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# Productivity Estimation of Bulldozers using Generalized Linear Mixed Models

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**Abstract**

The productivity estimation of construction machinery is a significant challenge faced by many earthmoving contractors. Traditionally, contractors have used manufacturers' catalogues or have simply relied on the site personnel's experiences to estimate the equipment production rates. However, various studies have demonstrated that typically, there are large differences between the estimated and real values. In the construction research domain, linear regression and neural network methods have been considered as popular tools for estimating the productivity of equipment. However, linear regression cannot provide very accurate results, while neural network methods require an immense volume of historical data for training and testing. Hence, a model that works with a small dataset and provides results that are accurate enough is required. This paper proposes a generalized linear mixed model as a powerful tool to estimate the productivity of Komatsu D-155A1 bulldozers that are commonly used in many earthmoving job sites in different countries. The data for the numerical analysis are collected from actual productivity measurements of 65 bulldozers. The outputs of the proposed model are compared with the results obtained by using a standard linear regression model. In this manner, the capabilities of the proposed method for accurate estimations of productivity rates are demonstrated.

Keywords: *construction equipment, productivity estimation, bulldozer, linear regression, generalized linear mixed model*

## 1. Introduction

The estimation of the productivity of construction equipment is a critical step in the scheduling and budget planning of earthwork projects. Traditionally, two major approaches have been employed to estimate the production rates of construction machinery prior to the start of actual operations. One approach uses data from previous projects and the personal experiences of the involved site personnel (e.g., operators and engineers), whereas the other takes advantage of the tables and information included in the manufacturers' instruction manuals and performance charts.

The data presented in this manner are usually based on ideal site and equipment conditions. Hence, several coefficients and correction factors must be applied to obtain accurate equipment production rates in each case and parameters such as the environmental conditions of the project, operator's experience, and jobsite management efficiency must be included (Anon, 1997; Komatsu Publications and Training Group, 2003).

Previous studies conducted on various earthwork projects in different countries indicate that the estimated equipment production rates calculated prior to the beginning of the project and the actual data from the operations have significant differences. In particular, this problem is critical in developing countries (Elazouni and Basha, 1996; Parsakhoo *et al*., 2009). The low productivity in the construction industry, especially the low construction equipment productivity in developing countries, is an old and well-known problem (Moavenzadeh and Rossow, 1975). There are several reasons for this issue. Both Elazouni and Basha (1996) and Alwi (2003) investigated the case of construction equipment usage in Egypt and Indonesia, respectively, and suggested that the main reason for the low productivity was the poor performance of operators. Additionally, according to Anon (1997), construction equipment manufacturers are primarily from developed countries (e.g., USA and Japan), and the graphs and charts provided for productivity measurements are not completely compatible with the jobsite conditions in developing countries. The reasons for the lack of productivity in construction-equipment-related operations in developing countries can be determined from an independent research study, but this is not within the scope of the current manuscript.

However, the abovementioned problem of significant discrepancies between the productivity rates computed by using manufacturers' manuals and charts and the actual rates is a significant challenge in typical earthwork operations (Han *et al*., 2008). As a result, in recent years, earthwork contractors have

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focused on developing deterministic methods that can be used to estimate the equipment productivity to a satisfactory degree of accuracy under different operational conditions. In the last two decades, numerous quantitative methods have been developed and implemented by researchers to determine the productivity in construction projects involving earthwork machinery (Panas and Pantouvakis, 2010). These methods can generally be divided into two main categories:

- **Linear Regression (LR) Models :** A Linear Regression (LR) model is the simplest and most straightforward method for predicting an unknown dependent variable, e.g., productivity, based on many known independent variables, e.g., the soil, operator skills, and ground grade; here, the dependent variable is considered to be a linear function of independent variables. However, LR models are not the most accurate tools for predicting the productivity of construction equipment, since the productivity calculation problem is extremely complex and the number of independent variables is excessively large. Nevertheless, LR models have been applied to the productivity estimation of construction equipment previously and such applications can be found in the literature (Smith, 1999; Smith *et al*., 2000; Edwards and Holt 2000).
- **Artificial Neural Networks:** Neural networks are a recurrent, associative, and adaptive method of associating variables (Mehrotra *et al*., 1997; Haykin, 1999). Several researchers have recommended Artificial Neural Network (ANN)-based models as effective productivity estimation tools (Karshenas and Xin, 1992; Chao and Skibniewski, 1994; Shi, 1999; Tam *et al*., 2002; Schabowicz and Hoła, 2007; Schabowicz and Hoła, 2008; Seung and Sinhaa, 2006; Rashidi *et al*. 2011; Jazebi and Rashidi, 2013).

However, ANN-based models cannot be employed directly for the productivity estimation of construction equipment because they require large amounts of empirical data for training, validation, and assessment (Cerny, 2001). Owing to difficulties in accessing many earthmoving job sites, lack of recorded historical data from jobsites, project complexity, and human errors, it is usually an extremely difficult and time-consuming task to measure the actual productivity for large numbers of machineries at different jobsites, especially in developing countries.

In this manner, both the approaches for calculating the productivity rates of construction equipment suffer serious shortcomings, and hence, there is increasing demand for methods that work with a limited amount of historical data and can provide results that are more accurate. In this paper, an innovative generalized mix model for the productivity estimation of a typical earthmoving machine is presented and validated. The proposed method is more accurate than conventional LR models; moreover, large volumes of data for training and evaluating the model, which is the main disadvantage of ANN-based models, are not required (UCLA: Statistical Consulting Group, 2013). A basic LR model for the productivity estimation of Komatsu D-155 A1 series bulldozer (commonly used in earthmoving projects in several countries) is developed first (Rashidi *et al*., 2009). In order to improve the accuracy of the results, the basic LR model is subsequently developed into a Generalized Linear Mixed Model (GLMM). It is important to mention that the term "productivity" in the context of this paper refers to the volume of loose soil excavated by a bulldozer per hour (Nunnally, 2000).

## 2. Collection of Site Data

Iranian earthmoving contractors typically use the Komatsu D-155 A1 series bulldozer for excavating and short-range dozing operations for the following reasons:

- It has the engine power required to perform earthmoving operations under the various topographical conditions and soil properties existent in Iran.
- In Iran, its cost is more reasonable than the costs of similar models such as the Caterpillar D8 series bulldozers.
- It is easy to maintain and service the D-155 bulldozer since its spare parts are readily available.
- The D-155 bulldozer is familiar to most equipment operators and maintenance workers in Iran.

The first step in developing a productivity prediction model is to collect actual jobsite data. To obtain the best results, we first considered all the factors affecting the productivity of bulldozers based on the manufacturer catalogues (Komatsu, 2003). Subsequently, in order to consider all other possible factors, we consulted several construction equipment experts working with major earthmoving contractors in Iran. All these experts have more than 20 years of experience in earthmoving operations in different projects and are well known in their fields. They were asked to list all the possible factors that might affect the productivity of the bulldozers. After combining and summarizing the different lists provided by the experts as well as a list of factors extracted from the catalogues, a final list containing 18 criteria was prepared. For the next step, the actual production rates of 65 bulldozers operating in 37 active construction sites in Iran were measured over a one-year period. We selected the earthwork projects by considering various geographical and climatic conditions in order to ensure that various options for different factors such as topography and weather conditions are included in our calculations.

Measuring real productivity rates of bulldozers is an error prone task due to subjective judgments made while measuring qualitative factors, such as operator's skill level and job site conditions. To address this issue and in order to improve the uniformity of the collected data, we asked one construction expert to coordinate all data collections from different job sites. The selected expert was a civil engineer with more than 25 years of experience in various earthmoving projects. The selected expert traveled to all job sites, spent at least 2-3 days observing the general conditions of jobsites, as well as various variables affecting the productivity rates. Then, a group of 3-6 earthmoving experts (the coordinator plus other construction engineers who work on the job site) measured the actual productivity rates of

Table 1. Factors Influencing Production and Data Collected for a Sample Bulldozer

| Factors | Description | Status | Sample |
|---|---|---|---|
| $X_1$ | Total service life time (hours) | 0-150,000 | 100,000 |
| $X_2$ | Service and maintenance condition | Good/Average/Rather poor/Poor | Good |
| $X_3$ | Type of blade | Straight tilt /U-tilt /Semi U-tilt /Angular | U-tilt |
| $X_4$ | Maximum blade capacity ($m^3$) | 4.8-11.8 | 8.8 |
| $X_5$ | Blade sharpness | Good/Average/Rather poor/Poor | Average |
| $X_6$ | Ripper used? | Yes/No | Yes |
| $X_7$ | Time between gear shifting (seconds) | Less than 5/Between 5~10/More than 10 | Less than 5 |
| $X_8$ | Operator's skill | Good/Average/Rather poor/Poor | Good |
| $X_9$ | Overall operator's condition during the operation | Good/Average/Rather poor/Poor | Good |
| $X_{10}$ | Site management quality | Good/Average/Rather poor/Poor | Average |
| $X_{11}$ | Number of consecutive operational days | Between 0 ~100 | 7 |
| $X_{12}$ | Predominant soil type | Sand/Sandy clay/Clay/Gravel/Broken rocks | Broken rocks |
| $X_{13}$ | Big pieces of rock exist on the site? | No/Rarely/Commonly | Commonly |
| $X_{14}$ | Equipment maneuvering space | Easy/Average/Rather difficult/Difficult | Easy |
| $X_{15}$ | Ground grade (%) | -25~25 | -10% |
| $X_{16}$ | Dozing distance (m) | 0~150 | 20 |
| $X_{17}$ | Operation time | Morning/Afternoon | Morning |
| $X_{18}$ | Average temperature during operation (°C) | -15~45 | 20 |
| | | Actual Measured Productivity(LM$^3$/Hour) | 150 |

bulldozers. Following this procedure, the qualitative (e.g., operator's skill levels and site management conditions) and quantitative data for all 65 pieces of equipment were collected and analyzed.

In this research, a bulldozer's actual production rate was determined by dividing the total volume of the soil loaded into trucks by the total operational hours per work period (usually 4 or 5 h). The total volume of the loaded soil can be calculated by adding the bucket capacities of all the loaded trucks used in the operations. It is important to note that when the values associated with any of the factors changed during the operations (e.g., changes in soil type, time of operation, or weather), the new conditions were considered as a new dataset. Table 1 lists 18 different parameters that contributed to the equipment production rate together with the actual site data collected for a sample bulldozer.

## 3. Linear Regression Models

LR techniques, (introduced by Legendre (1805) and Gauss (1809)), are commonly used in several scientific and engineering fields. In this paper, a basic LR 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 equation expresses the general form of a multiple LR approach (Berk, 2004):

$$y_i = \beta_0 + \sum \beta_p x_{pi} + \varepsilon_i \tag{1}$$

Here,

- $y_i$ 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 ($p = 1$), $\beta_0$ is the intercept and $\beta_1$ is the slope of the defined straight line.
- $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n$ are the error values that create a scattered point pattern around the linear relationship at the i$^{th}$ observation (i = 1 – n).

The least-squares errors estimator, which is a common method for obtaining the parameters of a regression model, is used to determine the parameters by minimizing the following function:

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

Here, in the case of a single model, the residual $e_i$ is the difference between the observed response $y_i$ and the estimated or fitted value $\hat{y}_i$ . $\bar{x}$ and $\bar{y}$ are the average values of $x_i$ and $y_i$, respectively (Berk, 2004).

$$e_i = y_i - \hat{y}_i \tag{3}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \tag{4}$$

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \tag{5}$$

Many statistical tests are required to validate an LR model.

### 3.1 T-test for Evaluating the Significance of Variables

The statistical t-test is used to initially determine the significance of each explanatory variable, and each computed coefficient is then subjectively checked for a rational cause-and-effect relationship. The t-statistic is the ratio of the coefficient to its standard error, and therefore, a large t-ratio is desirable. If the t-ratio obtained from standard t-distribution tables is greater than

$t_{\frac{\alpha}{2}, n-1}$, the regression coefficient will be considered significant.

### 3.2 F-test for Evaluation of Regression Model Significance as a Whole

An F-test is primarily used to assess the significance of the regression model as a whole.

### 3.3 Coefficient of Determination ($R^2$)

This quantity specifies the strength of the relation between the response ($y$) and the explanatory variables ($x_i$) of the regression model (Glantz, S.A. and Slinker, B.K., 1990). The higher the coefficient of determination $R^2$, the greater is the model precision. $R^2$ is calculated using the following equation:

$$R^2 = \frac{SSR}{SST} \tag{6}$$

where,

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

$$SSE = \sum(y_i - \hat{y}_i)^2 \Rightarrow SST = \sum(y_i - \bar{y})^2 \tag{7}$$

Before these three tests are conducted, it is necessary to satisfy the following conditions:

A) Independence: All the $y_i$ values should be independent of each other. In statistics, independency is measured through a standard test called "Durbin-Watson statistic". Details of the procedure can be found at (Durbin and Watson, 1971).

B) Constant variance: Variability of the data should not change with different response levels or explanatory variables. A method for checking whether this condition is satisfied is to use residual plots. If the constant variance condition holds, the residuals will follow a normal distribution, and a plot of the residuals for each $i$ versus the fitted $\hat{y}_i$ values will follow a random pattern.

C) Normality: All the $y_i$ values must be normally distributed. The Shapiro-Wilk test, which is typically used to check this condition, yields relatively more precise outputs for small sample volumes than other standard tests (Freedman, 2009; Rencher and Schaalje, 2008).

## 4. Generalized Linear Mixed Models

As discussed before, the development of an LR model requires many assumptions; for example, normality, constant variance, and linear responses have to be considered. In practice, it is extremely difficult to satisfy all these assumptions for complex problems such as the productivity estimation of bulldozers. As a result, researchers in the field of statistics have introduced other types of regression-based predicting models such as Poisson regression (Log linear), Logistic regression, Mixed Models (MMs) and GLMMs.

In statistics, Poisson regression (log linear) models are applied when the response variable (y) follows a Poisson distribution. A logistic regression model is commonly referred to specific group of problems in which the dependent variable is binary, i.e., the number of available categories is two. Considering the properties of our problem, neither of these techniques can appropriately model the situation.

MMs are statistical models containing both fixed effects (e.g., standard LR models) and random effects. An effect is classified as random when the researcher needs to make inferences about an entire population, and the experiments represent only a sample from that population. The soil type is an example of a random effect. It is possible to define infinite soil types but consider only a limited number of the more common soils found in construction job sites. MMs are particularly useful where repeated measurements are conducted on the same statistical units or when there are numerous variables but a limited number of observations.

A GLMM is a particular type of MM. It is an extension of the generalized linear model, in which the linear predictor contains random effects in addition to the usual fixed effects. These random effects are usually assumed to follow a normal distribution.

If we assume that $y$ is the vector of response variables and that $X$ and $Z$ are explanatory variables corresponding to parameters with fixed effects ($\beta$) and random effects ($b$), respectively, a GLMM is formulated as follows:

$$y = X\beta + Zb + e \tag{8}$$

Here, $e$ and $b$ are independent and follow a normal distribution. A detailed explanation of estimating the fixed and random parameters can be found in the papers of Neuhaus *et al.* (2008) and Demidenko (2004). Considering the random effects of variables in our problem, GLMM seems to have the potential of improving the accuracy of LR models.

## 5. Research Methodology

The research methodology implemented in this study consists of three major steps:

First, as previously mentioned, different factors affecting the productivity of bulldozers are listed and real productivity of 65 pieces of equipment were measured by job site observations. As the second step, a regular linear regression model would develop based on the data collected in the previous step (section 5-1). Finally, the linear regression model will be expanded to a generalized linear mixed model by considering the random effects of some of the input variables (section 5-2).

### 5.1 Development of a 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 the parameters listed in Table 1. The parameters in Table 1 are either quantitative (e.g., temperature of the operation environment, maximum blade capacity and dozing distance) or qualitative (e.g., soil type, time between gear shifting and type of blade). In this model, all the qualitative variables are converted to binary values (i.e., 0 or 1) before they are used for the regression process. For instance, the variable corresponding 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" blade is used as the base type, and "u-tilt," "angle dozer," and "straight" blades are denoted as $X_3$ ($u$), $X_3$ (angle dozer), and $X_3$ (straight), respectively. If all the three variables are equal to 0, it can be concluded that the dozer is equipped with a "semi u-tilt" blade (base condition). If $X_3$ ($u$) is equal to 1 while all the other variables are equal to 0, the dozer has a "u-tilt" blade. If $X_3$ (angle dozer) is equal to 1 and all the other variables are equal to 0, it indicates an "angle dozer" type. Finally, if $X_3$ (straight) is equal to 1 and all the other variables are equal to 0, the dozer has a "straight" blade. In other words, a value of 1 indicates that the corresponding blade type is used by the dozer, and vice versa for 0. As a result, for each qualitative parameter, only one state variable can be 1 and all the other state variables are considered equal to 0.

Similarly, the soil type (variable $X_{12}$) can be "clay," "sandy clay," "sand," "gravel," or "broken rocks"; here, "sand" is selected as the base type while the other types are $X_{12}$ (clay), $X_{12}$ (sandy clay), $X_{12}$ (gravel), and $X_{12}$ (broken rocks), respectively. Furthermore, variables such as "operator's skill" can have multiple states (i.e., "good," "average," "rather poor," or "poor"), and the appropriate numerical values are assigned to each state-4 for "good," 3 for "average," 2 for "rather poor," and 1 for "poor".

The regression model discussed in this paper was prepared using the SPSS-16 software package that employed actual site data collected from 65 D-155A1 series bulldozers.

Based on the output of SPSS software calculations, Eq. (9) was derived to estimate the bulldozer productivity:

$$\begin{aligned} y = {} & 69.56 + 0.000395X_1 - 10.4X_2 + 15.6X_4 \\ & -20.7X_3(u) + 16.7X_3(angle\ dozer) - 52.12X_3(straight) \\ & +0.74X_5 + 16X_6 + 9.8X_7 + 1.05X_8 + 24.4X_9 \\ & +1.15X_{10} + 0.8X_{11} - 126.25X_{12}(broken\ rocks) \\ & -24.5X_{12}(sandy-clay) - 90.99X_{12}(gravel) \\ & -84.02X_{12}(clay) + 4.31X_{13} - 8.79X_{14} - 0.99X_{15} - 2.032X_{16} \\ & -31.25X_{17}(morning) - 84.4X_{17}(afternoon) - 0.975X_{18} \end{aligned} \quad (9)$$

The F-ratio of this regression equation was equal to 8.547, which is considered as "significant" with a very high level of confidence (more than 99%). Therefore, the significance of the regression as a whole was regarded as "approved." In addition, the Shapiro-Wilk test was used to study the normality of the results presented in Table 2. This table confirms that the results satisfy the normalization condition.

The scattered plot shown in Fig. 1 was used to confirm if the constant variance condition was satisfied. It is apparent that points are scattered randomly across the plot area. In addition, a t-test was conducted to investigate the significance of each variable. The results indicated that the 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%). In addition, the coefficients of variables $X_1$, $X_5$, $X_8$, $X_{10}$, and $X_{13}$ have the least significance level, which is comparable to a statistical 0. Similarly, the significance level of other variables can be easily obtained by using the information provided in Eq. (9). $R^2$ is equal to 0.875, which indicates that the variables included in Eq. (9) describe 87.5% of the variations in the productivity of a bulldozer.

Table 2. Normality Results for Regression Model

| Tests of Normality | | | |
|---|---|---|---|
| Shapiro-Wilk | Statistic | df | Sig. |
| Standardized Residual for Productivity | 1.647 | 60 | 0.378 |

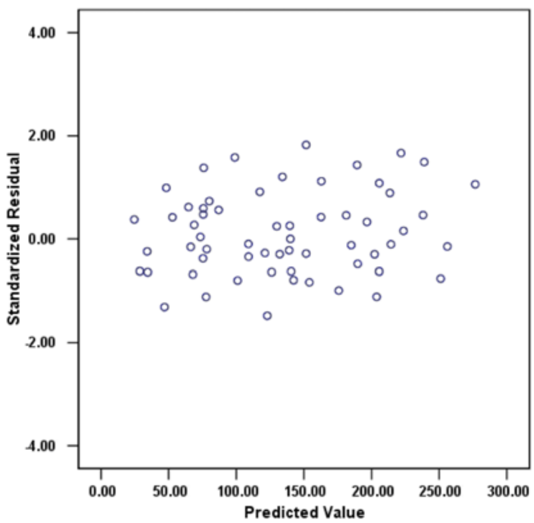


Fig. 1. Residual Plot for Linear Regression Model

After successfully developing the regression model, our next step was to improve the significance level of the model variables and the regression model as a whole. Hence, one insignificant variable was omitted each time, a new model was built, and the significance levels of the variables and the regression model as a whole were calculated for the new model. The final model was subsequently selected based on the calculated significance levels. In this research, a step-wise method was developed in Minitab to perform the abovementioned trial-and-error process. The calculations performed for various models indicated that the omission of variables $X_1$, $X_2$, $X_5$, $X_6$, $X_7$, $X_8$, $X_{10}$, $X_{11}$, $X_{13}$, $X_{14}$, and $X_{18}$ improved the model's capability to estimate the equipment productivity. Therefore, the new model is expressed as follows, with the parameters given in Table 3.

$$\begin{aligned} y = {} & 67.6 - 126X_{12}(broken\ rocks) - 1.47X_{16} \\ & -1.67X_{15} - 90.24X_{12}(clay) + 12X_4 + 23.5X_9 \\ & -27.45X_{17}(morning) - 34.7X_{17}(afternoon) \end{aligned}$$

Table 3. Parameters of Improved Regression Model

| Explanatory Variables | Coefficients | t-ratio | Sig.-ratio |
|---|---|---|---|
| (Constant) | 67.6 | 1.80 | 0.049 |
| $X_4$ | 12 | 3.24 | 0.019 |
| $X_3$ ($u$) | -15.7 | -1.18 | 0.097 |
| $X_3$ (*straight*) | -42.5 | -1.79 | 0.048 |
| $X_9$ | 23.5 | 2.76 | 0.006 |
| $X_{12}$ (*brokenrocks*) | -126 | -5.86 | 0.000 |
| $X_{12}$ (*sandy-clay*) | -34.3 | -2.79 | 0.038 |
| $X_{12}$ (*gravely soil*) | -68.6 | -4.37 | 0.000 |
| $X_{12}$ (*clay*) | -90.24 | -4.64 | 0.000 |
| $X_{15}$ | -1.67 | -2.37 | 0.017 |
| $X_{16}$ | -1.47 | -8.04 | 0.000 |
| $X_{17}$ (*morning*) | -27.45 | -2.73 | 0.007 |
| $X_{17}$ (*afternoon*) | -34.7 | -0.87 | 0.167 |
| $X_3$ (*angulardozer*) | 16.3 | 0.59 | 0.389 |

$$-68.6X_{12}(gravel) - 34.3X_{12}(sandy\text{–}clay)$$

$$-42.5X_3(straight) - 15.7X_3(u) + 16.3X_3(angle\ dozer) \quad (10)$$

The value of $F$ for this new model is equal to 16.24, which indicates a high significance level of the regression model as a whole. The $R^2$ value is equal to 0.897, which means that the variables included in Eq. (10) describe 89.7% of the variations in the productivity of a bulldozer.

From Table 3, it can be seen that only a few factors (9) have significant effects on the productivity of bulldozers. The interpretation of coefficients of the qualitative variables in Eq. (10) is also of critical importance. In fact, the coefficient corresponding to each qualitative variable in this equation shows the difference between the current and base states of that variable. For example, the coefficient value of –126 of the qualitative variable $X_{12}$(broken rocks) in Equation (10) implies that the average productivity in soil that mainly comprises broken rocks is 126% less than that in a base type (i.e., sand) soil. On the basis of the same argument, the average productivities in sandy clay, gravel, and clay soils are 34.3%, 68.6%, and 90.24%, respectively, less than the productivity in sand soil. The same argument also holds for the other qualitative variables in the regression model.

By applying the Durbin and Watson statistical test, the test statistics (d) is calculated as 2.048 which is very close to 2. As the result, the predictors are considered to be independent.

## 5.2 Conversion of LR Model to GLMM

It is possible to fit the data to a more accurate model by considering one of the explanatory variables as a variable with random effects. As explained previously, the effects of a variable can be treated as random effects if we consider the levels of the variables that we included in the model as a sample extracted from some larger population of levels that could have been selected (Linear models based on Littell *et al.* (2002) SAS for Linear Models).Variable $X_{12}$, i.e., the soil type, is the only variable that belongs to this category because there are several soil types and only a few, which are common in construction sites, are considered in developing the linear model. Fig. 2 illustrates the linear relationship between the different soil types and the predicted productivity of the equipment. Different lines for different soil types have different intercepts and this demonstrates the potential random effects for this variable.

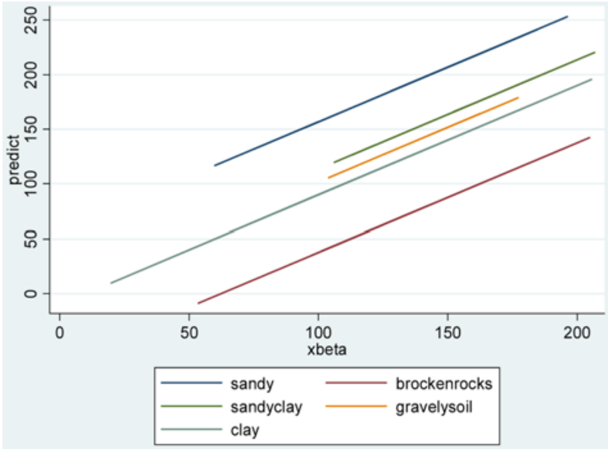


Fig. 2. Linear Relation between Different Types of Soil and Productivity of the Bulldozer

Another method for determining whether the “soil type” can be considered as a variable with random effects involves calculating the correlation coefficient matrix ($R$). $R$ is an indicator of the number of soil types, and in this model, $R$ is estimated to be equal to 0.819.

After defining the soil type as a variable with random effects, a GLMM can be formulated as

$$y_{ij} = \gamma_{00} + \gamma_{10}X_3 + \gamma_{20}X_4 + \gamma_{30}X_9$$
$$+\gamma_{40}X_{15} + \gamma_{50}X_{16} + \gamma_{60}X_{17} + U_{0j} + \varepsilon_{ij} \quad (11)$$

where,

$j = 1\ldots5$, $i = 1\ldots75$

$U_{0j}$ and $\varepsilon_{ij}$ are the residual errors for the variable with random effects (soil type) and the remaining variables with fixed effects, respectively, and they are given as follows:

$$\varepsilon_{ij} \sim N(0, \sigma_e^2) \& U_{0j} \sim N(0, \sigma_{u0}^2) \quad (12)$$

The calculation results for different coefficients of the GLMM model, which were obtained using the GLAMM software package, are summarized in Table 5. More detailed information on GLAMM can be found in the papers of Demidenko (2004) and Rabe-Hesketh and Everitt (2006). Therefore, the new model that used the parameters of Table 3 is presented as follows:

$$y_{ij} = 64.23 - 11.37X_3 + 6.86X_4 + 30.38X_9$$
$$-0.97X_{15} - 1.59X_{16} - 11.63X_{17} + U_{0j} + \varepsilon_{ij} \quad (13)$$

where,

$j = 1\ldots5$, $i = 1\ldots75$

In the next step, the assumptions made when the GLMM

Table 4. Coefficients of the Variables of the GLMM Model

| Explanatory Variables | Coefficients | Z | P>\|Z\| |
|---|---|---|---|
| Type of blade | -11.37 | -1.97 | 0.069 |
| Maximum blade capacity ($m^3$) | 6.86 | 3.76 | 0.004 |
| Overall operator's condition during the operation | 30.38 | 5.91 | 0.000 |
| Ground grade (%) | -0.97 | -3.76 | 0.007 |
| Dozing distance (m) | -1.59 | -7.37 | 0.000 |
| Operation time | -11.63 | -2.64 | 0.007 |
| Constant | 64.23 | 1.37 | 0.19 |

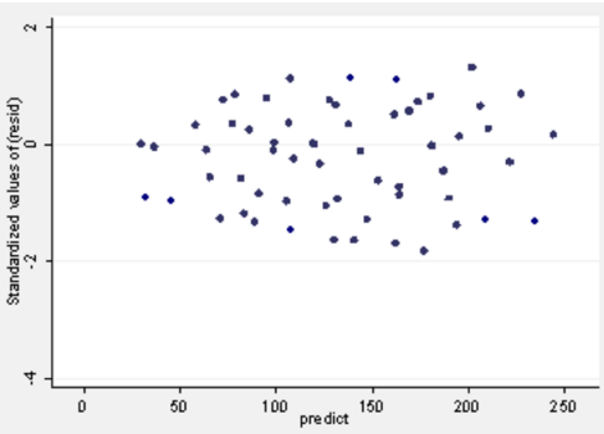


Fig. 3. Values of Residual Errors versus Predicted Productivity Values

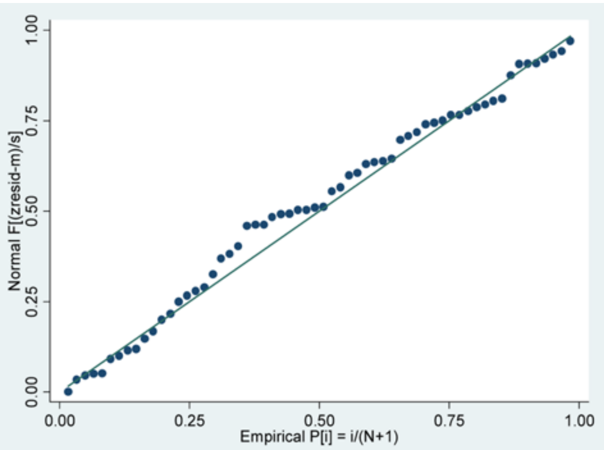


Fig. 4. P-P Plot for Normality Test

model was fitted must be checked and validated. Fig. 3 illustrates the values of the residual errors for variables with fixed effects ($\varepsilon_{ij}$) against the predicted values for productivity ($y_j$). Clearly, the points are distributed uniformly. As a result, the assumption of constant variance for variables with fixed effects is valid.

The data in Fig. 4 can be used to evaluate whether the distribution of the variables is normal. Points are located roughly on a straight line, and hence, the assumption of normality is valid. Fig. 5 shows the error bars for each case of productivity observation. Different soil types are categorized based on the rank of the estimate of effects, and the error bars illustrate the

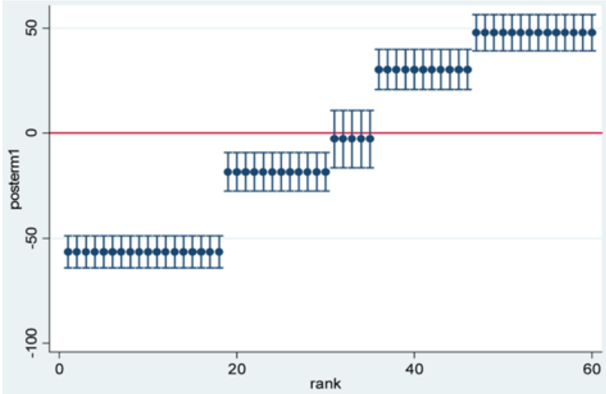


Fig. 5. Confidence Interval for Point Estimate of Productivity

predicted intervals around single estimates. Different soil types lead to different estimates for the average productivity values. Therefore, the soil type significantly affects the productivity distributions, and as a result, it should be considered as a variable with random effects.

Finally, the intraclass correlation of the model is calculated using the following equation (Stanish and Taylor, 1983):

$$\hat{\rho}(Y|x) = \frac{\sigma_b^2}{\sigma_e^2 + \sigma_b^2} = \frac{1699.34}{1699.34 + 1349.67} = 0.55 \qquad (14)$$

Here, $\sigma_b^2$ and $\sigma_e^2$ are the variances of variables with random and fixed affects, respectively. The intraclass correlation value equals 0.55, which implies that approximately 55% of the variability in production is governed by changes in the variable with random effects, i.e., the soil type. In addition to the soil type ($X_{12}$), the other significant factors that affect the productivity rate are type of blade ($X_3$), maximum blade capacity ($X_4$), overall operator condition during the operation ($X_9$), ground grade ($X_{15}$), dozing distance ($X_{16}$), and operation time ($X_{17}$). Other factors can simply be disregarded.

## 6. Evaluation of Results

In order to evaluate the performance of the two proposed models, the actual productivity values for 65Komatsu D-155A1 series bulldozers were compared with their theoretical productivity values obtained from the manufacturer's catalogues. In addition, basic LR and GLMM models were used to estimate the productivity of the same pieces of the earthmoving equipment. Subsequently, the degree of errors in the LR and GLMM models as well as the inaccuracies of the productivity estimates obtained using the data from the manufacturer's catalogue were calculated. Due to space limitations, it is not possible to present the results of the analysis for all 65 bulldozers, however the outcome for 31machines are shown in Fig. 6.

The absolute errors resulting from both the LR and the GLMM models are significantly less than those from the manufacturer's

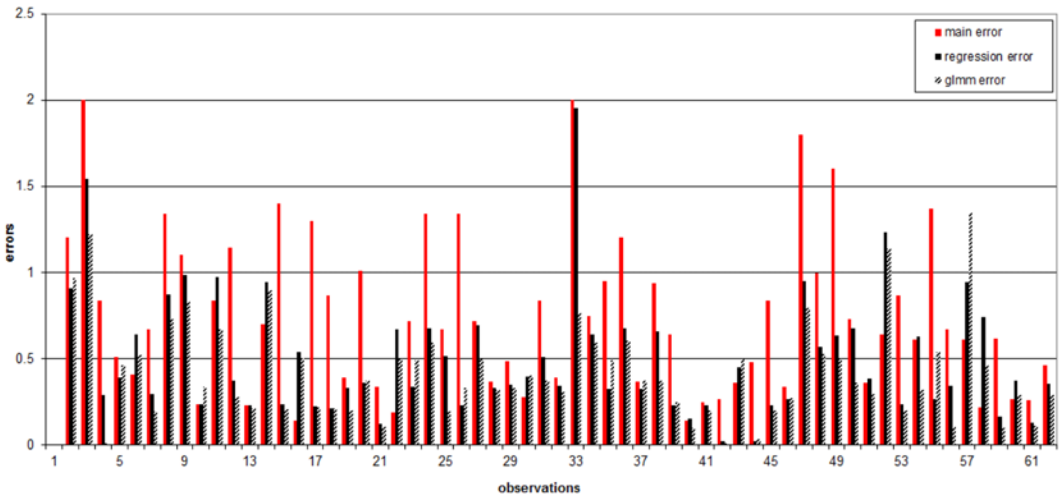


Fig. 6. Absolute Error in Three Cases: Catalogue (Main Error), Linear Regression Model, and GLMM Model

Table 5. Summary of the Results obtained from the Comparison Study

| Method | Average error (%) | Maximum error (%) | Standard deviation |
|---|---|---|---|
| Manufacturer Catalogue | 75.3 | 200 | 0.463 |
| Linear Regression | 44.42 | 195 | 0.359 |
| GLMM | 36.61 | 134 | 0.288 |

catalogue. The average absolute errors in using the manufacturer's catalogues and the LR and GLMM models are 75.3%, 44.42%, and 36.61%, respectively (Table 5). The obtained results reveal that GLMMs have the potential to improve the performances of productivity estimation models.

Interpretations of results obtained from the comparison study reveal a number of significant other facts:

- There is a relatively noteworthy difference between results obtained from using manufacturing catalogues and actual job site observations. This fact results in two major conclusions: 1) productivity rates of construction equipment are pretty low in comparison with standard values considered by the manufacturer (studying the reasons behind this phenomenon could be the topic of an independent study), and 2) using manufacturer's catalogues is not a reliable method for productivity estimation of construction equipment in Iranian job sites.
- Despite the fact there are several variables that might have an effect on the productivity rates of bulldozers (in this study we initially considered 18 factors), analysis demonstrated that only a few of them are significant and play an important role in the values of outcome. In other words, the values of other variables of the initial model during the data collection procedure need not be measured. The results of developing the GLMM revealed that type of blade, maximum blade capacity, overall operator condition during the operation, ground grade, dozing distance, and operation time, are the factors significantly affect the productivity rates of bulldozers. Obtained results are also compatible with the factors that are considered by manufacturers as significant (kumatsu, 2003). It is also important to mention that measuring the significance of each variable on the values of output is one of the major advantages of regression based methods over neural networks since in ANN it is very difficult to independently extract the impact of each variable on final outputs (Tu, 1996).
- Values of maximum and standard deviation of errors for different pieces of equipment demonstrate the use of statistical models (LR and GLMM) ultimately leading to more consistent (and therefore, more reliable) results. On the other hand, the amount of improvement for GLMM over LR does not follow a uniform pattern which is normal considering uncertainties involved in this study.

## 7. Conclusions

The productivity estimation of construction machinery is a significant challenge faced by many contractors, especially those involved in earthwork projects. Traditionally, the equipment production rate has been calculated using the data available in manufacturers' catalogues or from personal experiences and assessments of the site personnel. The actual production rates, which were obtained from various construction sites, demonstrate that most of these methods fail to provide accurate results. Consequently, there is increasing demand for more accurate models to calculate the productivity of construction equipment. In this paper, two models-an innovative GLMM and the common LR model-were applied to estimate the productivity of Komatsu D-155A1 bulldozers that are commonly used in many earthmoving operations in different countries. The data required for the numerical analysis were collected from actual site observations and productivity measurements of 65 pieces of the D-155A1 series currently being used in several earthmoving projects in Iran. The main findings of this research are as follows:

1. In Iranian earthmoving job sites, field studies have shown that there is a considerable difference between the predicted productivity rates obtained from manufacturers' catalogues and the actual values (the average difference based on our observations was 52.3%). Thus, there are increasing demands for models that are more reliable for the productivity estimation of construction equipment. The reasons for such large differences can be potential research projects.
2. Although field experts might consider various factors to significantly affect the productivity rates of the equipment, in reality, only a few factors play an important role in changing the productivity rates.
3. A comparative analysis of the output data of the presented models and existing productivity tables provided by the manufacturer shows that a significant increase in the accuracy and a remarkable reduction in the data variance can be achieved by using the presented models.
4. The obtained results also demonstrated that in comparison with the basic linear regression model, the proposed generalized linear mixed model leads to outputs that are more accurate.

There are a number of limitations associated with this study. The job sites scattered all around the country and accessibility issues in these types of studies prevent researchers from collecting many data sets. On the other hand measuring actual volume of excavated soil is an error prone task. Subjective judgment about some qualitative variables, e.g., operator's skills and job site conditions, is another significant issue that should be taken into account. As future research, the authors plan to extend the current study to address the following topics:

- Extending the concept of productivity estimation to other categories of construction equipment.
- Evaluating the reasons for poor productivity rates of construction equipment in Iranian job sites
- Implementing other available statistical models and comparing the results in terms of predicting the productivity rates of construction equipment.

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