end-to-end maintenance operations value chain. The blended optimised maintenance schedule provides a unique path to increase the availability and utilisation of the haul trucks and provides the additional potential to scale up. Some industry-specific nuances need to be incorporated in the model to leverage and deploy the combined optimised solution model to other industry segments. The advent of Quantum Computing and leveraging its components of molecular modelling, optimisation, risk assessment of catastrophic risk, and AI for better prediction is pertinent for developing the mining industry's maintenance processes and scaling its benchmarks compared to the manufacturing industry.

Overall, the maintenance schedule optimisation model provides foresight into improving process scope levers by horizontal and vertical integration across the maintenance value chain to create a sustainable mining enterprise.

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