PREDICTING THE RESIDUAL VALUE OF HEAVY CONSTRUCTION EQUIPMENT

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ABSTRACT

Heavy construction equipment is routinely used on construction projects that entail earthmoving operations. Owning and operating these machines may comprise a significant portion of the project costs. An important element of the owning costs is the residual value. However, the nature of the residual value of construction equipment is largely unknown.

Ongoing research at Virginia Tech examines the residual value of different types of construction equipment to provide a better approach than the rules of thumb currently used by equipment managers. This paper argues that the residual value can be predicted accurately based on publicly accessible data from equipment auctions and publications by manufacturers and their distributors. Related research in agriculture and forestry is reviewed. Data collection and preparation and results from the multi-linear regression analysis are described. Statistical measures of the goodness-of-fit for different possible functional forms of the regression model are given and a sample calculation is presented.
1 INTRODUCTION

Earthmoving operations requiring heavy construction equipment are found predominantly in the heavy and highway segment of the construction industry, but large construction equipment may also be utilized in other areas, depending on the requirements of the particular construction project. The more the construction project is dominated by earthmoving operations, the higher will be the share of equipment costs among the total project expenses. Cost analysis of employing construction equipment is at the core of the business function for the owner of such equipment and is vital for the success of the enterprise.

Focusing on individual machines rather than on an entire fleet, the costs associated with a unit of equipment are commonly broken down into the two categories of owning and operating costs. Individual cost elements as depicted in Figure 1 are assigned to one of the categories owning costs and operating costs. Owning costs are incurred simply by having ownership of a unit of equipment while operating costs are only incurred when it is actually utilized on an earthmoving job. Thus, operating costs depend on the hours of use.

Owning costs consist of the initial purchase price plus any associated sales and setup fees minus the residual value that is recovered at the end of the owning period. Other owning cost elements are loan interest and principal payments from financing the investment, if applicable, as well as insurance premiums and property taxes (Cross and Perry 1996). Operating costs include consumables such as fuel, oil, and grease, ground engaging tools or replaceable parts thereof, maintenance and repair costs, as well as “tire [or track] replacement, wages, and fringe benefits” for the equipment operator (Tsimberdonis 1993, p54).

Equipment managers, who are charged with cost analysis for machines under their supervision, need to keep track of these elements and examine them carefully. The depth of knowledge about individual elements, however, is not equal. Among the owning cost elements the purchase price and related fees are known by the owner with certainty, loan interest and principal payments can be calculated easily, and insurance premiums and property tax liabilities may be forecasted from their annual percentage rates (Cross and Perry 1996, Caterpillar 2001). The residual value occurs at the end of the owning period and is the most uncertain among these cost elements. Perry and Glyer (1990, p524) stated that even with “the importance and the amount of research conducted on depreciation, no clear consensus exists about the depreciation patterns followed by different types of capital goods.” Estimates of the residual value are essential for making investment decisions, as emphasized by various authors (Reid and Bradford 1983, Perry et al. 1983, Cross and Perry 1995). “The salvage or residual value of a piece of equipment, whether at the end of its useful life or at some age before, will affect cash flows, rates of depreciation, maintenance and repair decisions, and new and used machine purchase decisions” (Cubbage et al. 1991, p16).

This paper discusses whether the residual value of construction equipment can be predicted to satisfactory accuracy based on publicly available data about construction equipment sales at auctions. A clear and easy-to-follow methodology is developed to enable equipment managers to better predict residual value. Statistical measures are presented to assess what degree of accuracy can be achieved using this approach.
2 RESIDUAL VALUE

Residual value is defined as the price for which a piece of used equipment could be sold in the market at a particular time. Terminology that is used to describe this concept varies widely in the literature. Among the similar terms are resale value, remaining value, recovery value, salvage value, scrap value, terminal value, trade-in value, and fair market value. For the sake of clarity, the introductory definition of residual value shall be used throughout this paper.

Additional confusion is added when the term depreciation, meaning a lessening of the initial economic value, is used. Such value loss generates the residual value of the equipment. Depreciation can be related to the equipment itself (physical condition, age, deterioration or obsolescence) or to the economic situation (supply and demand for the equipment or its product) in which the value is assessed (Perry et al. 1990). This is different from the use of depreciation in the accounting context, where it refers to the process of determining the book value of an asset for administrative and taxation purposes by regularly charging expenses to the initial capital investment. The process of depreciation and its causes are outside the scope of this discussion.

2.1 Current Assumptions

In many owning and operating cost examples it is assumed that the residual value (usually abbreviated $RV$, $SV$, or $S$ for salvage value) is expressed as a dollar amount (Sears and Clough 1981) or as a fixed percentage of the purchase price (Corps of Engineers 2001). In examples provided by leading manufacturers (Caterpillar 2001, Deere 2002) the residual values are assumed to be derived from the experience of the equipment owner. Owner or distributor records, records from equipment auctions, and “comparing the current used machine value to the current new machine value” (Caterpillar 2001, p20-11) are mentioned as sources of information.

In other studies the residual value has even been set to 0%, notwithstanding that even a completely dysfunctional piece of equipment will have a minimum value as scrap metal.

Conversations with construction equipment managers have indicated that rules of thumb are often used that relate a (usually even) residual value percent to a particular age in years or cumulative hours of use. Such approaches necessarily suffer from simplification, as equipment type, manufacturer, condition, or any other parameters are hardly, if ever, considered. Rules of thumb only represent a few isolated points of residual value percent over time and do not offer the predictive capabilities exhibited by a mathematical function for the relationship.

Despite the apparent importance of heavy equipment for the construction industry, a comprehensive study of its residual value to date has not been carried out. Studies in other industries have dealt specifically with the determination of the residual value of their equipment. The following sections briefly describe studies in agriculture and forestry. These approaches provide valuable information for conducting research on the residual value of construction equipment.

2.2 Agricultural Equipment

A considerable amount of work has been conducted on the residual value of agricultural equipment. Reid and Bradford (1983), who studied optimal replacement of farm tractors,
reviewed previous research and found that those models had only included age as an explanatory variable. They additionally included horse power (HP) and average net farm income. Furthermore, two binary variables were used to code three different manufacturers and two binary variables captured time periods assumed to display different technological change. Data for fitting the model coefficients were obtained from reports published by a distributor association (Reid and Bradford 1983).

Cross and Perry (1995 and 1996) analyzed monthly reports of auction sales prices for the period of 1984 to 1993. Their dataset contained manufacturer and model, year of manufacture, hours of use, condition, size (three groups by HP, for tractors only), special options, and auction type and location for each transaction (Cross and Perry 1995). Age in years and hours of use were highly correlated. Condition had not been reported in all cases. Binary variables were used to model the manufacturer, condition, auction type, special options, and nine geographic regions within the U.S. Several macroeconomic measures were included to consider “the state of the agricultural economy” (Cross and Perry 1995, p196). The published list price was used as a substitute for the actual purchase price. Both list price and auction sales price were inflation-adjusted to a common year using the Producer Price Index (PPI).

Cross and Perry (1985) assumed were that the residual value would decrease with higher age or hours and with lower condition. The importance of age as a central factor determining the residual value of the equipment was underlined. A statistical analysis using a flexible functional form was carried out and a double square root function (of residual value percent and age) was selected as the best model. The researchers found statistically significant differences among different equipment types and found influences of the manufacturer, age, hours of use, and condition. In similar studies of a smaller scale, researchers have focused on farm tractors, e.g. Perry, Bayaner, and Nixon (1990), who examined data of auction sales for a three-year period. Possible interactions between HP (as a numerical variable) and age or hours of use and between manufacturer and age or hours of use were considered in this study.

Examining farm tractors and combines, Unterschultz and Mumey (1996) used reported distributor sales prices from 1972 to 1992 to develop their model. Reconditioning costs and a fixed markup percentage were deducted to generate comparable prices. The Consumer Price Index (CPI) was used for inflation adjustment. List prices were not used as they “are not observed transaction prices and confound depreciation estimates with the manufacturer’s marketing methods” (Unterschultz and Mumey 1996, p298). Data were separated into cohorts by manufacturer, model series, and year of manufacture. Three binary variables modeled the year of observation, age (in half-year increments), and equipment model. Introduction of a new equipment model within a series was assumed to signify technological change. A time-series analysis was performed for each cohort and a geometric annual value loss was found in most cases. Seasonal differences and differences between the value loss rates depending on manufacturer and model within a series were identified.

The American Society of Agricultural Engineers (ASAE) publishes Agricultural Machinery Management Data as ASAE D497.4 JAN98 (ASAE 1998). In this standard an equation for residual value percent and coefficients for 12 different types of equipment is provided, among them three sizes of farm tractors. Residual value is defined as current value over list price. Perry, Bayaner, and Nixon (1990) have discussed shortcomings of the ASAE approach, including that the original data were from 1965 (updated 1971), and that distributor sales prices were used. These did not include hours of use or condition, may have included
unknown financing arrangements, and assumed a fixed value loss rate, reconditioning cost, and percent markup.

2.3 Forestry Equipment

Residual values of logging equipment have also been examined. Cubbage et al. (1991) reviewed traditional rules of thumb, which “range from 15 to 25 percent of the original sales value of the machine... at the end of its assumed useful life span, generally 3 to 6 years depending on the type of equipment” (Cubbage et al. 1991, p16). However, none of these values were based on actual sales data. Data were collected from annual auction reports and an auction firm publication. They included the auction price, manufacturer and model, age (up to 10 years), condition, special options, and auction region. Adjustments for non-standard options (e.g. attachments) were made to the list price (or to the auction price for upgrades) using an average value for the respective option. Residual value percent was created by dividing auction price by list price. Equipment condition was coded numerically from 1 = poor to 5 = excellent and not with binary variables. It was found that the residual value percent could best be modeled using the inverse of the square root of age. Differences between geographic regions were not significant. The authors expressed the need to keep residual value analyses updated (Cubbage et al. 1991).

3 DATA COLLECTION AND PREPARATION

The following sections describe the types of data that were considered for performing a study of the residual value of used heavy construction equipment. Their sources and necessary preparations for a statistical analysis are included.

3.1 Auction Sales Records

Researchers investigating the residual value of machinery have generally agreed that clear “evidences of value” (Cowles and Elfar 1978, p141) should be used as data, in particular actual sales data (Koger and Dubois 1999). Using auction sales prices has been viewed as being superior to distributor sales prices, since the latter may contain distortions from marketing promotions, as well as from “the value of warranties, financing options, and trade-ins” (Perry et al. 1990, p318). Moreover, distributor information may be proprietary and thus difficult to obtain (Cross and Perry 1995).

Two data sources for auction records have been identified, as listed in Table 1. The Last Bid™ and Top Bid both offer online subscriptions to compilations of construction equipment auctions in the North American market and several other countries. Datasets available from Last Bid™ and Top Bid include manufacturer name, model number, serial number, year of manufacture, condition rating, auction firm, auction location, date, and price, and a brief description of special options, attachments, or other information. Meter hours or mileage of the equipment is not reported.

In order to acquire a sufficiently large number of data and produce results that are meaningful for equipment professionals in the construction industry at large, common types of
equipment and principal manufacturers of construction equipment in the U.S. and Canada were chosen. The equipment types to be considered are track and wheel excavators, wheel and track loaders, loader backhoes, integrated toolcarriers, rigid-frame and articulated trucks, track dozers, motor graders, and wheel-tractor scrapers. Specialty equipment was not included. Manufacturers selected were Caterpillar, Inc., Deere & Company, Komatsu America International Company, and Volvo Construction Equipment North America, Inc. Data on equipment between 1 and 15 years of age at the time of sale were considered. These dimensions defined the scope of the dataset.

After the data had been obtained electronically, it was necessary to review them to ensure uniformity and eliminate obvious errors. Missing entries could be filled by comparing data from the two data sources via the serial number and by using surrounding entries. Since the sales prices were obtained from auctions and not from distributors, it was not necessary to apply any corrections for markup or similar items. No adjustments were made for special options, e.g. non-standard attachments, or for expenses such as engine or undercarriage reconditioning, as descriptions for each transaction were too brief to determine consistent adjustment values.

Additional data columns were created. Equipment age in years is the difference between the auction date and the year of manufacture. The particular U.S. state or Canadian province or territory was extracted from the auction location to form binary variables for five geographic regions, one of them Canada. Condition rating was also transformed from a verbal into numerical variables. Auction prices were inflation-corrected to a common year using the PPI.

3.2 Equipment Parameters and List Prices

The data were grouped into equipment categories using equipment type and size. Size can be measured by performance parameters such as horse power, standard operating weight, or bucket volume, if applicable. Suitable parameters were selected and data for all affected equipment types were obtained from manufacturers’ performance handbooks, specification sheets, and product line documents. Additional information was obtained from the online version of the Green Guide™ handbooks. If no information could be found for a model listed in the auction records, the data were removed from the database. The overall dataset contains 28 individual equipment categories.

Price lists provided by equipment manufacturers and their distributors were the sources for Manufacturer Suggested Retail Prices (MSRP), also called list prices. If information for a particular year of manufacture was not available, the data were also removed. List prices were used to compensate for the fact that actual purchase prices are often based on proprietary manufacturer discount structures. Cross and Perry (1995, p195) describe that “Fenton and Fairbanks [1954] were the first to use the Remaining Value (RV) concept, i.e., to divide current market price by initial purchase price and then average these values across several different kinds of equipment. Subsequent work has used manufacturer’s list price as a proxy for sale price.” List prices were inflation-corrected in the same manner as the auction prices. Dividing the auction price by the MSRP generated the residual value percent.

Box plots of the residual value percent over age in years are shown in Figure 2 for the data from track-type tractors between 100 and 200 HP. The boxes extend between the first and the third quartiles of the respective data columns and contain the median values. Whiskers denote the range outside of which data points are considered outliers. All residual value
percentages are directly comparable with each other because of the normalization and the inflation correction.

4 DATA ANALYSIS

Using forward and stepwise selection of explanatory variables it was determined that equipment age indeed is the most important factor for the response variable, residual value percent. Based on the hypothesis that increasing age should decrease the residual value, several different functional forms were examined in a multi-linear regression analysis. These include first, second, and third-order polynomial models, exponential, and logarithmic models. The binary variables for manufacturer, condition, and region were present in all regression models.

Determining whether a satisfactory statistical model has been developed depends on the level of predictive power that the user deems acceptable. Different statistical parameters can be used to assess the quality of a statistical model. The coefficient of determination $R^2$ gives an indication of how much predictive power can be expected from the regression model versus how much of the variability in the residual value will remain unexplained due to unknown or random error sources. The adjusted coefficient of determination $R^2_{adj}$ is corrected for the effect of different sample sizes and is not affected by including superfluous factors in the regression model, which would increase the $R^2$. Values of 0.7 shall be considered satisfactory. The root mean squared error describes the average difference between the estimated value from the fitted regression model and the observed value. It shall be considered satisfactory when it is smaller than 0.1.

A multi-linear regression analysis was performed to determine these statistics. Among the regression models examined, four fulfilled the criterion for the coefficients of determination and one fulfilled it for the $R^2$. Actual ranges of $R^2$ across the 28 categories are provided in Table 2. All models yielded root mean squared errors lower than 0.1. In summary, several different functional forms are possible for modeling the residual value of heavy construction equipment yielding high coefficients of determination.

These results are promising for further analysis that will focus on selecting an optimum functional form for the different equipment categories. At the same time, macroeconomic indicators will be considered in the analysis for identifying statistically significant economic factors that impact the residual value of heavy construction equipment. These variables have been excluded in this examination of the viability of statistically modeling the residual value. Adding them to a regression model can improve the predictive power of the model and in turn would yield higher values for $R^2$ and $R^2_{adj}$.

5 PREDICTION EXAMPLE

An example shall illustrate the prediction that can be made based on regression analysis of the dataset. Again using track-type tractors between 100 and 200 HP, the optimum functional form is selected by the highest $R^2$ value, in this case 0.7911 for the third-order polynomial model 7. Its regression equation with numerical coefficients is as follows.
\[
\text{Percent RV} = 0.74157 - 0.00034 \cdot \text{age}^3 + 0.01091 \cdot \text{age}^2 - 0.12384 \cdot \text{age} + 0.00000 \cdot M_1 - 0.11302 \cdot M_2 - 0.02577 \cdot M_3 + 0.04703 \cdot C_1 - 0.02349 \cdot C_2 + 0.01950 \cdot C_3 + 0.03719 \cdot R_1 + 0.02444 \cdot R_2 + 0.02567 \cdot R_3.
\]

Equation 1

In Equation 1 \textit{age} is the age in calendar years, \(M_1\) to \(M_3\) are binary variables for the manufacturer, \(C_1\) to \(C_3\) are binary variables for the condition rating, and \(R_1\) to \(R_3\) are binary variables for the geographical region. Assuming the tractor with unknown residual value to be from Caterpillar and having an age of 7 years (Caterpillar 2001, p20-31) gives the binary variables \(M_1 = M_2 = 0\) and \(M_3 = 1\). Further assuming the tractor to be in very good condition yields \(C_1 = 1\) and \(C_2 = C_3 = 0\) and assuming the tractor to be sold in the northeastern region of the U.S. gives \(R_1 = R_2 = 0\) and \(R_3 = 1\). Thus, the predicted residual value percent turns out to be 0.3396 or 33.96% of the original list price. As with every statistical prediction, variability around this predicted mean can be expressed as a prediction interval for a certain level of confidence.

6 CONCLUSION

Residual value is a key uncertainty in determining the owning costs of equipment. Studies in forestry and agriculture have addressed the topic, but to date the residual value of construction equipment has not been examined to any level of detail. Instead, reliance in this area has largely been placed on traditional rules of thumb. Current research at Virginia Tech is focusing on developing a better understanding of the residual value for selected groups of main line construction equipment. Results from this research will assist construction equipment managers in making more accurate predictions of the residual value.

It has been shown in this paper that it is in fact possible to predict the residual value of construction equipment to a satisfactory degree based on available data from auctions reports. The straightforward methodology for collecting, preparing, and analyzing data has been presented. Input values were manufacturer, condition rating, geographic region, and age in calendar years. Regression models examined included polynomial models of different orders, exponential, and logarithmic models. The average coefficient of determination \(R^2\) achieved across all equipment size and type categories fell between 0.5856 and 0.7318, depending on the particular regression model used. Individual \(R^2\) values as high as 0.9139 were achieved. Including macroeconomic indicators can improve such regression models. An example of a prediction model equation was presented.

Confirming the feasibility of residual value prediction for construction equipment has laid the groundwork for further research. Future results will provide insights as to the influence of the overall economic situation. Macroeconomic indicators will be tested for their significance in regression models. It is also planned to develop a spreadsheet tool that allows performing the prediction in an interactive and intuitive manner.
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REFERENCES

AUTHOR BIOGRAPHIES

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Figure 1: Owning and Operating Cost Elements

Cost Analysis of Construction Equipment

Owning Cost Elements
- Purchase Price
- Sales and Setup Fees
- Loan Interest and Principal
- Insurance Premiums
- Property Taxes
  - less
- Residual Value

Operating Cost Elements
- Fuel, Oil, Grease
- Maintenance and Repair
- Ground Engaging Tools
- Tires and Tracks
- Wages and Benefits

Figure 1: Owning and Operating Cost Elements
Figure 2: Box Plot of Residual Value Percent over Age in Years for Track-Type Tractors (100-200 HP)
<table>
<thead>
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<th>Data Type</th>
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Table 2: Goodness-of-Fit Statistics for Different Mathematical Models

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<th>Number</th>
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<th>Minimum R^2 for 28 Categories</th>
<th>Average R^2 for 28 Categories</th>
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