

Logistic Regression for Early Warning of Economic Failure of Construction Equipment

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Equipment managers perform economic life analyses to define targets of average cost rate and service life useful in managing equipment fleets. The resulting targets are based on collective data, while machines must be managed individually, which is labor intensive and it may not be practical to apply an appropriate level of scrutiny to each machine in large fleets. An early warning system to identify economically troubled machines early in their service life will allow management to focus efforts. Economic success was defined as realized economic life greater than 75 percent of target life. Logistic regression based on cost and use metrics constructed from typical fleet data was used to accurately predict economic success or failure for 378 single axle dump trucks. Models were internally and externally validated to establish a predictive accuracy of approximately 70 percent, which is sufficient to allow managers to confidently focus their managerial efforts on those machines where failure is predicted.

Key Words: Heavy Equipment, Equipment Economics, Economic Life, Equipment Management

Introduction

Fleet managers routinely face a variety of difficult decisions when balancing the cost efficiency of a fleet with the requirements for capacity, safety, and productivity. Inherent into nearly all of these decisions is a consideration of cost and a need for accurate cost data. Economic life is perhaps the paramount consideration of cost efficiency, as it defines management targets for average cost rate and service life, as well as allowing for the development of annual owning and operating cost budgets for individual machines (Vorster 2009).

Typically, economic models of equipment are developed on the basis of cost minimization or profit maximization (Douglas 1975). In the case of heavy equipment, average cost minimization is the traditional model (Terborgh 1949). Existing cost minimization methodologies applied to construction equipment include the cumulative cost model (CCM), period cost based method (PCB), and annual cost method.

Vorster (1980) first proposed the CCM as a graphical representation of machine age versus cumulative cost, which is represented by either the sum of or net present value of all expenses to date. This model has been proven effective when applied to large equipment fleets that have data records for the life of each machine in the study. Hildreth and Williams (2013) applied the CCM to a range of equipment types within a state transportation agency fleet. The CCM is noted to be both stable and representative of similar machines, but also has the noted limitation of scarcity of quality available cumulative or life-to-date (LTD) data (Mitchell et al. 2011).

Mitchell et al. (2011) present the PCB methodology that based on the concept of CCM, but overcomes the data availability limitation by using data collected over a limited period of time. However, the authors note that PCB data tends to be less stable than LTD data and the results may not represent costs normally expected for machines over the data collection age range. Dulin and Hildreth (2013) applied the PCB methodology to a fleet of equipment and determined that it is a practical alternative to the CCM, provided data is collected over a minimum period of one year.

A third alternative for developing economic models is the annual cost method, where costs and use are modeled based on a snapshot in time. Presentation of this methodology applied to equipment fleets can be found in (Kaufmann et al. 2010) and (Kaufmann et al. 2012). Hildreth and Williams (2013) note that the results of the annual cost methodology compared well with those from the CCM, but that variability inherent in annual cost data may mask the increasing nature of operating costs required to estimate economic life.

The CCM relies on complete cost and use data and is the best option for developing economic models of construction equipment. The PCB relies on a snippet of cost and use data, which allows it to be applied to a broader population of equipment and particularly when previously owned machines are purchased. The PCB method is effective when models are carefully developed and applied appropriately. The annual cost method relies on a snapshot of cost and use data, but the likely noisy data results in models that can be difficult to apply.

Regardless of the methodology applied, economic life based on cost minimization remains the paramount analysis for fleet managers. Not only does it establish targets for service life and minimum average cost, but the results can be used to develop annual operating cost budgets and plan for equipment replacement to manage average fleet age.

Background

The North Carolina Department of Transportation (NCDOT) has sponsored three research projects to develop economic models for equipment classes in the fleet. Annual cost and use data were used to develop economic models by equipment class in the first two studies (Kaufmann et al. 2010, Kaufmann et al. 2012). Difficulty in predicting economic life was noted by Kaufmann et al. (2012) for some equipment classes because variability within the annual data masked the increasing nature of operating costs. Annual cost data is inherently noisy because it reflects annual economic performance, which varies from year to year. It was recommended that the cumulative cost model be explored because LTD cost and use data more accurately reflect the phenomena resulting in economic life.

Hildreth and Williams (2013) applied the cumulative cost modeling methodology to four select equipment classes in the third NCDOT study. Machine use, annual operating costs, and purchase price data was collected over the 10 year period from 2003 to 2012 for equipment model years ranging from 2003 to 2008. Cost data was adjusted for inflation using the Consumer Price Index (CPI) to a common basis. Inflation adjusted cumulative costs were then divided by the inflation adjusted purchase price to yield a normalized cumulative cost index (CCI) representing cost as a fraction of purchase price for each machine. Individual machine data was validated to ensure quality and to confirm the applicability of the Mitchell curve used in the cumulative cost methodology to model operating costs. Economic models were developed for each equipment class to include both owning costs and operating costs and used to produce the estimates economic life shown in Table 1.

Table 1

Economic life estimates

Equipment Class			**Economic Life**			
Code	**Description**	**Unit**	**Age (hrs or miles)**	**Owning Rate ($/hr or $/mile)**	**Operating Rate ($/hr or $/mile)**	**Total Rate ($/hr or $/mile)**
0201	5000 GVW pickup trucks	Miles	198,000	$0.09	$0.28	$0.37
0205	33000 GVW single axle dump trucks	Miles	105,000	$0.42	$0.90	$1.32
0314	Rubber tired backhoe loaders	Hours	5,900	$9.59	$19.84	$29.43
0900	Motor graders	Hours	6,000	$18.69	$33.58	$52.27

The resulting economic life estimates establish management targets based on collective data from each equipment class. However, machines must be managed individually with respect to repair/rebuild/replace decisions. For fleets with even a moderately large number of machines, individual machine management is labor intensive and it may not be practical to apply an appropriate level of scrutiny to each machine.

Significant differences in the economic performance of individual machines were noted by Hildreth and Williams (2013). To effectively manage a large fleet where economic performance varies within an equipment class, it would be beneficial to develop an early warning system to identify economically troubled machines early in their service life. Such a system would allow management to focus efforts on those troubled machined needing and deserving of close scrutiny.

The currently collected and maintained data regarding the costs and use of equipment allow for the development of metrics that may be useful in predicting whether an individual machine will realize an economic life similar to the target value. These metrics should reflect the LTD cost performance and use of the machine. To be beneficial to fleet managers, accurate predictions must be available early in the service life so that actions can be taken to avoid unnecessary and undesirable costs. Potential metrics include:

1. Ratio of repair costs to purchase price (R/P) – the LTD repair costs experienced normalized by purchase price to reflect the investment required to keep the machine operational
2. Ratio of repair costs to fuel costs (R/F) - the LTD repair costs experienced divided by LTD fuel costs to reflect use as well as repairs
3. Average annual use (AAU) – the LTD machine age in hours or miles divided by the age in years of the machine to reflect the use of the machine

Logistic Regression

Logistic regression is a mathematical modeling technique appropriate for describing the relationship between one or more independent variables and a dependent variable where the outcome is discrete in nature (Hosmer and Lemeshow 1989). The dichotomous probability of outcomes is measured by 0 or 1, representing failure and success respectively. A logistic regression model estimates the odds of occurrence for an event, which is the ratio of the probability of occurrence to the probability of non-occurrence. The natural logarithm of the odds follows a linear model constructed from the independent variables, as shown in Equation 1 for the instance where there is only one independent variable

$$\mathrm{Ln}\left(\frac{p}{1-p}\right) = C_0 + C_1 X_1 \qquad (1)$$

or

$$p = \frac{1}{1+ e^{-(C_0+C_1X_1)}} \qquad (2)$$

where p is the probability of occurrence, C_0 is a constant, C_1 is a coefficient estimated from the data, and X_1 is the independent variable. In this form, the probability of occurrence ranges from 0 to 1 as the natural logarithm of the odds ranges from $-\infty$ to $+\infty$.

In summary, logistic regression supports estimating the probability of an event with only two possible outcomes (i.e. occurrence or non-occurrence) based on the demonstrated effect of one or more independent variables. Logistic regression has been applied in construction research for predicting contractor failure (Russell and Jaselskis 1992), bid decisions (Lowe and Parvar 2004), contract disputes (Diekmann and Girard 1995) and satisfaction with dispute resolution (Cheung et al. 2010). Within the realm of an early warning system for economic failure of equipment, success is defined as the occurrence of realizing an economic life for a machine that is approximately equal to or greater than the target economic life for machines in the class, and the previously defined cost and use metrics are the independent variables.

Methodology

A fleet of 414 single axle dump trucks model years 2003 to 2008 were used to assess the potential of logistic regression for forecasting economic failure (and/or success) based on available cost and use metrics. LTD cost and age data were developed for individual machines from annual measures. Age data was in miles driven and the cost data used was in terms of total operating cost normalized by purchase price. The CPI was used to adjust all cost values for inflation and to the common economic basis of 2012 dollars. The Mitchell curve, a second order polynomial model of LTD normalized cost based LTD machine age, was developed for each machine in the form shown in Equation 3,

$$Y = A\,\mathrm{x}^2 + B\,x \qquad (3)$$

where Y is the LTD operating cost, A and B are coefficients estimated from the data, and x is machine age. As described in Hildreth and Williams (2013), data from 378 machines showed operating costs incurred at an increasing rate, as indicated by an A coefficient greater than zero. When cost data has been normalized by the purchase price, economic life is inversely proportional to the square root of the A coefficient (Mitchell et al. 2011). Considering a residual value of 20 percent of the purchase price, economic life can be estimated by Equation 4,

$$L^* = \sqrt{\frac{0.8}{A}} \tag{4}$$

where L^* is the age at economic life. Economic life was estimated for each of the 378 machines where A was greater than zero and used to categorize each machine as an economic success or failure. Economic success was defined as when economic life was greater than or equal to 75 percent of the target economic life for the equipment class. For the dump trucks, target economic life was 102,500 miles and the success threshold was 76,874 miles.

The R/P, R/F, AAU metrics were calculated through interpolation of the annual data for a machine age of 40,000 miles or approximately 40 percent of the target life. This machine age was selected to provide a balance of cost and use experienced by the machine with an age early enough for potential action to be taken to mitigate a high probability of economic failure. A total of 319 machines had reached an age of 40,000 miles, while 59 machines had not yet aged to 40,000 miles and could not be used in the analysis.

This set of 319 machines were randomly split to provide a dataset for model development and a separate dataset for model validation. Seventy percent, or 223 machines, were used for model development and 30 percent, or 96 machines, were used for validation. A separate model was developed and validated for each metric, and models based on the combined effects of metrics were not considered. Each model developed was assessed based on the statistical significance of the independent variable, the significance of the full model with respect to the null model (model with no independent variables), and the prediction accuracy within the development dataset. The Wald statistic was used to test the significance of the independent variable at the 95 percent confidence level (□ = 0.05). The log-likelihood statistic was used test the significance of the full model at the same confidence level.

The prediction accuracy was assessed at the cutoff value that provided the greatest accuracy. The cutoff value is the probability that delineates between predicted success and failure. Predicted probabilities of success greater than or equal to the cutoff are designated a success and predicted probabilities below the cutoff are designated as failure. The area under the receiver operating characteristics (ROC) curve is a measure of model discrimination, or the ability to correctly classify, and was used to assess predictive power.

The performance of predictive models is overvalued when it is measured only against the data used to develop the models (Steyerberg et al. 2001). The performance can be validated by assessing model accuracy using a dataset external to the model development dataset. External validation was performed by applying the developed model to the validation dataset and assessing the resulting predictive accuracy. Where the predictive accuracy achieved through external validation is similar to that found from the development dataset, the models can be considered valid in terms of prediction.

Results

Model development revealed that each metric (independent variable) was statistically significant and the resulting models were both significant and substantially accurate. The coefficients resulting from model development were all well below the 0.05 threshold value for significance and are shown in Table 2.

Table 2

Coefficients of logistic regression

	Constant Coefficient				Independent Variable Coefficient			
Metric	**b_0**	**S.E.**	**Wald**	**p-value**	**b_1**	**S.E.**	**Wald**	**p-value**
R/P	3.10	0.42	53.81	2.21E-13	-13.02	2.08	39.03	4.17E-10
R/F	2.80	0.40	47.80	4.71E-12	-3.81	0.67	32.72	10.7E-08
AAU	-2.45	0.59	17.40	3.03E-05	0.33	0.06	27.61	1.48E-07

The logistic regression model developed for the R/P metric was the most statistically significant with a p-value three to four orders of magnitude less than the other models, as shown in Table 3. The R/P model also had the greatest total accuracy largely due to ability to accurately predict economic success, although the total accuracy was similar to that from the R/F model. The AAU model had the least total accuracy at 72 percent. The R/F model provided the best balance of accurate predictions of both economic successes and failures.

Table 3

Significance and accuracy of logistic regression models

Metric	**Chi-Sq**	**Model p-value**	**Cutoff**	**Prediction Accuracy Success**	**Failure**	**Total**	**Area under ROC Curve**
R/P	58.23	2.33E-14	0.55	89%	53%	77%	79%
R/F	45.82	1.29E-11	0.60	85%	59%	76%	78%
AAU	38.35	5.92E-10	0.55	81%	54%	72%	74%

The cutoff values shown in Table 3 are the values that were used to delineate success and failure. In applying the models, success was predicted when the probability of economic success was greater than the cutoff, and vice versa. The cutoff value is also used to determine the threshold metric value, against which machine performance can be measured. The logistic model developed for the R/F metric is shown in Figure 1. From the figure, the R/F value corresponding to the 60 percent cutoff value is 0.63.

This R/F metric threshold can be directly applied to individual single axle dump trucks in this fleet. If the total repair costs are more than 63 percent of the total fuel costs when the truck reaches 40,000 miles, then it is predicted that the truck will not realize at least 75 percent of the target economic life. Similarly, it was found that economic success was likely when the total repair costs were no more than 22 percent of the purchase price, or when the truck averages more than 8,140 miles per year in operation.

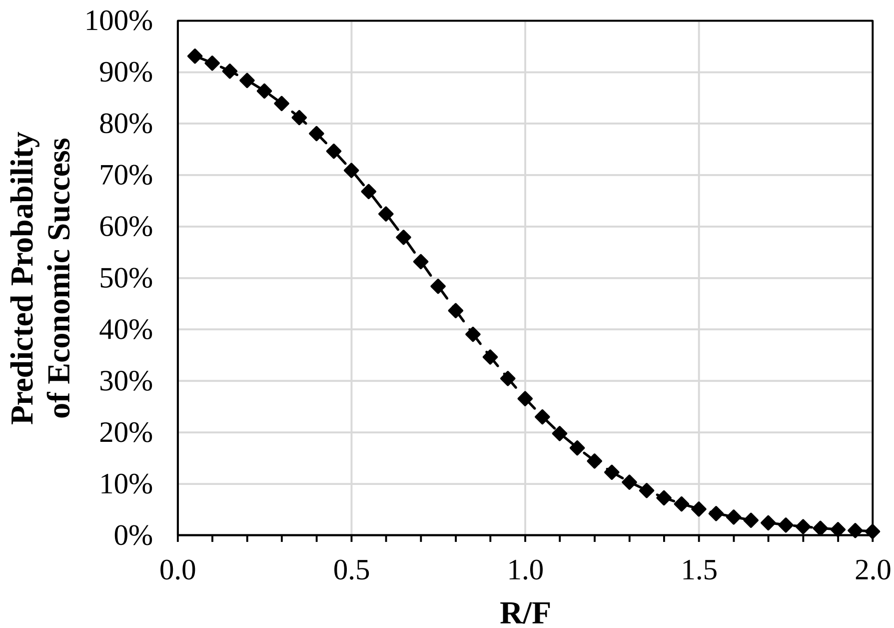

Figure 1: Logistic regression model of economic success based on R/F metric

The ROC curves for the developed models are shown in Figure 2. The diagonal represents a model with no ability to discriminate between successes and failures, which is equivalent to flipping a coin. The area under this diagonal is 0.5, and the ROC curve for an ideal or perfect model would follow the left and top edges and have an area under the curve of 1. Models where the area under the ROC curve is at least 0.7 are considered "fair" and an area of 0.8 is "good". Each of the developed models had a "fair" level of discrimination based on the area under the respective curves. However, both the R/P and R/F models were near the "good" level.

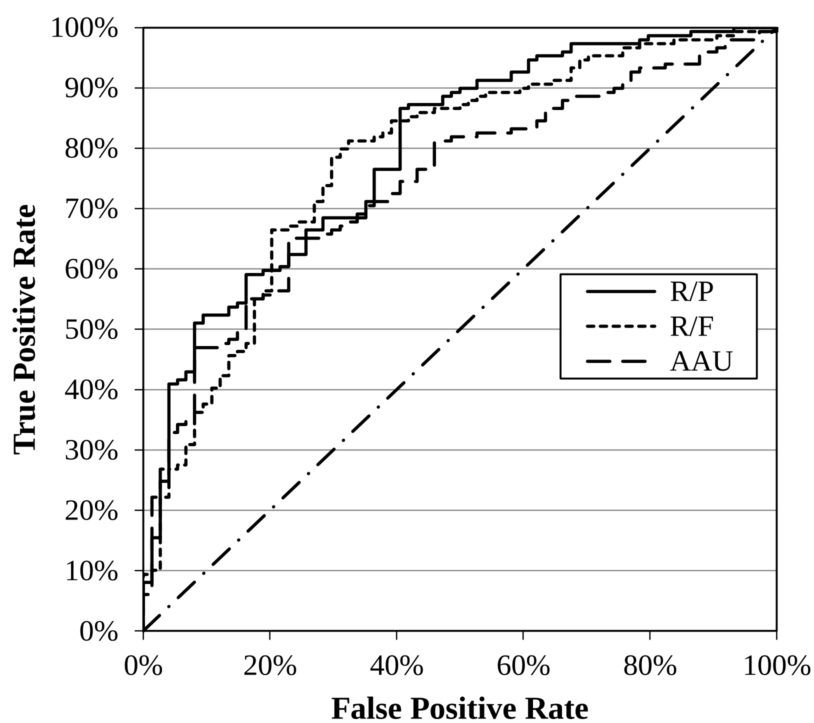

Figure 2: ROC curves for logistic regression models

At the previously established cutoff values, the validation results showed that the models were able to predict success or failure at accuracy rates near or above 70 percent. This is considered quite good for models developed from field data rather than from carefully designed and controlled experimentation. The model validation results are provided in Table 4. The total accuracy rates for each of the models was approximately equal to that found during model development. The area under the ROC curve was also similar for each model, with the values from validation slightly less for each model. These results indicate that the models can be used to not only provide reasonably accurate predictions of economic success, but also to discriminate between success and failure at a machine age of 40,000 miles, or approximately 40 percent of the target life.

Table 4

Model validation results

	Prediction Accuracy			
Metric	**Success**	**Failure**	**Total**	**Area under ROC Curve**
R/P	84%	51%	72%	79%
R/F	89%	37%	70%	76%
AAU	75%	46%	65%	70%

Conclusion

Logistic regression based on cost and use metrics is a viable method of accurately predicting economic success or failure early in the life of a machine. The proposed metrics, R/F, R/P, and AAU, are readily available from the data currently maintained as part of a fleet management program. While the model developed from the AAU data was acceptable, the models based on R/F and R/P were found to have greater predictive accuracy and to be better at discriminating between success and failure.

For the fleet of single axle dump trucks analyzed, economic success or failure was accurately predicted for greater than 70 percent of the machines. External validation confirmed this level of predictive accuracy. This level of accuracy would allow fleet managers to confidently focus their managerial efforts on those machines where failure is predicted. The cutoff limit determined through the analysis provides a single metric and value against which individual machines can be quickly and easily be assessed. The question of what, if any, remedial action should be taken remains and cannot be answered through a predictive model. Rather, a root cause analysis should be performed to determine the cause and evaluate corrective actions when failure is predicted.

It should be noted that this work focused on a single class of equipment at a single age, single axle dump trucks at age 40,000 miles. Future work should extend this to younger ages to determine if adequate models can be developed even earlier in machine life, and to older ages to determine the effect of age on the predictive performance. Additionally, the methodology presented should be extended to other classes of equipment to evaluate the potential for application across a fleet of equipment.

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