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Assessment and review of maintenance practices in the 4th industrial revolution using the cognitive analytics framework

This paper reviews past and the prevailing maintenance concepts practiced, evolved with industrial revolutions over the centuries and briefly outlines the cognitive process, methods and framework of tools and techniques which will be used in the days to come. The maintenance practices have continuously evolved in how the equipment was earlier managed using breakdown, corrective, preventive, total productive maintenance, condition-based maintenance, failure analysis reporting, risk-based maintenance and reliability centric maintenance. The core objective of maintenance remained the same "Increase useful life of an asset with minimal costs". The thinking now has changed from viewing maintenance as "costs" to maintenance as "investments". In the era of Industry 4.0, the maintenance value chain - an integrated cyber-physical system plays an important role in the maintenance of the mining equipment. A cognitive/AI (Artificial Intelligence) maintenance framework can be an effective tool in optimizing the maintenance programme with minimal costs when compared to the traditional maintenance programme in the industry. The optimal replacement policy can be calculated and determined by the computer to minimize the expected downtime or maximize the expected profit. The minimum expected downtime per unit time and maximum expected profit per unit time can also be determined. This replacement policy and mathematic models can be used as reference to the failure system maintenance and replacement.The evolution from traditional data-driven algorithms to blended intelligent algorithms is helping in developing new optimization models for maintenance management systems.

Keywords: *Equipment; industrial revolution; breakdown; AI; industry 4.0; cognitive.*

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1.0. Introduction

Whatever is innovated today will be adopted as standard practices tomorrow and has been customized from generic industries to specific industries. The mining industry is an asset-intensive industry.The new technology and advancement in big data mining and effectivereal-time calculations are helping new tools to be developed and designed. The attempts to use AI in maintenance is going on for years in developing models and utilizing it, but the wholistic view is still missing [1]. The integrated system architecture where all the systems are coherently integrated is still missing from the enterprise landscape. There are multiple silo systems due to which the maintenance management system faces challenges to address the integrated view of any maintenance activity.

In the past, the mining industry was mostly viewed as labour-oriented with low levels of mechanization and technological advancement. More than any other industrial activity, mining tends to leave a strong negative impact on the environment and society [2]. The situation has been reviewed by experts and scientists and, in the present decade, there has been a pronounced upgradation in the mining industry, especially in opencast mining. More technologically advanced, automated and capital-intensive heavy earth-moving machinery (HEMM) are now available and deployed to meet the high demand for minerals and the profitability of mining ventures. The availability of HEMM and its performance regarding productivity depends on the maintenance quality and reliability characteristics of the equipment[3]. The concept of absolute inherent reliability of a piece of equipment or item is a myth, and there is no such equipment or item which is completely reliable with respect to the work environment, the system of work or work activity; all are likely to fail[4]. Modern mining equipment is complex in design and use a large number of components or items. Evolution of maintenance practices since the industrial revolution has shaped the maintenance practices from breakdown, corrective, preventive, total productive maintenance, condition based maintenance, failure analysis reporting and reliability centric maintenance (RCM) [5].

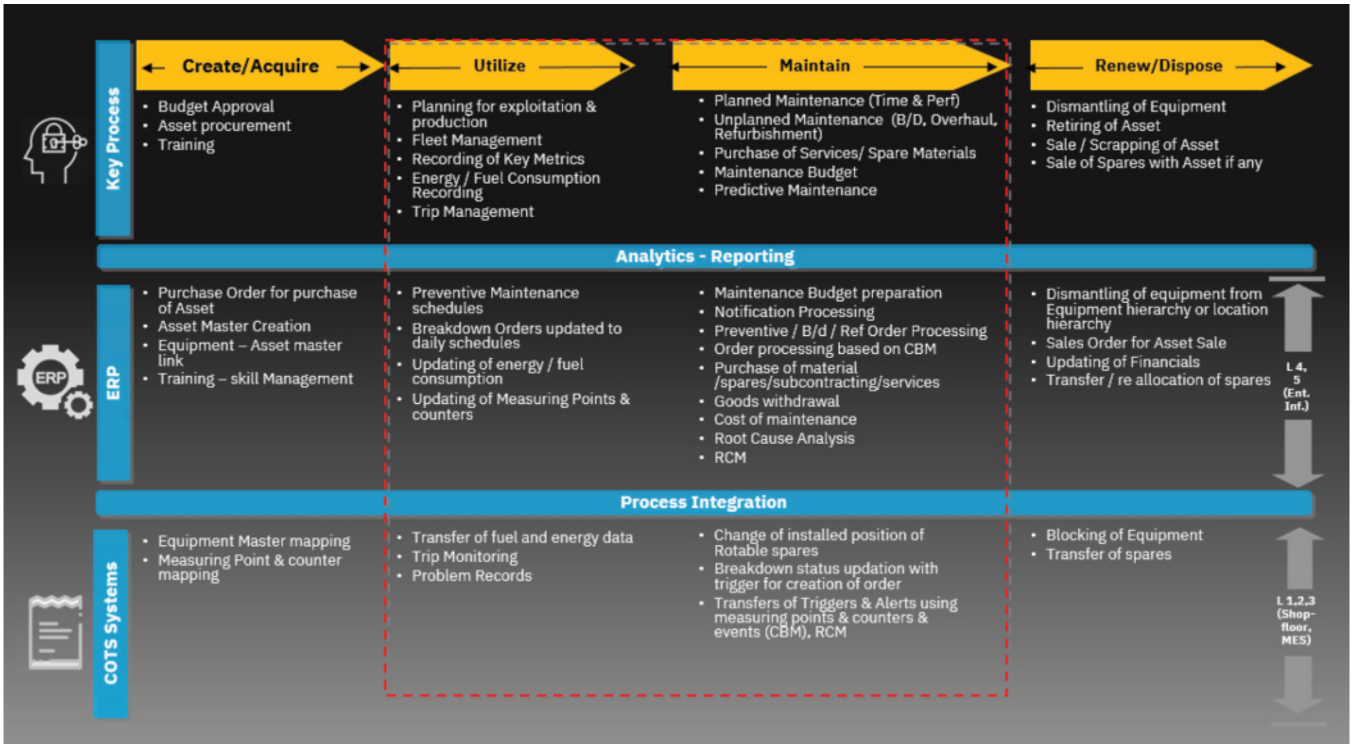

Fig.1 Asset end-to-end life cycle

Traditional maintenance programmes are based on the recommendations by manufacturers, on mine legislations and follow some set standards which may not hold good or show promising results in achieving higher availability of the machines in today's world of optimization [6][7]. Here the full production relies upon the availability of equipment and it has a cascading effect on the subsequent downstream processes in the entire mining supply chain. If the entire life cycle of an asset and its processes are considered, the primary focus will have to be on maintaining the equipment to enhance the life cycle effectively within the limit of constrained resources[8].

1.1 Asset management strategy

Every mining company frames an "Asset Management Policy". For executing these policies, the company must define enablers to perform and subsequently monitor these activities (maintenance performance management), which enables them to analyze results and take further decisions or actions to improve the performance indicators [9][10]. Before understanding the maintenance end to end life cycle, it is imperative to discuss ten asset management principles briefly as below:

- Maintenance policy and strategy – long term objectives and vision
- Maintenance management – organization and people management
- Data management/IT systems – data definition, CMMS, COTS
- Tactics – formalization of proactive programs,i.e. preventive, predictive
- Materials management – procurement and inventory of assets, spares and services (including annual maintenance services)
- Planning and scheduling of static and moving equipment – predefined scope of work and plans
- Measurement of key performance indicators – identification, definition and measurement of KPIs
- Reliability of equipment – RCM programme based on risk and condition monitoring
- Autonomous maintenance – maintenance by operator
- Process re-engineering – continuous improvement in process

These ten principles help the asset life cycle using a CMMS (computerized maintenance management system) integrated with COTS (commercial over the shelf) at a high level is depicted in Fig.1.

In the mining industry, multiple processes have been adopted to enhance the life cycle of an asset to ensure its maximum up-time, but somewhere these actions have affected the production, safety and reliability, duration etc. resulting in a reduction of availability of the equipment [11]. The entire maintenance process from acquisition of asset till the disposal has many processes and many stakeholders. The balancing act between production operations and maintenance still has a long way to go. This paper aims to explain the maintenance practices in mining in chronological order.

1.1 Current practices in maintenance

Maintenance departments generally do not synchronize their activity with the operation teams in the industry. Scheduled maintenance activity is seldom integrated with the production [12]. For every piece of equipment, a different preventive maintenance input is maintained that may increase the complexity, which ultimately affects the production of the mine. The current situation, where the maintenance team or department has individual maintenance inputs for individual equipment. Some of the preventive maintenance inputs come from individual systems, and production schedules are often neglected. Even after ERP (enterprise resource planning) implementation by 90% of the mining companies have around minimum 30-40 systems in the solution landscape which is not integrated with each other[10]. Furthermore, each input from these systems provides varying insights and objective is to synchronize them. In mining parlance, the maintenance schedule (time/performance) comes from system A (maintenance system ERP, CMMS, MIS etc.), the tyre replacement schedule comes from system B (tyre management system), safety inspection and safety-related activity is derived from system C (safety management system), RCM (reliability centric maintenance) results come from system D (RCM system) and so on and so forth. These insights should have integrated coherent view which should be the deciding factor for any maintenance activity [9].

Fig.2 demonstrates the evolution of maintenance practices over the years from the first generation to the present fourth generation. Initially, the starting concept was "fix when broke" to now relying on the latest technological advancement using IoT, AI, robotics automation which is helping the enterprises in developing new methods and techniques to achieve their organization objectives of increased availability and cost reduction [13][14].

A lot of new technology over the last 100 years has been applied in the mining industry. However, today seems different where all the innovation potential is available across the mining value chain. If we optimize the insights from various systems, we will be able to increase the availability and utilization as per the benchmarks in the next section [15].

1.2 Maintenance benchmarks

The maintenance is managed by resources, i.e. workshop equipment, manpower, workshop bay, subcontractor, spares, tools and SOPs. Each maintenance resource is being also measured for their performance in a specific period.

When the maintenance metrics were being started to be measured, the KPI's definition was being brought into play, mostly driven for the manufacturing industry and airlines industry. Initially, the benchmarks were too generic only

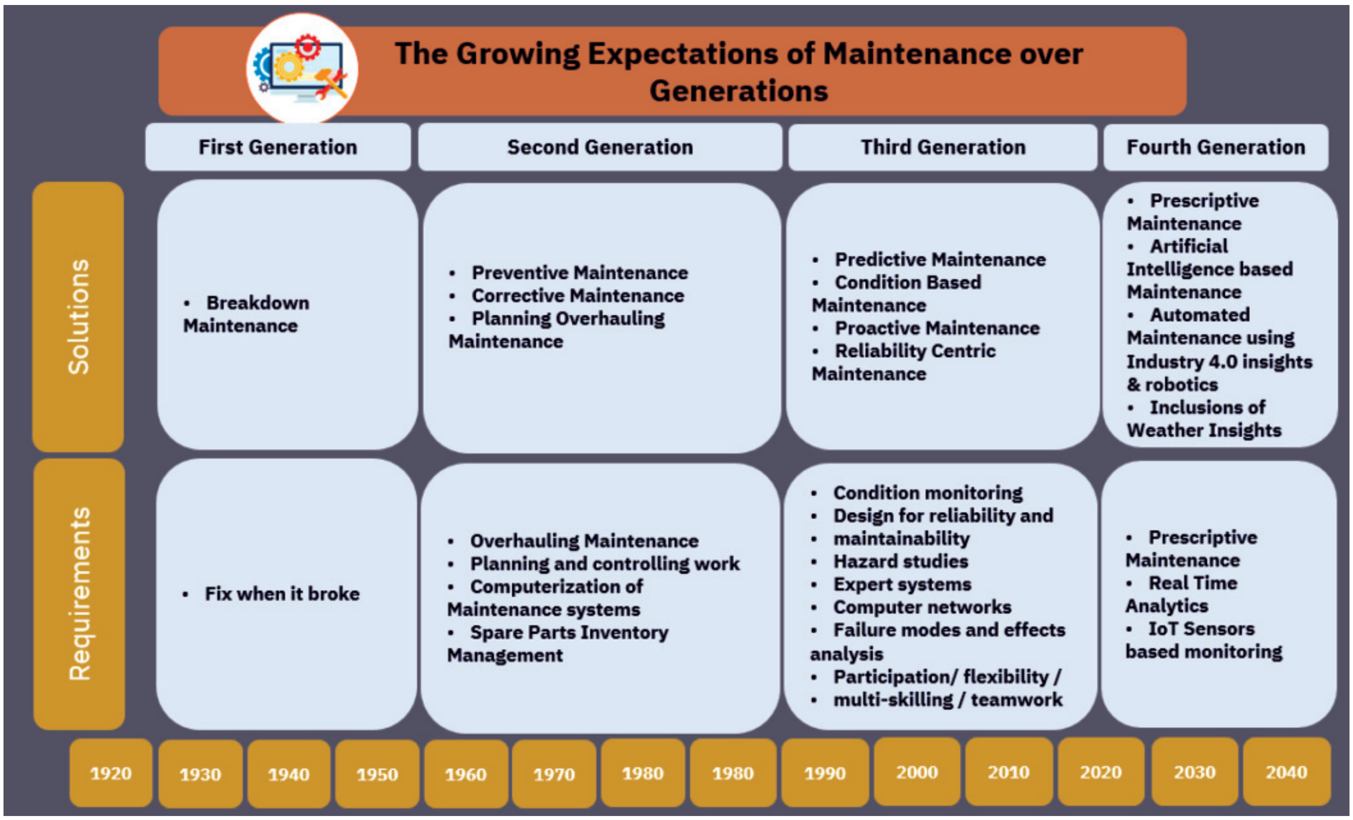

Fig.2 Maintenance practices over generations

TABLE 1: METRICS AND BENCHMARKS

Metric	Variables and Equation	Benchmark %
Equipment availability	$\% = \frac{\text{Hours each unit is available to run at capacity}}{\text{Total Hours during the reporting time period)}}$	>95
Schedule compliance	$\% = \frac{\text{Total hours worked on schedule jobs}}{\text{Total hours scheduled}}$	>90
Emergency maintenance percentage	$\% = \frac{\text{Total hours worked on emergency jobs}}{\text{Total hours worked}}$	<10
Maintenance overtime percentage	$\% = \frac{\text{Total maintenance overtime during period}}{\text{Total regular maintenance hour during period}}$	<5
Preventive maintenance completion percentage	$\% = \frac{\text{Prevnetive maintenance actions completed}}{\text{Preventive maintenance actions scheduled}}$	>90
Preventive maintenance budget/cost	$\% = \frac{\text{Prevnetive maintenance cost}}{\text{Total mainteance cost}}$	15-18
Predictive maintenance budget/cost	$\% = \frac{\text{Predictive mainteannce cost}}{\text{Total maintenance cost}}$	10-12

defined for maintenance jobs, but slowly it was defined for specific industries due to multiple operating constraints.

Table 1 shows the industry benchmarks for tracking and trending maintenance metrics [16].

However, the availability benchmark varies from industry to industry as shown in Table 2 and the objective of each industry is to increase the availability for increased utilization [17].

A typical maintenance job can be split into actual working time, break time, punching time, arranging for tools and parts, standard operating process collection, travel time to work site, idle time. These times wasted for non-productive activities has been decreased by around 20-30% by introduction of maintenance systems and is in the path of continuous improvement in the coming years.

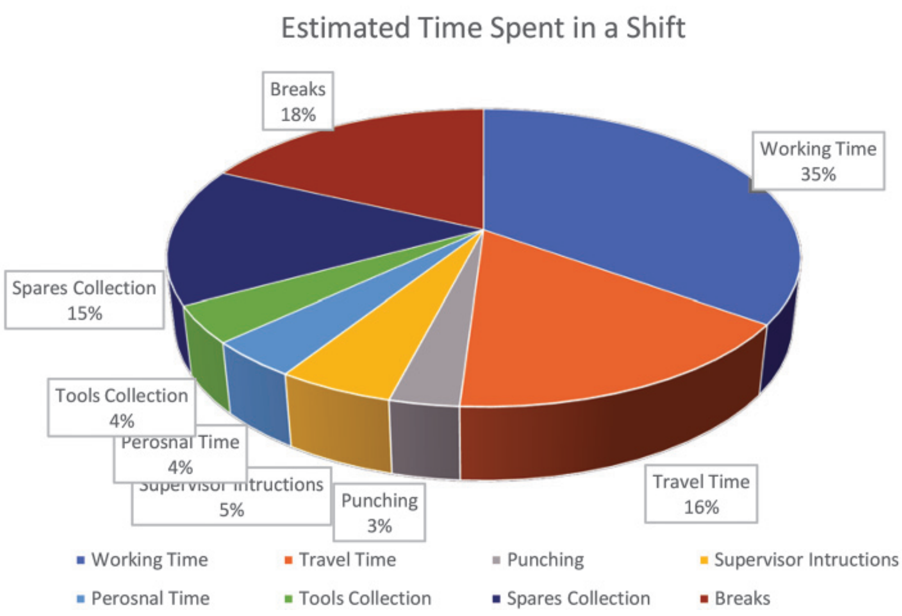

Fig.3 Time spent by a maintenance employee in a shift

The reduction in time spent on non-productive work or indirect work for the maintenance of equipment will help increase the equipment availability. So, if the focus is to optimize the above-mentioned non-productive times as indicate in Fig.3 effectively, then it will help in increasing the "equipment availability" and all other metrics as mentioned in Table 1.

1.3 EVOLUTION OF MAINTENANCE PRACTICES

The maintenance concept had changed a lot from "Fix when broke" to "Resolve to Maintain". In the year 1980s traditional preventive maintenance (PM) programmes were being challenged for giving a planned shutdown even if not required. The computerized interval-based maintenance which was proposed by specifying probabilities of failures, continued advances in the 1990s began to change maintenance practices yet again [18][19]. The development of technology and increased computer usage by the workforce made it possible to innovate on interval-based maintenance techniques. The emergence of condition monitoring (CM) or condition-based maintenance helped support the findings of F. Stanley Nowlan, Howard F. Heap and others. Nowlan and Heap gave the concept of RCM programmes for the airline industry which slowly took place in navy and then to other industries [20]. Now maintaining the equipment

TABLE 2: EQUIPMENT AVAILABILITY NORMS OF VARIOUS INDUSTRIES

Industry segment	Availability minimum %	Availability maximum %
Discrete manufacturing	78	91
Batch process	72	90
Process industry	85	95
Power	85	95
Paper	83	94
Mining	60	82

changed to maintain and retain the equipment functions. Next Toyota introduced TPM (total productive maintenance). Overall equipment effectiveness (OEE) was the main objective of TPM. TPM creates a collaborative environment between operators and equipment to create ownership [21][22].

Fig.4 describes the evolution of maintenance practices over the years in the industry. It is gone through all the nuances of predictive, prescriptive and now innovating using AI (artificial intelligence) the industry. These innovations over the years have improved in the reliability and sustainability of the equipment and increase in the OEA (Overall Equipment Availability).

2.0 Artificial intelligence environment

The OEM (original equipment manufacturer) recommends that the schedules can be time or performance-based whichever is earlier, with specific schedules provided for spare part replacement. Inputs are also received from RCM (reliability centric maintenance) for generation of schedules. The preventive maintenance schedules generated in this fashion are isolated and do not include the influence of other factors which results in greater production downtime.

AI is a branch of computer science which can help develop programmes to allow equipment to perform functions normally requiring human intelligence [23]. The objective of AI is to "think" to a certain extent under special conditions. Artificial computing is a self-learning system that uses data mining, pattern recognition, structured and unstructured data and natural language processing to mimic the way the human brain works [24][25]. The goal of the cognitive model is to help create automated information technology (IT) systems which learn continuously and can solve problems without requiring human assistance. These models can help resolve the complexity of analyzing big data and provide a decision framework for analysis and automated decision making.These systems use machine learning algorithms which refine the way patterns are analyzed as well as the way data is processed so that the systems develop the capability to anticipate future problems and propose probable solutions.

There are many ways the AI is being utilized for real-time decision making, some of them are as follows [26]. KBS (knowledge-based systems) uses the heuristics to determine a suitable action. CBR (case-based reasoning) utilizes past experiences to solve present day problems. It provides machine learning by updating the case base. Genetic algorithms (GA) solutions can evolve through mutation. Neural networks (NN) use back propagation algorithm to emulate the behaviour of the human brain. The solution comprising partly or fully of the concepts mentioned above coupled with IoT (internet of things) is the future of maintenance [27][28].

3.0 Artificial intelligent system and analytics in the mining industry

The development of IT-enabled systems is imperative in the world of automation, so including in the mining industry, for

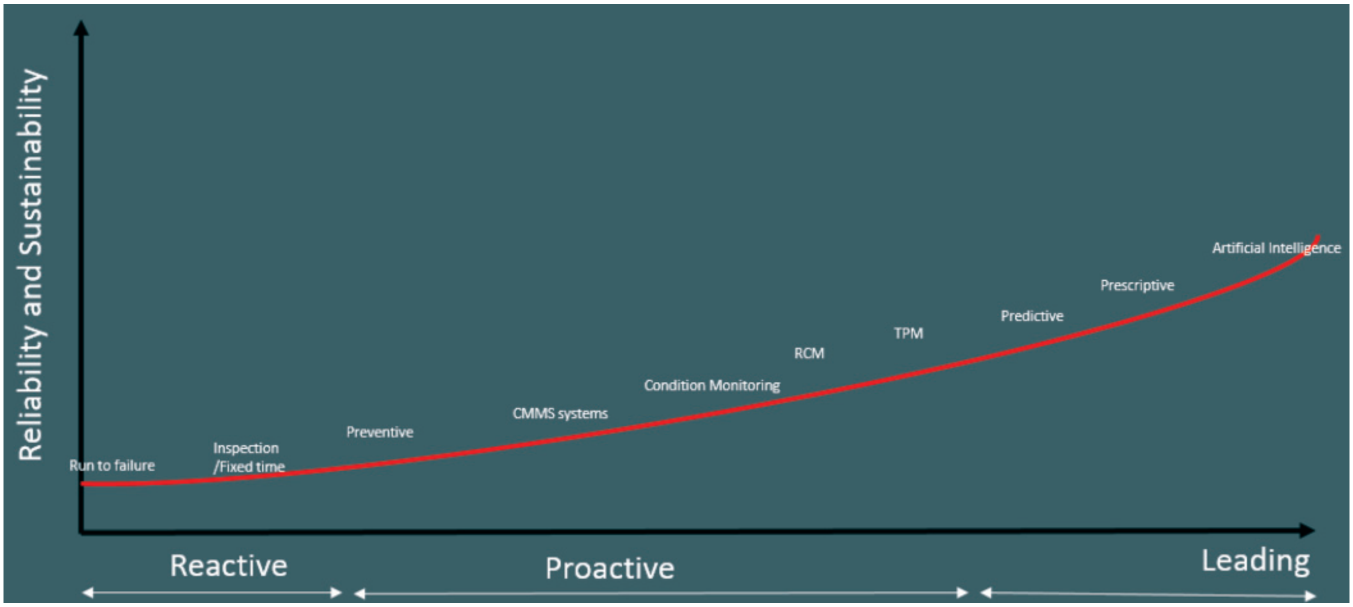

Fig.4 Evolution of maintenance practices over the years

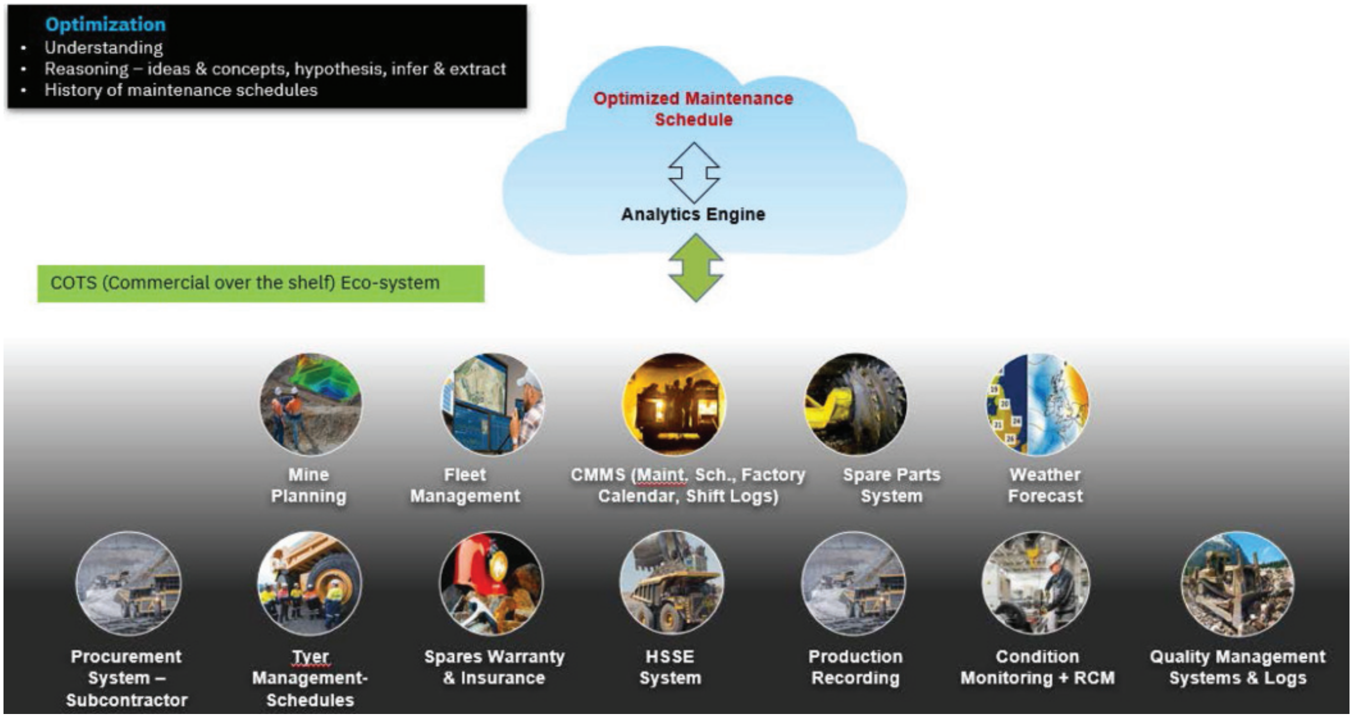

Fig.5 Maintenance value chain and COTS (commercial over the shelf) integration - mining industry

higher production and safety [29]. The global mining industry is moving towards following the best practice of the manufacturing industry. Learning and adapting from the manufacturing industry is transitioning to the 4th generation industrial revolution or IoT 4.0[30]. Fig.5 presents the application of analytics in the mining process and how it can help in integration various sub systems for better optimization.

Fig.5 depicts the various mining value chain integration component systems which help in deriving the analytical model. The data is extracted using the appropriate APIs (application programming interfaces) and based on the AI algorithm, a machine learning model is proposed. Since the 1980s, several artificial intelligence applications have been developed in various industries of engineering and management [31]. The concept in Alan Turingís 1950 article “Computing machinery and intelligence”, AI is now getting implemented in every supply value chain starting from product development to end use [32].

The power of machine learning is to detect anomalies in predictive maintenance. The capacity of deep learning’s is to analyze very large amounts of multi attributable data that re-sequence existing preventive maintenance systems for optimization. Additional data, such as audio, video and image, from sensors, neural networks can enhance and replace traditional methods. AI’s prediction ability to and planned interventions can help reduce downtime and operating costs while improving production yield. For example, AI can extend the life of a mining equipment which was not possible earlier using traditional analytic techniques by combining IoT sensor insights, historical maintenance data and optimization model data which is generated for an equipment.

4.0 AI model

The general preventive maintenance concept is as per the OEM (original equipment manufacturer) standard operating procedures on time or performance or component replacement date which is linear on a time scale.The preventive maintenance dates will not be exact time based or performance based, but each schedule will have dynamic dates considering every attribute as per the weight [33]. The weight can be variable as per the asset class/equipment type, and the operating region as the same equipment operating in a dusty region or steep gradient requires more frequent maintenance. Another important aspect to be considered during the preventive maintenance is part replacement with a repaired part [34]. The reliability of a repaired part is not the same as that of a new one [35]. This will negatively influence the overall reliability of the equipment owing to the negative weight attributed to the repaired part [36]. This AI model will predict failures and recommend maintenance as supervised machine learning problems [37]. The historical data will serve as the testing and training the samples. These AI model will be fed with real-time insights using the IoT sensors.

An AI model framework acts as an advisor by connecting to the equipment for real time insights, preempt issues by discovering non-obvious patterns, aid during repairs and finally apply reasoning and learning for continuous

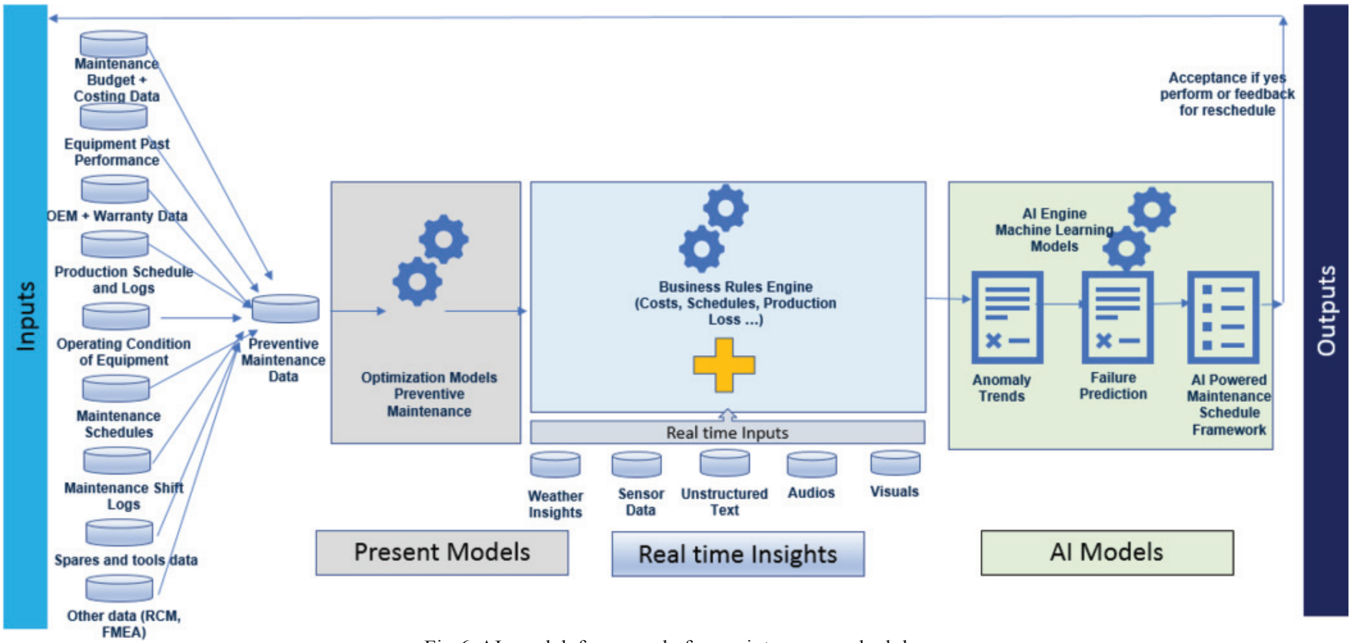

Fig.6 AI model framework for maintenance schedules

improvement. Data-driven insights usually employ pattern recognition and machine learning techniques to detect changes in the states of the equipment performance and physical attributes. These patterns help in providing the decision-making insights.

An AI model for asset maintenance planning should consider asset operation requirements, asset condition and maintenance requirements, weather forecast, spare parts availability as well as other repair shop constraints to produce a joint operations/service plan which maximize asset up-time and minimize maintenance costs. Such a model would work with the below objectives:

1. Minimizethe time the asset is down for service turn around time – MTTP (mean time to perform) [38]
2. Minimize the number of outages
3. Minimize waste of spare parts useful life
4. Balance workload across outages
5. Improve visibility for production planning [39], resource planning and service parts planning by providing maintenance, resource demand and service parts forecast[40].
6. Improve collaboration between asset operators, repair shops and spare parts suppliers. The availability of resources, for example, manpower, spares, workshops, subcontracted or subcontractor availability [41].

5.0 Conclusion

This study presents an overview of AI applications in planning and modelling in maintenance.

The AI coupled with "Internet of Things" insights has evolved as a new area of innovation in mining for maintenance as well as productivity improvement by real-time feed by sensors through multiple wifi (wireless fidelity), GPRS (general packet radio services) and GPS (global positioning system) communication channels. The real-time decision making using these insights with the help of mobility devices help achieve increase the overall equipment effectiveness (OEE) of the mining equipment. The AI uses languages, texts, audio, visuals and structured data (historical, non-historical) as inputs for decision-making framework. There is huge data structured and unstructured data generated in the mines which is now lying idle in the database. As of now only 20% of the data is analyzed, the scope for improvement in data analysis using AI tools will help increase the performance of an equipment. These new system of innovation helps drive and generate outcome-based decision making.

Cognitive models help move beyond the constraints of programmable computing. It helps unlock the world of global, unstructured data and to move from decision tree-driven, deterministic applications to probabilistic systems that co-evolve with continuous learning over the time. The development of cognitive schedules and preempting the resource requirements will help increase the equipment availability and increase the productivity at the mine operations. It improves planning and the adaption of resources, which can be further utilized for innovation in the mines.

The OEM (original equipment manufacturer) or the mine owner can utilize the data generated by the user as per the feedback and support required from time to time and help reduce the SLA's (service level agreement) during the AMC (Annual maintenance contract) and equipment user can utilize their historian and online help from the OEM for maintenance.

Further increased usage of IoT (Internet of things) in the mining industry will bring in new avenues of AI insights and effective decision making.

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