Liner Wear Prediction Using a Bayesian Hierarchical Model

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Abstract

Chute liners of bulk handling operations are subject to vastly different rates of wear, making early estimation of remaining useful life a challenge for planning maintenance. Following advancements in IOT (Internet of Things) technology in industry, real-time wear monitoring has since become possible, rendering the more laborious and unsafe historical methods of inspection undesirable. The current remaining useful life estimation method in industry involves a simple linear regression for each device. This has been identified as an area of improvement for this project. Through creating a Hierarchical Bayesian learning model which clusters knowledge from historical sensors with currently deployed sensors, the relationships between spatial, temporal, and engineering factors are captured. Remaining useful life predictions with uncertainties can be made from the moment the sensor records its first change in thickness. Along with earlier estimation of remaining useful life, a secondary benefit resulting from the proposed methodology is that anomalies in wear rates can be detected. The approach allows plant operators to incorporate data driven decision making in both maintenance planning and operation control.

1. Introduction

Bulk commodities are a major contributor to the Australian economy with $426 billion worth of goods shipped in 2021 (Trade Statistics, 2022). In the mining sector, the safe and efficient transfer of bulk ore is achieved through a network of assets and systems across a mine site. These include conveyor systems with multiple feed chutes, transfer chutes, bins, and hoppers, as well as assets such as stackers, reclaimers, and mobile plant such as trucks. Due to the high-throughput and coarse nature of the ore, sacrificial wear liners are installed on the inside of many of these assets to protect against abrasive wear. If these liners wear too far, there is damage to the structural steel, and if they wear too quickly, there can be unplanned downtime resulting in lost production. The replacement of liners on worn chutes is more convenient and cost effective than a repair of the underlying structure. Premature failure of liners can lead to up to 50% more time dedicated to lining maintenance (Malone et al., 2013). Traditionally, liners are monitored, and data recorded by means of manual inspection, ultrasonic thickness testing (Padole et al., 2002) or 3D laser scanning (Vanicek et al., 2012). These methods all require a shutdown to allow operators to enter a high-risk area to conduct inspections, the accuracy of which is dependent on the skill of that operator.

A safer alternative, developed by Metso Outotec, is an IOT sensor monitoring system for chute wear monitoring known as WearSense. The WearSense system embeds a sensor in the liner to monitor the remaining thickness. The sensor can also be incorporated into a fastener, a patented innovation which serves the dual purpose of bolting the liner to the chute wall, while also monitoring liner thickness. Each sensor has a small probe that penetrates through the liner to the wear surface. The probe wears with the liner as material flows through the chute, recording thickness as point estimates in the process. A schematic of the installation of the wear sensor is shown in Figure 1. The sensors are connected to a cloud-based data warehouse where the data is processed and then displayed on a web user interface. The current method used in industry to predict future thickness values is a simple linear regression for each sensor. This has been identified as an area for improvement.

The primary objective of this project is to develop a pipeline for a chute lining wear prediction algorithm that incorporates some combination of temporal, spatial and engineering factors and is updatable as new observations are received. Predictions must have uncertainties associated with them so that inference about the probability of time to failure can be made. Improved prediction accuracy will allow plant operators to better prepare for planned maintenance and allow liner life to be extended towards its real maximum, reducing cost. The proposed methodology incorporates a learning mechanism whereby knowledge from historical sensor data informs the models of currently deployed sensors in a Bayesian framework, presenting a marketing advantage for the client.

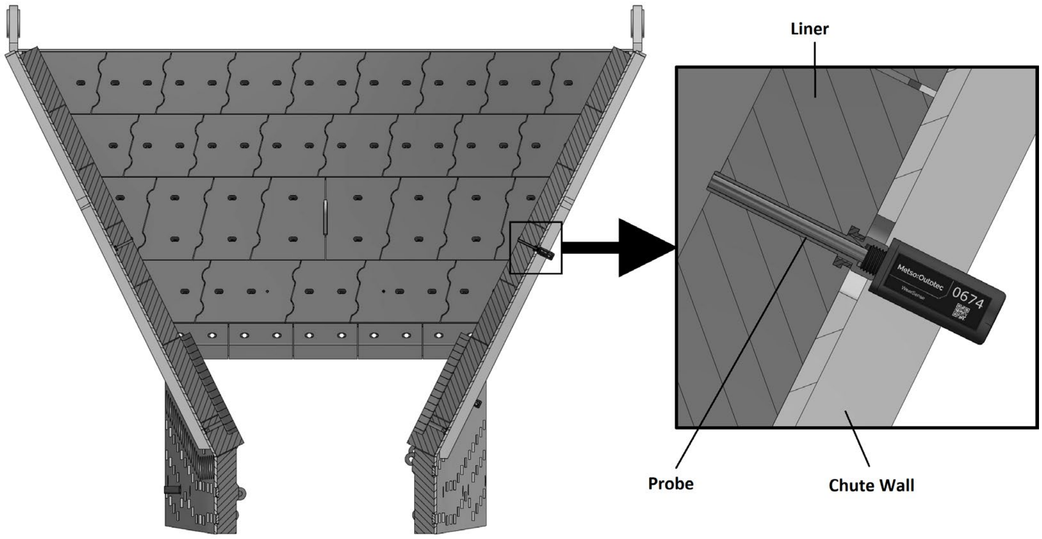

Figure 1 Schematic representation of a sensor installed on a single liner of a chute.

1.1 About the Data

The data is raw telemetry data for 968 sensors distributed across 17 assets from 9 mine sites. Only three of these assets (Hopper 1, Hopper 2 and Train Loadout) have been identified to contain historical data whereby sensors have reached the end of their remaining useful life (RUL-0) and have either been decommissioned or replaced. Information about the number of RUL-0 sensors is presented in Table 1. This is important for training a model, as the model needs to be able to describe the complete process of wear. As Hopper 1 contains the most RUL-0 data, it is the focus of this study.

Challenges for prediction include: 1) there is only calendar data, rather than throughput information which would better model the wear process, 2) limited training data set, 3) each sensor measures a discrete point in space and time, and 4) there is no data on different liner materials in the same chute.

Asset	No. Sensors	No. RUL-0 Sensors
Hopper 1	88	20
Hopper 2	43	7
Trian Loadout	101	11

Table 1 Total sensor counts and RUL-0 sensor counts for assets which contain historical data.

1.2 Goals of the analysis

1. Can we determine whether a sensor in a specific location is showing anomalous behaviour by using the data from other sensors in the chute?
2. Can we predict the point in time when a specific sensor reaches a pre-determined threshold within a 95% credible interval (time to failure)?
3. Given a sensor in a new location, can we predict the time to failure?

2. Process

The pipeline involved data acquisition, filtering, training and test set preparation, model construction and model evaluation (Figure 2).

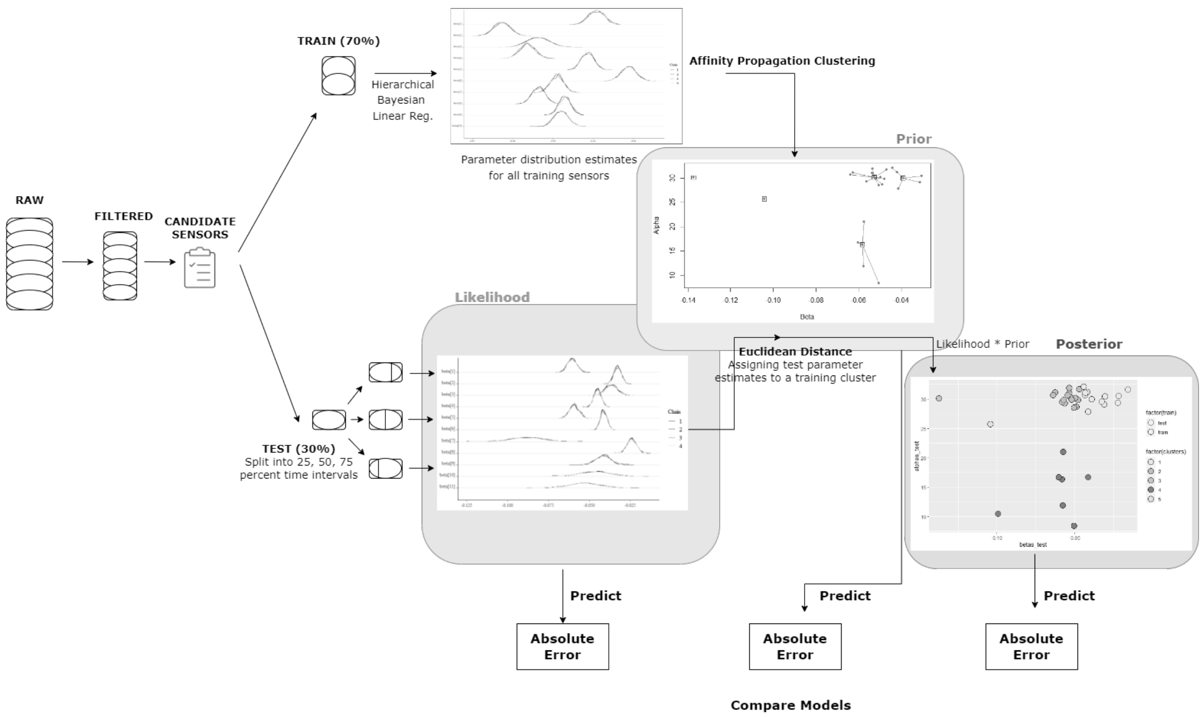

Figure 2 Process flow diagram representing the entire workflow from raw data to predictions.

2.1 Data Preprocessing

A SQL script was written to extract liner thickness values and other relevant information. All subsequent processing and analysis were performed in R, a programming language for statistical computing and graphics. The data is noisy, and filtering combined with business rules were used to manage outliers, ensuring monotonic decreasing sensor values. A separate function was developed to select RUL-0 sensors. The resulting clean data was split into training and test sets.

2.2 Bayesian Learning Model - Construction and Evaluation

The modelling approach used a Bayesian hierarchical linear regression as this allows for the leveraging of temporal and spatial information. Bayesian statistical methods are also preferable to allow for incorporation of engineering knowledge. The initial training model does not make use of any engineering knowledge.

Following training, affinity propagation (AP) clustering was performed on the resulting standardized parameter estimates from the training model. This has the effect of grouping similar wearing sensors to each other. In AP clustering, one sensor from the cluster of sensors is assigned as the exemplar, meaning that its parameter estimates are representative of all sensors within that cluster.

The test data was modelled linearly, initially with no prior engineering knowledge. The returned parameter estimates are assigned to a training cluster by measuring the minimum distance from a test sensor to all of the exemplars. Test sensors are re-modelled, however this time incorporating prior knowledge in the form of a closely related historical sensor (resulting from cluster assignment).

The pipeline produces three models which can be evaluated: 1) The current industry method, 2) The closest related model, 3) A combination of (1) and (2). Models are evaluated by iterating over 10% intervals of observed test data. The mean absolute error of the estimated “time to 0 thickness” across all test sensors were calculated and compared.

3. Results and Discussion

3.1 Data quality

The clustering results in Figure 3 show a clear spatial grouping between the fast-wearing sections (cluster 1) and the comparatively slower wearing sections (clusters 2 and 3) of the asset. The clustering process validates the model by recognizing that sensors exhibit different wear profiles and that this can be partly attributed to their location on the chute. This provides value for plant operators, as without having to inspect the chute, operators can identify areas of high or low wear and identify sensors that are exhibiting anomalous behaviour (cluster 4) or poor data quality. The clustering of training data also serves to inform models (2) and (3).

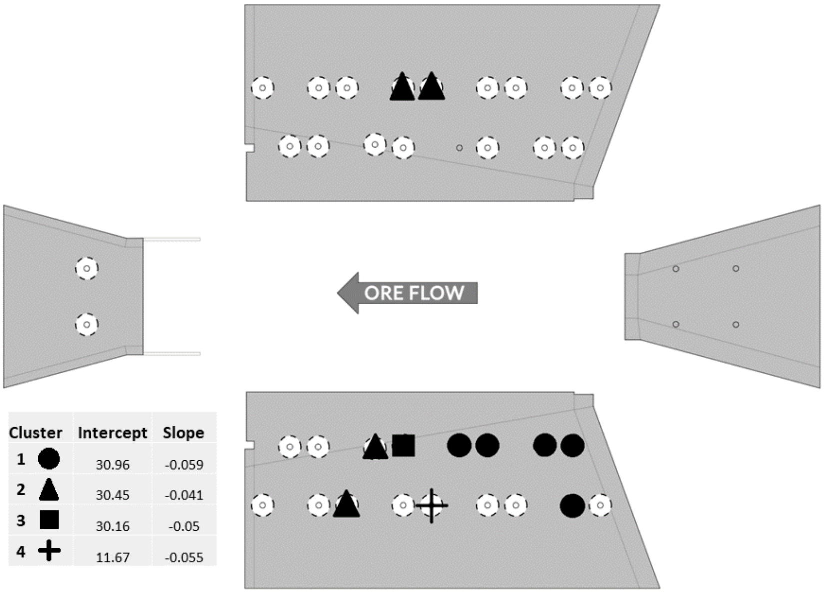

Figure 3 Clustering results related back to a fold-out schematic diagram of the chute interior (Hopper 1). Each polygon represents an interior panel of the asset. White icons represent non-RUL-0 sensors while the black icons represent RUL-0 sensors with their respective cluster assigned.

3.2 Hierarchical Model – Predictions

The results displayed in Figure 4 indicate an improvement in the predictive accuracy of models 1 and 2 compared to the current industry method especially in the case where less than 50% of data has been observed. From 50% onwards, all prediction errors slightly increase. We postulate that this may be because the pattern of wear changes, indicating that the wear process may not be linear. From 60% observed data onwards, there is minimal difference in predictive accuracy of all three models.

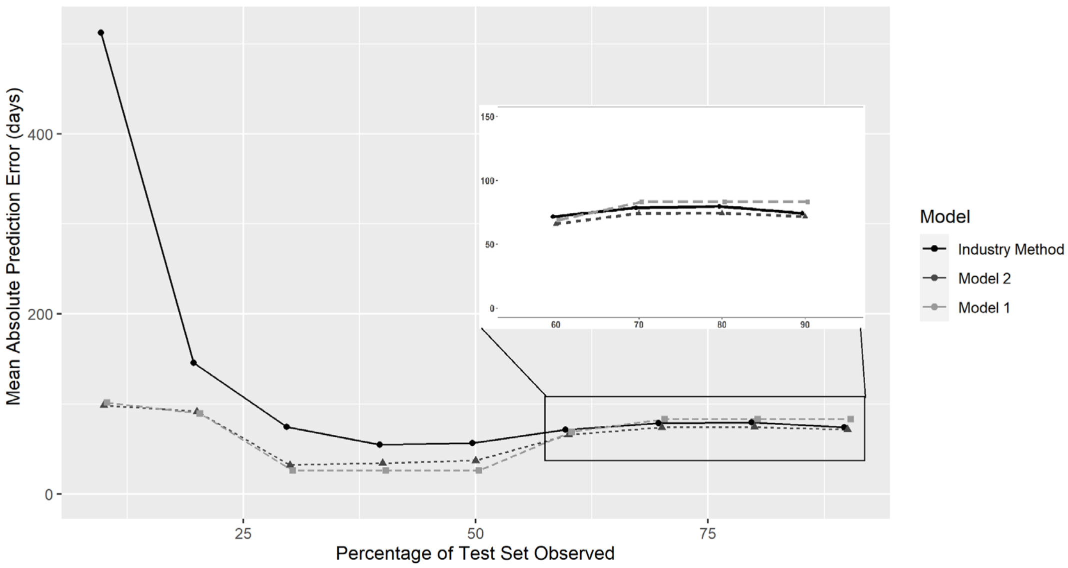

Figure 4 Model fits at each 10% interval of observed data from the test set of Hopper 1. Mean prediction error measured in absolute days from ground truth of six test sensors.

4. Conclusions and Future Work

The results show that a Bayesian Hierarchical model can be used to inform data quality, prediction and decision making. Thus far, the aims have been achieved, however models have not undergone significant robustness testing due to the lack of historical data. It is hypothesized that with more historical data, the predictions for models 1 and 2 will improve. Future work within the timeline of this project includes testing a non-linear model, testing predictions on non-RUL-0 sensors and using different subsets of training and test sensors as a cross validation method. For future work outside the timeline of this project; it has been identified that the rate of wear is more strongly correlated with cumulative throughput than with time. For this project throughput data is unavailable, it is predicted that replacing time with cumulative throughput will result in more accurate prediction.

5. Acknowledgements

I would like to extend my appreciation to my supervisors, Professor Melinda Hodkiewicz and Associate Professor Adriano Polpo for their mentorship and guidance. I wish to acknowledge Piero Velletri, Alessandro Canestrari and the wider WearSense team, whose subject expertise, availability and support for me and this project has been immense. Furthermore, special mentions to Jeremy Leggoe and Kimberlie Hancock of the CEED office for ensuring students get the opportunity to take part in industry-based projects.

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