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Reliability analysis of heavy earth machinery, for Predictive Scheduling using Kolmogorov-Smirnov Probability Test and Convolutional Neural Network

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ABSTRACT

Predictive maintenance is undoubtedly one of the foremost deeply divisive topics in asset management and maintenance. I investigated numerous publications, whitepapers, and analysis methods so on critically assess the facts and certain outputs. We used a paradigm that identifies four degrees of predictive maintenance maturity to look at the instant practices. This is the aim at which the digital revolution collides with routine maintenance. Fronted with fierce global competition, every sector is continuously trying to take care of equipment efficiently and effectively to fulfill planned production and productivity standards. As a result, it's even more critical to gauge equipment performance. With this in mind, this study uses a convolutional neural network (CNN) model of a load haul dumper (LHD) to forecast the share of reliability, availability, and preventative maintenance schedules.

Keywords— *MATLAB, Predictive Maintenance, Run to Failure, Convolutional Neural Network Architecture*

1. INTRODUCTION

LHD (load haul dump machine) machines are one of the toughest used for rock mining applications, with overall flow economy, safety, and reliability. It features especially robust construction, good maneuverability, and exceptional productivity. The use is principally in low-profile underground mines and large underground operations including the founding, mining, and tunnel excavations. By not limiting the length in underground tunnels, the loader is meant to be long enough and to extend the axial weight distribution to extend the bucket capacity.

As firms undergo these phases, the amount of data they use to predict failures grows. During this approach, visual inspections are level 1, whereas instrument inspections and real-time condition monitoring are levels 2 and three. At level 4 big data analytics starts to drive decision-making. At this level, you'll use machine learning approaches to hunt out meaningful patterns in massive amounts of knowledge and develop new, actionable insights for increasing asset availability.

1.1 Terminologies

- Visual inspections at Level 1: periodic physical inspections; judgments are purely dependent on the inspector's competence.
- Instrument inspections at Level 2: are performed daily and conclusions are reached employing a mixture of the inspector's knowledge and instrument readouts.
- Level 3 Real-time asset condition monitoring: continuous real-time asset monitoring with alerts supported pre-defined rules or critical thresholds.
- Level 4 PdM 4.0: Assets are continuously monitored in real-time, with alarms sent out based on predictive techniques like multivariate analysis

1.2 LHD Load Haul Dump machines

These are front-end loader machines mostly used for mining applications. The built of an LHD is touch and are safe.

1.3 Scheduled Available Hour

These are theoretically expected periods of the LHD's availability, avoiding further conditions like breakdowns and service.

1.4 Machine available hours

These are the real available hours. The available can vary from the scheduled available hours due to different circumstances in the environment.

1.5 Scheduled working hours

These are theoretically expected working hours of an LHD machine. These are calculated neglecting unexpected breakdown hours.

2. RESEARCH METHODOLOGY

These are the practically recorded working hours of an LHD. These can also vary from the Scheduled working hour.

Machine	Parameter	SSE	SSBr	SSBo	SSTy	SSH	SSEl	SSTr	SSM
LHD1	FF (No/.)	5	4	4	9	5	7	2	8
	TBF (Hrs)	1615	2021	2019	897	1614	1153	4046	1008
	TTR (Hrs)	153	190	192	87	155	111	376	98
LHD2	FF (No/.)	6	3	3	6	3	8	2	6
	TBF (Hrs)	1340	2683	2681	1338	2684	1003	4026	1340
	TTR (Hrs)	127	250	252	129	250	97	375	127
LHD3	FF (No/.)	3	4	3	7	3	11	4	7
	TBF (Hrs)	2691	2017	2690	1150	2690	731	2018	1151
	TTR (Hrs)	250	189	251	111	251	71	187	110
LHD4	FF (No/.)	7	4	6	5	6	12	4	10
	TBF (Hrs)	1150	2012	1340	1602	1342	665	2014	800
	TTR (Hrs)	111	194	131	163	129	70	192	82
LHD5	FF (No/.)	5	4	5	8	5	9	6	7
	TBF (Hrs)	1627	2035	1627	1027	1628	902	1356	1162
	TTR (Hrs)	132	164	132	87	131	75	110	94
LHD6	FF (No/.)	5	5	3	8	3	10	3	11
	TBF (Hrs)	1618	1617	2699	1008	2698	806	2698	730
	TTR (Hrs)	144	145	237	93	238	75	237	70
LHD7	FF (No/.)	5	4	5	10	6	9	5	9
	TBF (Hrs)	1615	2021	1617	804	1345	894	1616	895
	TTR (Hrs)	146	181	145	76	122	85	146	84

The ratio of machine working hours or used hours to scheduled working hours is known as UP.
UP=Machine working hours/Scheduled working hours*100(Utilization Percentage)

Machine	Scheduled Available Hours	Machine Available Hours	Machine Working Hours	AP%	UP%
LHD1	8614	5204	3618	59.24	41.88
LHD2	8475	6177	4077	70.32	46.41
LHD3	8467	6495	4035	73.94	45.93
LHD4	8514	6471	4767	73.66	54.26

AP= Machine Available hours/ Scheduled working hours*100 (Availability Percentage)

Machine	Scheduled Working Hours	Scheduled Service Hours	Breakdown Hours	Idle Hours
LHDI	8784	170	3410	1586
LHD2	8784	309	2298	2100
LHD3	8784	317	1972	2460
LHD4	8784	320	2043	1704
LHD5	8784	170	3410	1586
LHD6	8784	309	2298	2100
LHD7	8784	317	1972	2460

Average TTR hours

3. KS TEST FOR RELIABILITY (DATA PREPARATION)

The analysis of the goodness of-fit (best-fit) approximation for TBF datasets is the next stage in this research. The Kolmogorov-Smirnov (K-S) method was used to do the best fit analysis. The idea here is to see how far the chosen distribution deviates from the real dataset, or how closely the chosen distribution represents the observed distribution

LHD1 = 170.25 hours, LHD2 = 200.87 hours
LHD3 = 177.50 hours, LHD4 = 134.00 hours
LHD5 = 115.60 hours, LHD6 = 154.80 hours
LHD7 = 123.12 hours
AVERAGE LHD≈ 116 hours

Machine	Average TTR(f)	Rank	Weibull 1	Weibull 2	Expo (KS)	ML η estimate	ML β estimate	Best Fit
LHD1	170.25	1	0.4268	0.486	Not essential	200	1⁄2.0	Wei 1
LHD2	200.87	2	0.3678	0.3678	Not essential	200	1⁄2.0	Wei 2
LHD3	177.50	3	0.411	0.455	Not essential	200	1⁄2.0	Wei 1
LHD4	134.00	4	0.511	0.638	Not essential	200	1⁄2.0	Wei 1
LHD5	116.00	5	0.559	0.714	Not essential	200	1⁄2.0	Wei 1
LHD6	154.80	6	0.461	0.549	Not essential	200	1⁄2.0	Wei 1
LHD7	123.12	7	0.540	0.685	Not essential	200	1⁄2.0	Wei 1
LHD avg	153.80	8	0.463	0.553	Not essential	200	1⁄2.0	Wei 1

Kolmogorov-Smirnov (K-S) Test Results of LHDs
To evaluate the value of KS
D+ = Max 1≤i≤n {i
/n - Ri}
D- = Max 1≤i≤n {Ri - (i-1)/n} (N=8)

	I	Ri	D+	D-
LHD5	1	115.6	Na	115.6
LHD7	2	123.12	Na	122.99
LHD4	3	134	Na	133.75
LHDavg	4	153.8	Na	153.42
LHD6	5	154.8	Na	154.3
LHD1	6	170.25	Na	169.62
LHD3	7	177.50	Na	176.72
LHD2	8	200.87	Na	199.992

KS Distribution table
For LHD 5:
D+ = {1/8 – 115.6} =-115.6 (since -ve, avoid)
D- = {115.6 - 0}= 115.6

To calculate reliability on Weibull properties:
R + F = 1

Where, R is reliability and F is unreliability
F(+) = 1 - e^(-(t/η))^β
R(+) = e^(-(t/η))^β

Where η is life, β is shape parameter.
At t = η,
R(η) = e^(-(η/η))^β = e^-1 = 0.368
F(η) = 1-R(η) = 1- 0.368 = 0.632
At t = η, P(failure) = 63.2%

Weibull depiction:
Weibull 1 and 2 Calculation
For LHD1:   η = 170.25, β = 1
R(wb1) = e^(-(t/η))^β = 0.4268
R(wb2) = e^(-(t/η))^β = 0.486
F(wb1) = 1-R(wb1) = 0.5732
F(wb2) = 1-R(wb2) = 0.514

For LHD2:   η = 200.87, β = 1
R(wb1) = e^(-(t/η))^β = 0.3678
R(wb2) = e^(-(t/η))^β = 0.3678

F(wb1) = 1-R(wb1) = 0.632
F(wb2) = 1-R(wb2) = 0.632

For LHD3: $\eta = 177.50$, $\beta = 1$
R(wb1) = $e^{(-(t/\eta))^\beta}$ = 0.411
R(wb2) = $e^{(-(t/\eta))^\beta}$ = 0.455
F(wb1) = 1-R(wb1) = 0.589
F(wb2) = 1-R(wb2) = 0.545

For LHD4: $\eta = 134.00$, $\beta = 1$
R(wb1) = $e^{(-(t/\eta))^\beta}$ = 0.511
R(wb2) = $e^{(-(t/\eta))^\beta}$ = 0.638
F(wb1) = 1-R(wb1) = 0.489
F(wb2) = 1-R(wb2) = 0.362

For LHD5: $\eta = 116.00$, $\beta = 1$
R(wb1) = $e^{(-(t/\eta))^\beta}$ = 0.559
R(wb2) = $e^{(-(t/\eta))^\beta}$ = 0.714
F(wb1) = 1-R(wb1) = 0.440
F(wb2) = 1-R(wb2) = 0.285

For LHD6: $\eta = 154.80$, $\beta = 1$
R(wb1) = $e^{(-(t/\eta))^\beta}$ = 0.461
R(wb2) = $e^{(-(t/\eta))^\beta}$ = 0.549
F(wb1) = 1-R(wb1) = 0.538
F(wb2) = 1-R(wb2) = 0.450

For LHD7: $\eta = 123.12$, $\beta = 1$
R(wb1) = $e^{(-(t/\eta))^\beta}$ = 0.540
R(wb2) = $e^{(-(t/\eta))^\beta}$ = 0.685
F(wb1) = 1-R(wb1) = 0.459
F(wb2) = 1-R(wb2) = 0.314

For LHDavg: $\eta = 153.80$, $\beta = 1$
R(wb1) = $e^{(-(t/\eta))^\beta}$ = 0.463
R(wb2) = $e^{(-(t/\eta))^\beta}$ = 0.553
F(wb1) = 1-R(wb1) = 0.536
F(wb2) = 1-R(wb2) = 0.446

The manual calculation and predictions pose the problem of inaccuracies and delay. Hence a digital model of calculation and prediction is of utmost need. The following shows an experimental study of the use of the predictive maintenance toolkit of MathWorks MATLAB.

The study shows condition-based monitoring as its input depends on several sensory data to observe and to measure the condition of the equipment while performing. As soon as the data set shows a fall in the performance has decreased or there is a chance of failure, the requirement of maintenance is indicated.

In this study, the Predictive Maintenance toolkit of MathWorks Matlab is exploited to test the viability of predictive maintenance of the above-mentioned machines. The RUL using the convolutional neural network model enables us to estimate the number of remaining years of the machine and also keep a track of the performance of the machine while performing.

the RUL or the Remaining Useful Life model utilizes three fundamental modes of data, depending on the availability
1. Lifetime data indicating how long it took for similar machines to reach failure
2. Run-to-failure histories of machines similar to the one you want to diagnose
3. A known threshold value of a condition indicator that detects the failure

Lifetime data
Proportional hazard models and probability distributions of component failure times are used to estimate RUL from lifetime data. Run-to-failure. These methods capture degradation profiles and compare them with new data coming in from the machine to determine which profile the data matches most closely.

Threshold value
In many cases, run-to-failure or lifespan data was not recorded, but you do have information on required threshold values—for example, the temperature of a liquid in a pump cannot exceed 160 degrees Fahrenheit (71 degrees Celsius) and the pressure cannot be less than 2200 pounds per square inch (155 bar). You may fit time series models to condition indicators taken from sensor data, such as temperature and pressure, which rise and fall with time, using this information.

In our study, we have collected and classified Run to failure data of various subsystems as mentioned earlier. This method helped us find the degradation profiles over the set of the data and predict the failure based on the current data.

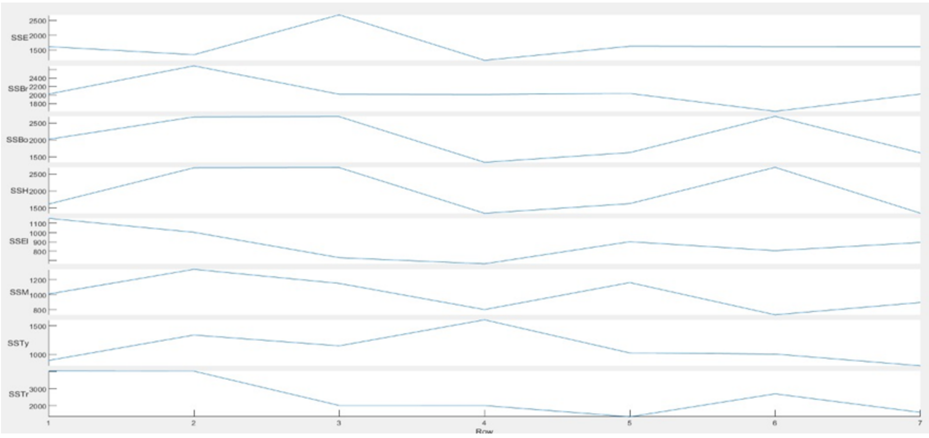
4. PROCEDURE

The Convolutional Neural network model uses a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other. The system plans to graphically visualize all the data and then predict the future by comparing the previous data with the current one. The following steps are followed

1. Plotting the data
2. Feeding/training the system to deduce and learn about failure.
3. Predict on the current data

Datasheet of time between failures.

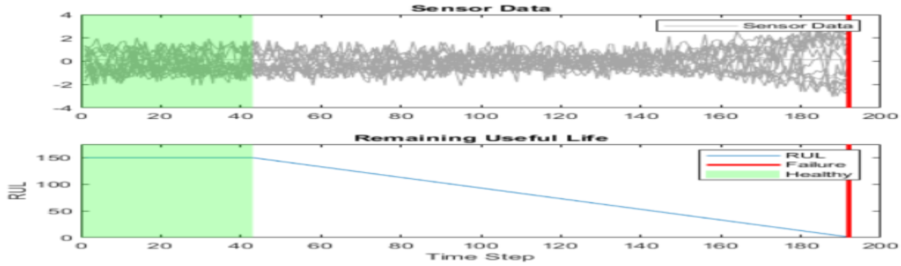
MACHINE	SSE	SSBr	SSBo	SSH	SSEl	SSM	SSTy	SSTr
LHD1	1615	2021	2019	1614	1153	1008	897	4046
LHD2	1340	2683	2681	2684	1003	1340	1338	4026
LHD3	2691	2017	2690	2690	731	1151	1150	2018
LHD4	1150	2012	1340	1342	665	800	1602	2014
LHD5	1627	2035	1627	1628	902	1162	1027	1356
LHD6	1618	1617	2699	2698	806	730	1008	2698
LHD7	1615	2021	1617	1345	894	895	804	1616



The input data is processed and sorted in a sequence format, with the first dimension indicating the number of selected features and the second indicating the duration of the time sequence. Convolutional layers are stacked together for feature extraction after being packed with a batch normalization layer, followed by an activation layer. To get the final RUL value as an output, the fully connected layers and regression layer are employed at the end.

Only 1D convolution is used in the time sequence direction in the chosen network architecture. This means that the order of features has no bearing on the training and that only trends in one feature are analyzed at a time.

All the sensory data after analysis are used up to calculate the extent or a threshold value beyond which the equipment starts to break down.



5. CONCLUSION

The plan and organization of appropriate managerial practices can improve the equipment's continuous operation. Based on the analysis, the following results were reached:

- One of the machine's Key Performance Indicators (KPI) is availability. When compared to comparable systems, LHD3 has the highest availability percentage (73.94 percent). Production rates are reduced as a result of unavailability and inefficient utilization. Strict adherence to PM schedules, excellent equipment, and crew management, a skilled operational staff, and effective and efficient machinery management will all help. It is feasible to raise this by 25-30% by shift overlapping.

- In performance evaluation, reliability estimation is critical. The maximum degree of reliability was found to be 55.90 percent (LHD5), while the lowest level was found to be 36.78 percent (LHD2). The dramatic drop in reliability is due to often recurring failures with fewer TBFs. As a result, it is advised that low-efficiency equipment be kept in good working order by planning the best maintenance strategy.
- Reliability-based PM time intervals were estimated to forecast the early failure of the system. If the reliability requirement is 42.68% for LHD1, then PM should be performed every 9 hours. Timely conduct of PM enables to achieve the projected life.

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