Conveyor Belt Wear Life Modelling

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Abstract

Understanding conveyor belt wear rate is key for BHP Billiton Iron Ore (BHPBIO) maintenance strategies as it owns and operates over three hundred conveyor systems across the Pilbara region. Analysis of 114 belts installed on 22 conveyors, completed by Callum Webb (2013), produced a statistical understanding of belt wear rate considering the following variables: conveyor duty, belt speed, belt width, cycle time, belt strength and throughput material. Of the 5 alternate linear models explored, the 1D throughput based measure, which captures utilisation data unaccounted for in the conventional time base wear rates, proved most descriptive.

This project confirms that throughput linear models better characterise belt wear rates. In addition, via dataset expansion to 211 belts installed on 98 conveyors, more robust regression models have been obtained. Further analysis of additional parameters has shown material drop height, loading characteristics and selected interaction terms have little effect on wear rate prediction. Finally, the expanded 1D thoughput model has undergone successful cross validation using an unseen test dataset of 71 belts to provide prediction intervals for future estimates of belt wear. This outcome forms the basis for tool integration and improved reliability of BHPBIO's conveyor maintenance scheduling.

1. Introduction

BHP Billiton Iron Ore (BHPBIO) owns and operates over three hundred conveyor systems across operations in the Pilbara region. During utilisation, belts reduce in thickness due to constant wear and impact damage until a minimum thickness is reached and belt replacement is required. Understanding the wear process to enable accurate prediction of when a belt will reach minimum thickness is therefore important for BHPBIO's maintenance scheduling.

The client's current approach to planning belt replacement is based on staff experience, historical belt replacement frequency and extrapolating thickness worn per unit of time from Belt Condition Monitoring Reports. This approach does not fully utilise all available data and BHPBIO wishes to embed an evidence-based understanding of factors that influence wear into an accurate and repeatable approach to belt replacement.
A preceding study of 114 belts installed on 22 conveyors completed by Callum Webb (2013), has produced a statistical understanding of belt wear rates. Six linear models were explored; 1D, 2D and 3D time and throughput-based measures. They each considering the following

parameters: conveyor duty, material type and throughput, belt grade, speed, length, strength and cycle time. It was concluded that throughput-based wear rates have greater explanatory power due to utilisation accountability yielding more linear wear over belt lifetime. The most useful model developed was the 1D throughput-based wear rate measure, which included the statistically significant variables: conveyor duty, belt width, strength, speed and cycle time.

Implementation and potential benefits have not yet been realised due to the following:

- Data set limitations to specific conveyor types and two BHPBIO sites.
- Potential wear factors, such as drop height and loading parameters, are not included.
- Interaction terms between established parameters are not considered.
- Model validation and prediction error confidence has not been quantified.

The aim of this project is to increase model precision by confirming, expanding and validating the predictive tool using statistical techniques. Thus improving BHPBIO's accuracy and confidence in predictive belt maintenance.

2. Methodology

The project follows 3 stages: confirmation, expansion and validation. All data processing and analysis was performed through *Microsoft Excel* and statistical package *R*.

2.1 Model Confirmation

The previous analysis was critically analysed to identify errors and improvements. A traditional multiple linear regression technique considering p-values and standard errors was implemented to determine the best fitting models to the original data set. This sought to confirm the previous models' significance and improve application transparency compared with the AICc automated averaging approach used previously (Burnham & Anderson 2001).

2.2 Model Expansion

2.2.1 Data Collection

All required information is summarised into four source categories in Table 1. A total subset of 211 belt observations from 98 conveyor systems was considered for analysis. Belts were shortlisted by availability of condition monitoring reports, with preference given to high use conveyors. Preference was also given to include belts with variables not previously considered; Figure 1 displays additional duty, strength, width and grade categories captured.

Consulting literature and BHPBIO staff, material drop height and belt loading (tonnes/m) were considered key variables to include in the expanded analysis (Andrejiova & Marasova 2013, Fedorko et. al 2014, Jurdziak & Hardygora 2000). Product drop heights for shortlisted conveyors were sourced from a case-by-case search of technical drawings and site measurements. Vertical distance from conveyor head to impact point was recorded and where multiple material inputs existed an average drop height was estimated. Assumptions regarding chute designs were made in reference to site personnel and rounded to the nearest 0.1m or 0.5m accordingly. Belt loading information was gathered by combining material throughput and operational belt speeds to determine the tonnes per meter length on the belt during a given utilisation period.

Belt Condition Monitoring	Material Tracking	Belt Specifications	Technical Drawings
• Thickness test results • Belt material grade • Belt strength • Belt width	• Throughput • Product type • Operation time	• Belt length • Belt speed • Conveyor duty	• Product drop height

Table 1 Data sources (Webb 2013).

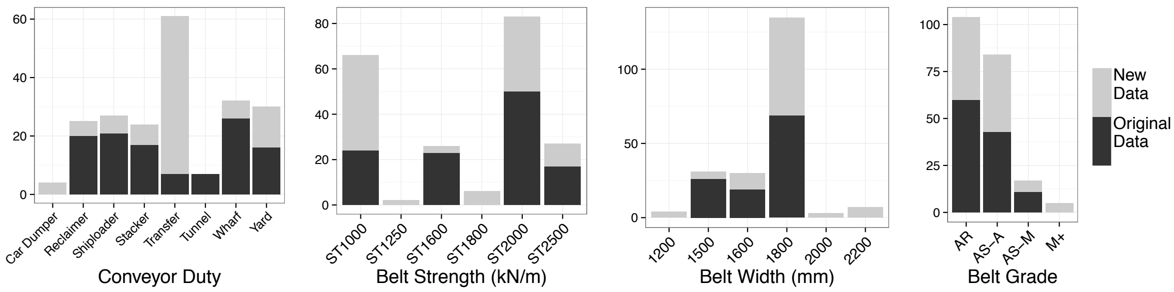

Figure 1 Frequency of categorical variables in expanded dataset.

2.3 Validation

Validation of the wear rate models is required to confirm accuracy and confidence for predictive application (Fox 1997). Cross-validation has been implemented on the 1D throughput model using an unseen 'test' data set of 71 belts installed on 69 conveyors. The accuracy of the model's predictivity was evaluated using error estimates sourced from packages within R. This approach was selected due to evidence of successful application to nozzle and machine tool wear rate regressions (Krishnaswamy & Krishnan 2002).

3. Results and Discussion

3.1 Confirmation of Original Analysis

Approaching the original data with the traditional p-value parameter selection approach yields identical significant variables and adjusted coefficient of determinations ($\bar{R}^2$) for all throughput based wear rate models. A small difference in the 2D time based model results from the averaged model including the duty variable, deemed insignificant according to the traditional approach. Although a difference exists, these results confirm that the significant variables identified by the preceding study are accurate and explain belt wear rates.

3.2 Exploratory Analysis of Expanded Set

3.2.1 Variable Categorisation

To derive the predictive tools, discrete explanatory variable categorisation is performed. Belt lengths were segmented into six intervals to remove linearity assumption issues. One impact of this coding change is a higher correlation between belt length and conveyor duty. Client preference also dictates that belt grades, previously described by supplier brand, are categorised into Australian Standards or BHPBIO equivalent (Standards Australia 1994).

Duty based wear rates categorisation remains an important variable for all wear rate measures where each individual duty displays a characteristic mean wear rate; 1D thoughput wear rate distribution is shown in Figure 2a.

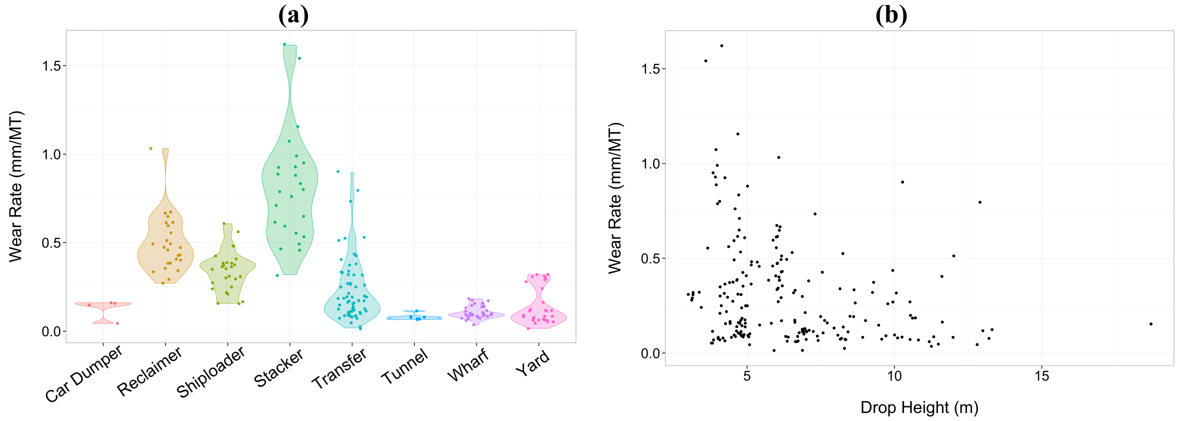

Figure 2 1D throughput wear rate distribution by (a) conveyor duty and (b) drop height.

3.2.2 New Variables

As expected the loading parameter shows positive correlation to throughput terms (fines and lump rates) due to higher material rates increasing the tonnes/m on the belt. This expectation is extended to time based belt wear rates to a lesser extent, indicating potential significance of loading in time based explanatory models. Unexpectedly drop height does not exhibit direct correlation to any wear rate measure, see Figure 2b. Reasons for this include the vertical measurement not accounting for factors affecting the presentation of the material to the belt such as chute design, loading direction and relative impact velocity.

3.2.3 Interaction Terms

Due to the unexpected insignificance of drop height to wear rate estimation, three interaction terms with drop height were introduced into the regression models; lump rate, fines rate and conveyor duty. During model selection none of these interactions were deemed significant when explaining wear rates.

3.4 Predictive Tool Selection

Linear models for all six wear rate measures were developed using the transparent p-value approach. Collinearity between the categorised belt length and conveyor duty results in belt length being immediately excluded from all models. The values of the adjusted coefficient of determination ($\bar{R}^2$) for each wear rate model are shown in Table 2; a perfect explanatory model would have an $\bar{R}^2$ value of one. $\bar{R}^2$ values increase with wear rate dimensions and when using a throughput based measure, indicating the throughput approach provides a better explanation of wear rates for the expanded dataset.

	1D	2D	3D
Time Based	0.751	0.788	0.863
Throughput Based	0.809	0.829	0.941

Table 2 Coefficient of determination ($\bar{R}^2$) for expanded models.

All $\bar{R}^2$ values are below the originally analysed dataset by an average of 2.6% due to the expanded dataset including additional parameters within the original categorical variables. Although the $\bar{R}^2$ reduction impacts the models' goodness of fit, the expansion of explanatory categories provides flexibility in future wear rate prediction.

The 1D throughput model, deemed most useful due to its independence to wear profile distribution information and higher $\bar{R}^2$, is presented in Table 3. By substituting values for an individual belt's parameters and setting all other factors to zero, the wear rate in mm/MT is estimated. Categorical variable estimators are indexed to a baseline within each category, with baseline coefficients accounted for in the intercept estimator. For example; all conveyor duties are indexed to Car Dumper belts, indicating Reclaimer belts have a higher wear rate than Car Dumpers if considered in isolation to all other factors. See Equation 1 for the predicted wear rate calculation of a Yard, 1600mm wide, ST2000 strength, AR grade belt.

Variable	Intercept	Conveyor Duty		Belt Width [mm]		Belt Strength [kN/m]		Belt Grade	
Coefficient Estimate	0.512	Reclaimer	0.418	1500	0.042	ST1250	0.367	AS-A	-0.131
		Shiploader	0.273	1600	-0.391	ST1600	-0.331	AS-M	-0.117
		Stacker	0.772	1800	-0.468	ST1800	-0.062	M+	-0.220
		Transfer	0.221	2000	-0.720	ST2000	0.003		
		Tunnel	-0.044	2200	-0.262	ST2500	0.206		
		Wharf	0.028						
		Yard	0.120						
Residual Standard Error: 0.1287 on 199 degrees of freedom						Adjusted $\bar{R}^2$ = 0.809			

Table 3 1D Throughput multiple linear regression model summary.

$$\frac{\widehat{mm}}{MT} = 0.512 + 0.120_{Yard} - 0.391_{Width1600} - 0.003_{ST2000} + 0_{GradeAR} = 0.238\,\frac{mm}{MT}$$

Equation 1 Sample wear rate prediction for a Yard, 1600mm, ST2000, AR belt.

3.5 Validation of Model

The predicted residual by fitted value of the 1D throughput model, when applied to the cross validation test set, is shown in Figure 3. A bias is seen in high wearing belt predictions indicating the current model may overestimate wear rates for these observations; further investigation may lead to model refinement. However, the overall small relative variation between predicted and actual test values provides evidence for a functioning model, valid for implementation. 95% prediction intervals have been obtained for each current belt observation to facilitate construction of a belt maintenance prediction monitoring tool.

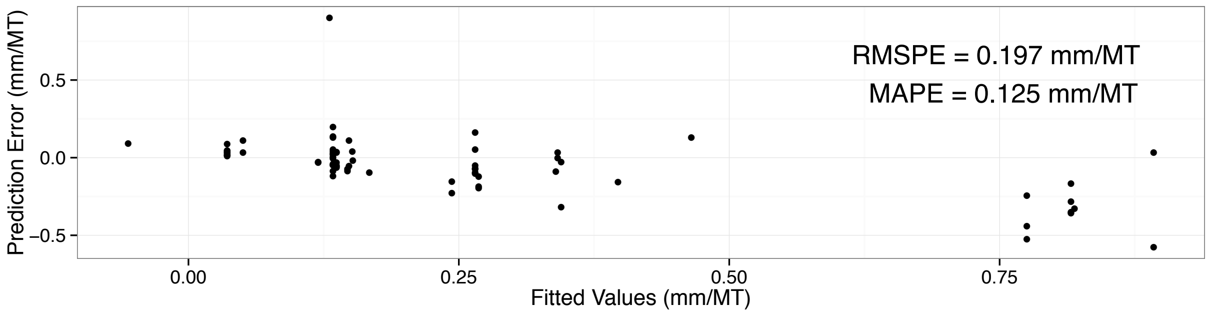

Figure 3 Predicted Errors of the 1D Throughput Model. RMSPE - root mean squared prediction error, MAPE - mean absolute prediction error.

4. Conclusions and Future Work

Using traditional statistical methods this project confirms conclusions by Webb (2013) that throughput linear models better characterise belt wear rates. More robust multiple linear regression models have been obtained by expanding the dataset to 211 belts installed on 98 conveyors. Further analysis has shown material drop height, loading characteristics and selected interaction terms have little effect on wear rate prediction. Finally, the expanded 1D throughput model has undergone successful cross validation using an unseen test dataset of 71 belts to provide prediction intervals for future estimates of belt wear. This outcome forms the basis for tool integration and improved reliability of BHPBIO's conveyor maintenance.

Predictive tool application development, using 95% prediction intervals and future throughput estimates, is currently being undertaken. Loading point parameterisation is still required with vertical drop heights potentially insufficient in fully describing product presentation to the belt. Expansion of the dataset to include a variety of BHPBIO sites will capture new variables such as material size and belt specifications, increasing model robustness. Finally, analysis of wear distribution between multiple thickness measurements over the same time period may present arguments for 2D and 3D wear rate measures to become feasibly implemented.

5. References

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