MULTIPLE LINEAR REGRESSION APPROACH FOR PRODUCTIVITY ESTIMATION OF BULLDOZERS

Abbas Rashidi[1], Hoda Rashidi Nejad[2], Amir H. Behzadan[3]

[1] Lecturer, Department of Civil Engineering, Islamic Azad University, Semnan, Iran
E-mail: a.rashidi@semnaniau.ac.ir
[2] Graduate Student, Department of statistics, University of Isfahan, Isfahan, Iran
[3] Assistant Professor, Department of Construction Management and Civil Engineering Technology, New York City College of Technology, The City University of New York, NY, USA
Email: abehzadan@citytech.cuny.edu

ABSTRACT: Productivity measurement of construction machinery is a significant issue faced by many contractors especially those involved in earthwork projects. Traditionally, equipment production rate has been estimated using data available in manufacturers' catalogues, results of previous construction projects, or personal experience and assessments of the site personnel. Actual production rates obtained after the completion of a project demonstrate the fact that most of these methods fail to provide accurate results and as a direct consequence, may lead to unrealistic project cost estimations prepared by the contractors. What makes this more critical is that in most cases, inadequate cost estimations lead the entire project to exceed the initial budget or fall behind the schedule. In this paper, a linear regression method to estimate bulldozer productivity is introduced. This method has been developed using SPSS-16 software package. The presented method is used to estimate the productivity of Komatsu D-155A1 series which is commonly used in many earthmoving operations in Iran. The data required for the numerical analysis has been collected from actual site observation and productivity measurement of 60 pieces of D-155A1 series currently being used in several earthmoving projects in Iran. Comparative analysis of the output data of the presented regression method and the existing productivity tables provided by the manufacturer shows that when compared to the actual productivity data collected on the jobsite, a significant increase in accuracy and a remarkable reduction of data variance can be achieved by using the presented regression method.

Keywords: Construction Equipment; Productivity Estimation; Bulldozer; Multiple Regression Model.

1. INTRODUCTION

Productivity estimation of construction equipment is a critical step in scheduling and budget planning of earthwork projects. Traditionally, there have been two major approaches to estimate construction machinery production rates prior to the start of the actual operations. One method uses data from previous projects and the personal experience of the involved site personnel (e.g. operators, engineers) whereas the other takes advantage of the tables and information included in manufacturers' instruction manuals and performance charts. It is also a common practice for major construction firms to produce their own production rate tables and diagrams based on actual site data which can be used to estimate equipment productivity rates for future projects. The data presented this way are usually based on ideal site and equipment conditions and as a result, several coefficients and correction factors must be applied to obtain equipment production rates in each case while including parameters such as the environmental conditions of the project, operator's experience, and the efficiency of jobsite management [1, 2].
Previous studies conducted on various earthwork projects in Iran as well as other countries indicate that there is a relatively significant difference between the estimated equipment production rates calculated prior to the beginning of the project and the actual data obtained during the operation [3, 4]. If not properly taken into account, this will eventually have a major impact on how accurate and reliable project planning and time and cost management is achieved in a typical earthwork operation. In recent years, earthwork contractors have concentrated more on the deterministic approaches that enable them to estimate equipment productivity with satisfactory degree of accuracy under different operational conditions.
Moreover, a number of computational models have been developed by several researchers to determine the productivity in construction projects including earthwork operations. Smith proposed the concept of a linear regression technique for productivity estimation of earthmoving operations [5, 6]. Chao and Skibniewski developed a neural network based approach for construction productivity estimation [7] and Tam et al. applied artificial neural networks model for predicting excavator production rate [8]. Although the application of intelligent models such as artificial neural networks and fuzzy expert systems in various civil engineering disciplines has been recently discussed by several researchers [7, 8, 9], the authors pursued a linear regression technique for productivity estimation of bulldozers in construction projects in Iran mainly due to the following reasons:

- Intelligent models such as artificial neural network systems require a large amount of empirical data for validation and assessment.
- Due to reasons such as site topography, project complexity, and human errors, measuring actual jobsite data in many projects is usually a very difficult and time consuming if not an impossible task. Since linear regression based methods require less site date collection, they prove to be more effective under harsh jobsite conditions such as earthmoving operations.
- Site engineers in many construction projects (including those in Iran) seem to be more familiar with the concept of regression analysis due to the fact that most of the required mathematical background is taught in colleges and universities nationwide as a standard component of the curriculum.

As a result, a linear regression approach for productivity estimation of Komatsu D-155 A1 series bulldozer (commonly used in earthmoving projects in Iran) is presented in this paper. The term "productivity" in the context of this paper refers to the volume of loose soil excavated by a bulldozer per hour

2. INTRODUCTION TO THE D155-A1 KOMATSU BULLDOZER

Komatsu D-155 A1 series bulldozer is considered as one of the most commonly used earthwork equipment in Iran especially for excavating and short range dozing operations since:

- It provides enough engine power required to perform earthmoving operations under various topographical conditions and given different soil properties in Iran.
- It has a reasonable price in Iranian construction market compared to other similar models such as Caterpillar D8 series bulldozers.
- The Iranian construction market provides easy access to spare parts, service, and maintenance of this model.
- Most equipment operators are more familiar with operating and performing basic maintenance on this model.

In Table 1, average hourly cost for Komatsu D-155 A1 series is compared with other commonly used construction resources in Iran. The fact that the D-155 A1 series costs significantly more compared to other resources shows the importance of conducting accurate production rate estimation during the project budget planning phase for this piece of equipment in a typical construction project.

Table 1. Average cost of construction resources in Iran

Type of Resource	Approximate Cost ($/Hour)*
Bulldozer D-155 A1	34-38
Loader W-120	15-18
Truck (6 m^3)	5-6
Site Engineer	4-8
Unskilled Labor	1.5-2.5

* Based on a survey conducted by authors (October 2008, Tehran, Iran)

3. COLLECTION OF SITE DATA

The first step in developing a regression model is to collect actual jobsite data. In order to achieve the best results, a number of field experts were consulted and a list of all factors affecting the productivity of a bulldozer was created. Consequently, actual production rates of 60 bulldozers operating in 38 active construction sites in Iran were observed and measured over a one year period. The following assumptions were made when evaluating actual equipment production rates:

- In order to provide uniformity in data collection, only one construction expert who was completely familiar with earthwork operations was asked to measure qualitative data (e.g. operator's level of skill, site management conditions) for all 60 pieces of equipment.
- Earthwork projects were selected by taking into account various geographical and climatic conditions with the aim of including factors such as topography and weather conditions into calculations.

In this research, a bulldozer's actual production rate is determined by dividing the total volume of soil loaded in trucks by the total operational hours per work day. Total volume of loaded soil can be calculated by adding up the bucket capacities of all loaded trucks used in the operations. Table 2 lists 18 different parameters that contribute to the equipment production rate together with actual site data collected for a sample bulldozer.

Table 2. Factors influencing production and data collected for a sample bulldozer

NO.	FACTOR	STATUS	SAMPLE
1	Total service life time (hours)	0 – 150,000	100,000
2	Service and maintenance condition	Good/Average/Rather poor/Poor	Good
3	Type of blade	Straight tilt dozer/U-tilt dozer/Semi U-tilt dozer/Angle dozer	U-tilt
4	Maximum blade capacity (m^3)	4.8/6.8/8.8/11.8	8.8
5	Blade sharpness	Good/Average/Rather poor/Poor	Average
6	Ripper used?	Yes/No	Yes
7	Time between gear shifting (seconds)	Less than 5/Between 5~10/More than 10	Less than 5
8	Operator's skill	Good/Average/Rather poor/Poor	Good
9	Overall operator's condition during the operation	Good/Average/Rather poor/Poor	Good
10	Site management quality	Good/Average/Rather poor/Poor	Average
11	Number of consecutive operational days	Between 0 ~100	7
12	Predominant soil type	Sand/Sandy clay/Clay/Gravel/Broken rocks	Broken rocks
13	Big pieces of rock exist on the site?	No/Rarely/Commonly	Commonly
14	Equipment maneuvering space	Easy/Average/Rather difficult/Difficult	Easy
15	Ground grade (%)	-25~25	-10%
16	Dozing distance (m)	0~150	20
17	Operation time	Morning/Afternoon/Night	Morning
18	Average temperature during operation (°C)	-15~45	20
		Actual Measured Productivity (Lm^3/Hour)	**150**

4. LINEAR REGRESSION ANALYSIS

Linear regression techniques, first introduced by Legendar (1805) and Gous (1809), are commonly used in several scientific and engineering fields. In this paper, a multiple linear regression model is used to determine the statistical relationship between a response (e.g. estimated productivity) and the explanatory variables x_i (e.g. soil type, dozing distance, and blade type). The following equations present general forms of single and multiple linear regression approaches [11],

$$y = \hat{\beta}_0 + \hat{\beta}_1 x + \varepsilon \tag{1}$$

$$y_i = \beta_0 + \sum \beta_p x_{p_i} + \varepsilon_i \tag{2}$$

In which,

- y_i is the response corresponding to the levels of the explanatory variables $x_{1i}, x_{2i}, \ldots, x_{pi}$ at the i^{th} observation.
- $\beta_0, \beta_1, \ldots, \beta_p$ are the coefficients in the linear relationship. For a single factor ($p = 1$), β_0 is the intercept, and β_1 is the slope of the straight line defined.
- $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n$ are errors that create a scattered point pattern around the linear relationship at the i^{th} observation (i ranges from 1 to n).

Using the least squares errors estimator, a common method for obtaining parameters of a regression model, parameters are determined using the following equation,

$$SSE = \sum_{i=1}^{n} e_i^2 \tag{3}$$

In which, the residual e_i is the difference between the observed response y_i and the estimated or fitted value $\hat{y}_i$;

$$e_i = y_i - \hat{y}_i \tag{4}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \tag{5}$$

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \tag{6}$$

The statistical t-test is used to initially determine the significance of each explanatory variable, with each computed coefficient subjectively checked for a rational cause and effect relationship. The t-statistic is the ratio of the coefficient to its standard error; a large t-ratio is therefore desirable. If the obtained sig.-ratio is less than a certain value (usually 0.05) regression coefficient will be considered as significant.

$$t = \frac{\hat{\beta}_i}{\sqrt{\operatorname{var}(\hat{\beta}_i)}} \tag{7}$$

$$Var(\hat{\beta}_i) = \frac{\sigma^2}{\sum_j (x_{ij} - \bar{x}_i)^2}$$

$$\sigma^2 = \frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n-1} \tag{8}$$

5. F-TEST FOR EVALUATION OF REGRESSION SIGNIFICANCE AS A WHOLE

In order to assess the significance of a regression model as a whole, F-test is used as follows,

$$F = \frac{SSR/df(R)}{SSE/df(E)} \tag{9}$$

$$SST = SSR + SSE$$
$$SSR = \sum (\hat{y}_i - \bar{y})^2$$
$$SSE = \sum (y_i - \hat{y}_i)^2$$
$$\Rightarrow SST = \sum (y_i - \bar{y})^2$$

In which,
SST: sum of total squares
SSR: total regression squares
SSE: sum of squares errors
df (T): degree of total freedom = n – 1
df (R): regression freedom degree = number of parameters (β_i) in model
df (E): Error freedom degree = *df (T) – df (R)*

The F-ratio calculated in Equation (9) is compared with the existing $F_{df(R),df(E),\alpha-1}$ of standard tables. If the calculated F is larger than $F_{df(R),df(E),\alpha-1}$, the regression is considered to be significant as a whole.

6. COEFFICIENT OF DETERMINATION (R^2)

This quantity specifies the rate of relation between response (y) and explanatory variables (x_p) of the regression model. The higher this quantity, the higher precision should be made in the model. R is calculated using the following equation,

$$R^2 = \frac{SSR}{SST} \tag{10}$$

In addition to performing this test, the following conditions have to be satisfied:

A) Independence: y_i s should be independent from each other.
B) Constant variance: Variability of the data should not change for different levels of the response or explanatory variables. One way to check whether this condition is fulfilled is by using residual plots. If the constant variance condition holds, then residuals will follow a normal distribution and a plot of the residuals for each i versus the fitted $\hat{y}_i$ values must follow a random pattern, and
C) Normality: y_i s must have normal distribution. Shapiro-Wilk test is typically used to check for this condition which yields to relatively more precise output for small sample volumes compared to other normal tests [12].

7. PREPARATION OF REGRESSION MODEL FOR PRODUCTIVITY ESTIMATION

The explanatory variables, used in our model, have been generated in order to estimate the productivity of bulldozers while including all parameters listed in Table 2. The parameters in Table 2 are either quantitative (e.g. temperature of the operations environment, dozing distance) or qualitative (e.g. type of soil, type of blade). In this model, all qualitative variables are converted to binary values (i.e. 0, 1) before being used for the regression process. For instance, the corresponding variable to the blade type (X_3) can represent an “angle dozer”, a “u-tilt”, a “semi u-tilt”, or a “straight” blade. For this specific variable, “semi u-tilt” is used as the base type and other blade types are denoted in the model as X_3(u) for u-tilt blade, X_3(angle dozer) for angle dozer, and X_3(straight) for straight blade. If all these three variables equal to 0, the conclusion will be that the dozer is equipped with a “semi u-tilt” blade (base condition). X_3(u) being equal to 1 while other variables are all equal to 0 indicates that the dozer has a “u-tilt” blade, and if X_3(angle dozer) is equal to 1 and all other variables are equal to 0, it indicates an “angle dozer” type. Finally, if X_3(straight) is equal to 1 and all other variables are equal to 0, the dozer has a “straight” type of blade. In other words, a value of 1 indicates the existing blade type while 0 shows that the corresponding blade type is not used by the dozer. As a result, for each qualitative parameter only one state variable can be 1 and all other state variables will be considered to be equal to 0.
Similarly, for type of soil (variable X_{12}) which can be either “clay”, “sandy clay”, “sand”, “gravel”, or “broken rocks”, “sand” is selected as the base type while other types are shown as X_{12} (clay), X_{12} (sandy-clay), X_{12}(gravel) and X_{12} (broken rocks) respectively. For

variables such as “operator’s skill”, which consist of multiple states (e.g. “good”, “average”, “rather poor”, and “poor”), appropriate numerical values are assigned to each state (e.g. 4 for “good”, 3 for “average”, 2 for “rather poor”, and 1 for “poor”).

As noted earlier, the regression model in this paper was prepared using the actual site data collected from 60 D-155A1 series bulldozers using SPSS–16 software package. Table 3 shows outputs of SPSS software package which consists of coefficient of variables of approach and values of *t* and *F* ratios.

Table 3. Parameters of initial regression model

Explanatory Variables	Coefficients	t-ratio	Sig.-ratio
(Constant)	78	0.650	0.520
X_1	.000041	0.439	0.664
X_2	-11.8	-1.065	0.294
X_4	17.2	2.677	0.011
$X_3(u)$	-19.9	-1.102	0.278
$X_3(angledozer)$	18.9	0.619	0.540
$X_3(straight)$	-50.8	-1.836	0.075
X_5	0.5	0.037	0.971
X_6	15.8	0.950	0.349
X_7	9.2	0.910	0.369
X_8	1.8	0.158	0.875
X_9	28.6	2.178	0.036
X_{10}	1.06	0.110	0.913
X_{11}	0.701	1.031	0.310
$X_{12}(brockenrocks)$	-124	-5.559	0.000
$X_{12}(sandy-clay)$	-29.5	-1.370	0.180
$X_{12}(gravel)$	-92.5	-3.354	0.002
$X_{12}(clay)$	-82.1	-4.154	0.000
X_{13}	4.2	0.339	0.737
X_{14}	-9.4	-0.748	0.459
X_{15}	-1.18	-1.787	0.083
X_{16}	-1.52	-5.084	0.000
$X_{17}(afternoon)$	-34.3	-2.375	0.023
$X_{17}(night)$	-83.3	-1.479	0.148
X_{18}	-0.702	-0.966	0.341

Based on the values of Table 3, Equation (11) was derived to estimate bulldozer productivity,

$$\begin{aligned} y = {} & 78 + 0.000041X_1 - 11.8X_2 + 17.2X_4 - 19.9X_3(u) \\ & + 18.9X_3(angledozer) - 50.8X_3(straight) + 0.5X_5 \\ & + 15.8X_6 + 9.2X_7 + 1.8X_8 + 28.6X_9 + 1.06X_{10} \\ & + 0.701X_{11} - 124X_{12}(brockenrocks) \\ & - 29.5X_{12}(sandy-clay) - 92.5X_{12}(gravel) \\ & - 82.1X_{12}(clay) + 4.2X_{13} - 9.4X_{14} - 1.18X_{15} \\ & - 1.52X_{16} - 34.3X_{17}(evening) - 83.3X_{17}(night) \\ & - 0.702X_{18} \end{aligned} \quad (11)$$

The F-ratio of this regression equation is equal to 6.365 which is considered to be "significant" with very high level of confidence (more than 99%). Therefore, significance of regression as a whole is regarded as "approved". Also, Shapiro-Wilk test was used to study the normality the results of which are shown in Table 4. This Table confirms that the results meet the condition of normalization.

Table 4. Test of normality results test for regression model

Tests of Normality			
Shapiro-Wilk	Statistic	df	Sig.
Standardized Residual for Productivity	0.981	60	0.462

The scattered plot shown in Figure 1 was used to check if the constant variance condition is satisfied. It is apparent that points have been scattered randomly all across the plot area. In addition, t-test was conducted to investigate the significance of each variable. The results indicated that coefficients of variables X_4, X_9, X_{12}(clay), X_{12}(gravel), X_{12}(broken rocks), X_{16}, and X_{17}(evening) have the highest significance level (above 95%). Also, coefficients of variables X_1, X_5, X_8, X_{10}, and X_{13} have the least amount of significance level which is comparable to a statistical 0. Along the same direction, significance level of other variables can be easily obtained by using the information provided in Table 3. The value of R^2 is equal to 0.814 which indicates that the variables included in Equation (11) describe %81.4 of variations in productivity of a bulldozer.

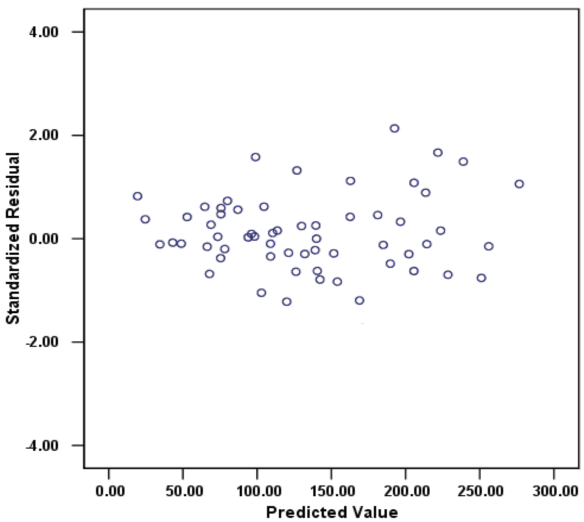

Figure 1. Residual plot for linear regression model

8. IMPROVEMENT OF THE REGRESSION MODEL

Having successfully developed the regression model, the next step was to improve the significance level of model variables and the regression model as a whole. For this reason, one insignificant variable was omitted each time, a new model was built, and the significance level of variables and the regression model as a whole were calculated for the new model. The final model was then selected based on the calculated levels of significance. In this research, a step-wise method was developed in Minitab to conduct the trial and error process described above. The calculations carried out for various models indicated that omission of variables X_1, X_2, X_5, X_6, X_7, X_8, X_{10}, X_{11}, X_{13}, X_{14} and X_{18} (with significance levels shown in Table 3) would improve the model capability to estimate the equipment productivity. Therefore, the new model is presented as follows in which parameters of Table 5 are used,

$$\begin{aligned} y &= 78.9 - 122X_{12}(brockenrocks) - 1.28X_{16} \\ &- 1.25X_{15} - 81.9X_{12}(clay) + 11.5X_4 \\ &+ 25.1X_9 - 29.6X_{17}(evening) - 39.9X_{17}(night) \\ &- 70.2X_{12}(gravel) - 33.2X_{12}(sandy - clay) \\ &- 43.2X_3(straight) - 14.7X_3(u) \\ &+ 14.1X_3(angledozer) \end{aligned} \quad (12)$$

The value of F for this new model is equal to 13.11 which indicates a high level of significance of the regression model as a whole. R^2 ratio is equal to 0.787 which means that the variables included in Equation (12) describe %78.7 of variations in productivity of a bulldozer.

Table 5. Parameters of improved regression model

Explanatory Variables	Coefficients	t-ratio	Sig.-ratio
(Constant)	78.9	1.83	0.074
X_4	11.5	2.28	0.027
$X_3(u)$	-14.7	-1.22	0.229
$X_3(straight)$	-43.2	-1.88	0.067
X_9	25.1	2.79	0.008
$X_{12}(brockenrocks)$	-122	-7.92	0.000
$X_{12}(sandy - clay)$	-33.2	-2.02	0.049
$X_{12}(gravelysoil)$	-70.2	-3.28	0.002
$X_{12}(clay)$	-81.9	-5.06	0.000
X_{15}	-1.25	-2.18	0.035
X_{16}	-1.28	-6.08	0.000
$X_{17}(afternoon)$	-29.6	-2.64	0.011
$X_{17}(night)$	-39.9	-0.95	0.345
$X_3(angledozer)$	14.1	.60	.553

Figure 2 shows the new linear regression model. In this Figure, y and x axes respectively correspond to productivity per hour and the values of explanatory variables as used in the regression.

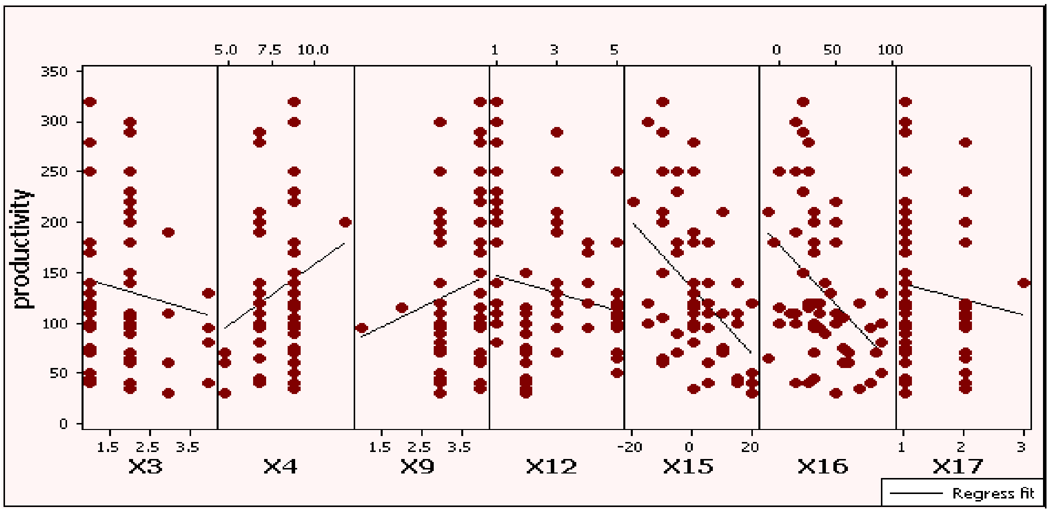

Figure 2. Actual productivity plotted versus fitted productivity for the linear regression model

The interpretation of coefficients of the qualitative variables in Equation (12) is also of critical importance. In fact, the corresponding coefficient to each qualitative variable in this equation shows the difference between the current and base states of that same variable. For example, the coefficient value of -122 of the qualitative variable X_{12}(broken rocks) in Equation (12) means that the average productivity in a soil which mainly consists of broken rocks is %122 less than that in a base type (i.e. sand) soil. Following the same argument, the average productivity in sandy clay, gravel, and clay types of soil is %33.2, %70.2 and %81.9 less than that in sand type of soil. The same argument also holds for other qualitative variables in the regression model.

9. CASE STUDY

The productivity of an actual bulldozer was formulated using the developed regression model and according to the following assumptions and conditions:

Type of soil: gravel soil
Blade capacity: 6.8 m^3
Overall Operator's condition during the operation: rather poor
Dozing distance: 25 m
Operation time: afternoon

By substituting the above parameters and data in Equation (12), the numerical value of the bulldozer productivity per hour is calculated based on the following equation,

$$y = 78.9 - 1.28\times 25 + 11.5\times 6.8 + 25.1\times 3 - 29.6 - 70.2$$
$$= 100.6 \qquad LM^3$$

10. CONCLUSION

Actual productivity values for 60 Komatsu D-155A1 series bulldozers were measured on several construction sites and were compared to their theoretical productivity obtained from the manufacturer's catalogue. In addition, the developed regression models in Equations (11) and (12) were used to estimate the productivity of the same pieces of earthmoving equipment. Figure 3 shows a comparison of the results obtained from actual onsite measurements, manufacturer's catalogue, and the developed regression model.
In order to evaluate the degree of error inherited in the regression model as well as the inaccuracy of the productivity estimation obtained using the data from the manufacturer's catalogue absolute errors were also calculated in both methods and are shown in Figure 4.
As shown in this Figure, the absolute errors resulted from the developed regression model are significantly less than those of the manufacturer's catalogue. In conclusion, the developed regression approach is capable of producing more accurate estimates of the equipment productivity.

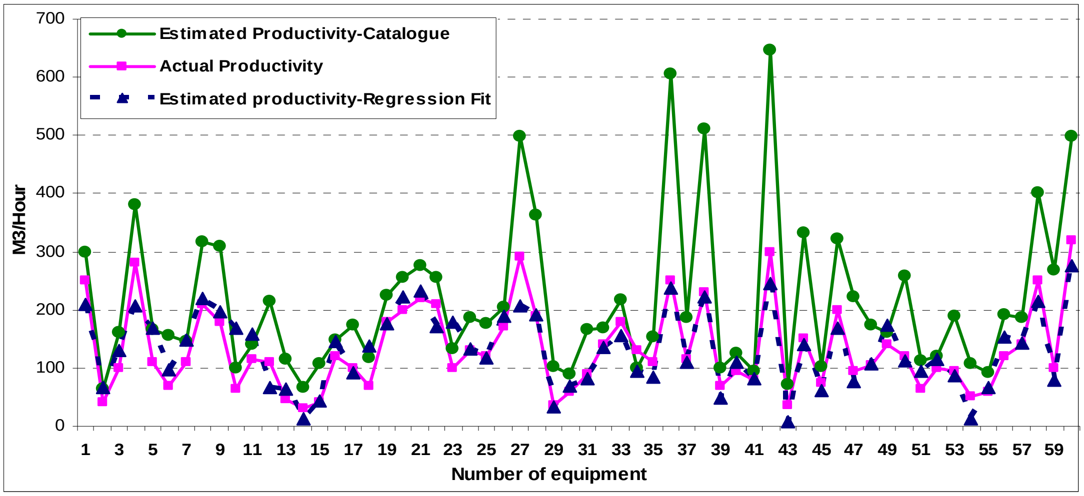

Figure 3. Comparison between actual and estimated productivity

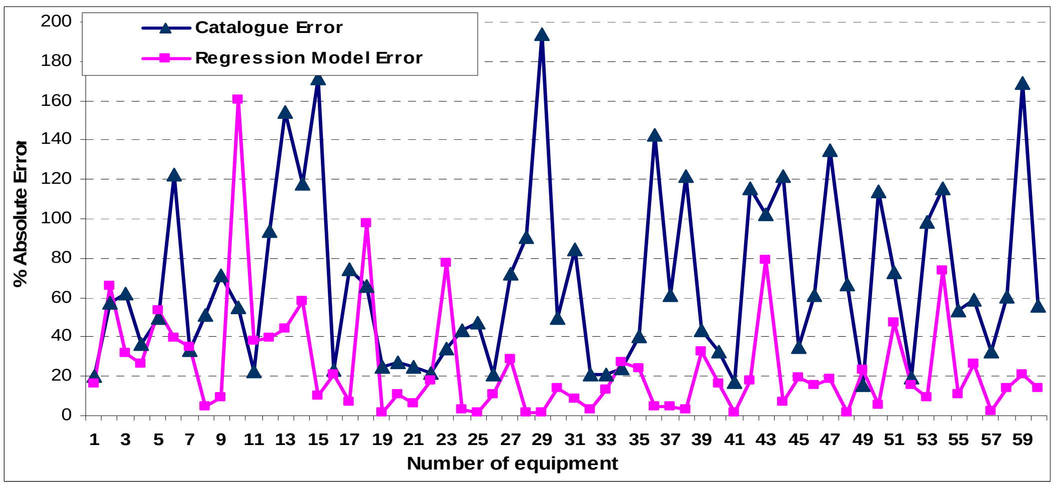

Figure 4. Absolute errors inherited in the regression model and the manufacturer's catalogue

REFERENCES

[1] G.D. Anon, "Caterpillar performance Handbook", *Caterpillar, Illinois*, USA, 1997.

[2] "Specifications and Application Handbook", 24th Edition, *Komatsu Publications and Training Group,* Tokyo, 2003.

[3] A.M.Elazouni, I.M.Basha, "Evaluating the Performance of Construction Equipment Operators in Egyp"t, *ASCE Journal of Construction Engineering and Management, Vol.* 122 (2) pp.109-114, 1996

[4] D.W.Halligan, L.A.Demsets, J.D.Brown and C.B.Pace, "Action-response Model and Loss of Productivity in Construction", *ASCE Journal of Construction Engineering and Management*, Vol.120 (1) pp.47-64, 1994

[5] S.D.Smith, "Earthmoving Productivity Estimation Using Linear Regression Techniques", *ASCE Journal of Construction Engineering and Management*, Vol.125 (3) pp.133-141, 1999

[6] S.D.Smith, G.S.Wood, M.Gould, "A New Earthworks Estimating Methodology", *Journal of Construction Management and Economics,* 18 (2) (2000) 219-228.

[7] L.Chao, M.J.Skibniewski, "Estimating Construction Productivity: Neural-Network-Based Approach", *ASCE Journal of Computing in Civil Engineering,* Vol.8 (2) pp.234-251, 1994

[8] C.M. Tam, T. K.L. Tong & S. L. Tse, "Artificial neural networks model for predicting excavator productivity, Engineering, Construction and Architectural Management", Vol.9 (5) ,pp.446 - 452 ,2002

[9] H.Adeli, "Novel Computing for Intelligent Infrastructure, Proceedings of 12th International Conference on Computing in Civil and Building Engineering", October 2008, Beijing, China

[10] S.W.Nunnally, "Managing Construction Equipment, 2nd Edition", *Prentice-Hall*, June 2002, N.J., USA

[11] Richard A. Berk, "Regression Analysis: A Constructive Critique", *Sage Publications*, 2004

[12] David A. "Freedman, Statistical Models: Theory and Practice", *Cambridge University Press*, 2005