METHODOLOGY FOR PREDICTING DRILLING PERFORMANCE FROM ENVIRONMENTAL CONDITIONS

A Thesis

by

JOSE ALEJANDRO DE ALMEIDA

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2010

Major Subject: Petroleum Engineering

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Approved by:

Chair of Committee,	Gene Beck
Committee Members,	Jerome Schubert
	Michael Sherman
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ABSTRACT

Methodology for Predicting Drilling Performance from

Environmental Conditions. (December 2010)

Jose Alejandro de Almeida, B.S., Colorado State University

Chair of Advisory Committee: Dr. Gene Beck

The use of statistics has been common practice within the petroleum industry for over a decade. With such a mature subject that includes specialized software and numerous articles, the challenge of this project was to introduce a duplicable method to perform deterministic regression while confirming the mathematical and actual validation of the resulting model. A five-step procedure was introduced using Statistical Analysis Software (SAS) for necessary computations to obtain a model that describes an event by analyzing the environmental variables. Since SAS may not be readily available, the code to perform the five-step methodology in R has been provided.

The deterministic five-step procedure methodology may be applied to new fields with a limited amount of data. As an example case, 17 wells drilled in north central Texas were used to illustrate how to apply the methodology to obtain a deterministic model. The objective was to predict the number of days required to drill a well using environmental conditions and technical variables. Ideally, the predicted number of days would be within +/- 10% of the observed time of the drilled wells. The database created contained 58 observations from 17 wells with the descriptive variables, technical limit (referred to as estimated days), depth, bottomhole temperature (BHT), inclination (inc), mud weight (MW), fracture pressure (FP), pore pressure (PP), and the average, maximum, and minimum difference between fracture pressure minus mud weight and mud weight minus pore pressure.

Step 1 created a database. Step 2 performed initial statistical regression on the original dataset. Step 3 ensured that the models were valid by performing univariate analysis. Step 4 history matched the models-response to actual observed data. Step 5 repeated the procedure until the best model had been found. Four main regression techniques were used: stepwise regression, forward selection, backward elimination, and least squares regression. Using these four regression techniques and best engineering judgment, a model was found that improved time prediction accuracy, but did not constantly result in values that were +/- 10% of the observed times.

The five-step methodology to determine a model using deterministic statistics has applications in many different areas within the petroleum field. Unlike examples found in literature, emphasis has been given to the validation of the model by analysis of the model error. By focusing on the five-step procedure, the methodology may be applied within different software programs, allowing for greater usage. These two key parameters allow companies to obtain their time prediction models without the need to outsource the work and test the certainty of any chosen model.

DEDICATION

To my father, mother, and sister, who always support me in my decisions and are present to guide me with their advice. To my fiancé and her love towards me.

ACKNOWLEDGEMENTS

I would like to give special thanks to Texas A&M University's Statistics Department. Their Statistical Consulting Team and PhD graduate student Karl Gregory have taught me more about statistics then I ever thought I would learn.

NOMENCLATURE

AD	Actual Days
BHT	Bottomhole Temperature
βi	Regression Coefficient
Cp	Mallow Cp Value
CV	Coefficient of Variance
D	Depth
F	F-number
FP	Fracture Pressure
inc	Inclination
k	Number of Regressor Coefficients
MS	Mean Squares
MS_T	Model Mean Square
MW	Mud Weight
n	Number of Observations
N	Number of Data Points
p	number of parameters
PP	Pore Pressure
R^2	Coefficient of Determination
$adjR^2$	Adjusted R-squared
RMS_E	Root Mean Squared

$\hat{\sigma}^2$	Estimator of Variance
SS_E	Error Sum of Squares
SS_R	Model Sum of Squares
SS_T	Total Sum of Squares
Tbh	Bottomhole Temperature
Te	Estimated Days
x_i	Regressor Variable
Y	Dependent Variable
Yi	Calculated Values from Models
$\hat{Y}$	Observed Experimental Values
$\bar{Y}$	Overall Mean

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CHAPTER I

INTRODUCTION

Statistical regression allows the influence and significance of variables to be chosen without bias. The method to produce a statistical deterministic model has well been established through the use of analytical techniques. The objective of this thesis was to introduce a methodology applicable to petroleum engineering to find a deterministic model from data through the use of statistics.

The goal of this project was to create a model that explains how certain variables affect an outcome. By combining the variables and finding out how much influence each variable has, a predictive model can be found that emulates observed results. Shown below is the general formula for a multiple linear model (Montgomery and Runger 2007).

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \quad \ldots\ldots(1.1)$$

β_i are regression coefficient and x_i regressor variables. First, significant regressor variables and regression coefficients are found. Using the significant variable and regression coefficients, $Y_i s$ are calculated from the model. Experimental values are $\hat{Y}$. The smaller the difference between Y_i and $\hat{Y}$, the better the model follows the observed data. Residuals, also known as error or deviation, are the individual values calculated from the difference between $\hat{Y}$ and Y_i (Dallal 2008). An assumption for model fitting was that all residuals, ε, are independent of one another. To test the adequacy of the model, univariate calculations and residual plots were used.

This thesis introduces a regression methodology for creating a prediction model that requires five steps. Step 1 creates a database with a dependent variable and

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This thesis follows the style of the *SPE Drilling & Completion.*

independent variables that are believed to affect the dependent variable. Step 2 performs the initial statistical regression on the original data. Software with statistical capabilities determines which variables are significant and calculates the regression coefficients. An alternative allows individually chosen independent variables to be tested through least squares regression. Step 3 ensures that the models are valid by performing univariate analysis. Step 4 history matches the model's response to actual observed data. Step 5 repeats the procedure till the best model has been found. If no significant models are found after performing the calculations using the initial dataset, data manipulation may be required.

This thesis introduces a methodology to obtain a predictive model that explains the relationship between a dependent and multiple independent variables through the use of linear regression. The methodology was tested using actual data from north central Texas. The number of days required to drill a well was the dependent variable. The independent variables tested were technical limit (referred as estimated days), depth, bottomhole temperature (BHT), inclination (inc), mud weight (MW), fracture pressure (FP), pore pressure (PP), and the average, maximum, and minimum difference between fracture pressure minus mud weight and mud weight minus pore pressure.

Many available commercial software perform specific analysis for predicting the amount of time required to drill a well, and others have the ability to calculate the necessary mathematical equations. A common basic software package used is Microsoft Excel; add-ons for Microsoft Excel assist users with prediction calculations. Independent of the software, the primary method for prediction calculations involves statistical analysis of data. Statistical Analysis Software (SAS) was specifically chosen since the software tailors to all statistic calculations. The second software used to perform statistical calculations is simply called R. Statistical analysis typically does not produce a unique answer but requires interpretation of results. A certain amount of intuition and individualized decision making are needed, and if these are not used carefully, calculation that result may have no real-world descriptive capabilities.

CHAPTER II

UNDERSTANDING SAS'S STEPWISE REGRESSION, FORWARD SELECTION, BACKWARD ELIMINATION, AND LEAST SQUARES REGRESSION

SAS performs stepwise regression, forward selection, backward elimination, and least squares regression. All four methods are a particular type of analysis of variance, ANOVA. Stepwise regression, forward selection, and backward elimination calculate regressor coefficients and significant regressor variables, while least squares regression calculates the regressor coefficients. All basic equations required for regression are described below and written out in Appendix A.

The sum of squares, also known as the sum of squared deviations, measures the dispersion or variability in the model's response. There are three different types of sum of squares in ANOVA calculations: total corrected sum of squares, error sum of squares, and model sum of squares. Model sum of squares is also known as regression sum of squares. Total corrected sum of squares, SS_T (Montgomery and Runger 2007), is used to see the deviation from the simplest model, $Y = \beta_0$, where β_0 equals the average value of $\hat{Y}$ (Orlov 1996).

$$SS_T = SS_E + SS_R \quad \text{(2.1)}$$

SS_E takes into account the randomness of the data set. It tests the models ability to replicate $\hat{Y}$ using a combinations of settings (Montgomery and Runger 2007).

$$SS_E = \sum_{i=1}^{n} (Y_i - \hat{Y})^2 \quad \text{(2.2)}$$

Smaller values of SS_E correlate to more accurate regression coefficients. While SS_E illustrates the randomness of the data, SS_R describes the regressor variables in the model (Dallal 2008).

$$SS_R = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 \quad (2.3)$$

Type II Sum of Squares indicates the amount each variable reduces the total sum of squares. More significant variables have large Type II Sum of Squares values while insignificant variable have small values.

Mean squares are estimates of variance. They are determined by dividing a sum of squares by the degrees of freedom. Degrees of freedom are defined by the difference between the number of observations and number of parameters. Total mean square, MS_T, equals SS_T divided by the degrees of freedom of SS_T. Since SS_T has only one parameter, β_0, the equation for MS_T equals SS_T divided by n-1(Montgomery and Runger 2007).

$$MS_T = \frac{SS_T}{n-1} \quad (2.4)$$

Error mean square, MS_E, is SS_E divided by the degrees of freedom of SS_E. The parameters associated with SS_E are all regressor variables, so the degree of freedom equals n-k where n equals the number of observations and k represents the number of regressor variable (Orlov 1996).

$$MS_E = \frac{SS_E}{n-k} \quad (2.5)$$

RMS_E is the square root of the MS_E. Smaller values of RMS_E, more accurate the model response.

$$MS_T = \frac{SS_R}{k-1} \quad (2.6)$$

k-1 represents the difference between the total mean square degrees of freedom and error mean square degrees of freedom (Orlov 1996).

The F-number found through the F-test indicates whether the model has statistically significant predictive capability (Dallal 2008). It tests the difference between two variances. Examples of variances are mean squares.

$$F = \frac{MS_R}{MS_E} \qquad (2.7)$$

The F-number determines if the null hypothesis, that all the regressor coefficients are equal to zero, is false(Montgomery and Runger 2007). SAS calculates the probability value, also known as the p-value, from the F distribution using the F-number and the degrees of freedom of the variables being tested. The probability that the variances are different equals 1 minus the p-value; this is known as confidence level (Orlov 1996). An F-test p-value has significance if it has a value less than α. α may be independently chosen; for this thesis α has a value of 0.05. If the F-number shows no significance, the p-value should be ignored (Dallal 2008).

The t-value tests the null hypothesis that the parameter estimator equals zero. Small values of standard errors of the mean represent sample means that are near true means. Larger t-values and smaller p-values occur for small standard error of the mean values (2007).

Both the F-test and t-test test their hypotheses by assuming that the samples came from a normal residual distribution. The chi-squared test checks whether the variances of the errors are constant throughout all observations. Constant variance errors, residuals with the same variance, are known as being homoscedastic. If the variances of the errors differ, then they are known as heteroscedastic. If the variances are constant, then the chi-squared p-value will be larger than 0.05 (2010).

Standard errors are the standard deviation of the estimator, the square root of the mean square error. R squared, also known as the coefficient of determination, describes the proportion of variance and response that the model fits (Montgomery and Runger 2007).

$$R^2 = \frac{SS_R}{SS_T} \quad (2.8)$$

Caution must be used when analyzing R-squared values because though an R squared value near one may indicate a good fit to the data; the model may actually be a bad fit. With the addition of each new variable, the R-squared will increase or stay the same, independent whether the added variable was significant. The adjusted R-squared, or adjusted coefficient of determination, takes into account the number of parameters within a model. As the number of parameters increases, the adjusted R-squared value decreases.

$$R_{adj}^2 = 1 - \frac{SS_E/_{(n-p)}}{SS_T/_{(n-1)}} \quad (2.9)$$

Multiple Rs are the square root of R-squared which estimates the influence of variables on the dependent variables (Orlov 1996).

The dependent mean represents the mean of the dependent variable (2007). The coefficient of variation represents a unitless measure of the variation in the data.

$$CV = \frac{RMS_E}{\bar{y}} \quad (2.10)$$

Mallows Cp values are used to measure the accuracy of the model response.

$$Cp = \frac{SS_E}{SS_T} - n + 2k \quad (2.11)$$

A model with the a Cp value nearest to $1+x_i$ indicates a good model (Beal 2007).

The variance inflation factor tests how variables are intercorrelated. Any value greater than 10 indicates that the variables are too intercorrelated. Pearson's correlation coefficients also measure how intercorrelated variables are. Pearson's correlation tests whether a linear relationship exists between two variables. If a positive correlation exists between two variables, then when one variable increase the other increases. A negative correlation indicates that as one variable increases, the other decreases. As the Pearson correlation value approaches one or negative one, the greater the intercorrelation is (Lawrence 2010).

If any changes are done to the model, such as the removal or addition of a regressor coefficient, the regression has to be redone. Many times one regressor coefficient may affect another one such that the removal of one variable may impact the model in ways unknown. Designers should always check the values of both hypothesis tests to best understand how the model mirrors the sample data.

CHAPTER III

UNDERSTANDING UNIVARIATE OUTPUT

After obtaining the regressor variables and regression coefficients, a univariate analysis tests the accuracy of the model by performing multiple tests on the model's residuals. Residuals are the unexplained variations from the regression model. A key assumption for regression analysis requires that all residual points have a normal distribution variation; Figure 3.1 illustrates the concept.

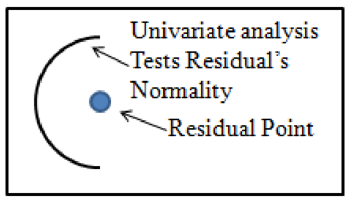

Fig. 3.1- Normal Distribution Around Residual Point

SAS splits univariate output into six tables: Moments, Basic Statistical Measures, Tests for Location, Tests for Normality, and Quantiles.

Moments are standardized descriptive statistics. SAS provides details of the data distribution under the Moments table. N equals the number of data points. Weights are the value given to each data point. In this regression, all the data points are considered equal so each point has a value of one and the sum of weights equals the number of data points (2000). The mean of residual points equals the average of the difference between the predicted values and the observed data. Note that a residual mean equal to zero does not ensure that the model follows the observed data's trend (Montgomery and Runger 2007).

$$\hat{\sigma}^2 = \frac{SS_E}{n-p} \quad \text{(3.1)}$$

Standard deviation equals the square root of the variance.

Skewness measures the standardization of the mean and mode and illustrates the asymmetry of the distribution. A positive value for skewness represents the tail extending to the right while a negative number has the opposite trend. Normal data would have a skewness of zero while a large number would indicate that outliers play an important role in the data. Kurtosis describes the flatness of the top of a symmetric distribution compared to a normal distribution (Wuensch 2007). A normal distribution has a kurtosis value of zero while a positive value indicates a peaked distribution and a negative number a flat distribution .

The corrected sum of squares equals the squared difference between the response variable and the mean response variable. Uncorrected sum of squares should equal the square of the sum of the response variable. If the uncorrected sum of squares and the corrected sum of squares do not equal each other, then the mean of the residuals does not equal zero and there is a discrepancy within the model (2007).

The standard error of the mean equals the standard deviation divided by the square root of the number of data points. Confidence intervals are multipliers of standard errors. Calculate a 90% confidence interval requires multiplying the standard mean error by +/- 1.64; 95%, standard mean error multiply by +/-1.96; and 99%, standard mean error multiply by +/-2.58 (Montgomery and Runger 2007).

Basic statistical measures illustrate the central tendency and spread of the model. The mean equals the sum of all data points divided by the number of data points. The median represents where half the points are larger and the other half smaller, locating the exact middle. The mode represents the number that occurs with greatest frequency. The range gives an indication of the dispersion by subtracting the largest value by the smallest (Croarkin and Guthrie 2006). The range is based on the extremes. It does not indicate if majority of the data are in the middle or out in the tail. Interquartile range represents the value of the 75th percentile minus the value of the 25th percentile. The interquartile range attempts to measure the variability in the middle (Croarkin and Guthrie 2006).

There are three tests for location: student's t-test, sign test, and Wilcoxon signed rank test. All three test the null hypothesis that the mean or median equals a certain number. This number may be assigned, but for these tests the mean equals zero (2007). The student's t-test works best when the data has a normal distribution while the sign and signed rank can be used with nonnormal distributions. The student's t-test calculates a t value by subtracting the sample mean from the actual mean and dividing by the standard error of the sample mean. The sign test illustrates whether the model over or underestimates (Montgomery and Runger 2007). The Wilcoxon signed test ranks the differences between observations and not the mean. A negative signed rank number means that the model has a tendency to underestimate, and a positive value indicates a tendency to overestimate (2007).

The test for normality assesses whether a normal distribution occurs for the residuals. Each of the following four tests has a different method to obtain this conclusion. The Shapiro-Wilk number calculates the ratio of the best estimator of variance to the corrected sum of squares. If the Shaprio-Wilk number equals one, that indicates a normally distributed sample (Park 2008). Small values of W for Shapiro-Wilk indicate departure from normal distribution. Kolmogorov-Smirnov does not depend on any specific distribution; instead it tests the hypothesis that the data follow a selected distribution. Anderson-Darling identifies the distribution the data come from. Modified from Kolmogorov-Smirnov, Anderson-Darling places more emphasis on the tails. Critical values of Anderson-Darling determine the distribution (Croarkin and Guthrie 2006). Cramer-von-Mises tests the hypothesis if the data came from a certain distribution by having tabulated data. If the value are larger than the tabulated, data then the hypothesis is rejected (2007).

Q-Q plots can graphically tell if the residuals follow a normal distribution. If the residuals follow a normal distribution, then a straight line is formed with the residual mean as the intercept and the residual standard deviation as the slope. The x-axis indicates which percentiles of residuals have values below the matching y-point (1999).

CHAPTER IV

PROCEDURE FOR STEPWISE REGRESSION, FORWARD SELECTION, AND BACKWARD ELIMINATION

The objective of this project was to find the significant regressor variables and regressor coefficients that describe the behavior of the dependent variable from a selected data set. Selection of regressor variables was done using different regression methods. All significant variables or combinations of variables have p-values less than α. Within this thesis, α was assigned a value of 0.05.

Stepwise regression happens to be the mostly widely used variable selection technique (Montgomery and Runger 2007). Variables are added one at a time as long as the F-statistic p-values are less than or equal to α. After the addition of a variable, all of the variable's F-statistic p-values are evaluated with a larger $\alpha_{2,}$ equal to 0.15. Any variable with the an α_2 value greater than 0.15 is removed (Beal 2007). It is possible that no variables are removed; then the stepwise regression acts as a forward selection regression. Forward selection simplifies stepwise regression by removing backward elimination, the process of removing variables after selection. In forward selection, regressor variables are introduced one at a time until no significant p-values remain. A weakness of forward selection occurs because it does not take into account the effects of the added regressor variable on previous regressor variables. Backward elimination begins will all regressor variables in the model. The regressor variable with the largest F-test p-value gets removed, and the process repeats till all regressors have an F-test p-value less than α (Montgomery and Runger 2007).

4.1 Method for Stepwise Regression (Loucks 2003)

1. Compute F-number on all individual regressor variables not included in the model.
2. Select the variable with the lowest p-value.
    a. Value of variable has to be less than 0.05 to be selected.
3. Compute F-number on all regressor variables within the model.
4. Remove any regressor variable with p-value larger than α_2.
    a. α_2 has been set to 0.15 by SAS.
5. If no regressor variables are removed, restart from Step 1.

4.2 Method for Forward Selection (Loucks 2003)

1. Compute F-number on all individual variables.
2. Select the variable with the lowest p-valve.
    a. Value of variable has to be less than 0.05 to be selected.
3. The first variable selected in kept and of the remaining variables, the one with the smallest p-value is added.
4. If the p-values of all remaining variables are larger than α, then stop the forward selection.
5. If p-values are less than α, continue the forward selection.
6. Continue this process till p-value calculations are greater than α.

4.3 Method for Backward Elimination (Loucks 2003)

1. Start with a model that includes all regressor variables.
2. Calculate the individual F-number for all variables in the model.
3. Remove the variable with the highest p-value.
4. Calculate the F-number on all remaining variables.
5. Remove the variable with the highest p-value.
6. Continue this procedure till all remaining variables have p-values less than α.

CHAPTER V

REASON FOR A NEGATIVE INTERCEPT

After obtaining a negative intercept for some of the preliminary models, I decided not to force the intercept to pass through the origin. The reason was that forcing the intercept hinders the model and gives a deceptively higher R-squared value.

The increase in R-square was an artificial increase. Simple linear regression tests whether the null hypothesis of β_1=0 is true for equation;

$$y = \beta_0 + \varepsilon = \mu + \varepsilon \qquad (5.1)$$

The values of $\hat{Y}_i$ are calculated using β_1 and compared to Y_i. The SS_T equals Eq. 8.2:

$$SS_T = \sum_{i=1}^{n}(Y_i - \bar{Y})^2 = \sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 + \sum_{i=1}^{n}\left(\hat{Y}_i - \bar{Y}\right)^2 \qquad (5.2)$$

If there is no intercept, β_1=0 and the linear model equals Eq. 8.3:

$$y = \varepsilon = 0 \qquad (5.3)$$

The SS_T then equals Eq. 8.4:

$$SS_T = \sum_{i=1}^{n}(Y_i)^2 = \sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 + \sum_{i=1}^{n}\left(\hat{Y}_i\right)^2 \qquad (5.4)$$

R-squared equals SS_R/SS_T. The goal behind regression is to minimize the sum of squares. With no intercept, there are larger SS_R and SS_T values are larger, and the R-squared value will be higher because of the difference between the mathematical operations on each side of the equals sign. High SS_R and SS_T value indicate a bad model. For a model with an intercept, the SS_R and SS_T values and R-squared value are lower. Lower SS_R and SS_T indicate a better model (Truong).

CHAPTER VI

APPLYING THE METHODOLOGY FOR WELLS IN NORTH CENTRAL TEXAS

To test the proposed methodology, I constructed a model using SAS to find the number of days required to drill a well in northern central Texas from a total of 57 observations. Each observation was the number of days required to drill, test, case, and cement a particular section of a well. Initially 13 variables were tested, technical limit (referred as estimated days), depth, bottomhole temperature (BHT), inclination (inc), mud weight (MW), fracture pressure (FP), pore pressure (PP), and the average, maximum, and minimum difference between FP-MW and MW-PP.

All the independent variables were collected using daily drilling reports or daily mud reports. I ran two rounds of tests. The first round of tests used all 13 variables. An issue arose when testing the models that had FP or PP in the model: estimated values of FP and PP available prior to drilling were higher than actual FP or PP encountered within the wellbore. This caused all the models to overestimate the number of days required to drill. Since the only information available prior to drilling a well is analogous data (values derived from adjacent wells) I removed FP, PP, and MW from the analysis, reducing some of the uncertainty factor of the second test using technical limit (referred as estimated days), depth, BHT, and inc.

SAS's output contains many results. Though all results of analysis of variance and univariate help describe how a model fits the data, some test results are more meaningful to a model's validation than others. To validate a model, I analyzed seven basic criteria: residual plot, Shapiro-Wilk residual p-values value, chi-squared p-values, variance inflation factor, R-squared, Mallow Cp (if applicable), and F-test p-value. The following criteria for each test indicate whether any assumption needed for regression analysis has been violated.

- Residual plot should have no discernable pattern and the residual points should be evenly distributed above and below the origin x-axis.
- Both the Shapiro-Wilk p-value and chi-squared p-value need to be above an α value of 0.05 not to reject their null hypothesis that the residuals are normally distributed.
- Variance inflation factor values need to be below 10 to indicate no inter-correlation behavior between variables.
- R-square ideally equals 1. The closer the value to 1, the better the match between predicted and observed values. This comparison may only be done when models are similar to one another since models with more variables will have higher R values. The reasoning why some poor model may have a higher R-squared values has been discussed in Section 5.
- Mallow Cp values are only calculated for stepwise regression, forward selection, and backward elimination. The Mallow Cp value should equal one plus the number of regressor variables within the model.
- F-test p-value have to be less than α for every variable to be considered significant.

This order established a systematic approach to obtain the most significant model.

CHAPTER VII

SAS RESULTS FOR REGRESSION ANALYSIS OF NORTH CENTRAL TEXAS WELLS

Eleven runs of the regression methodology were applied to the wells drilled in north central Texas. To better compare the results of each run, I show SAS results in Section 7, followed by the history match done in Microsoft Excel. SAS code, output, and Microsoft Excel charts and tables are found in the Appendix.

The first model (Eq.7.1) found estimated days and bottomhole temperature (BHT) to be significant regressor variables by all three regression techniques: stepwise regression, forward selection, and backward elimination.

$$y_A = -16.84055 + (0.87604 \times Te) + (0.09255 \times Tbh) \quad \text{.............................} (7.1)$$

To test the significance of the model, I verified all parameters in the validation method. The residual plot for Model A fans out and clusters towards the middle (Fig 7.1). Residual plots should have no discernable pattern and be evenly scattered along the origin horizontal axis.

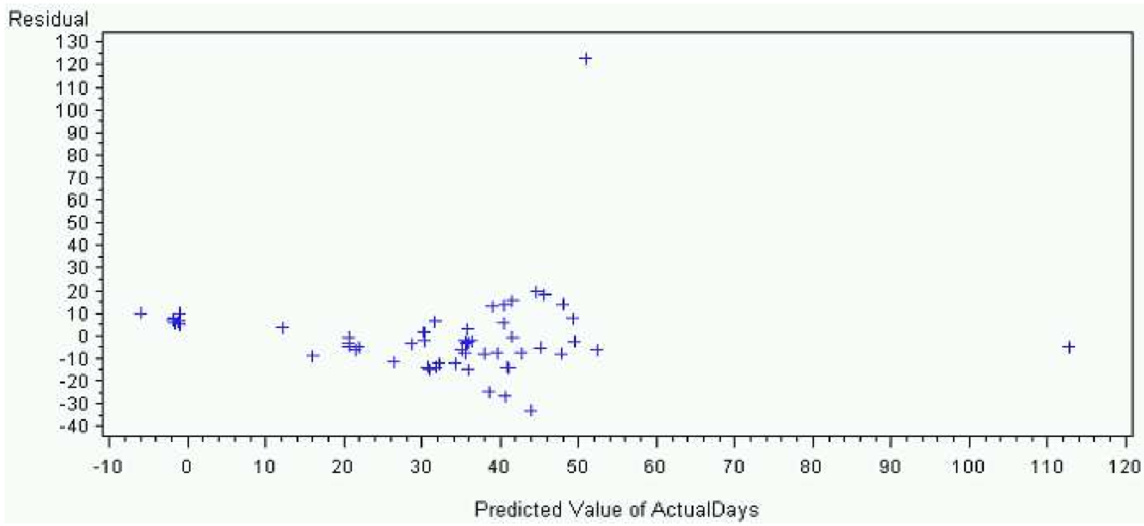

Fig. 7.1-Model A's Residual Plot. Actual Days = f(Te,Tbh)

Model A's Shapiro-Wilk p-value was less than 0.0001. If the Shapiro-Wilk p-value does not equal a value greater than 0.05, then the null hypothesis of the Shapiro-Wilk test-that the residuals are normal-gets rejected. A Q-Q plot helps visualize how the data deviates from the normal distribution. A normal residual distribution will have the data points on a linear line with a slope equal the standard deviation and intercept equal to the mean. Model's A Q-Q plot slope (Fig. 7.2) was less than the residual standard deviation slope line, confirming the Shapiro-Wilk test result that the residuals are not normal.

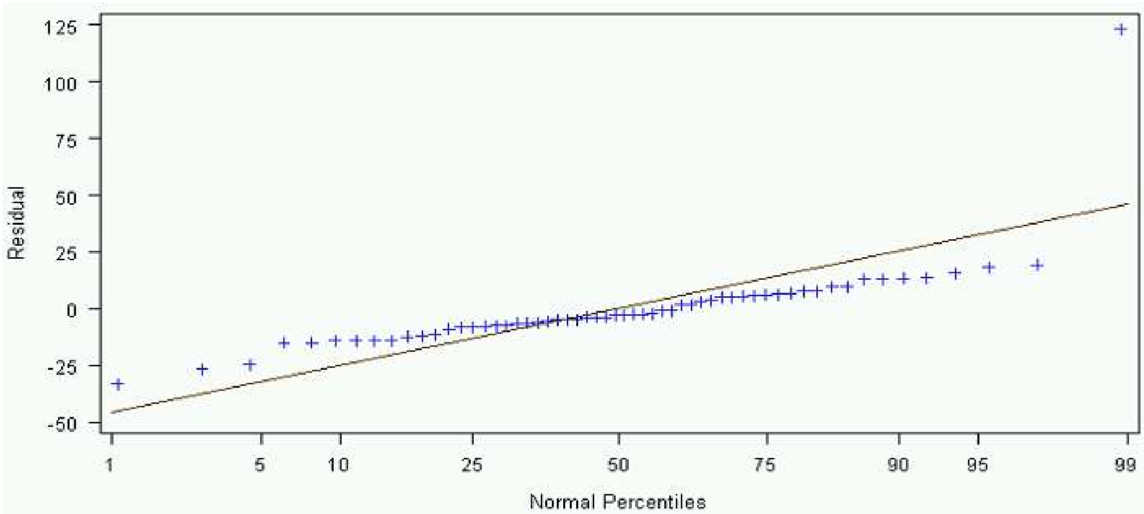

Fig. 7.2-Model A's Q-Q Plot. Actual Days = f(Te,Tbh)

Since the Shapiro-Wilk test was rejected for Model A, all results of the regression are not significant (Nau 2005).

Though all three previous regressions obtained the same significant regressor variables for Model A, it appeared as though depth would be a more significant regressor variable than BHT. To test this conclusion I selected actual days, estimated days, and depth. Model B (Eq. 7.2) incorporates the desired variables, allowing SAS to calculate the regressor coefficients and the significance of each variable.

$$y_B = -9.88984 + (0.90118 \times Te) + (0.00150 \times D) \ldots\ldots (7.2)$$

The residual plot for Model B (Fig. 7.3) appeared almost identical to that of Model A.

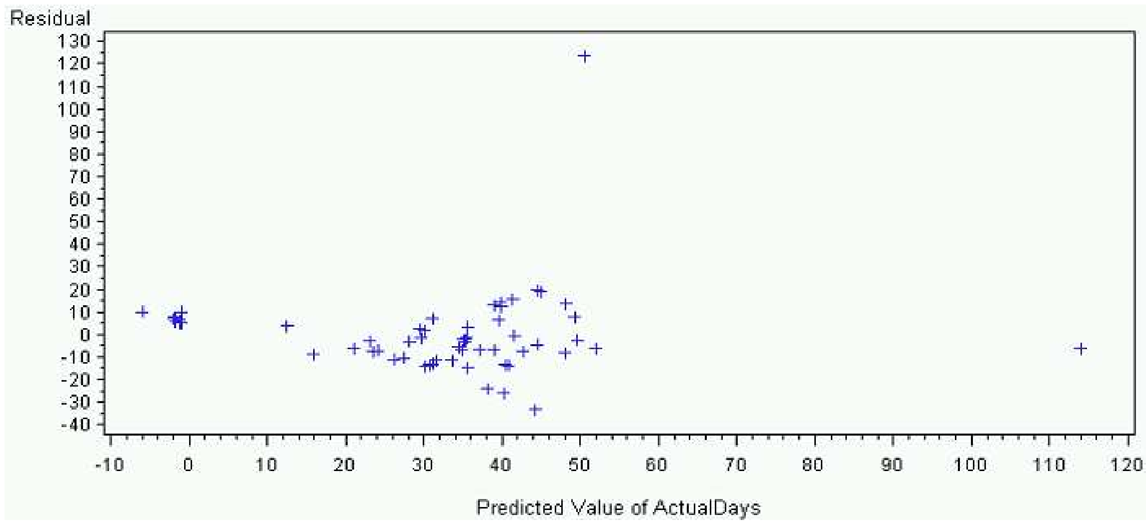

Fig. 7.3-Model B's Residual Plot. Actual Days = f(Te,D)

All the key results were similar to Model A's, leading to the same conclusion: Model B does not adequately model the data. When observing the residual plots of both Model A and B, a residual outlier with a value of 130 stands out. That point corresponds to a problem well section that took many days to resolve. Though a well may encounter serious issues that take a long time to remediate, they occur sporadically. To improve the model's ability to predict the number of days required to drill a well, I removed that data.

Model C (Eq. 7.3), resulted from a new dataset created without the problem section. The regressor variables were inputted into SAS and the following regression coefficients calculated.

$$y_C = -5.28257 + (0.87691 \times Te) + (0.00104 \times D) \quad \text{(7.3)}$$

The residual plot of Model C (Fig. 7.4) has a discernable bow-tie pattern, but the residual plot appears better than Model A or B's residual plot.

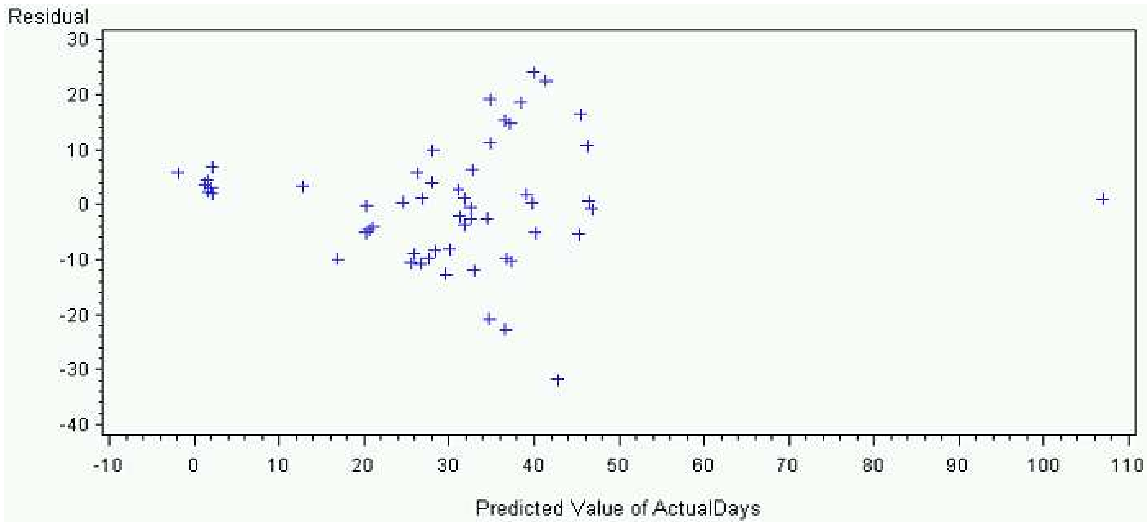

Fig. 7.4-Model C's Residual Plot. Actual Days = f(Te,D)

The Shapiro-Wilk p-value was greater than 0.05, so the null hypothesis-that the residuals are normal-was not rejected. The Q-Q plot for Model C (Fig. 7.5) had a normal trend but deviation occurred at lower percentiles.

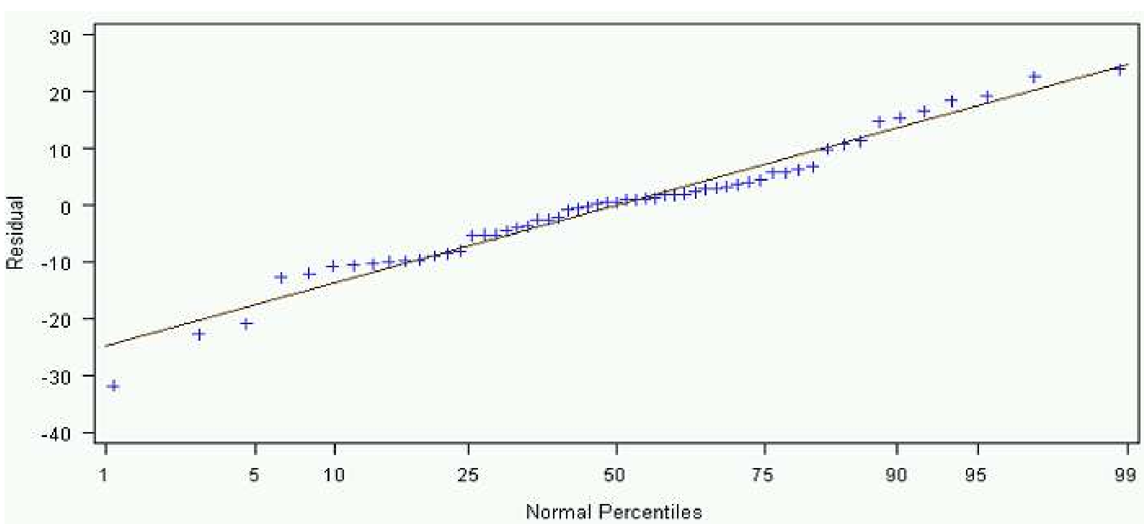

Fig. 7.5-Model C's Q-Q Plot. Actual Days = f(Te,D)

The chi-squared p-value was barely above the rejection value of 0.05. Chosen regressor variables had low inflation variance factors, and the F-test p-value was less than 0.0001. The R-squared value was 0.71.

Using previous regressor variables selected by stepwise regression, forward selection, and backward elimination, I found new regressor coefficients by performing least squares regression with the new data set. Model D (Eq. 7.4) had many validation parameters similar to Model C.

$$y_D = -9.98231 + (0.86113 \times Te) + (0.06342 \times Tbh) \qquad (7.4)$$

Models C and D passed all the required validation parameters. A reason that Models C and D may lack significance was the residual plots scatter and low chi-square p-values. Residual plots of both models showed a slight double bow pattern while chi-squared values were near the rejection criteria of 0.05. To better understand why the models barely passed the validation process, I examined the dynamics between each individual variable and the dependent variable. The goal was to see if there was a linear relationship between the dependent variable and independent variables. Plots of actual days versus all independent functions were done. Shown below in Fig. 7.6, 7.7, and 7.8, are three key plots indicating the relationship between Actual Days and Estimated Days, Depth, and BHT. Figure 7.6 shows the linear relationship found between Actual Days verse Estimated Days. Both Depth and BHT appeared to have an exponential relationship when plotted against Actual Days as shown in Fig 7.7, and 7.8.

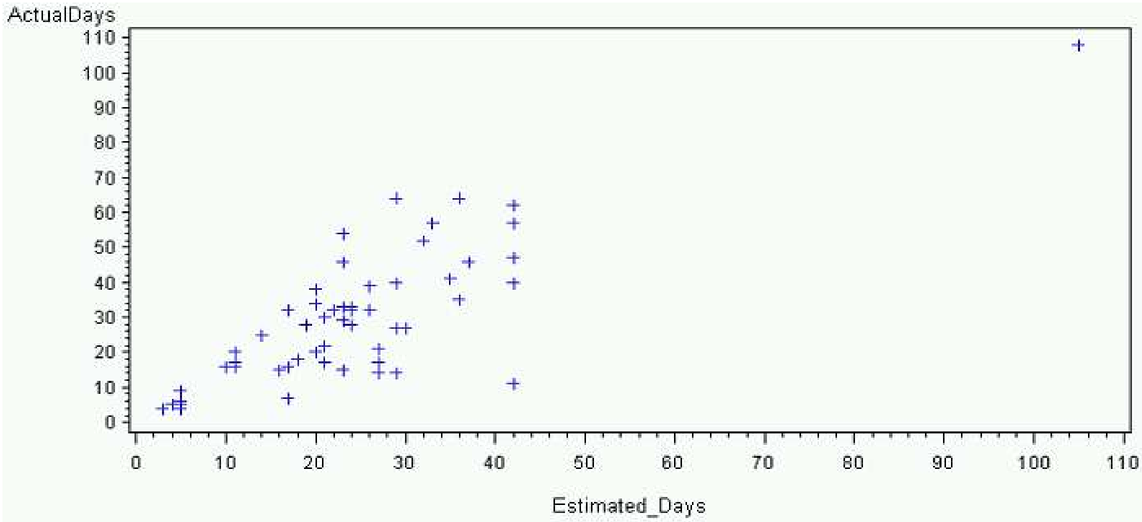

Fig 7.6–Actual Days vs. Estimated Days

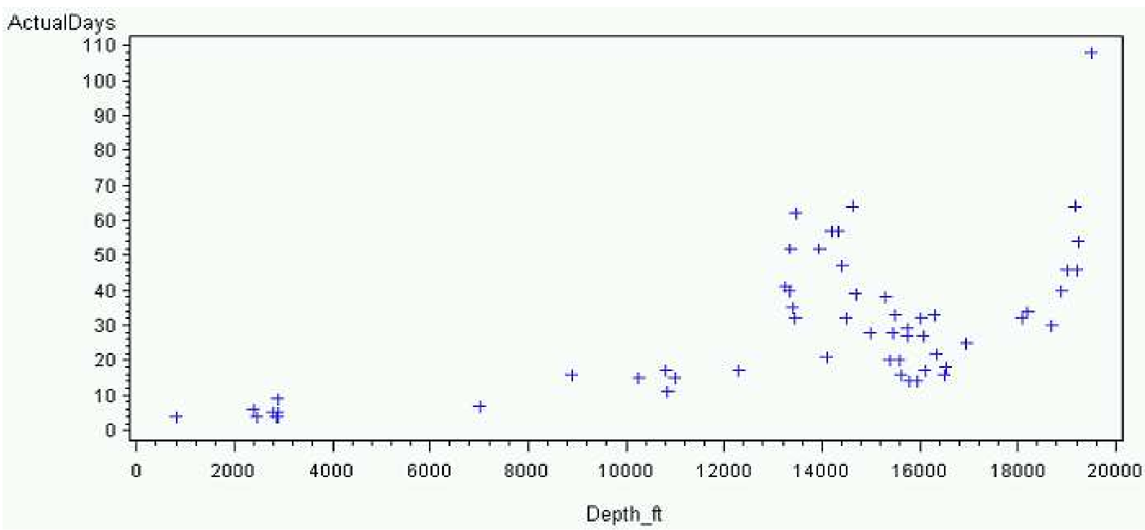

Fig 7.7–Actual Days vs. Depth

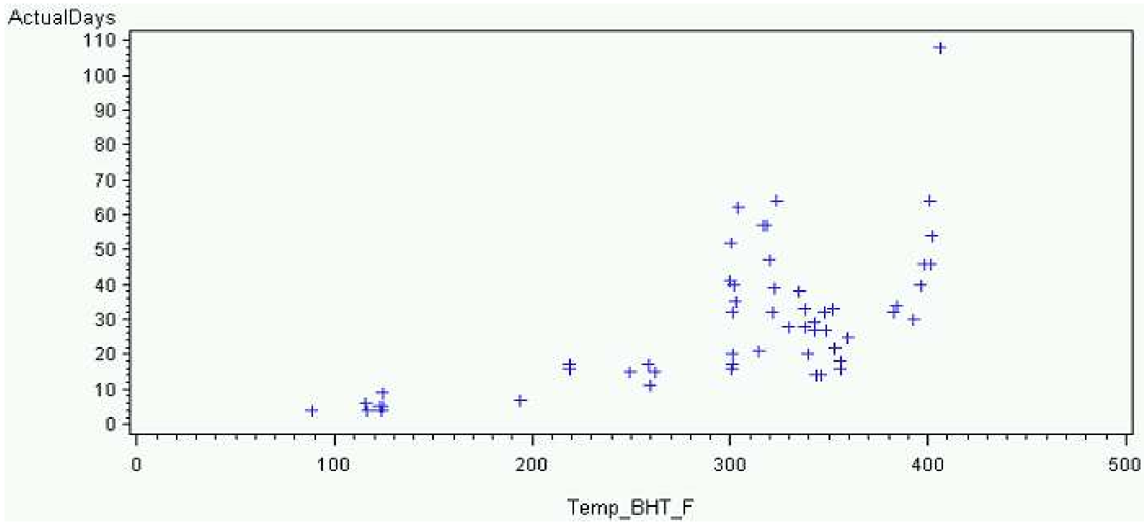

Fig 7.8–Acutal Days vs. BHT

To linearize the relationship, transformation of certain variables were done. Shown below are all the transformations done to the dataset. In statistics, the use of log is synonymous with natural log.

- logactualdays=log(actualdays)
  - The log command in SAS represents natural log
- exp_estimated_days=exp(estimated_days)
- estimated_days_sq=estimated_days^2
- log_estimated_days=log(estimated_days)
- logdepth_ft=log(Depth_ft)
- logTEMP_BHT_F=log(TEMP_BHT_F)
- DepthbyEst_days=Depth_ft*Estimated_Days
- EstDaysbyBHT=Estimated_Days*Temp_bht
- logTempBHTbyEst=logTEMP_BHT_F*Estimated_Days
- logdepthbyEstDays=logDepth_ft*Estimated_Days

After transforming the dataset, plots were done to test the linearity of the variables.

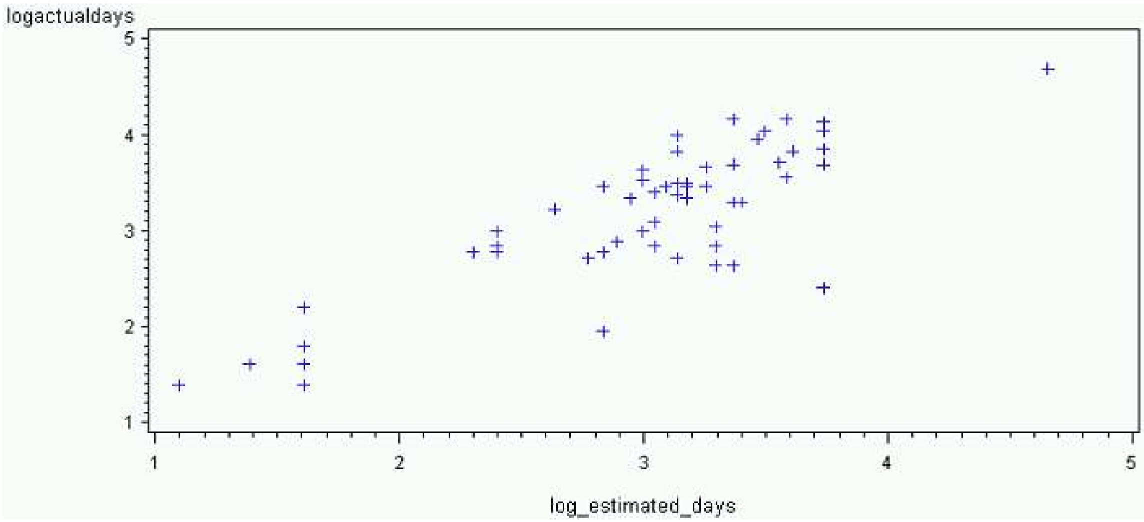

Fig 7.9–ln(Actuald Days) vs ln(Estimated Days)

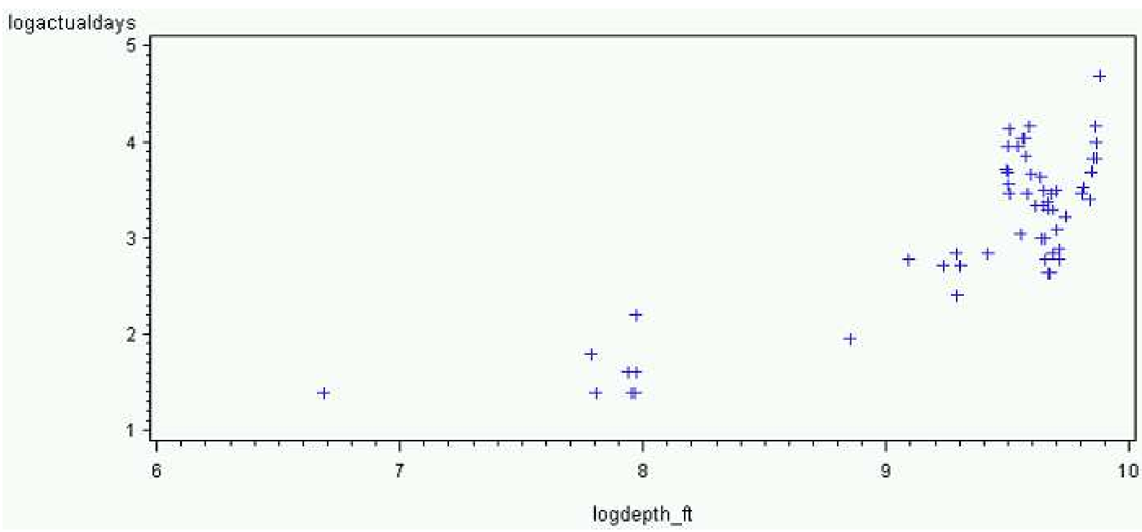

Fig 7.10–ln(Actual Days) vs ln(Depth)

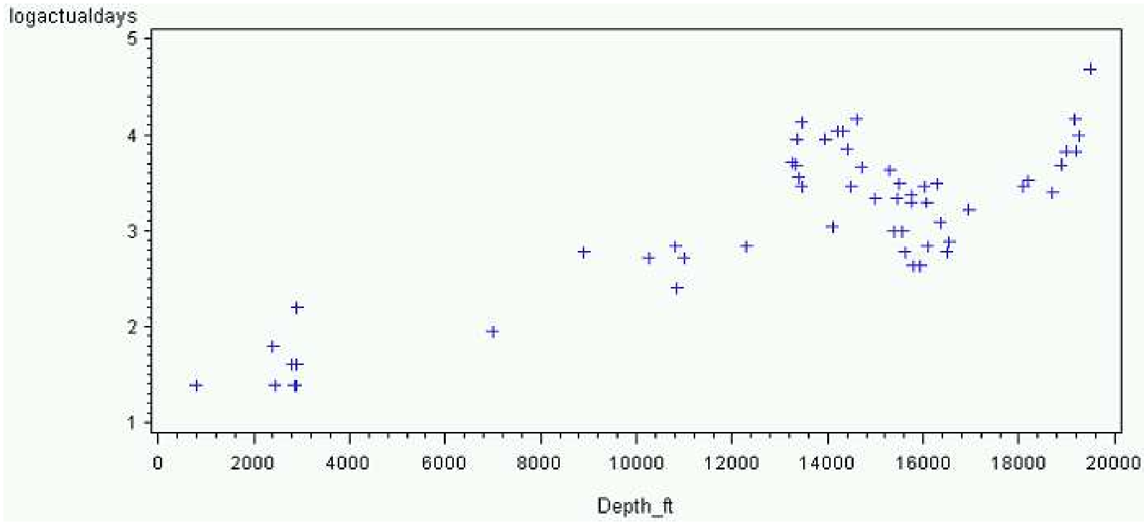

Fig 7.11–ln(Actual Days) vs Depth

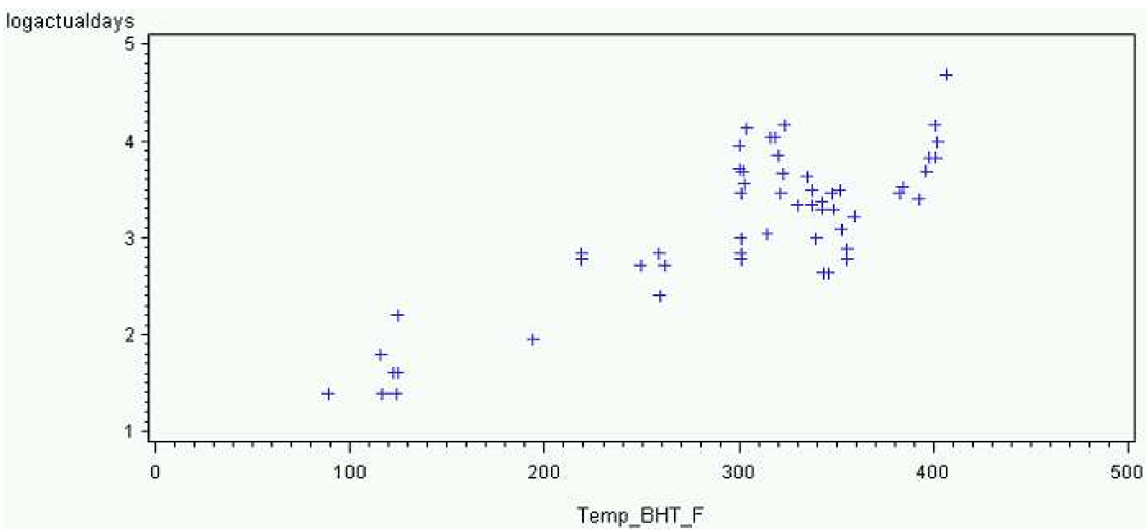

Fig 7.12–ln(Actual Days) vs BHT

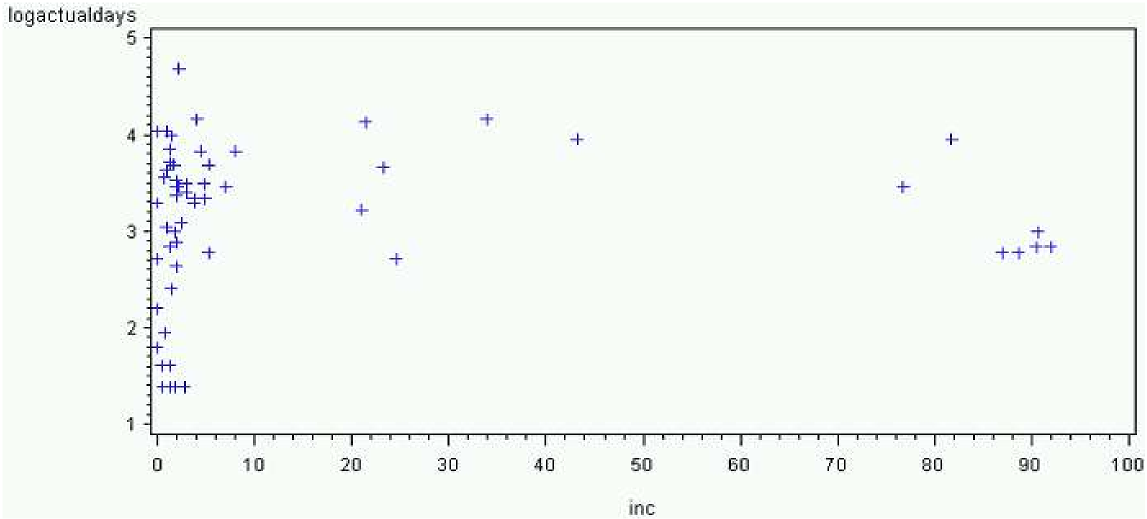

Fig 7.13–ln(Actual Days) vs Inclination

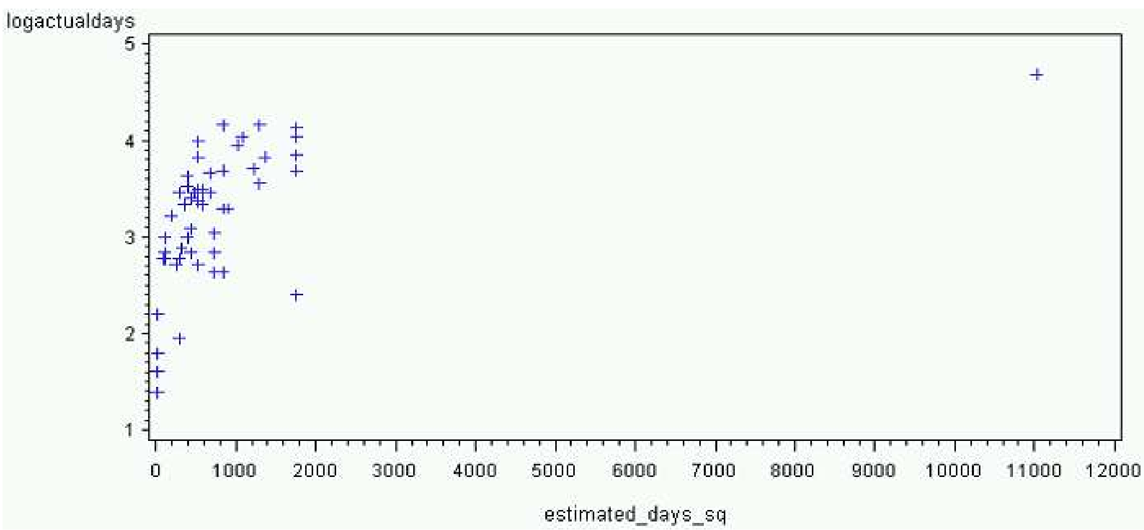

Fig 7.14–ln(Actual Days) vs (Estimated Days)^2

The ln(actual days) vs. ln(estimated days), shown in Fig, 7.9, had a linear relationship. Fig 7.10, ln(actual days) vs. ln(depth) did not have a linear relationship. ln(actual days) vs. depth and ln(actual days) vs. BHT, shown in Fig,7.11 and 7.12, also showed linear relationships. Figure 7.13 and 7.14 did not produce a linear relationship for the specific transformations between ln(actual days) vs. inclination and ln(actual days) vs. (estimated days)[2]. The key variables for the new dataset were ln(actual days), ln(estimated days), depth, and BHT.

I performed stepwise regression, forward selection, and backward elimination to the new dataset. The three regressions did not return the same regressor variable combinations. Model E (Eq. 7.5), was found through stepwise wise regression.

$$\ln(y_E) = 0.44017 + (0.60152 \times \ln(Te)) + (0.00006721 \times D) \quad \text{.....................(7.5)}$$

The residual plot for Model E (Fig. 7.15) had not improved from Models C and D.

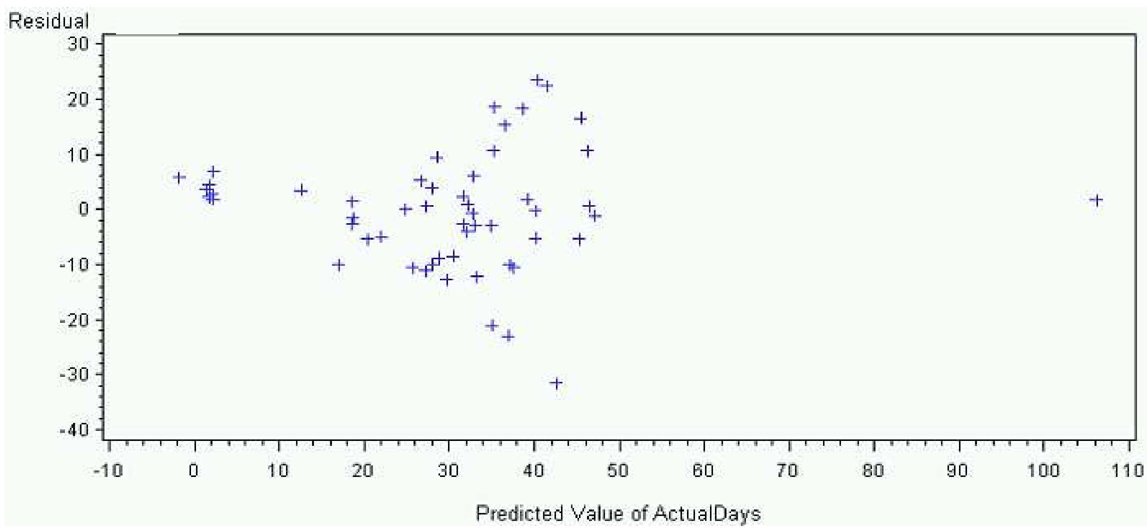

Fig. 7.15-Model E's Residual Plot. ln(Actual Day) =f(ln(*Te*),*D*)

The Shapiro-Wilk p-value of 0.0524 did not reject the null hypothesis. The Q-Q plot had noticeable deviation at the lower and higher percentiles with a staggered pattern from the 50th to 90th percentile.

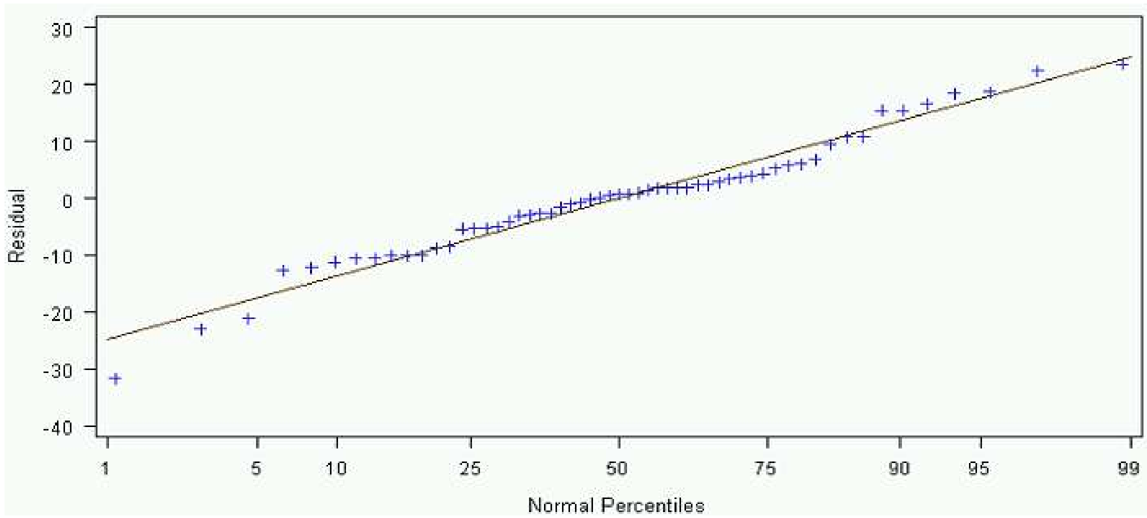

Fig. 7.16-Model E's Q-Q Plot. ln(Actual Day) =f(ln(Te),D)

Though the Shapiro-Wilk almost got rejected, the chi-squared p-value increased to 0.14. The variance inflation factor was low for both regressor variables, and the R-squared value equaled 0.7995. The F-number p-value was also very small.

Forward selection and backward elimination chose the same regressor variables. Model F (Eq. 7.6), included all variables being tested.

$$\ln(y_F) = -0.72931 + (0.57459 \times \ln(Te)) - (0.0001936 \times D)$$
$$+(0.01549 \times Tbh) + (0.00743 \times Inc) \ldots\ldots\ldots\ldots\ldots\ldots \text{(7.6)}$$

The residual plot of Model F still had the double bow appearance of models Eq. 7.3 , Eq. 7.4, and Eq. 5.5. The Shapiro-Wilk p-value and chi-squared p-values were high. Mallow Cp with 4 regressor variables had a value of 5. The R-squared value of 0.82 indicated a very good fit. The problem with Model F was that the variance inflation factor for regressor variables depth and BHT was 130.5. Since all variables have to be independent for regressions to be useful, Model F was unacceptable.

Model F indicated the strong interrelationship between depth and BHT. All regressor variables must be independent of one another. Model E selected the regressor variable depth, while previous regressions selected BHT. To test the significance of

BHT, I analyzed the dependent variable actual days and regressor variables estimated days and BHT. The returned regressor coefficients are seen in Model G (Eq. 7.7).

$$\ln(y_G) = 0.18264 + (0.58106 \times \ln(Te)) + (0.00408 \times Tbh) \text{……………….(Eq. 7.7)}$$

Model G's residual plot (Fig. 7.17), had a better scatter pattern than the previous models, with scatter evenly distributed along the horizontal axis.

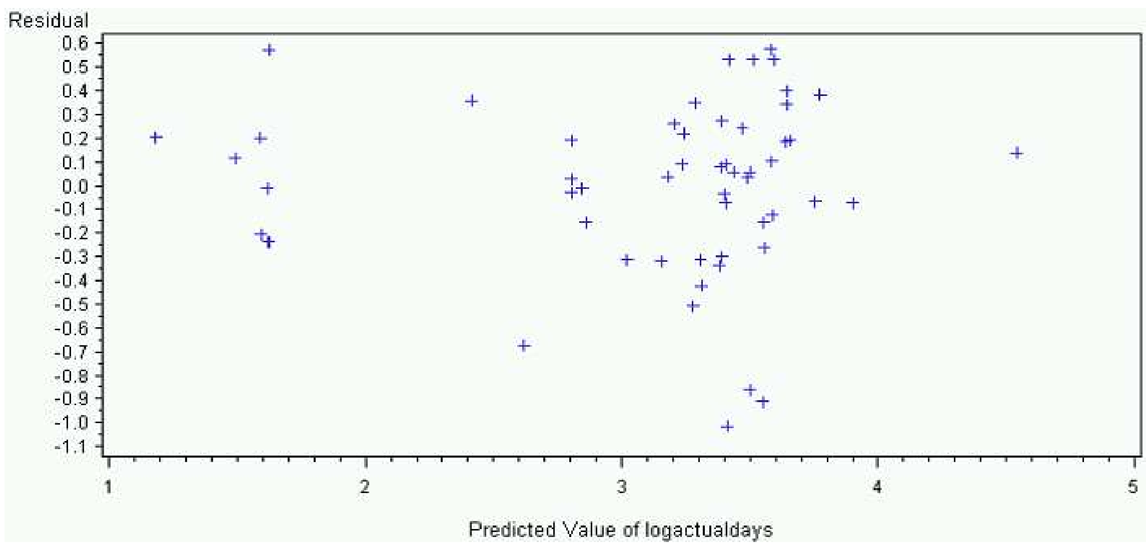

Fig. 7.17-Model G's Residual Plot. ln(Actual Days) = f(ln(Te),Tbh)

Even with the better residual plot, the Shapiro-Wilk p-value rejected the null hypothesis. The Q-Q plot for Model G (Fig. 7.18), does not follow the normal unit slope at the lower percentiles and staggers stepwise at higher percentiles.

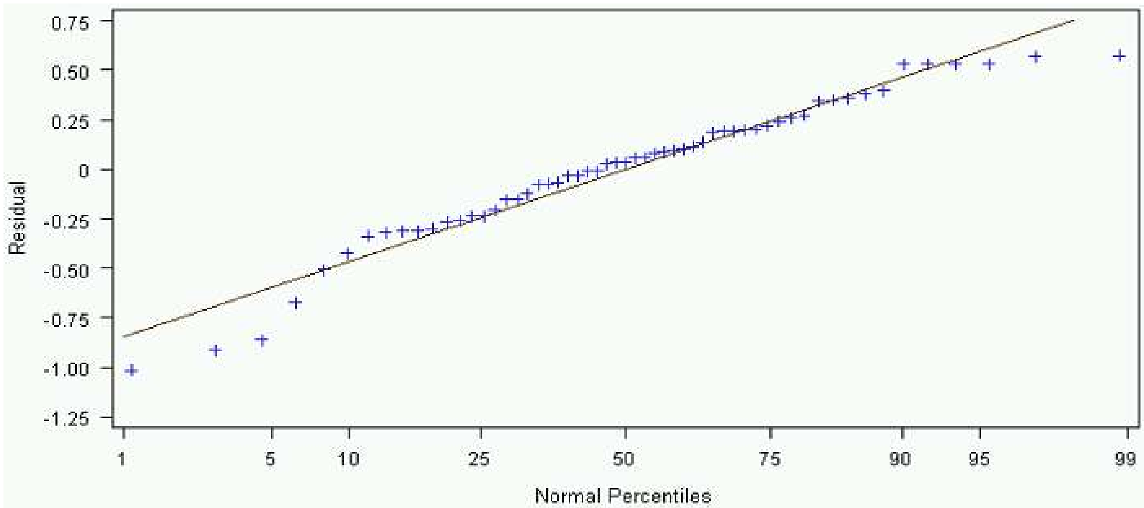

Fig. 7.18-Model G's Q-Q Plot. ln(Actual Days) = f(ln(Te),Tbh)

Though the chi-squared p-value, R-squared value, and F-number all showed good trends, Model G does not pass the Shapiro-Wilk test and was considered inadequate.

Looking at previous regressions, the three most significant regressor variables were estimated days, depth, and BHT. Models C, D, and E barely passed the validation process. The next step required further analysis of the transformed variables in an attempt to obtain a better model. The variables actual and estimated days and depth were selected and only actual days was kept transformed to ln actual days. The regression coefficients of Model H are shown in Eq. 7.8.

$$\ln(y_H) = 1.30916 + (0.02003 \times Te) + (0.00010005 \times D) \quad (7.8)$$

Model H's residual plot (Fig. 7.19), had a similar scatter to Model G's residual plot. It had better scatter distribution than Models C, D, and E.

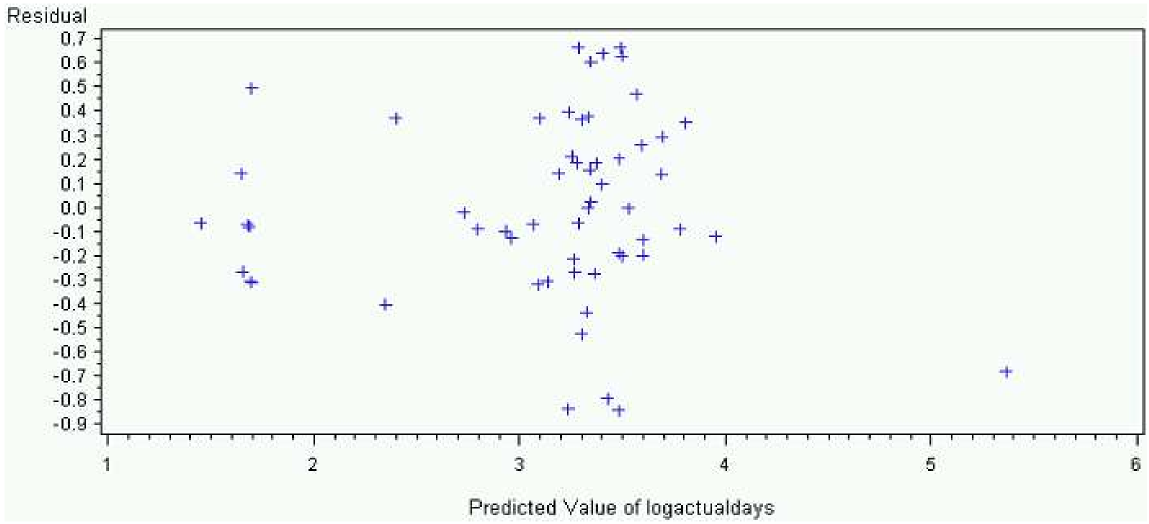

Fig. 7.19-Model H's Residual Plot. ln(Actual Days) = f(*Te*,D)

The Q-Q plot appeared better than previous models, with a reduction in the stepwise stagger that was present for Model G. The central points fluctuate more above and below the unit slope, while at the top and lower percentile deviation still occurred.

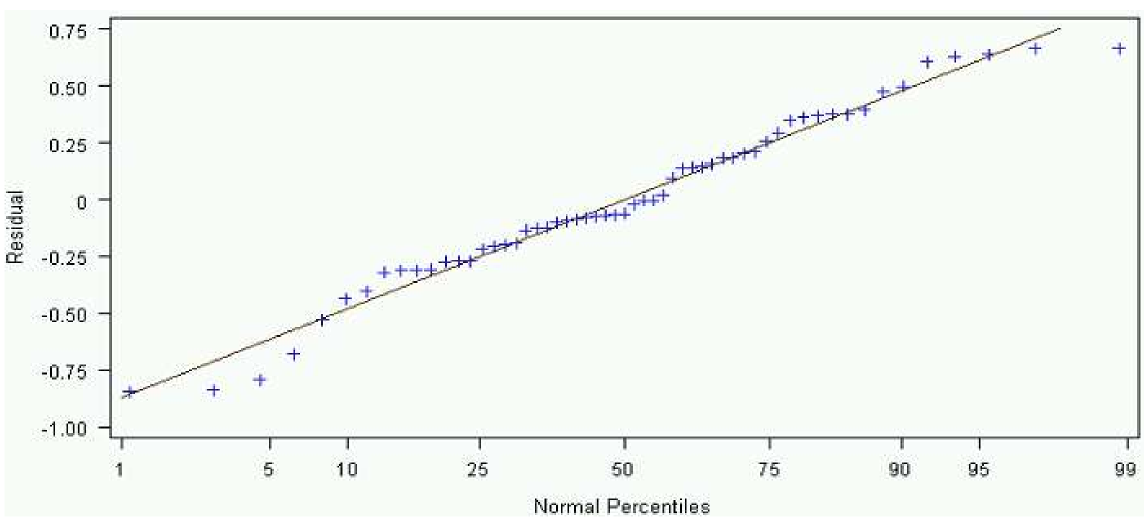

Fig. 7.20-Model H's Q-Q Plot. ln(Actual Days) = f(*Te*,*D*)

Both the Shapiro-Wilk p-value of 0.25 and chi-squared p-value of 0.0807 do not reject the null hypothesis. Though the chi-squared p-value was small, it still passed the cutoff value of 0.05. Variance inflation factor of 1.35 confirmed that all variables were independent. R-squared was high with a value of 0.787. The F-test p-value was also below 0.05. Model H passed all validation criteria.

Even though Model H passed all validation criteria, an optimal model, if possible, would not have validation parameters that barely pass. I continued testing to try and find a model with higher validation parameters. BHT has often been used in previous models and was significant in Model D. Another test was done using ln Actual Days, Estimated Days, and BHT. Model I (Eq. 7.9), was the result of the analysis.

$$ln(y_I) = 0.88750 + (0.01893 \times Te) + (0.00598 \times Tbh) \text{.............................(7.9)}$$

Model I had a near-identical residual plot to that of Model H. Model I's univariate analysis also calculated values similar to Model H. Model I did not reject the Shapiro-Wilk or chi-squared tests. Variance inflation factors were low. R-squared had a value of 0.787, the same as Model H. The only concern was that the chi-squared value was 0.073, a decrease from Model H's chi-squared value of 0.0807.

Although models H and I are both valid models, it would be preferable to have a higher chi-squared p-value. To attempt to find a higher chi-squared, Model H and I were modified by transforming regressor variables Depth and BHT to ln Depth and ln BHT. The resulting regressor coefficients of Model J are shown in Eq. 7.10 and Model K in Eq. 7.11.

$$\ln(y_J) = -4.1396 + (0.02007 \times Te) + (0.72552 \times \ln(D)) \text{..........................(7.10)}$$

$$\ln(y_K) = -4.98991 + (0.01828 \times Te) + (1.36169 \times \ln(Tbh)) \text{...................(7.11)}$$

Model J's residual plot (Fig. 2.11), appeared slightly more homogenous than Models G, H, and I. The scatter pattern looked evenly distributed along the horizontal axis.

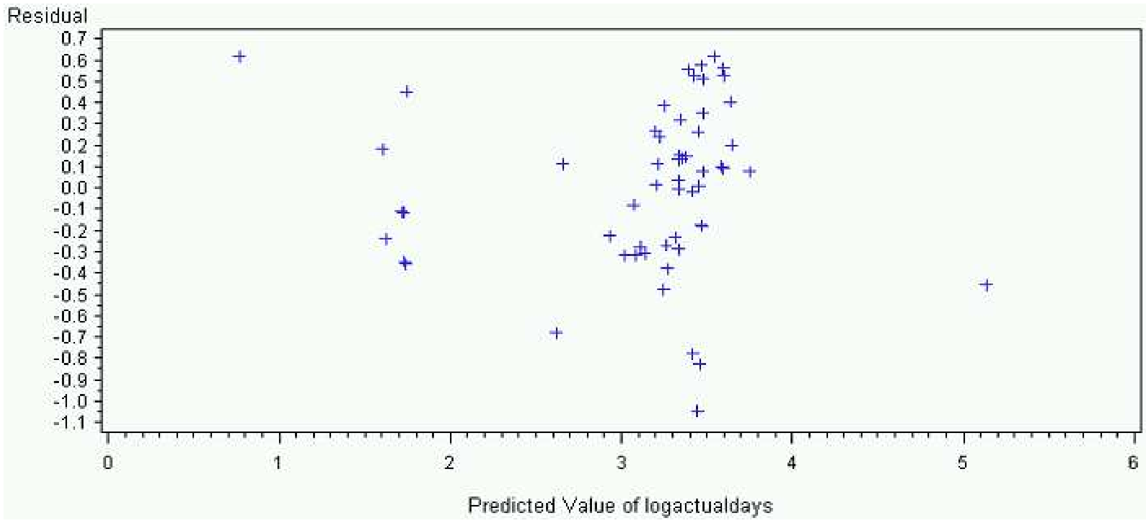

Fig. 7.21-Model J's Residual Plot. ln(Actual Days) = f(*Te*,ln(*D*))

Model J's Q-Q plot (Fig. 7.22) improved from Model's I Q-Q plot; it does not stagger along the unit slope. The lower percentiles did not deviate as in previous models, while deviation still occurred at the upper percentiles.

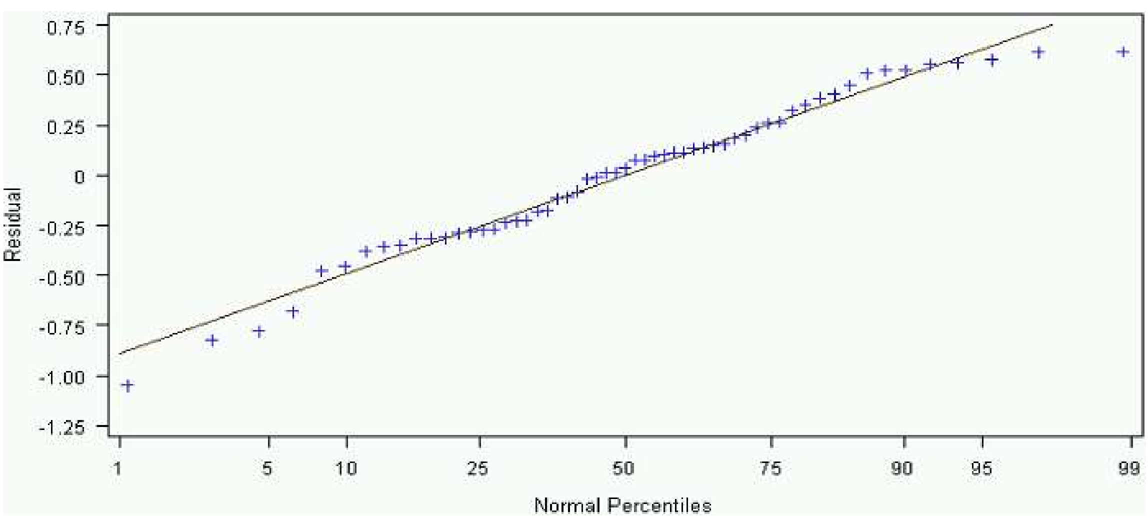

Fig. 7.22-Model J's Q-Q Plot. ln(Actual Days) = f(*Te*,ln(*D*))

The Shapiro-Wilk and chi-squared tests did not reject the null hypothesis. The Shapiro-Wilk p-value was 0.16 and the chi-squared p-value was 0.25. The variance inflation factor was low, and the F-test p-value was very low. The R-squared value was 0.775. Model J had the desired validation criteria.

Both the residual plot and Q-Q plot of Model K appeared near identical to Model J's. Model K's Shapiro-Wilk and chi-squared tests were not rejected. The chi-squared value did reduce to 0.11 from Model J's chi-squared value of 0.25. The variance inflation factor was low and the F-test p-value was very small. The R-squared vale was 0.797. Model K has a lower chi-squared value than Model J but a higher R-squared value. Both Models J and K are valid models to use for predicting the amount of time required to drill a well.

A final test was done to see if combining the variables in each valid model would result in a significant positive change. New regressor variables were made by combining estimated days and ln depth into estimated days by ln depth. Estimated days and ln BHT were combined into estimated days by ln BHT. No positive significant results were obtained.

CHAPTER VIII

HISTORY MATCHING OF SIGNIFICANT MODELS

Seven models-Eq. 7.3, 7.4, 7.5, 7.8, 7.9, 7.10, and 7.11-passed all validation parameters. The next step checked the accuracy of each model by comparing predicted data to historical data.

$$\text{Percent Error} = \frac{Actual - Predicted}{Actual} \text{...(Eq. 8.1)}$$

By looking at the difference between actual and predicted and by comparing the percent error per well section, the best model was chosen.

Shown below, Table 8.1 illustrates an overall tendency to overestimate or underestimate and how many times each model predicted a value that was +/- 10% of the actual number of days required to drill a well interval.

Table 8.1
Summation of Percent Error and Number of Times the +/-10% Objective was Obtained per Well Section

Per Well Section	Technical Limit	Model C	Model D	Model E	Model H	Model I	Model J	Model K
Over or Under Estimated	2.57	-16.06	-4.41	-4.11	-4.12	-4.07	-4.47	-4.02
+/- 10% out of 57 intervals	11	10	16	15	13	12	12	14

The parameter, Overestimated or Underestimated, was found by summing all percent errors for every well section. A smaller number indicates a smaller difference between actual and predicted values. Table 8.2 compares the same properties as in Table 8.1 but the individual well sections have been summed.

Table 8.2
Summation of Percent Error and Number of Times the +/-10% Objective was Obtained per Well

Per Well	Technical Limit	Model C	Model D	Model E	Model H	Model I	Model J	Model K
Over or Under Estimated	4.69	-3.36	-0.33	0.86	0.23	0.44	0.45	0.58
+/- 10% out of 17 wells	0	8	8	6	5	5	6	6

Both Table 8.1 and Table 8.2 showed that Model D best predicted the actual data. Overall Model D had a 47% success rate for comparing the total number of days to complete a well. The accuracy rate decreased to a 17.5% success rate when measuring individual well sections. Though the original estimate for technical limit had the lowest difference between the number of days per individual well interval, overall original estimate for the total number of days required to drill a well was greater than all models and never had an estimate within the +/- 10% time difference. The original estimates do not take into account the increase time required to drill the deeper hole sections while the predictive model do.

No model gave the optimum +/-10% time difference for every well section. Using regression techniques to find Model D, there was an improvement on the prediction of the total number of days to drill a well. To improve upon Model D, more observations would be required and the regressions redone.

CHAPTER IX

LITERATURE COMPARISON WITH METHODOLOGY AND RESULTS

Kaiser and Pulsipher (2007) found the generalized function model through regression in four basic steps. Step 1 required the selection of independent descriptor variables. Step 2 defined the bounds of individual parameters for each well. Step 3 constructed a regression model from the well data and tested the model's coefficients for significance. Step 4 maintained all significant variables and factors with p-values less than 0.05. As stated previously, the five step methodology introduced in this thesis was similar to Kaiser and Pulsipher's: Step 1 created a database. Step 2 performed initial statistical regression on the original data. Step 3 ensured that the models are valid by performing univariate analysis. Step 4 history matched the model's response to actual observed data. Step 5 repeated the procedure till the best model was found. If no significant models were found after performing the calculations using the initial dataset, data manipulation was required.

Step 1 creates a database. If a dataset of all wells with all parameters were to be done, it would cause significant variability to the output due to the heterogeneity of the data (Kaiser and Pulsipher 2007). To avoid heterogeneity problems, the first step requires defining a specific question. A dataset should represent a group of wells or well sections from similar geology, depth, and drilling method (Adams et al. 2009). In this thesis, data was used from wells that were drilled in the same fashion, using a top drive, and located in the same county in north central Texas.

The number of observations available determines the number of independent variables that may be analyzed. According Adams et al. (2009), 100 wells was the bare minimum for statistical accuracy and 200 or 300 wells were optimal. Jablonowski and MacEachern (2009), claim that 30 observations allow for enough significance. An observation may be the data obtained from a certain well segment or the total values for a single well. With a small dataset, 10 independent variables can be tested and for larger datasets, 20 independent variables (Kaiser and Pulsipher 2007). Noerager et al. (1987)

produced a model using 640 wells in the North Sea that included 489 platform wells and 51 subsea wells within a time span of 10 years, from 1976 to 1986. They tested 9 variables. Even with a large dataset with detailed measurements, the model did not obtain the +/- 10% time-deviation goal. They attribute the large amount of scatter to operational differences among the wells. If they had a more specific initial question, like "how long does it take to drill a subsea well in the North Sea using data from 1981 to 1986?", a more accurate model could have been possible. The dataset form north central Texas created to test the regression methodology had 57 observations with 12 independent variables.

In Step 2, boundaries were set to normalize the data. Normalizing data has many advantages for flat time activities and the addition of new descriptive variables. An example of a new descriptive variable would be, assigning a value of 1 if bottomhole temperature got above 300°F, 0 if it did not. Though there are many advantages standardizing variables, normalizing rate dependent variables, such as drilling and tripping, can cause errors in the model (Adams et al. 2009). In this thesis the dataset had some variables manipulated to linearize key interactions, but none were normalized.

Many software programs perform the necessary calculations for Step 3. Some options are as accessible as Microsoft Excel, other programs are dedicated to statistics, and some are specific to drill-time prediction. SAS and R were chosen to perform the statistical calculations in this project. Both offer the flexibility to test many parameters that specific prediction software may not allow or does not calculate. Step 4 keeps all significant variables with an F-test p-value less than 0.05 within the final model.

Noerager et al. (1987) produced two deterministic nonlinear models that contained dimensionless variables, penalty factor in learning curve, rate of learning, half-life of learning curve, and annual improvement factor (Noerager et al. 1987). The authors claimed that 21 days, or 35% of the mean, was the smallest deviation possible by any method of predicting the time required to drill and complete an individual well. Table 9.1 shows the standard deviation of actual and predicted values for the well drilled in north central Texas.

Table 9.1-Average Standard Deviation

Days	Technical Limit	Model C	Model D	Model E	Model H	Model I	Model J	Model K
Per Well Section	7	6.64	5.46	5.54	6.91	6.75	6.38	6.10
Per Well	28	29	32	34	37	36	34	34

That same year, Thorogood (1987) created a model using 85 wells that includes a linear formula for daily progress rate and additional values for flat-time unit operations. When the standard deviation of the drilling progress and unit operations were combined the total standard deviation equaled 10% of the total time of Noerager's model, which tried to incorporate too many parameters that are not easily measured, such as learning curves. Working with a more targeted approach, as Thorogood had done, resulted in a more accurate, straightforward model that had better predictive capabilities. The models created using SAS and R emulated Thorogood's strategic approach to deterministic estimator modeling.

Many operators use probabilistic instead of deterministic modeling. Some engineers claim that deterministic estimates tend to be optimistic and that many decisions are made ignoring the prediction errors (Loberg et al. 2008). In 1993, Peterson et al calculated drill time predictions using @Risk software to perform Monte Carlo simulations. In their model, total time equals total problem-free time plus total problem time, which required that the probability distribution functions of depth variation, drilling and evaluation problem days, and the problem-free drilling and evaluation days be chosen. Due to the large uncertainty present while drilling a well, deciding which probability distribution function to select may be difficult. Softwares are available to assist with the selection process, and some have preselected probability distribution functions if data is limited. To allow for a new field with a small datasets, my deterministic methodology gave a more direct approach to obtain a time-predictive model.

Peterson et al. (1993) gave two examples, a 20,090 ft and 17,907 ft well. Using a probabilistic approach and the @ Risk software, they calculated problem-free days and problems day and validate their approach by showing that the difference between predicted and actual drill time was only 3 days. In the north central Texas example, Model D estimated three wells, 16,500 ft, 19,500 ft, and 12,300 ft, with less than 2 days' error for the 17 wells tested. Peterson et al. does not describe the accuracy of the method when tested in a larger scale.

Kaiser and Pulsipher (2007) and Jablonowski and MacEachern (2009) calculated their predictor model using regression analysis. Jablonowski and MacEachern (2009) used the standard deviations of the model's results to demonstrate the effectiveness of their model; Jablonowski and MacEachern (2009) showed R-squared values, standard error, and t-test values to indicate the adequacy of their model. The mean for the number of days required to drill a well in the Gulf of Mexico was 34.7 days with a standard deviation of 19.2 days using Louisiana Kaiser and Pulsipher (2007) model. Though both research teams gave statistical parameters to describe their models, they still lack the accuracy presented with the five-step methodology. To standardize the selection process and testing of model significance, I created a list of criteria for model selection and testing.

Jablonowski and MacEachern (2009) deterministic approach to allowed probabilistic range of values by changing the confidence interval. Using 66 observations and 30 independent variables, they developed a model with an R-squared value of 0.86 using a 95% confidence interval, whereas I used 57 observations with five independent variables. Using Model D as the optimal model with a 95% confidence interval, the R-squared value was 0.716. A possible improvement on predicting the time required to drill a well in north central Texas may occur with the introduction of new independent variables, such as hole size or indicating a variable for certain formations, similar to the 30 variables Jablonowski and MacEachern (2009) tested.

No article had proven the significance of their model. A model found using statistical regression needs to make sure certain key statistical test indicates whether the assumption required to create the model are accurate. Previous reported models included a calibration to fit historical data when using regression techniques. If certain key parameters such as Shapiro-Wilk residual normality test do not hold true, F-test p-values may indicate significant variables, but in actuality the model would be flawed and the final result may be a calibrated incorrectly. To avoid that problem, I developed a validation check list using results from univariate calculations. After the creation of a model by analysis of variance, every model had to pass the seven key parameters to decide if the model has mathematical significance. The seven models shown in Table 10.1 all passed the seven criteria. Historical matching of the data with predicted values of valid models then determined which model has the greatest predictive accuracy.

CHAPTER X

CONCLUSION

Deterministic models have a single value response, so a deterministic approach was chosen for this project because a linear model may be found with small amounts of data. The five step methodology introduced in this thesis includes validation parameters that ensure the required statistical assumptions for regression are followed. Step 1 created a database. Step 2 performed initial statistical regression on the original data. Step 3 ensured that the models are valid by performing univariate analysis. Step 4 history matches the model's response to actual observed data. Step 5 repeated the procedure till the best model was found.

When the applied methodology was tested on the example case using SAS and R, the overall objective of having the predicted model within 10% of the actual time to drill a well was only achieved 50% of the time using Model D. When individual well sections were predicted, the 10% objective was achieved only 28% of the time. To improve the model, different options may be considered.

The first option would be to create a more homogenous database by redefining the example case. By changing the objective question, "How many days are required to drill a vertical well in north central Texas?"; the data could be more concise and may improve the accuracy of the model. A second option would be to include more data by including other analogous wells near the area of the well tested. The third option would be changing the independent variables. By removing the estimated days and keeping the more physical descriptive variables, a better model may be found.

Having a methodology that may be quickly implemented allows for greater flexibility. The most time-consuming labor was creating the database. After applying the methodology to the example case, greater accuracy was found than previously predicted values. The methodology helped improve prediction estimation but did not ensure the +/- 10% time deviation from actual observations.

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APPENDIX A

PROCEDURE FOR PERFORMING ANALYSIS OF VARIANCE IN SAS

The chapter explains the basic code necessary to perform variable analysis within SAS. The process of transferring a dataset from Microsoft Excel to SAS 9.2, the basic format and commands required for stepwise regression, forward selection, and backward elimination will be shown and the code for least squares regression are given for testing of individually selected independent variables. To validate the response of SAS, the commands for univariate calculations are given.

A.1 Transferring Data from Microsoft Excel to SAS

The procedure starts with the initial dataset in Microsoft Excel. Figure A.1 shows how individual variables and values are arranged for a given dataset. Short, concise names are recommended when labeling individual variables. At the end of this section, the reason for short concise names has been given.

						BHT F				
Well	cumAcutal	cumEstim	ActualDay	Estimated	Depth ft	Temp BHT	inc	MW	FP	PP
A	19	28	15	23	10260	249	24.60	10.1	11.0	9.2
A	51	54	32	26	14496	321	2.15	10.1	12.1	9.8
A	83	71	32	17	16025	347	2.00	13.7	17.0	13.3
A	137	94	54	23	19250	402	1.50	19.0	18.5	18.5
B	70	40	64	36	14620	324	33.85	13.2	18.0	12.8
B	92	61	22	21	16350	353	2.50	13.7	18.0	13.4
B	122	82	30	21	18700	393	2.99	18.5	19.5	18.1
C	69	48	62	42	13470	304	21.37	10.5	11.0	10.0
C	97	72	28	24	15449	338	3.75	15.2	16.2	14.9
C	129	96	32	24	18100	383	7.00	17.3	18.5	17.1
D	21	31	17	27	10820	259	1.25	10.1	13.5	9.5
D	53	53	32	22	13460	301	76.80	13.0	15.0	9.5
D	70	64	17	11	16102	301	92.07	14.2	15.0	13.9
D	57	37	52	32	13953	300	81.78	12.0	15.0	11.2
D	73	48	16	11	15618	301	88.72	12.1	15.0	11.4
E	45	38	41	35	13255	300	1.25	12.0	17.0	11.9
E	78	62	33	24	15499	338	3.00	16.3	19.0	15.7
E	96	80	18	18	16550	356	2.00	18.0	19.0	17.6
E	135	106	39	26	14700	323	23.21	18.0	19.0	17.6
E	160	120	25	14	16950	359	21.02	17.5	19.0	17.3

Fig.A.1- Example Dataset from North Central Texas Wells

The next step is to save the worksheet as a comma-separated file, .csv file type. Though SAS can import workbooks from Microsoft Excel, certain issues arose when trying to import the data via a virtual access using the internet. There were no issues when the dataset was a .csv file, and it imported with no problems using a virtual access.

Described below is the procedure for importing a dataset into SAS 9.2. This procedure also works for older versions of SAS.

1. Click on the File tab
    a. Under the File tab, click on Import data.

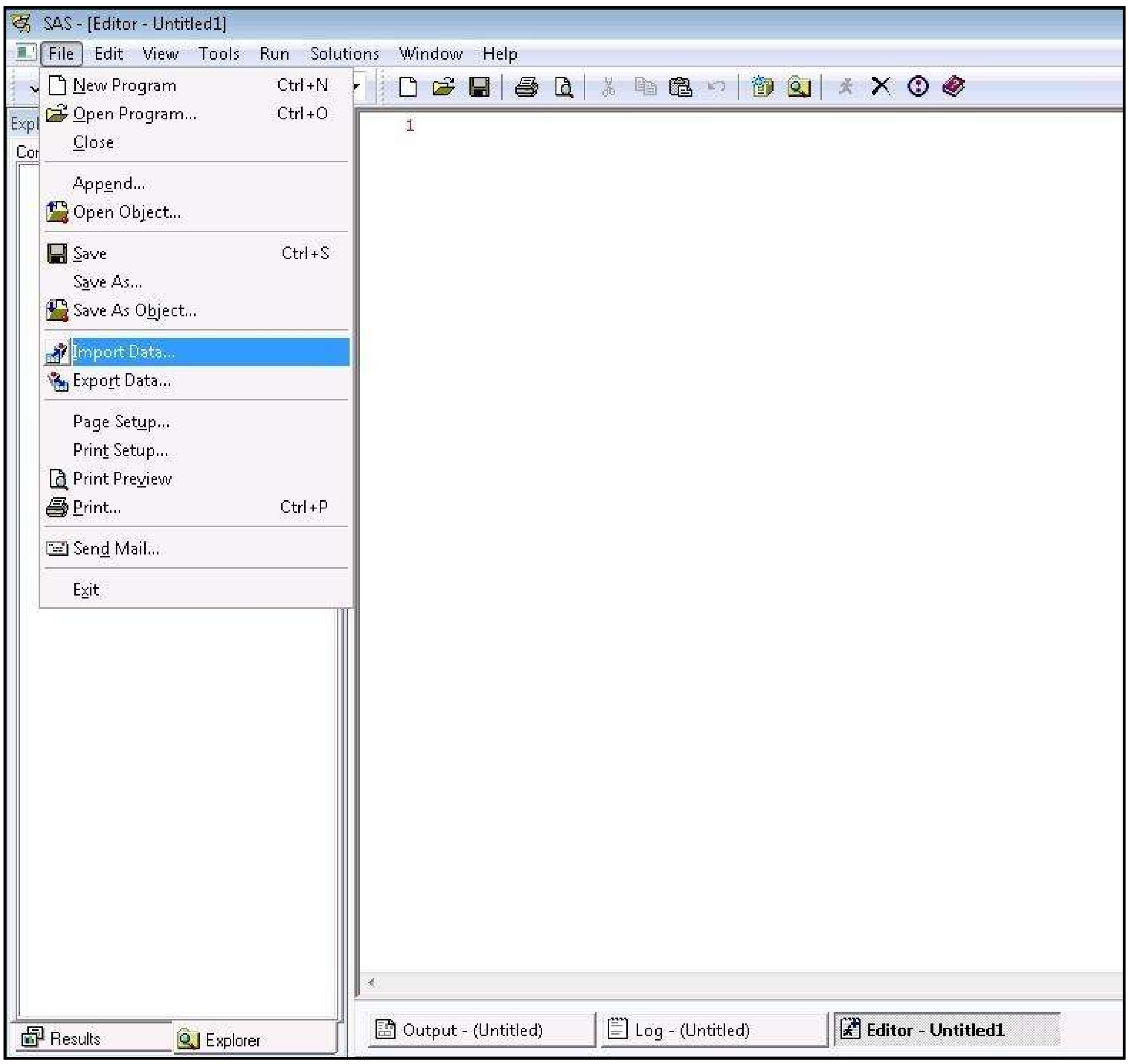


Fig. A.2-Initial Steps to Import a Dataset into SAS

2. Click on the square marked, Standard Data Source.
3. Click on the pull-down bar marked Selected a data source from the list below.
4. Click on the fourth option, Comma-Separated Values (*.CSV).
5. Then hit Next on the bottom of the window.

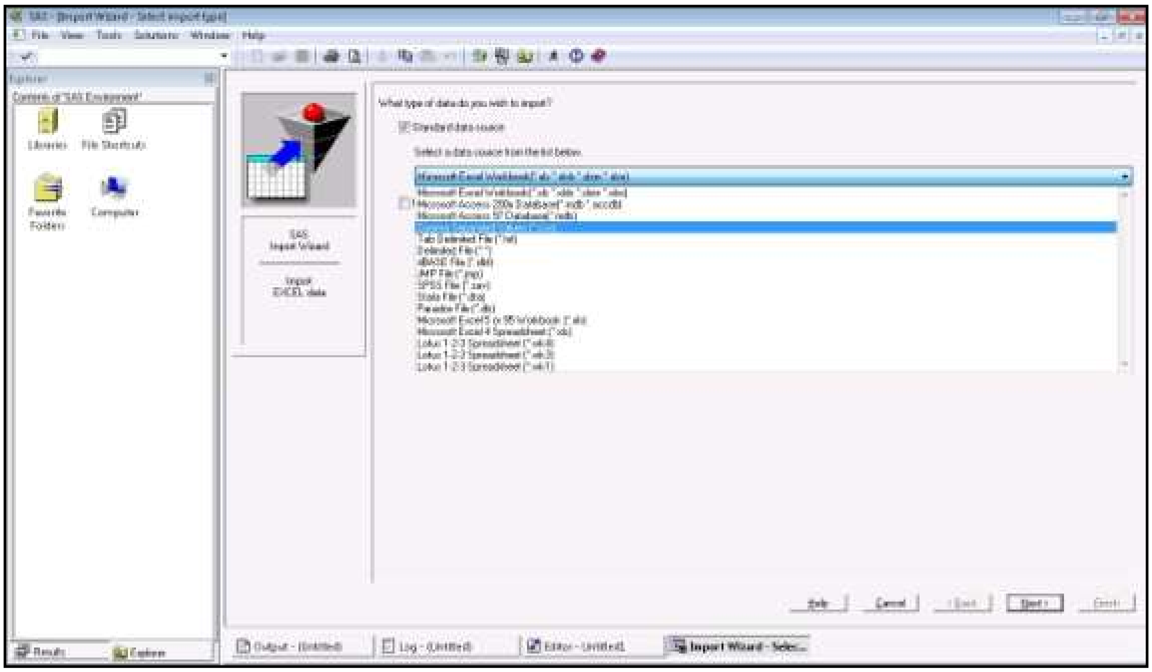


Fig. A.3-Middle Steps to Import a Dataset into SAS

6. Find your data file by clicking on the Browse tab.
7. Once the data file has been selected click Next.
8. Under library, make sure that the pull down bar has Work selected.
    a. Under Member, create a name for your dataset. This name will be used to access the dataset when writing the program necessary to perform calculations on SAS

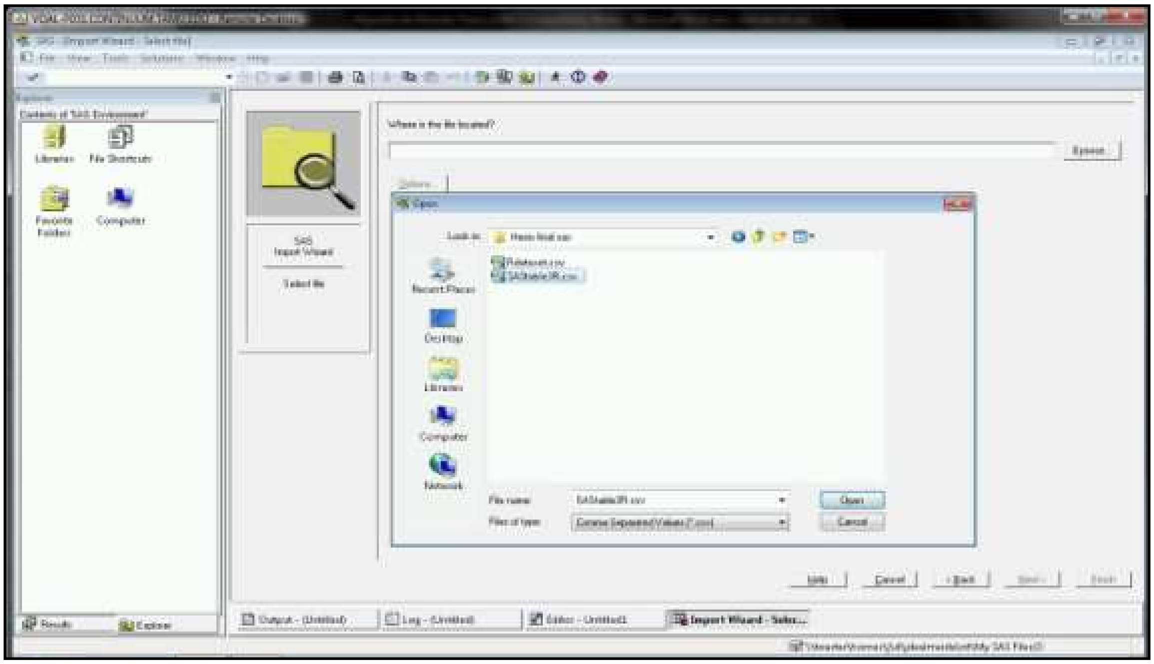


Fig. A.4-Final Steps to Import a Dataset into SAS

9. After naming the dataset, click on Finish.

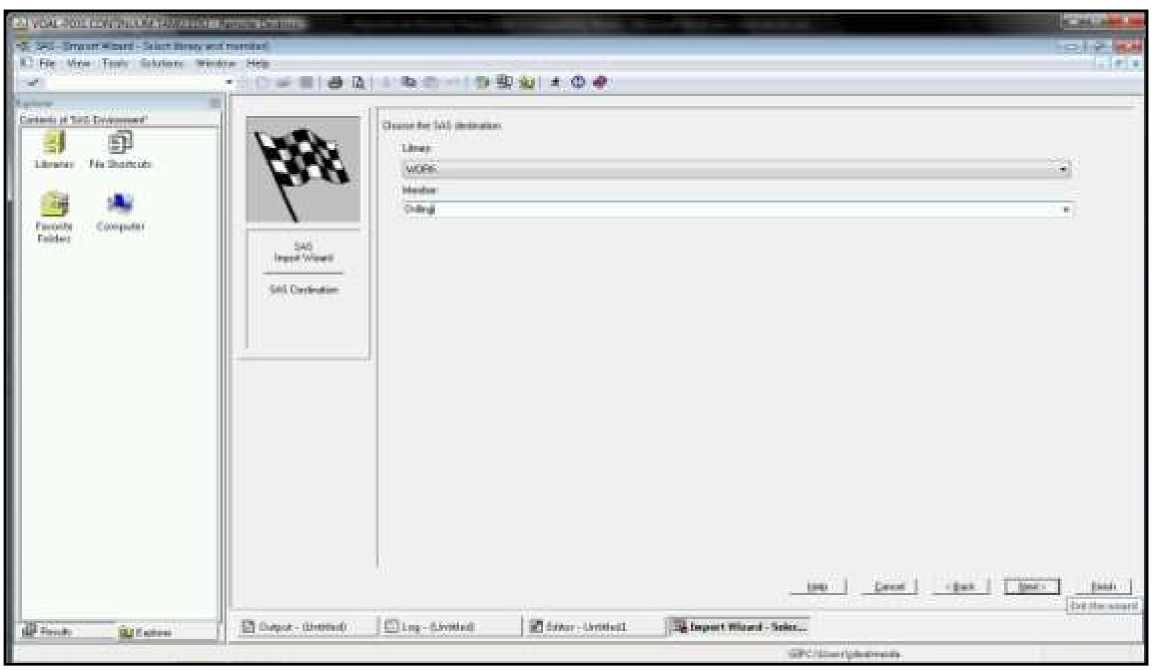


Fig. A.5 – Last Step to Import a Dataset into SAS

10. If SAS is readily available, you can construct personal user SAS libraries and store information.

After the dataset has been inputted, you can see the individual names of each variable under the, Log-(Unititled) window. Once the Log-(Untitled) window has been selected, scroll down to find the Input area. All variable names will be shown below. When working with SAS, specific variables have to be written as shown within the Log worksheet. For that reason, short, concise names are recommended when creating the initial dataset in Microsoft Excel. The symbol $ means that the variable has nonnumerical character values associated with it. When a variable has an underscore within the name, it represents a space that was given when the variable name was written within Microsoft Excel.

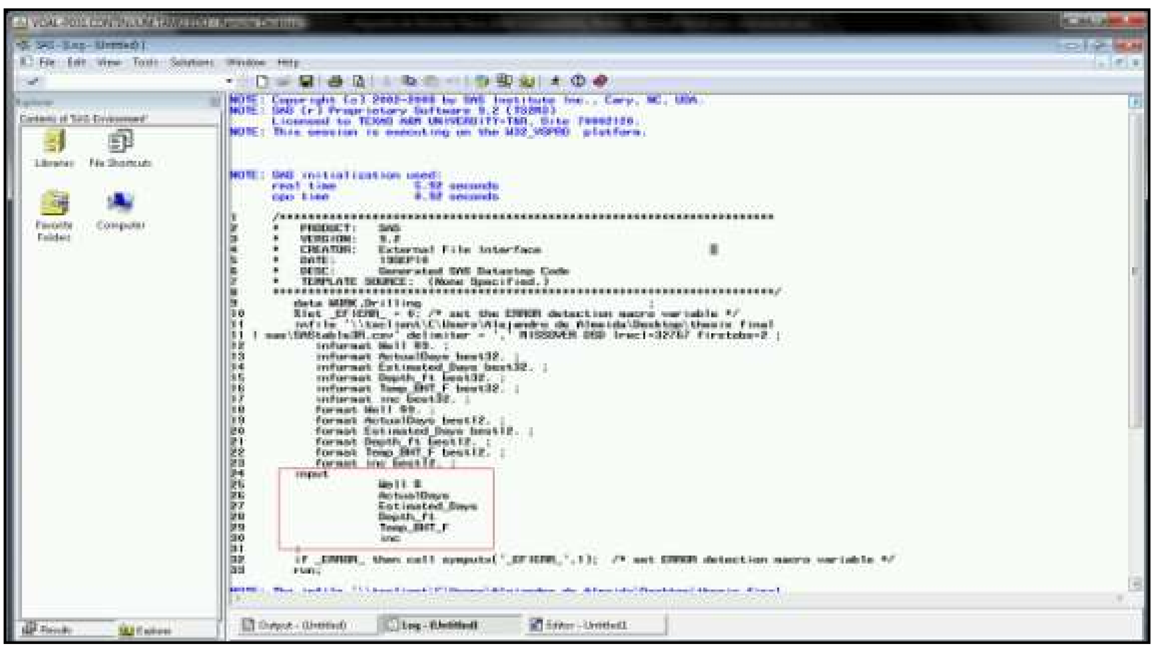


Fig. A.6-Variable Names Seen within the Log Window

A.2 Basic Code Necessary to Perform SAS Regression and Model Validation

The basic commands to perform the different calculations within SAS are explained below. All source code needs to be written within the Editor page. SAS requires an exact format when writing the open source code. Semicolons have to be placed at the end of every command. The floppy icon on the upper left-hand side of the toolbar saves the written code on the Editor page.

The first lines of code open up the dataset saved within SAS workspace:

```
proc contents data=filename;
run;
```

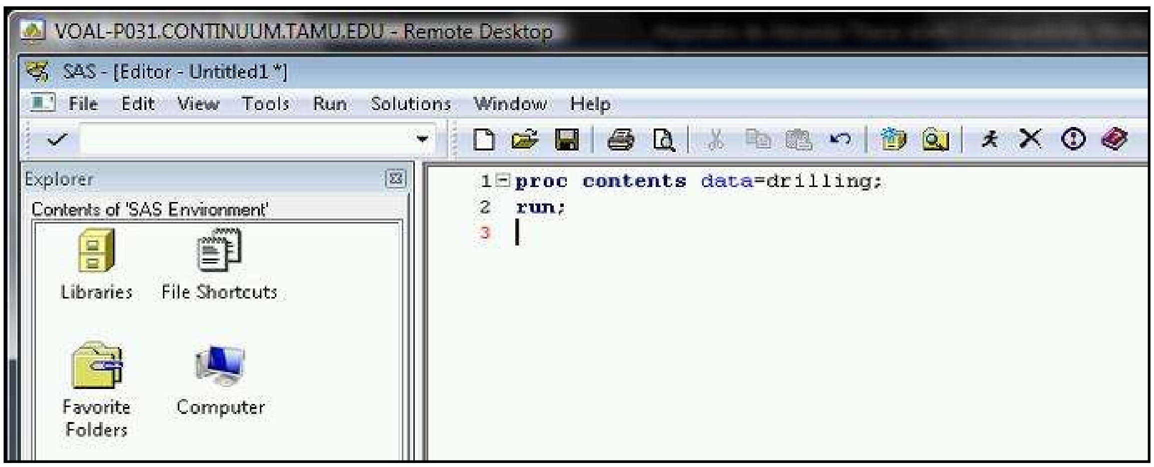


Fig. A.7-Attach Dataset into SAS Workbook

SAS recognizes individual variables by the space between them. Commands are differentiated by the use of a semicolon. A single command may take up multiple lines. Some backslashes appear below the model equation because there of a lack of space within the margins.

The command *spec* and *vif* are used for model validation. The code *spec* outputs analysis of variance results and *vif* outputs variance inflation factor. A full description of outputs can be found in CHAPTER III of this thesis.

The models presented have used the following basic code for stepwise regression, forward selection, backward elimination, and least square regression.

Stepwise Regression

```
proc reg data=filename;
model dependent_variable = variable_A variable_B variable_C
/selection=stepwise spec vif;
run;
quit;
```

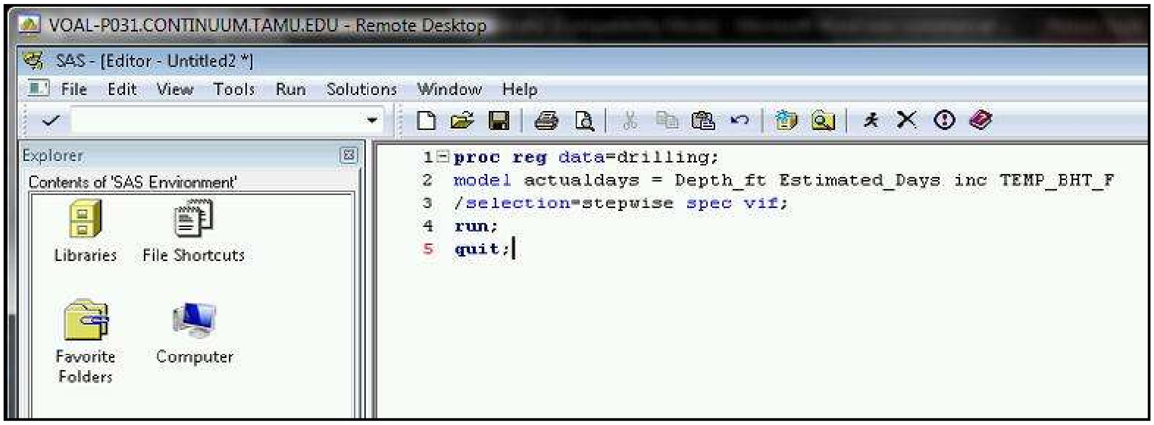


Fig. A.8-Example SAS Input for Stepwise Regression

Forward Selection

```
proc reg data= filename;
model dependent_variable = variable_A variable_B variable_C
/selection=forward spec vif;
run;
quit;
```

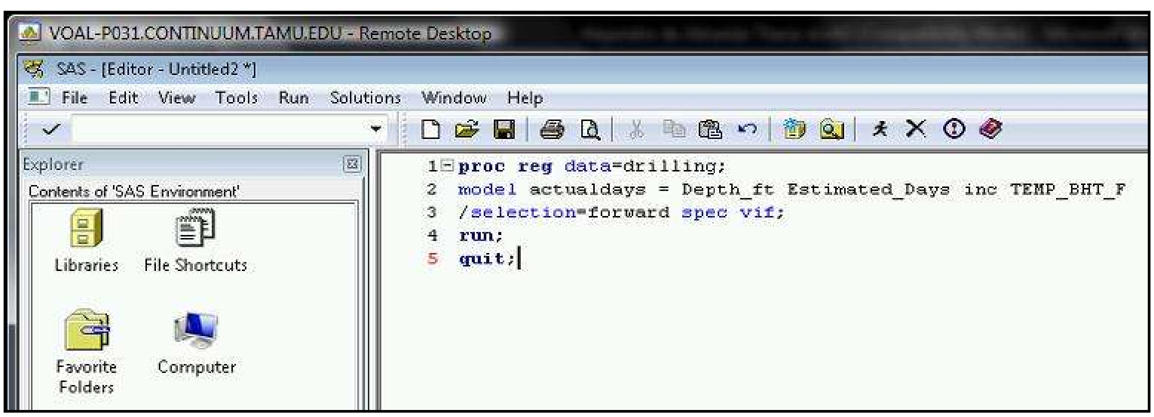


Fig. A.9-Example SAS Input for Forward Selection

Backward Elimination

```
proc reg data= filename;
model dependent_variable = variable_A variable_B variable_C
/selection=backward spec vif;
run;
quit;
```

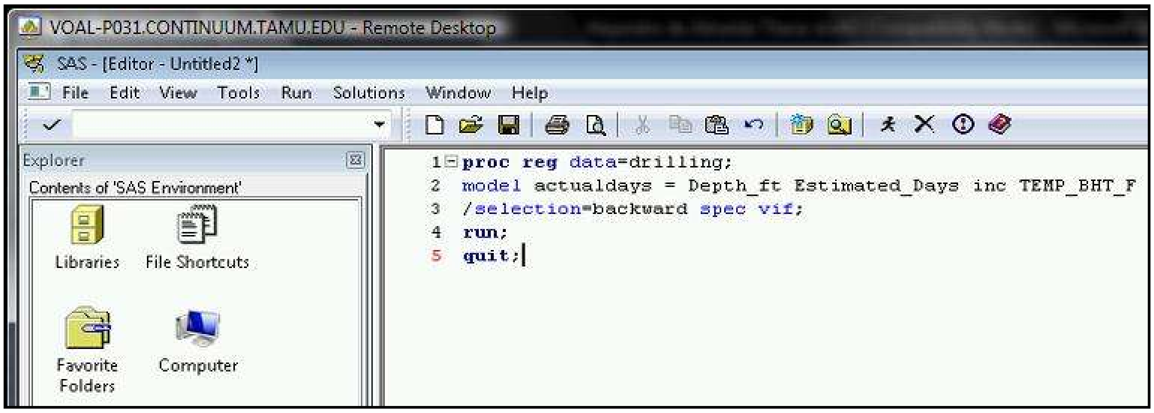


Fig. A.10-Example SAS Input for Backward Elimination

Least Squares Regression

```
proc reg data= filename;
model dependent_variable = variable_A variable_B variable_C /spec vif ;
output out=results r=resid p=fits;
run;
quit;
```

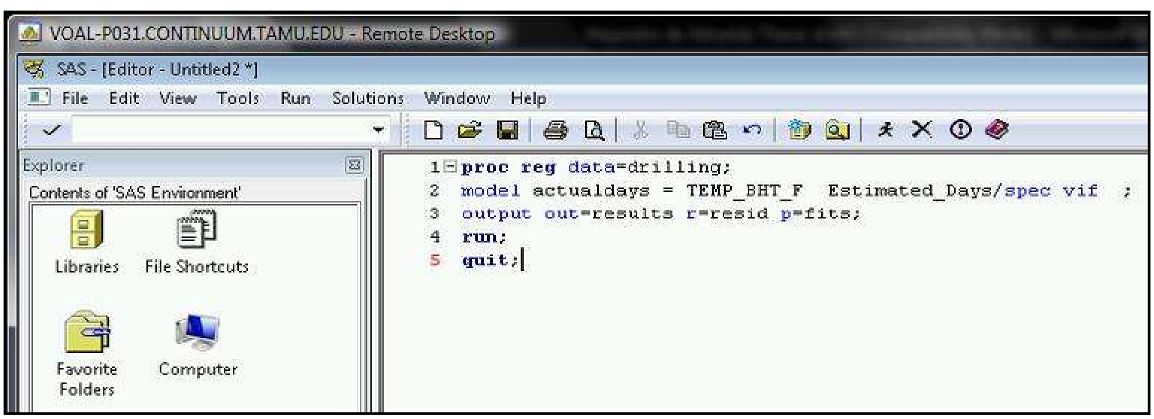


Fig. A.11-Example SAS Input for Least Squares Regression

The univariate code and residual plot test the normality of the residuals. The significance of the univariate output can be found in CHAPTER IV of this thesis. Residual plots are discussed in CHAPTER VII.

This model uses the following basic codes for univariate analysis and residual plots.

Univariate

```
proc univariate data=results normaltest ;
var resid;
probplot resid / normal(mu=est sigma=est);
run;
```

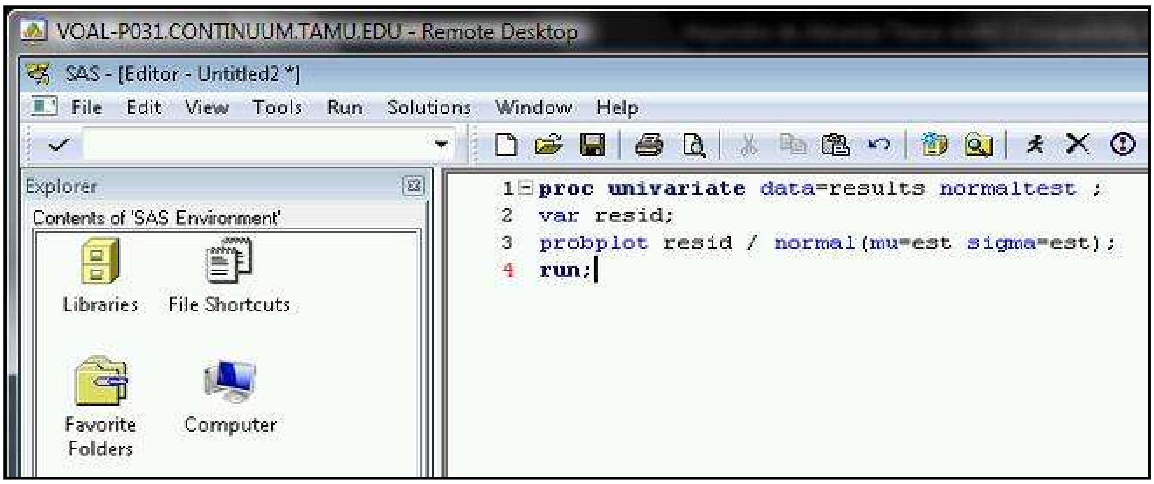


Fig. A.12-Example SAS Input for Univariate Calculations

Residual Plot

```
proc gplot data=results;
plot resid*fits;
run;
```

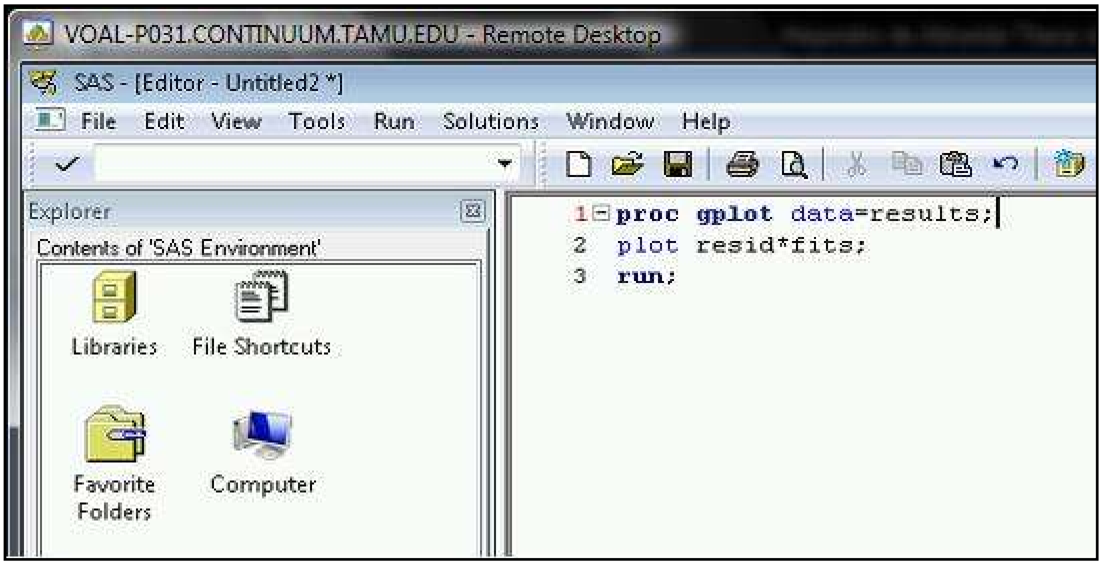


Fig. A.13-Example SAS Input for Residual Plot

A recommended method to test the dataset would be to run the regression followed by the univariate calculation. This helps keep the output of the program organized with the results of the regression followed by the test of the residual normality. The title command places a header on the graphs. This helps differentiate if many graphs are made. The title command has to be written as shown in the example. The stepwise regression example below illustrates this concept.

```
proc reg data=filename;
model dependent_variable = variable_A variable_B variable_C
/selection=stepwise spec vif;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: Step Regression of Dependent Variable and Variables A,
B, C';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: Step Regression of Dependent Variable and
Variables A, B, C';
plot resid*fits;
run;
```

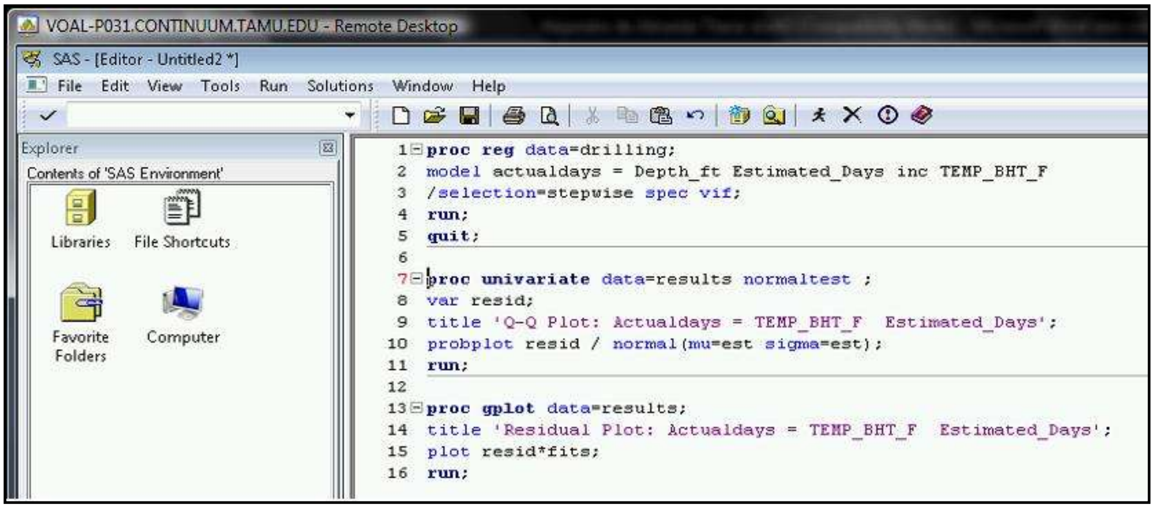


Fig. A.14-Example SAS Input for Stepwise Regression,
Univariate Calculation, and Residual Plot

Specific models can be entered and tested using least squares regression. If an individual wants to have a model with certain variables, the example below illustrates the method to perform that analysis.

```
proc reg data= filename;
model dependent_variable = variable_A variable_C variable_F /spec vif
;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: Least Squares of Dependent Variable and Variables A,
C, F';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: Least Squares of Dependent Variable and Variables
A, C, F';
plot resid*fits;
run;
```

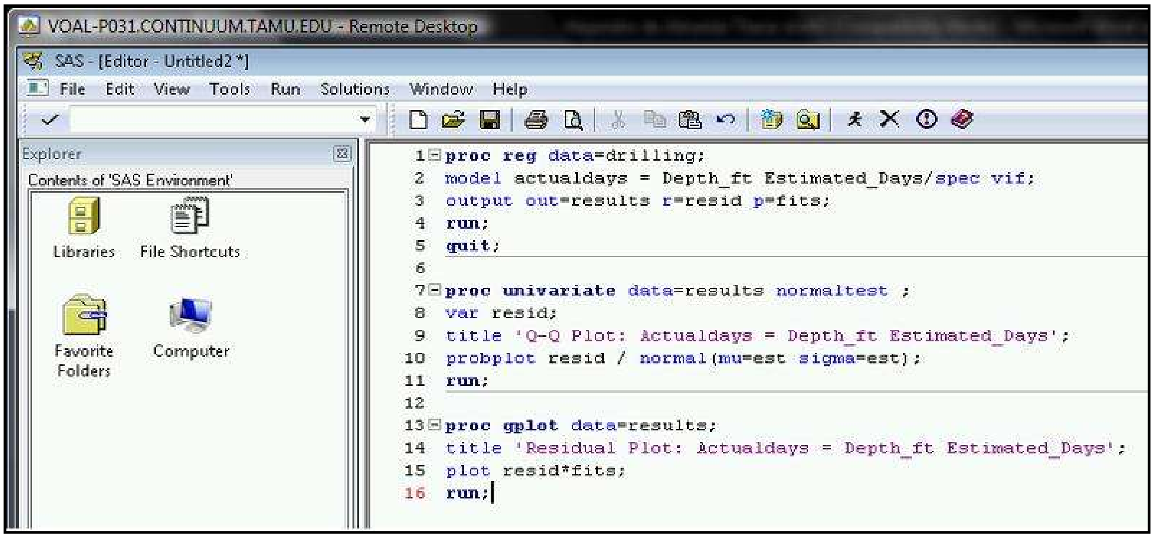


Fig. A.15-Example SAS Input for Least Sum Regression,
Univariate Calculation, and Residual Plot

The code above allows linear regression to be done on the dataset. To run the written commands, click on the icon of the running man on the tool bar. Any errors will be identified within the Log-(Unititled) window. To clear the Log or Output window, select the window and click Edit, clear text. The Edit icon can be found in the menu bar. As a shortcut to execute the same command, hold the control button and E at the same time.

A.3 Manipulation of Variables and Dataset

Outliers

If the resulting models do not prove to be significant, they may include a single or multiple outliers. Caution must be taken when deciding to remove outliers. Though a single outlier might be a unique event, multiple outliers may be a trend instead of an anomaly. There are two methods to remove outliers: the original dataset may be changed and uploaded again into SAS, or a new dataset may be created within SAS without the outlier/s. The following code demonstrates how to create a new dataset by removing unwanted data points.

```
data newfilename;
set filename;
where variable_name ne #;
run;
```

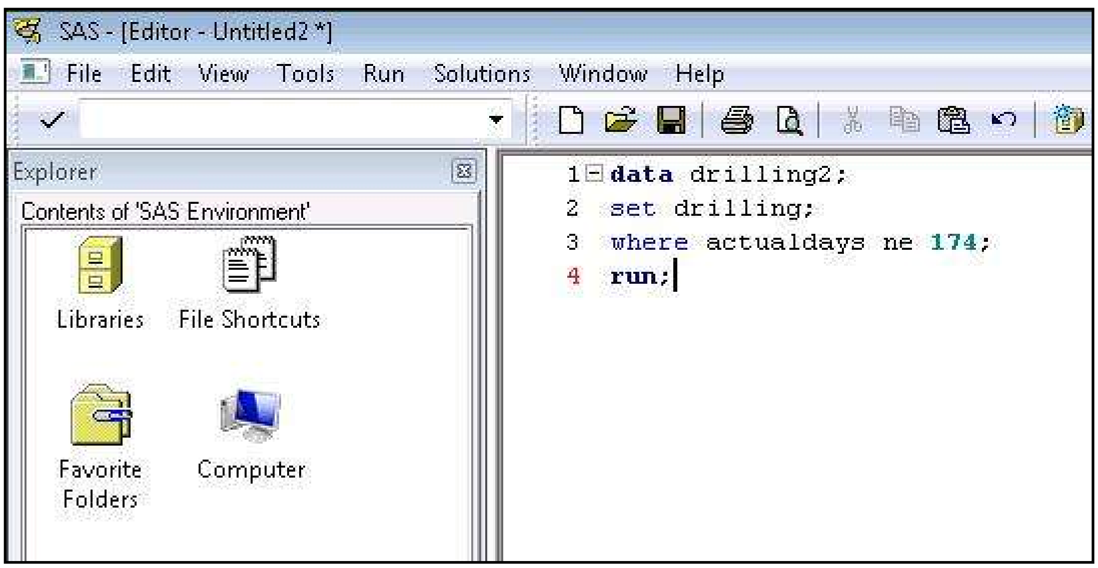


Fig. A.16- Example SAS Input for Removal of a Data Point

The new dataset removes any data point from a given variable that has a value greater than the numerical value given to #. Many different lines of code to perform basic manipulations of the dataset may be found at SAS's homepage (2010) or its online user guide (1999).

A.4 Variable Trends

Plotting the dependent variable against the independent variable helps identify if the relationship follows a desirable linear trend. Shown below is the command to make a plot in SAS.

```
proc gplot data=filename;
title 'Independent Variable vs. Variable A';
plot independent_variable*variable_A;
run;
```

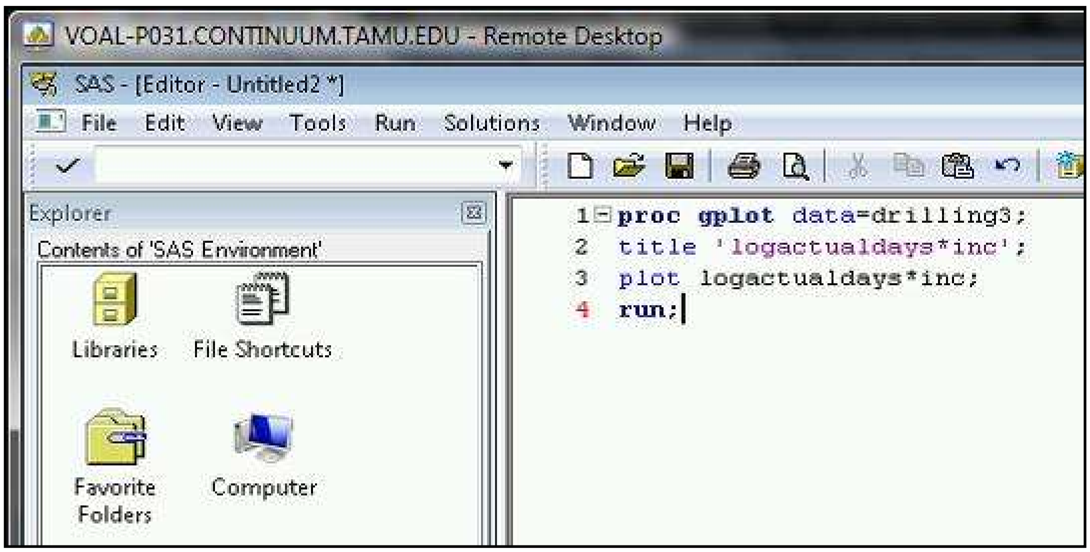


Fig. A.17- Example SAS Input for Creating a Plot

To create multiple plots, just repeat the previous code with the desired variables.

If a plot shows a nonlinear relationship, it may be possible to linearize the relationship by manipulating certain variables. First time users of SAS should use caution when using the *log* command. In SAS, the *log* command represents the natural log. *Log10* calculates base 10 logs. New datasets are recommended whenever variables are manipulated. An example of variable manipulation appears below.

```
data newfilename;
set filename;
lnindependent_variable=log(independent_variable);
exp_variable_B=exp(variable_B);
variable_D_sq= variable_D _days**2;
log_variable_F=log10(variable_F);
run;
```

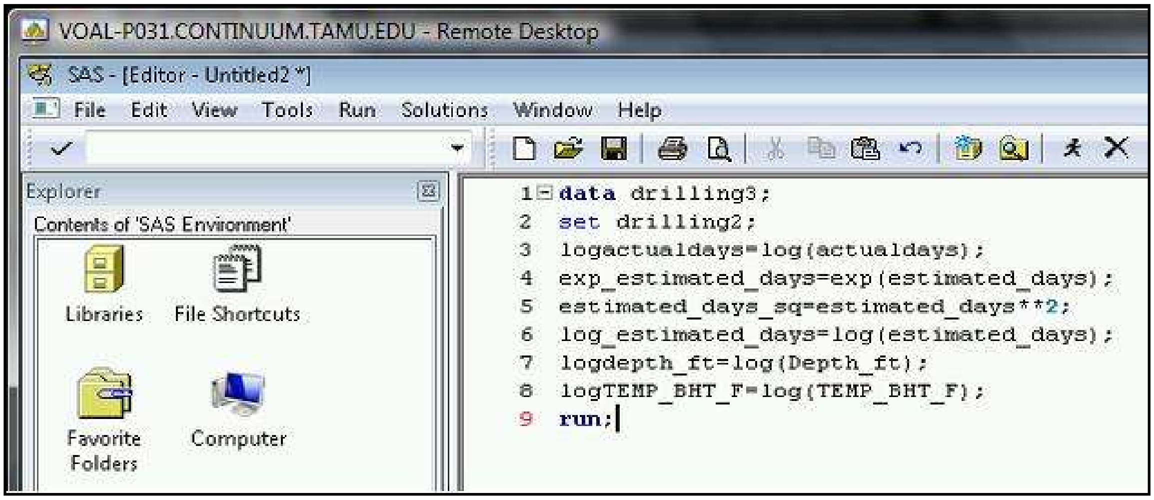


Fig. A.18- Example SAS Input for Variable Manipulation

The new dataset, newfile, has four new variables that were not present in the original dataset newfile. Given names of the manipulated variables are left of the equal sign. The names were chosen to describe the action performed.

Appendix E contains the written code used in SAS for the example dataset of north central Texas. This may be used as a guide or template for future data regressions.

APPENDIX B

R SOFTWARE CODE

SAS's cost can deter usage of the software. R software performs statistical operations and may be downloaded for free from www.r-project.org (2010). The same methodology and concepts used within SAS are applicable for R. A basic review of the code necessary to operate the software is explained below.

B.1 Transferring Data from Microsoft Excel into R

R does not import Microsoft Excel files; instead, the database has to be saved as a comma-separated file or text file. In Microsoft Excel, a database may be created and saved as a comma-separated file or text file (2010). The database has to be constructed similar to the example database of north central Texas wells. Unlike SAS, R does not allow empty cells within the database (Ripley et al. 2010). After working with R, I recommend that the first column be the dependent variable values and the following columns have the independent variable values. In R, having text within the first column and not the dependent variable caused problems.

Shown below are the steps to import a saved comma-separated file into R followed by an example using north central Texas database (Gardener) The following code will insert the saved .csv file as the work database in R. The following code has to be typed after the prompt " >". Labeled names of the columns are transferred from the .csv file. To clear the console screen in R at any time, hold down control L.

- > databasename= read.csv(file.choose(), header=T)

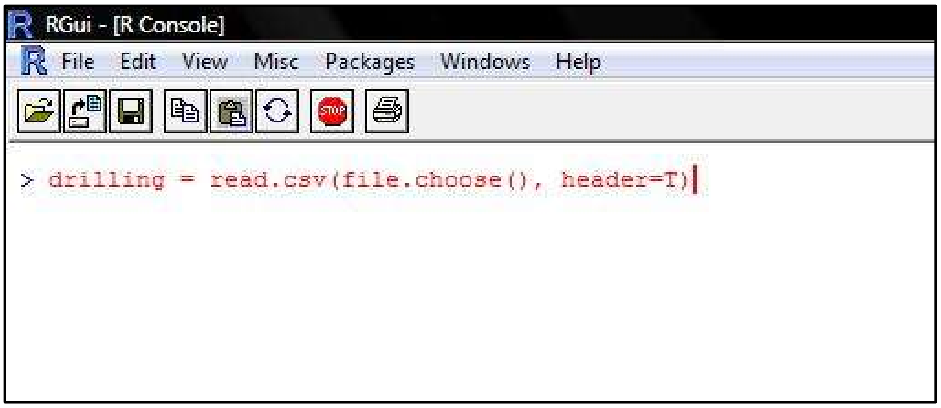


Fig.B.1-Code to Open Window to Import Database

To see the inserted database and to know how to call upon individual variables, after the prompt, type the name of the dataset (Gardener).

- >drilling

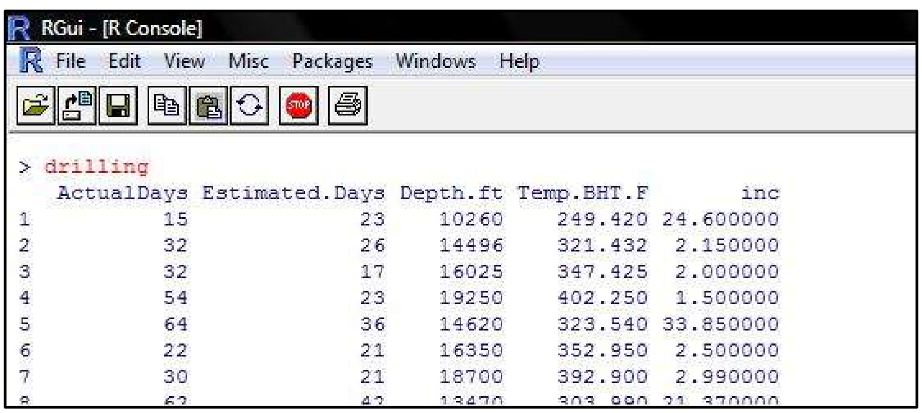


Fig. B.2-Code to See Database Values

To make the data accessible to R, insert the command after the prompt, attach(name of the file). In the previous example the file name was “drilling”. To allow R to work with the variables within the example database, >attach(drilling).

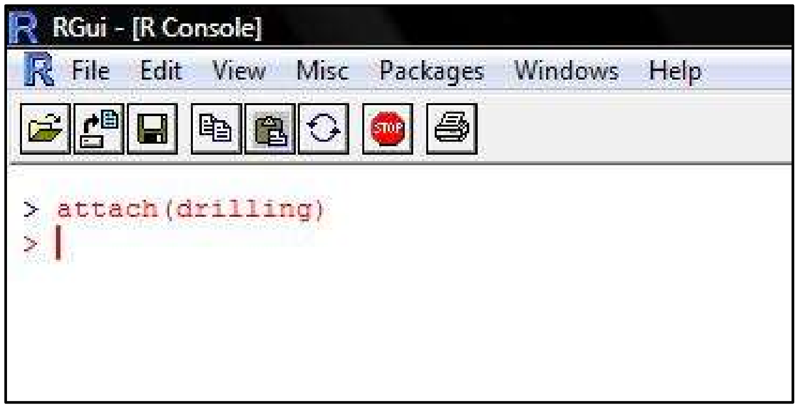


Fig. B.3-Code to Attach Database

B.2 Basic Code Necessary to Perform Regressions
and Model Validation in R

The next step shows how to perform four types of regressions, least squares regression, stepwise regression, forward selection, and backward elimination. The example above is used to keep variable names constant; it is based on the example dataset for north central Texas. Least squares regression introduces a basic understanding of how to work with R before performing stepwise regressions, forward selection, and backward elimination. The code shown below represents the generic model fitting for assigned independent variables followed by an example (Venables et al. 2002).

- >LSR <- lm(y~x1+x2+x3,data)

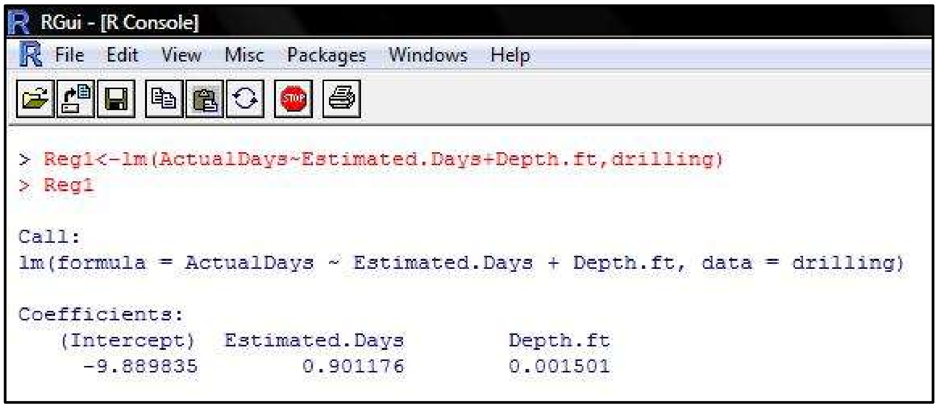


Fig B.4-Code to Perform Least Squares Regression

This code returned the same regressor coefficients as SAS for Model B.

Stepwise regression uses a similar form of the previous code to perform regression (Venables et al. 2002). Instead of indicating which independent variable to use, all independent variables are included. First a "full" model has to be created. >full <- lm(y~.,data)

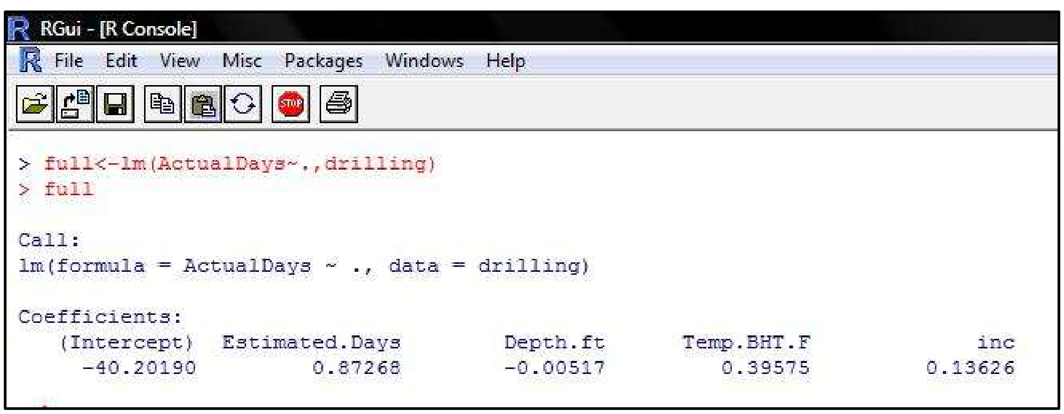


Fig. B.5-Code to Create a Model with all Variables

The use of a period indicates to R that all independent variables are to be included. After creating the full model, type "step" to perform a stepwise regression. R will perform the regression without requiring an initial variable name. A variable name has been added to the example to differentiate between stepwise regression, forward selection, and backward elimination (Venables et al. 2002).

- >step(full)

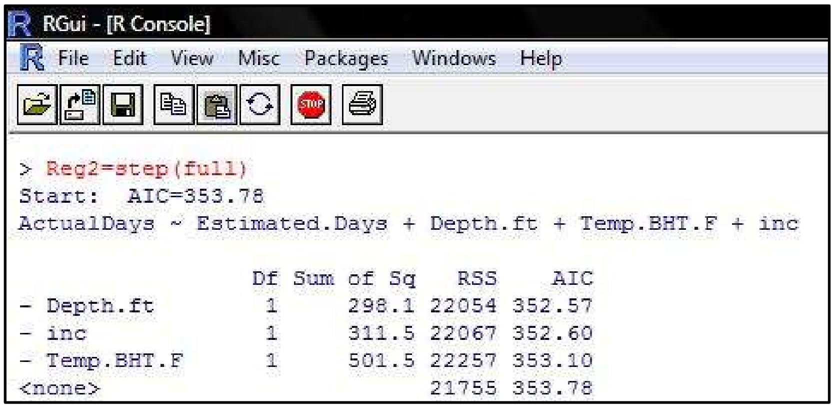


Fig. B.6-Code to Perform Stepwise Regression

After running the above code, I found the same regressor coefficients of Model A in SAS with R.

R has the basic code, >step(model, data, direction, scale, k, trace), to perform regressions (Phoa 2007). In, R forward selection comes from defining the step command, not to eliminate variables. Similar to stepwise regression's full model, forward selection requires a "null" model with only one variable to start.

- >null<-lm(y~1,data)

```
RGui - [R Console]
File  Edit  View  Misc  Packages  Windows  Help

> null<-lm(ActualDays~1,drilling)
> null

Call:
lm(formula = ActualDays ~ 1, data = drilling)

Coefficients:
(Intercept)
      31.98
```

Fig. B.7-Code to Create a Model with 1 Variable

To chose between stepwise regression, forward selection, or backward elimination, the "direction" part of the command may be written as, direction=" both", direction=" forward", and direction=" back". As shown above, step has "both" as the default direction. Below, the necessary inputs for the step command are shown for forward selection (Phoa 2007).

- >step(null, scope=list(lower=null, upper=full, direction="forward")

```
RGui - [R Console]
File  Edit  View  Misc  Packages  Windows  Help

> Reg3=step(null,scope=list(lower=null,upper=full,direction="forward"))
Start:  AIC=384.93
ActualDays ~ 1

                  Df Sum of Sq   RSS    AIC
+ Estimated.Days  1     18023 24708 355.16
+ Temp.BHT.F      1     13331 29400 365.24
+ Depth.ft        1     12476 30255 366.90
<none>                        42731 384.93
```

Fig. B.8-Code for Forward Selection R

The code for backward elimination matches closer to stepwise regression. Shown below, the necessary code to perform backward elimination in R (Phoa 2007).

- >step(full, direction="backward")

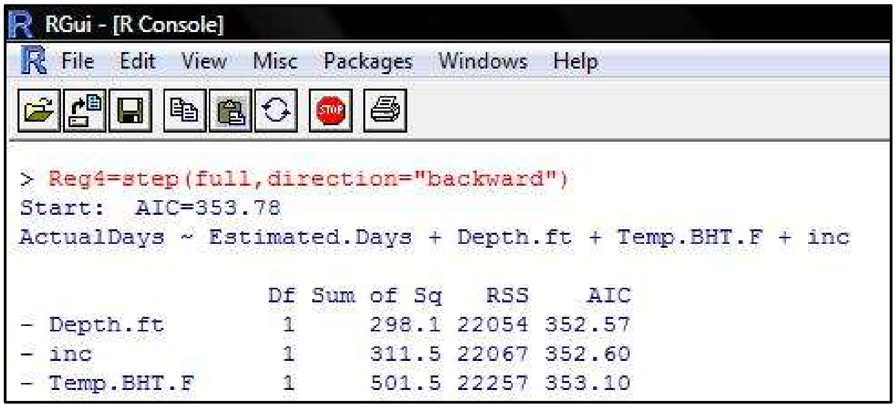
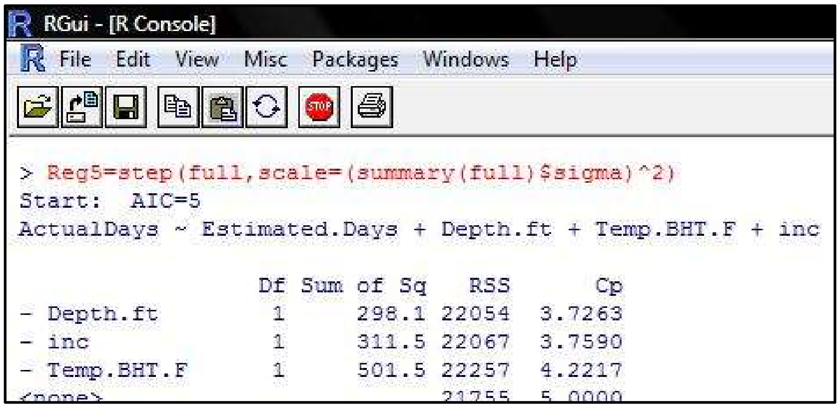


Fig. B.9-Code for Backward Elimination

The key parameters for validation were residual plots, Shapiro-Wilk p-value, Q-Q plot, chi-squared p-value, variance inflation factor, R-squared value, Mallow Cp, and F-test p-value. Stepwise regression, forward selection, and backward elimination within R use Akaike Information Criterion (AIC) to determine the optimal model. The step command may also be changed to perform regressions using Bayes Information Criterion (BIC) or Mallow Cp(Faraway 2002). To find the Mallow Cp of the regression as shown in SAS, the scale code needs to be adjusted. For Mallow Cp, scale=(summary(full)$sigma)^2 (Phoa 2007). Mallow Cp values in SAS equal the values found in R next to the variable named, none. Shown below, the code written using the examples are for Mallow Cp stepwise regression, forward selection, and backward elimination.

- >Reg5=step(full,scale=(summary(full)$sigma)^2)

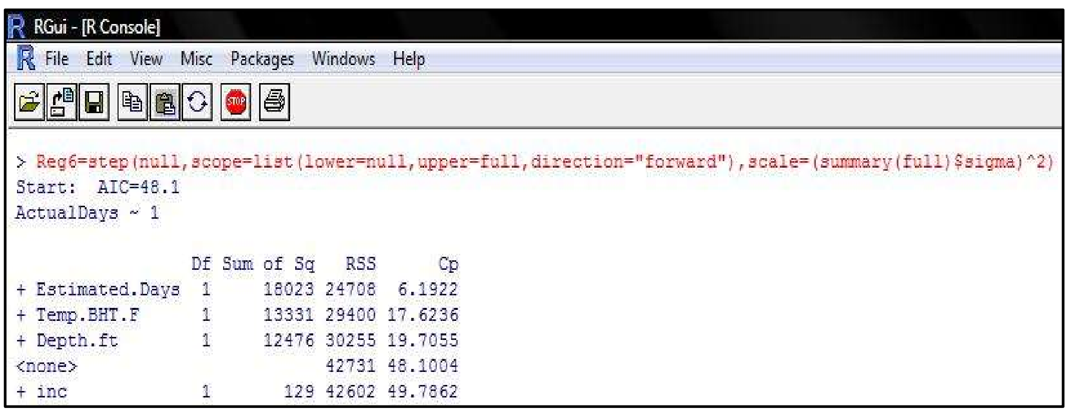



```
> Reg5=step(full,scale=(summary(full)$sigma)^2)
Start:  AIC=5
ActualDays ~ Estimated.Days + Depth.ft + Temp.BHT.F + inc

                Df Sum of Sq   RSS     Cp
- Depth.ft       1     298.1 22054 3.7263
- inc            1     311.5 22067 3.7590
- Temp.BHT.F     1     501.5 22257 4.2217
<none>                       21755 5.0000
```

Fig. B.10-Code for Stepwise Regression with Mallow Cp

- >Reg6=step(null,scope=list(lower=null,upper=full,direction="forward"),scale=(summary(full)$sigma)^2)




```
> Reg6=step(null,scope=list(lower=null,upper=full,direction="forward"),scale=(summary(full)$sigma)^2)
Start:  AIC=48.1
ActualDays ~ 1

                 Df Sum of Sq   RSS      Cp
+ Estimated.Days  1     18023 24708  6.1922
+ Temp.BHT.F      1     13331 29400 17.6236
+ Depth.ft        1     12476 30255 19.7055
<none>                      42731 48.1004
+ inc             1       129 42602 49.7862
```

Fig. B.11-Code for Forward Selection with Mallow Cp

- >Reg7=step(full,direction="backward",scale=(summary(full)$sigma)^2)

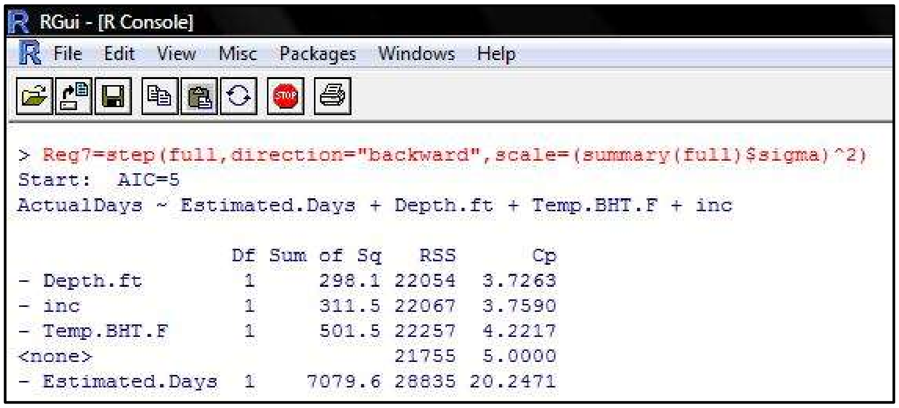


Fig. B.12-Code for Backward Elimination with Mallow Cp

Residuals of the regression models are seen by using "$res" after the model name. The code "plot.lm()" provides users with a method to see residual and QQ plots. After the prompt type, plot.lm(model name) to obtain Residual vs Fitted, Normal QQ, Scale Location, and Residual vs Leverage plots (Ricci 2005) . Using par(mfrow=c(2,2)) will allow the four plots to be seen within a single window.

- >par(mfrow=c(2,2))
- >plot.lm(model)

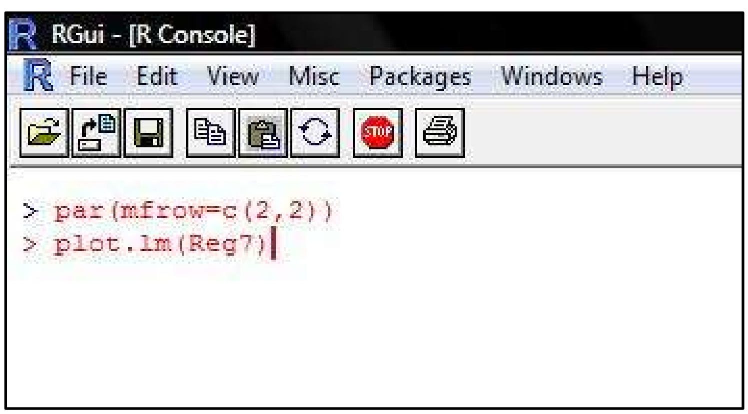


Fig. B.13-Code to Create Four Plots

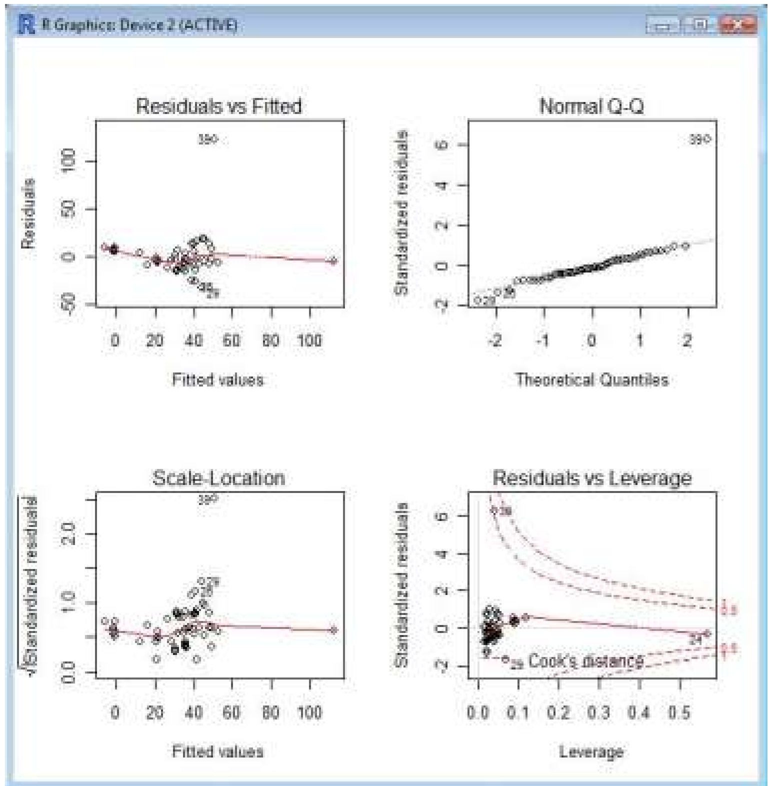


Fig. B.14-Results of plot.lm Code

Residual plot have the same attributes as seen with SAS's residual plots. R's QQ plot use standardized residuals instead of the raw data residuals as seen within SAS. Standardized residuals are residuals divided by their standard error (Dallal 2001). Scale location helps to assess nonconstant variance. Similar to a residual plot, a random scatter indicates a constant variance. The Loess line indicates the local trends of the residuals within the scale location plot. If the residuals have constant variance, then the Loess line will appear horizontal (Maathuis 2008). Within the residual vs leverage plot, the red lines correspond to Cook's distance. Cook's distance measures how much each point influences the estimated regression function and how much each point pull the function to itself (Maathuis 2008). Leverage indicates the difference between an observation from the given predictor value. It looks at the x's and compares the difference between the individual groups of x's with other groups of x's. The majority of the points in the residual vs. leverage plot should be bunched. Outliers indicate xs that are either higher or lower than the normal values of majority of the data (Maathuis 2008).

Residual plots in R can also be done using the plot command where the y-axis, x-axis, and title can be labeled within the plot code. The generic code for creating a residual plot and an example are shown below.

- >plot(model$res, ylab="y-axis", xlab="x-axis", main="title")

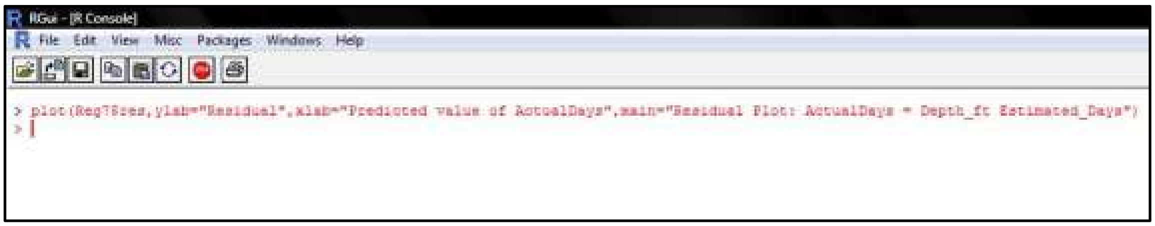


Fig. B.15-Code for Residual Plot

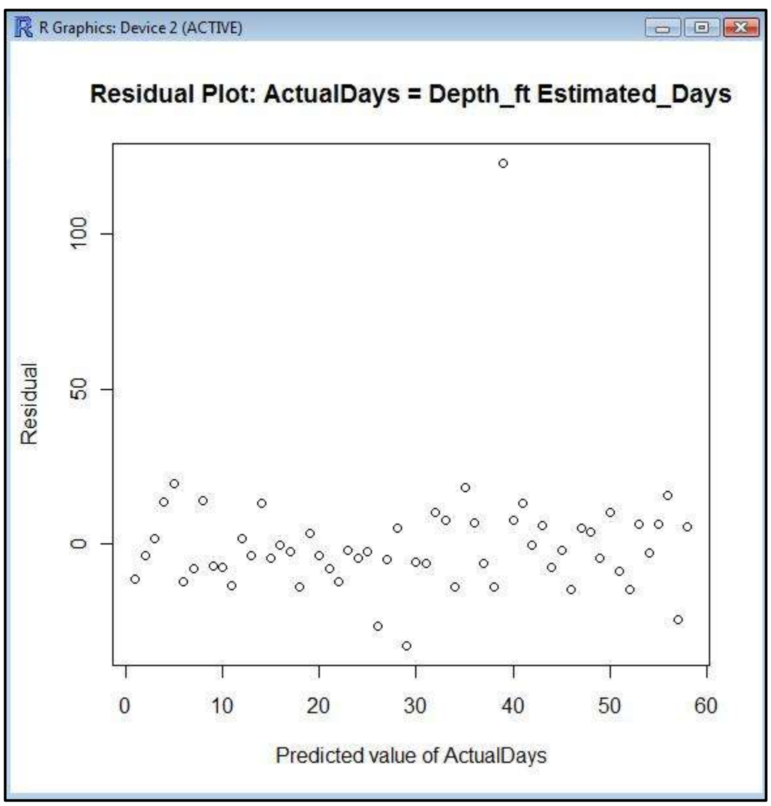


Fig. B.16-Residual Plot

Using the code shown below creates a QQ plot in R that resembles SAS's QQ plot.

- >a<-modelname$res
- >u<-(1:length(a)-.5)/length(a)
- >Q<-quantile(a,u,type=5)
- >plot(qnorm(u),Q)
- >abline(lm(Q~qnorm(u)))

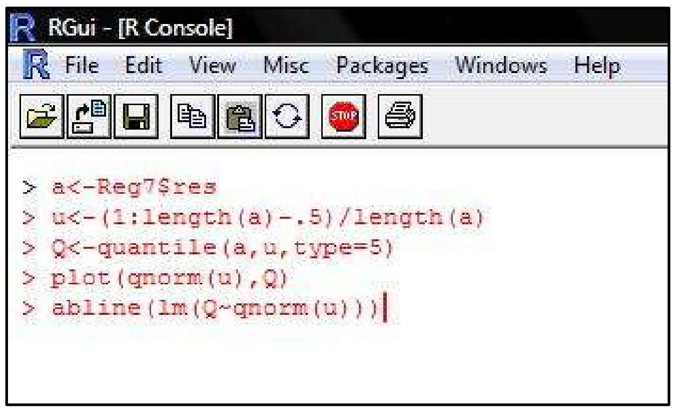


Fig. B.17-Code for QQ Plot in R

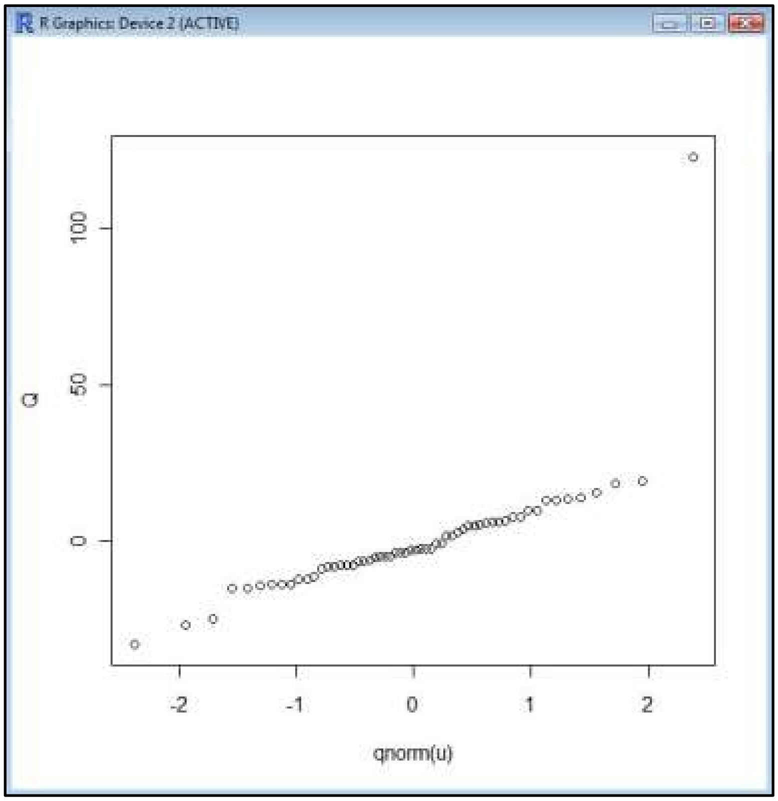


Fig. B.18-QQ Plot from Previous Code

The Shapiro-Wilk residual normality p-value and Pearson chi-squared residual normality test require a single line of code. These tests are looking at the normality of the residuals and not the predicted values of the model. The code shown below tests the residuals normality using Shapiro-Wilk p-value and Pearson chi-squared test.

- >shapiro.test(x)

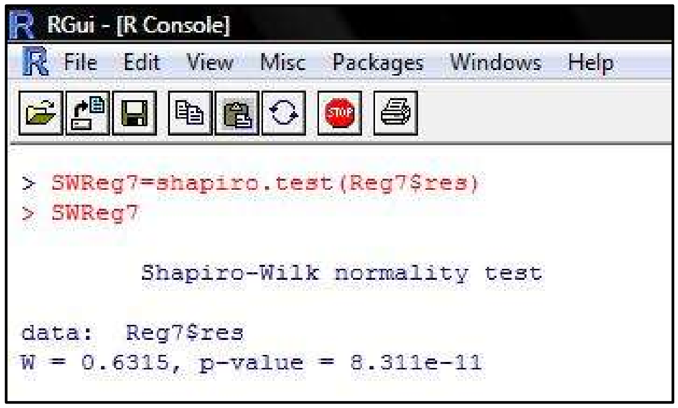


Fig. B.19-Code for Shapiro Wilk Normality Test

- >pearson.test(x)

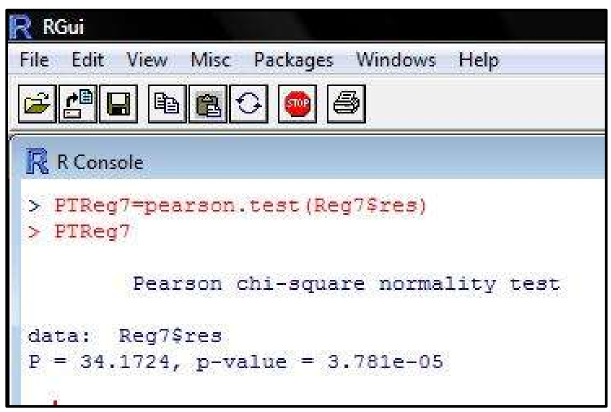


Fig. B.20-Code for Pearson Normality Test

R-squared and F-test p-values are found by looking at the summary of the model. After the prompt type “summary(model)” to see R-squared and F-test p-value.

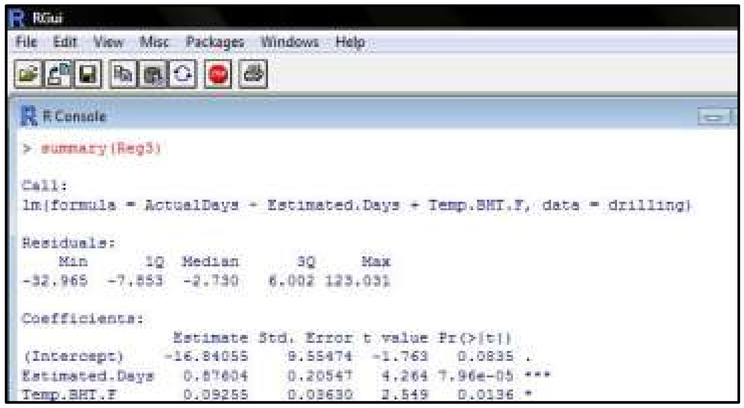


Fig. B.21-Code for Summary Information

B.3 Manipulation of Variables and Dataset

To look at the relationship between two variables, the plot command, shown above, may be used. When using the plot command, the first variable represents the x-axis and the second variable separated by a comma represents the y-axis. If manipulation of variables is needed to linearize the data, shown below are examples of basic variable manipulation in R.

- >lndepth<-log(Depth.ft)
- >logdepth<-log10(Depth.ft)
- >depthsqr<-(Depth.ft)^2

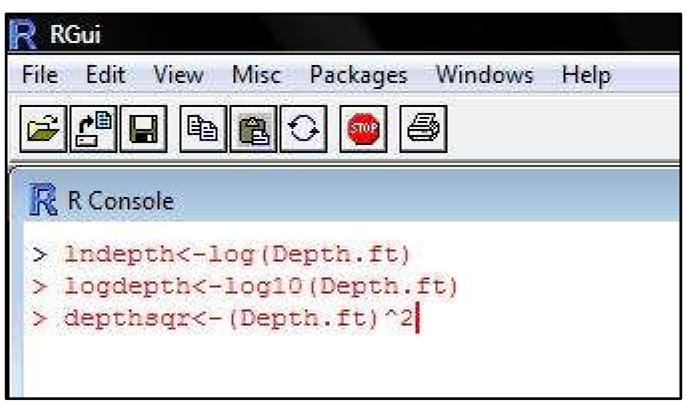


Fig. B.22-Example Code of Basic Variable Manipulation

After creating a new variable, the "bind" command will add the new variable to the dataset being used. Every time a dataset changes, to minimize problems, a new dataset name should be made:

- >drilling2<-(cbind(drilling,lndepth))

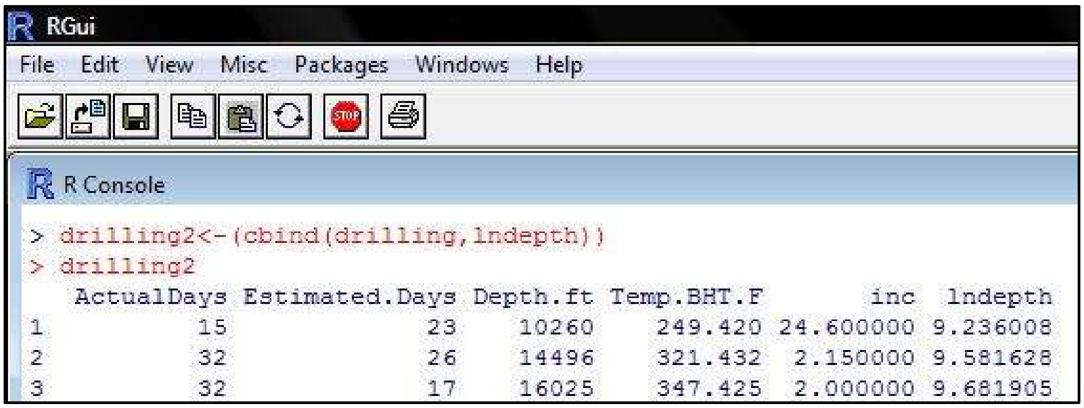


Fig. B.23-Code to Bind a New Variable to an Existing Database

If an outlier or data point needs to be removed, it may be done in R or by changing the dataset outside of R and importing it again. The code below removes any points within the variable ActualDays that has a value of 174. All other independent variables also are removed. When the new dataset gets called, >drilling3, the row with Actual days equal to 174 and all other independent variables associated with that row will be removed.

- > drilling3<-drilling2[which(ActualDays!=174),]

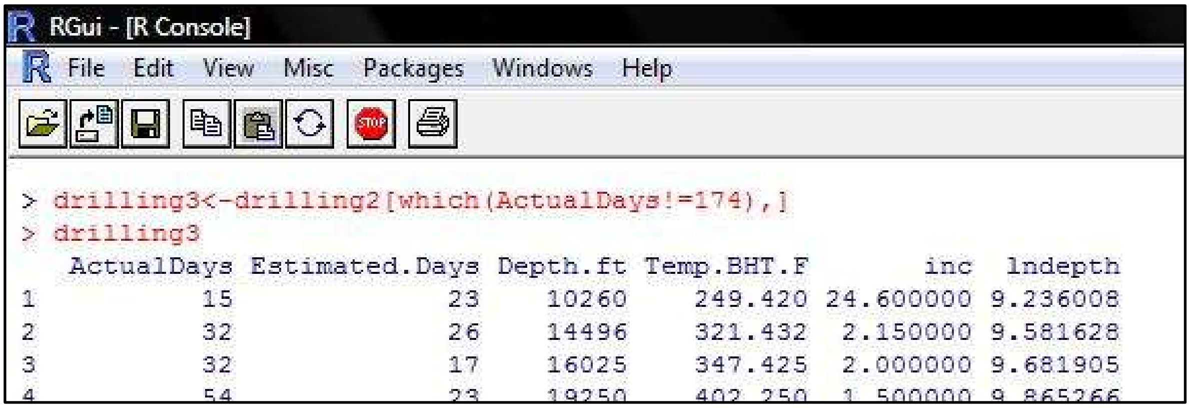


Fig. B.24-Code to Remove Outliers

If any command shows the error message, "could not find function" the package for R with that command may not have been installed. To install them just click on the, Packages tab and select Install Packages. After choosing a server a list of packages will appear. Select the package of interest and click on the OK button. After installation has been completed, upload the package by returning to the, Packages, tab and select, Load Packages. After loading the package, the command should work. To avoid redundancy and the need to upload the same packages when R initiates, within R's application file, make sure that wanted packages are found in the library folder. R creates a separate file within the user's document file for new packages. Transfer the packages from the user R folder to the R's library folder that may be found in R's main application folder.

APPENDIX C

MODELS C, D, E, H, I, J, AND K'S MODEL EQUATION, RESIDUAL PLOT, QQ PLOT, AND THREE HISTORY MATCH CURVES

$$y_C = -5.28257 + (0.87691 \times Te) + (0.00104 \times D) \qquad (7.3)$$

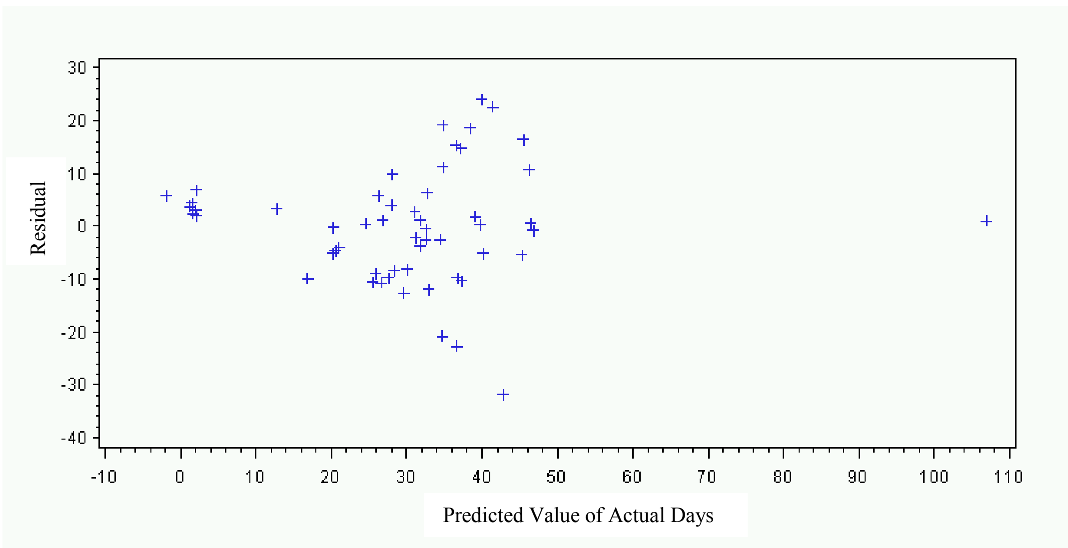


Fig. C.1–Residual Plot of Model C

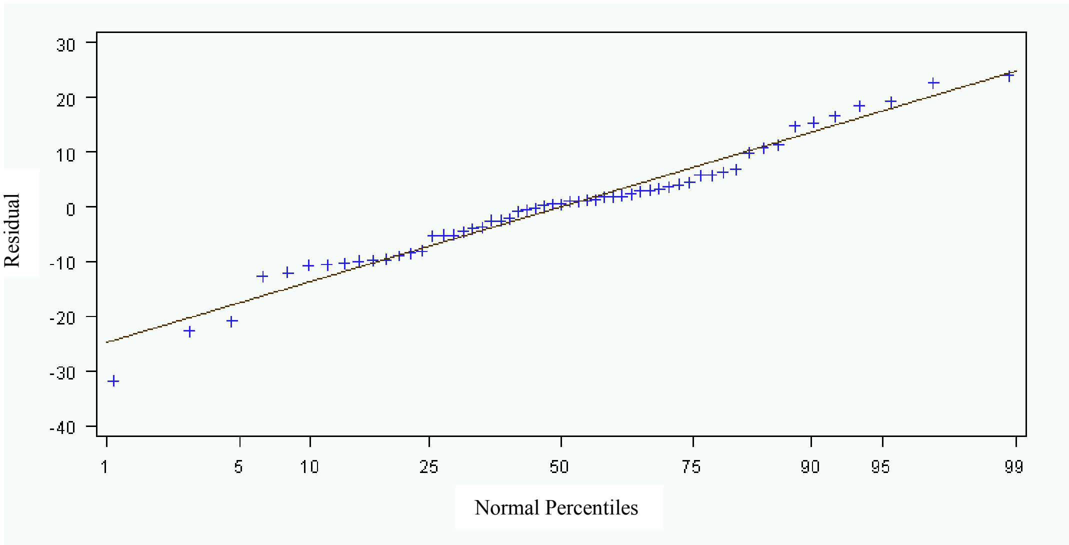


Fig. C.2–QQ Plot of Model C

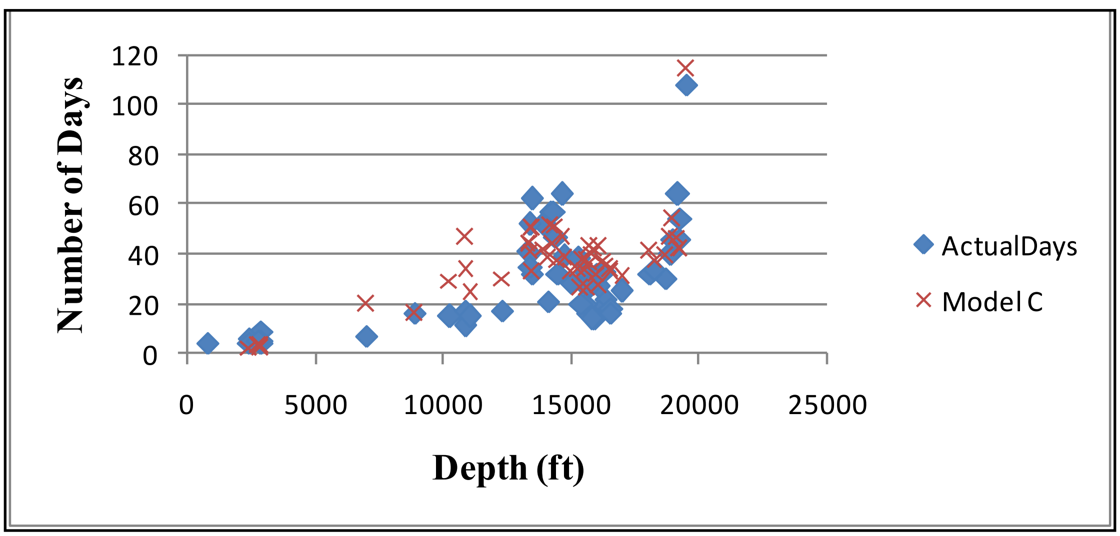


Fig. C.3–History Match between Actual and Predicted Days for Model C

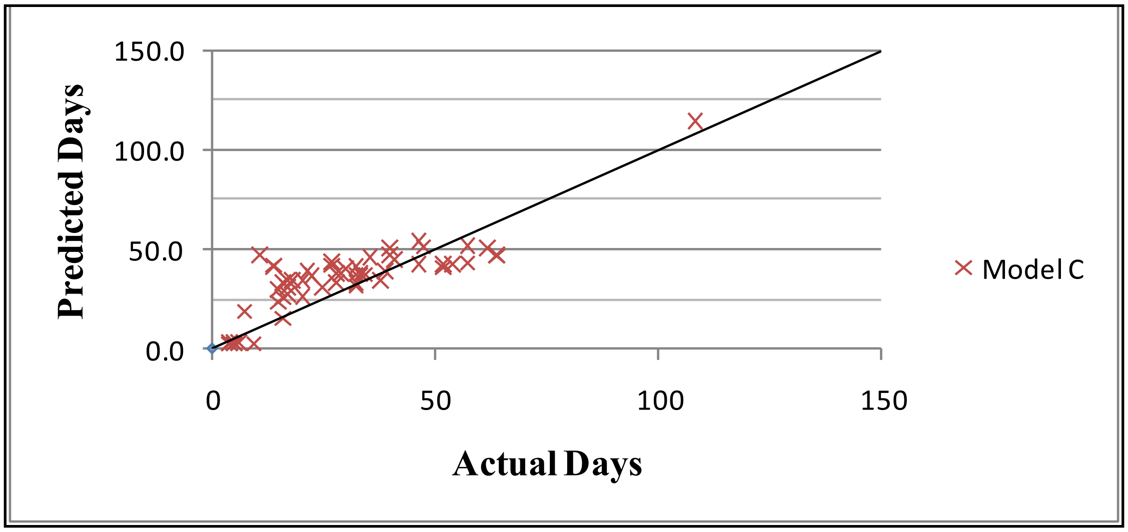


Fig. C.4–History Match, Predicted vs Actual Days for Model C

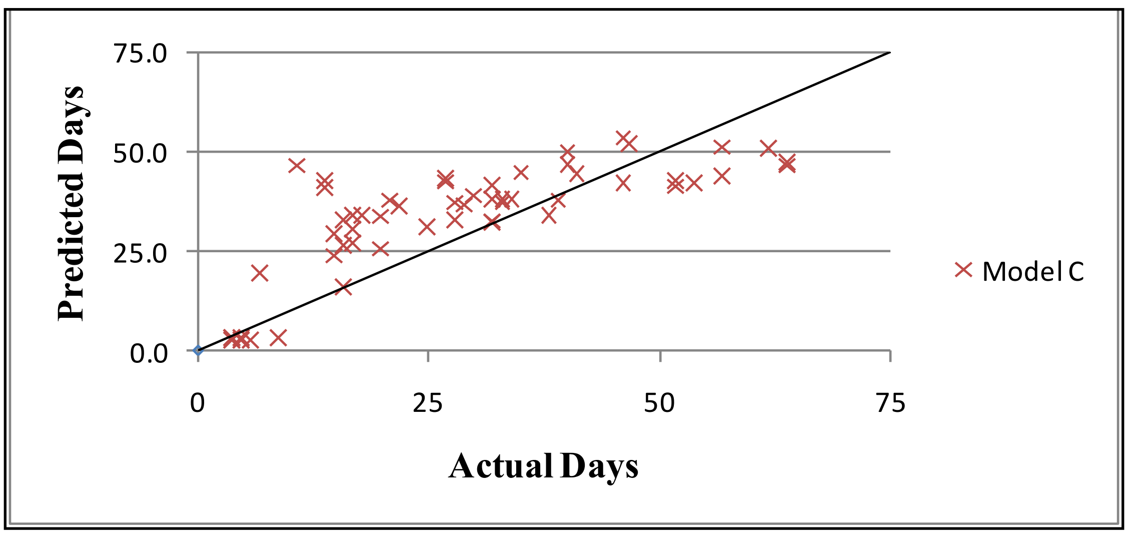


Fig. C.5–History Match, Predicted vs Actual Days for Model C Zoomed In

$$y_D = -9.98231 + (0.86113 \times Te) + (0.06342 \times Tbh) \quad (7.4)$$

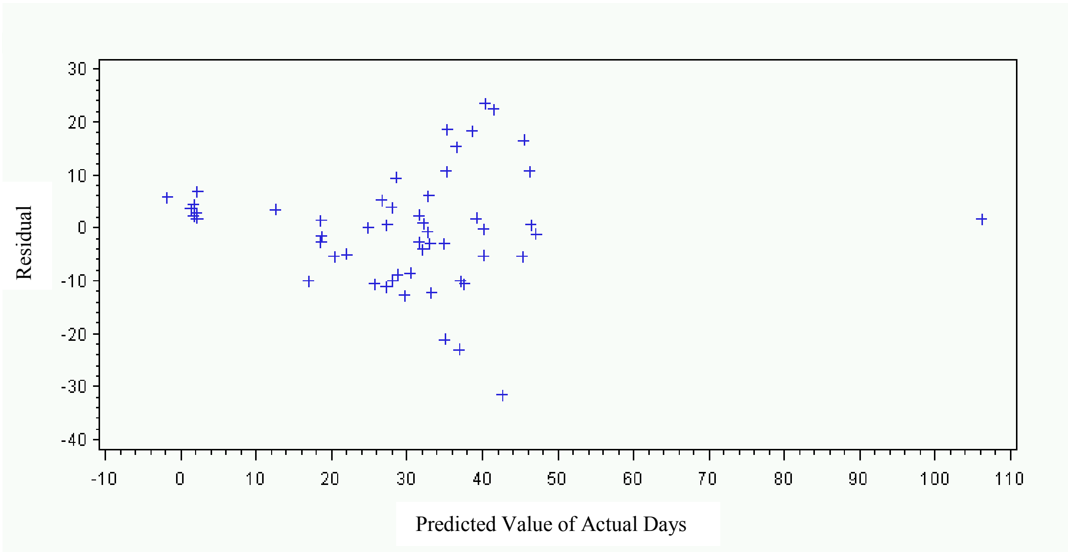


Fig. C.6–Residual Plot for Model D

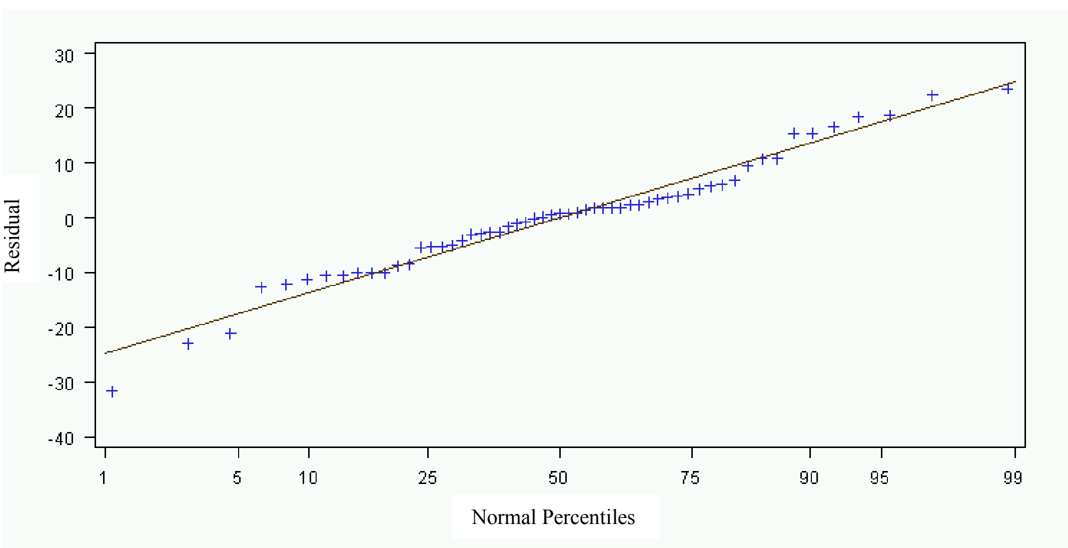


Fig. C.7–QQ Plot for Model D

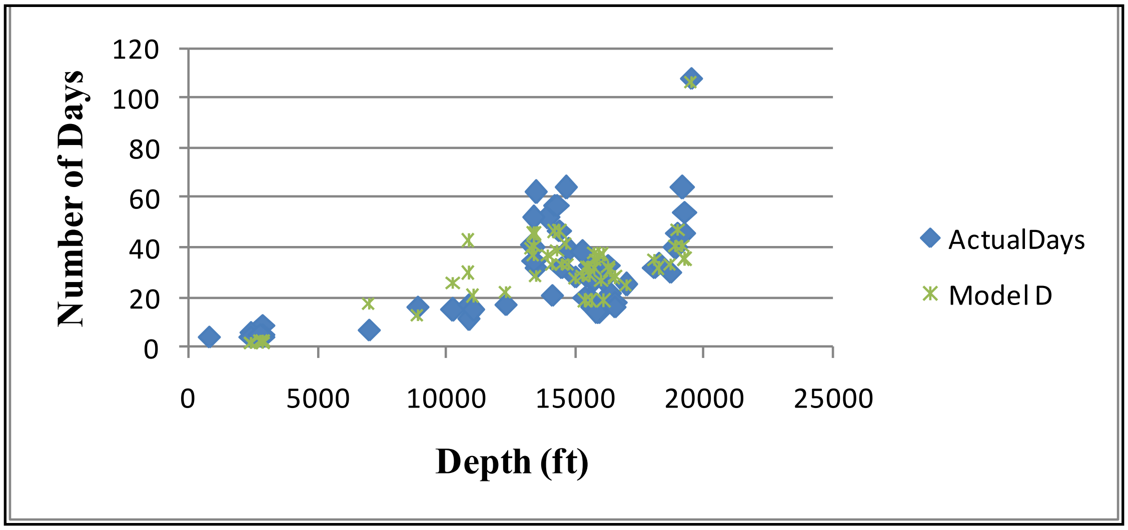


Fig. D.8–History Match between Actual and Predicted Days for Model D

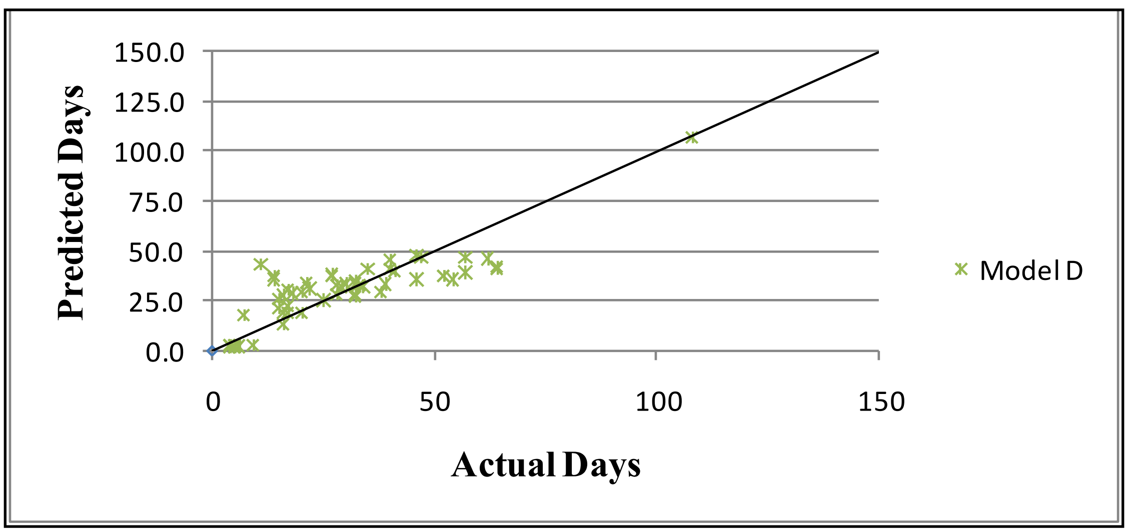


Fig. D.9–History Match, Predicted vs Actual Days for Model D

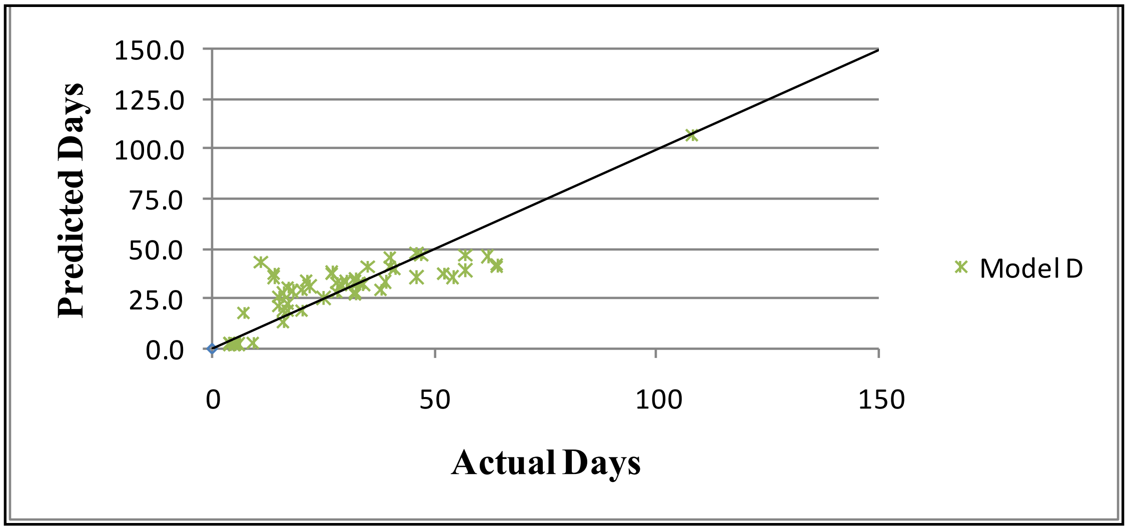


Fig. D.10–History Match, Predicted vs Actual Days for Model D Zoomed In

$$\ln(y_E) = 0.44017 + (0.60152 \times \ln(Te)) + (0.00006721 \times D) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (7.5)$$

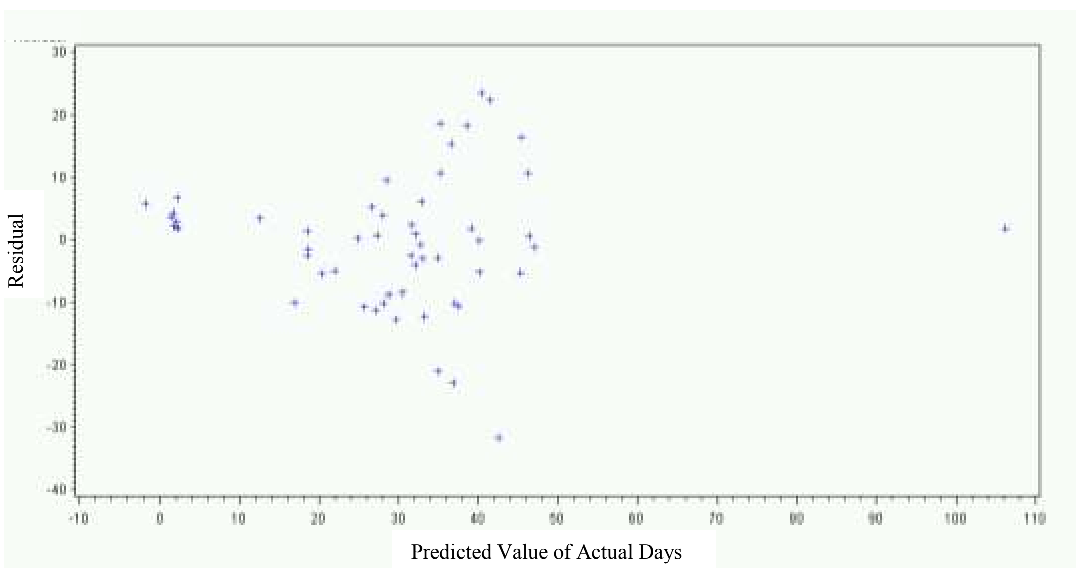


Fig. C.11–Residual Plot for Model E

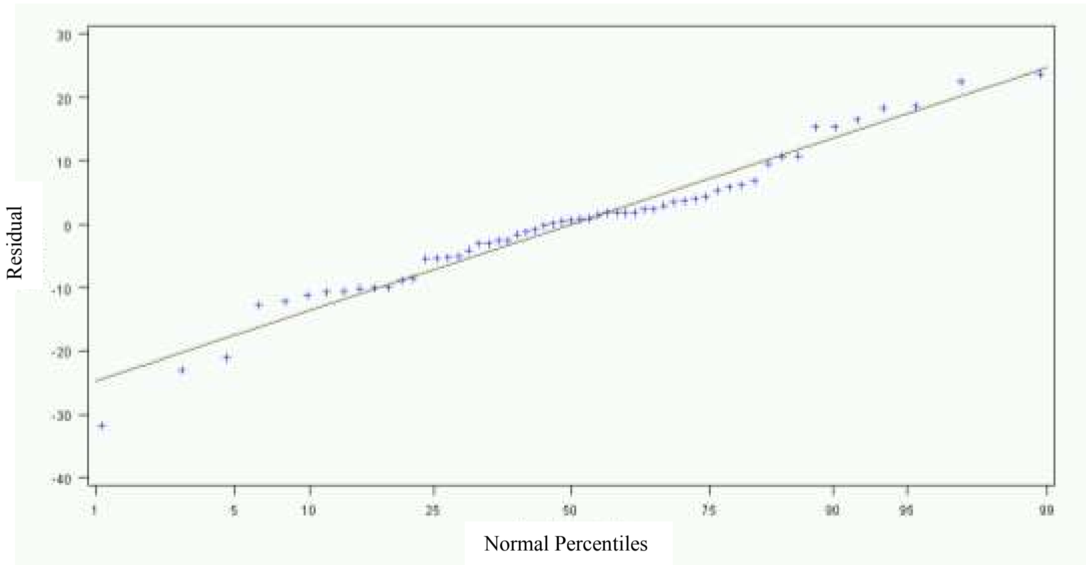


Fig. C.12–QQ Plot for Model E

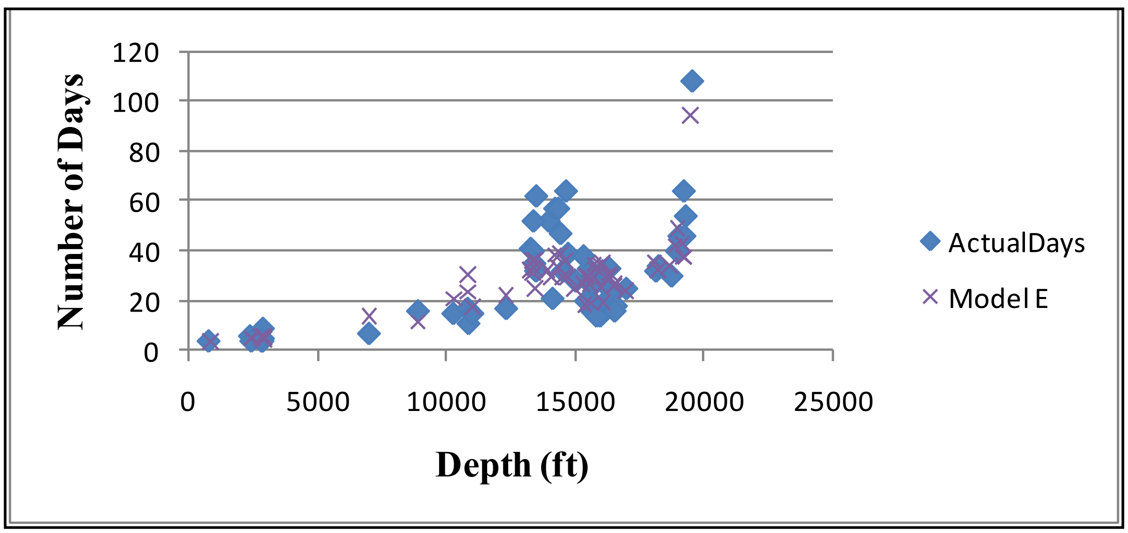


Fig. C.13–History Match between Actual and Predicted Days for Model E

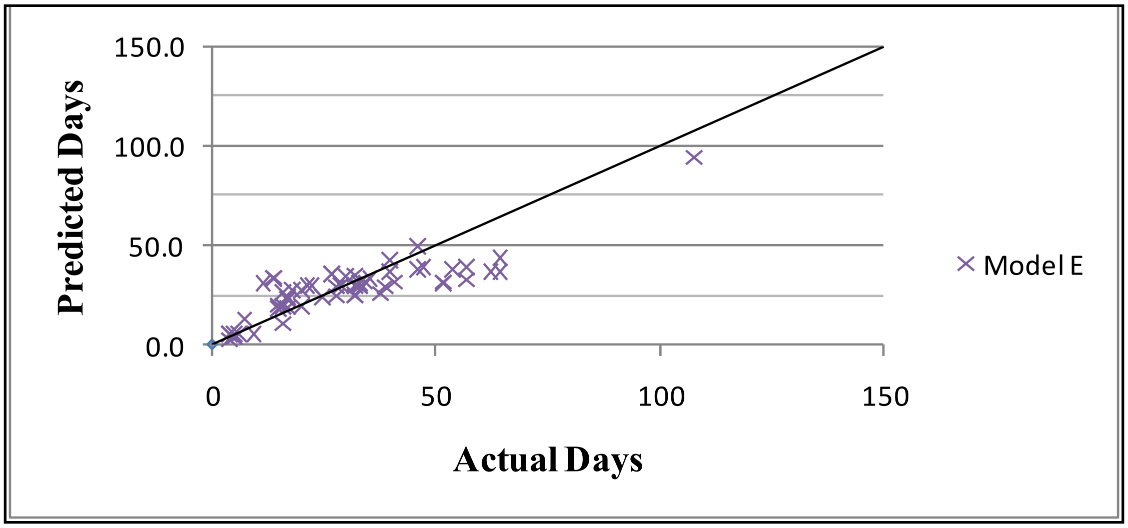


Fig. C.14–History Match, Predicted vs Actual Days for Model E

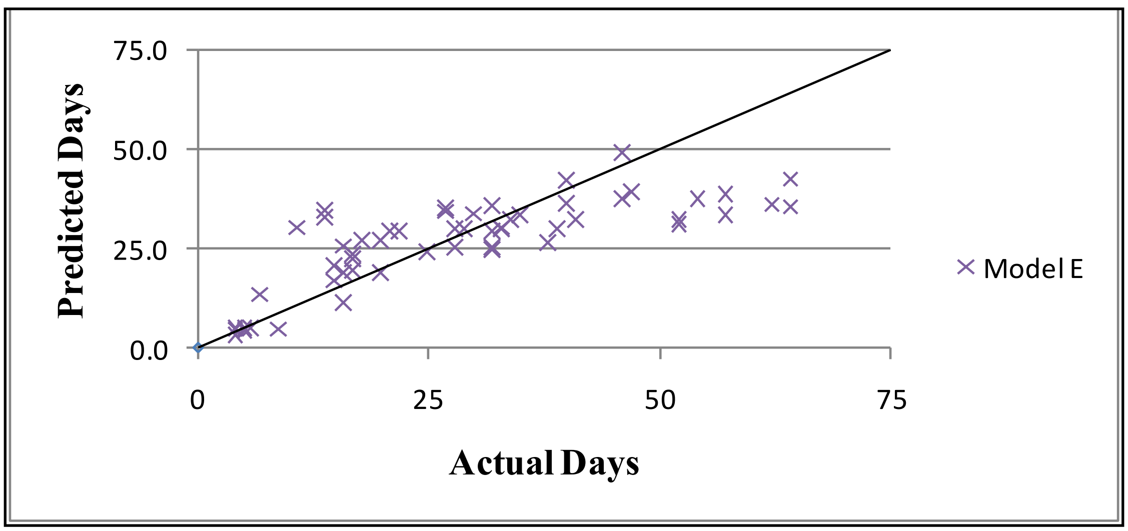


Fig C.15–History Match, Predicted vs Actual Days for Model E Zoomed In

$$\ln(y_H) = 1.30916 + (0.02003 \times Te) + (0.00010005 \times D) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7.8)$$

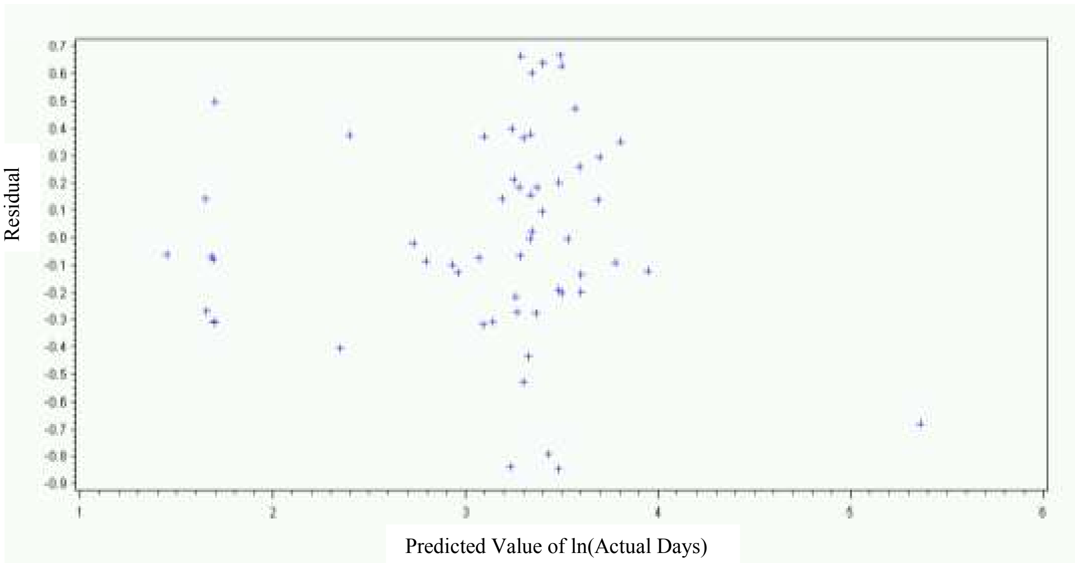


Fig. C.16–Residual Plot for Model H

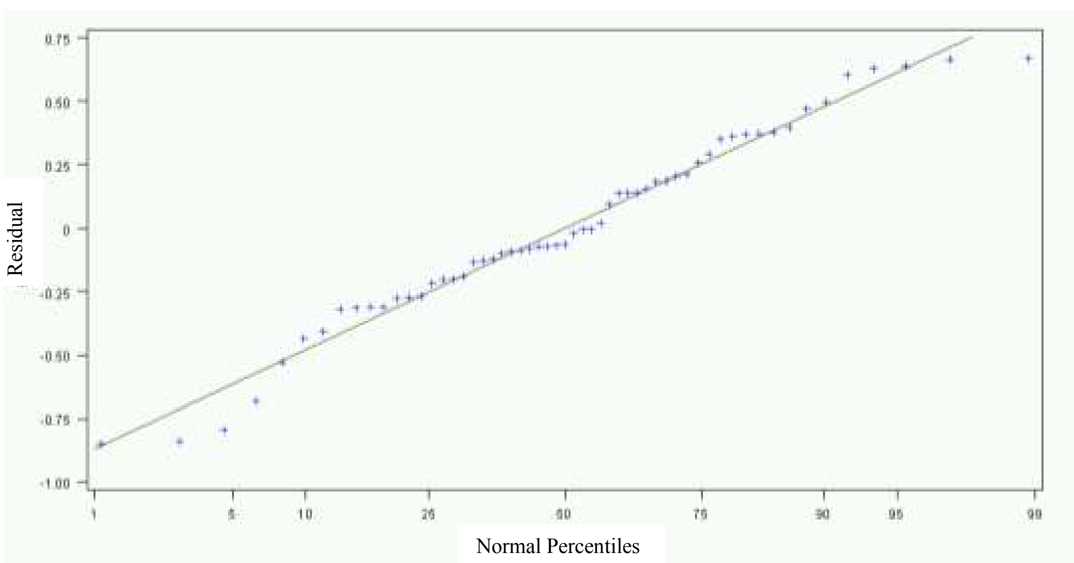


Fig. C.17–QQ Plot for Model H

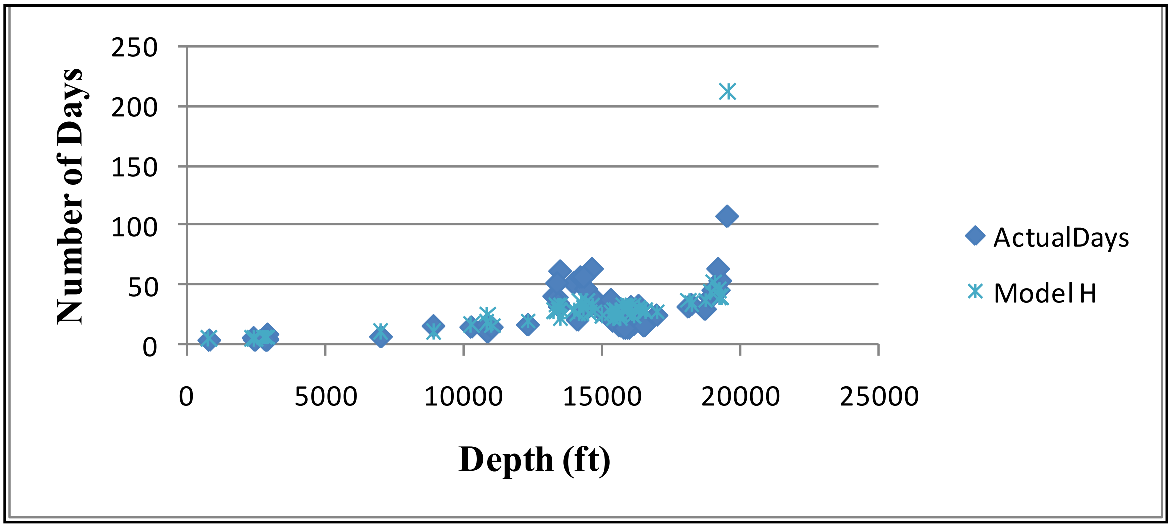


Fig. C.18–History Match between Actual and Prediced Days for Model H

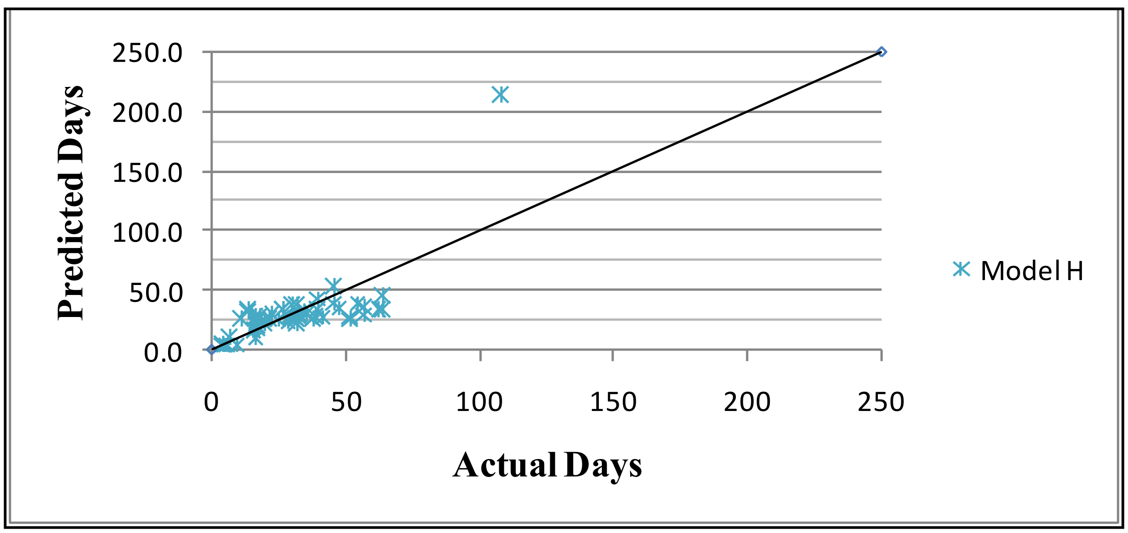


Fig. C.19–History Match, Predicted vs Actual Days for Model H

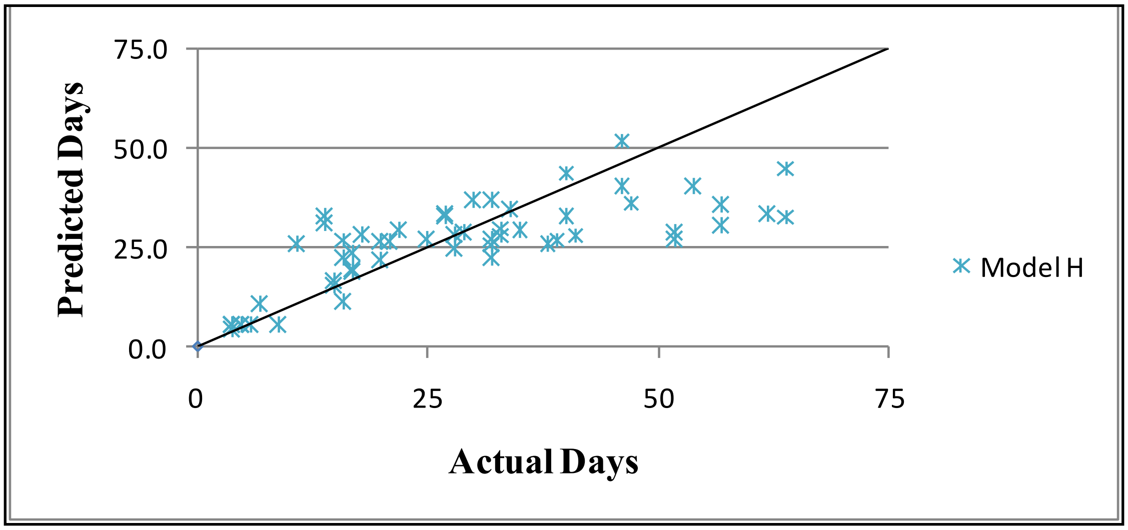


Fig. C.20–History Match, Predicted vs Actual Days for Model H Zoomed In

$ln(y_I) = 0.88750 + (0.01893 \times Te) + (0.00598 \times Tbh)$…………………………...(7.9)

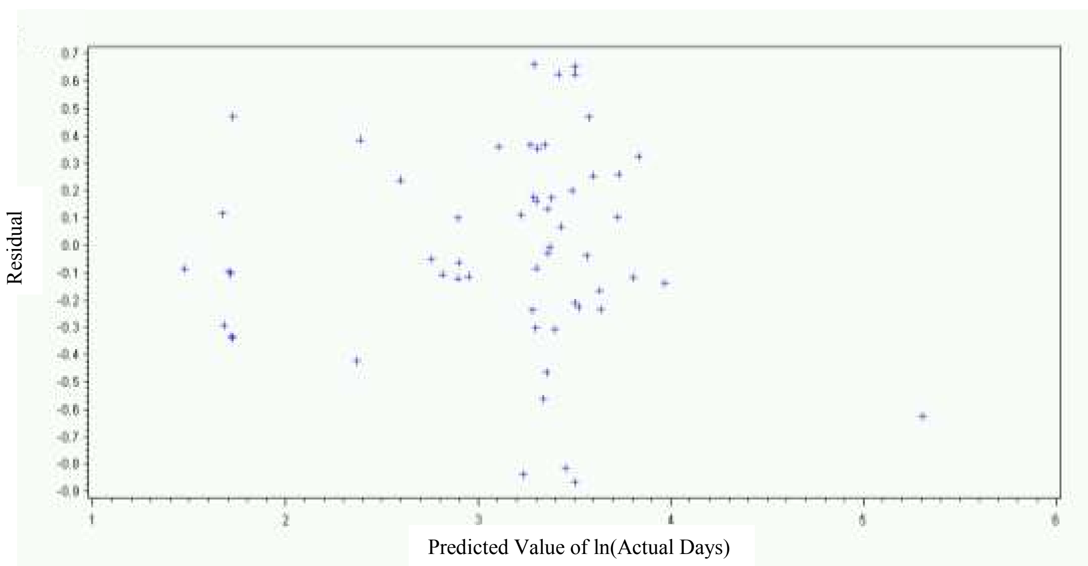


Fig. C.21-Residual Plot for Model I

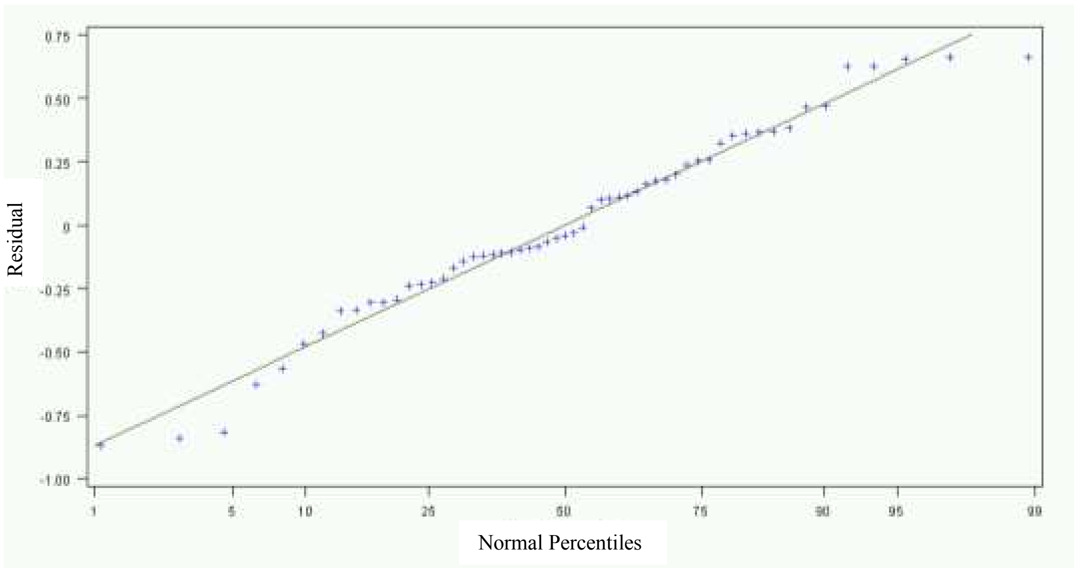


Fig. C.22–QQ Plot for Model I

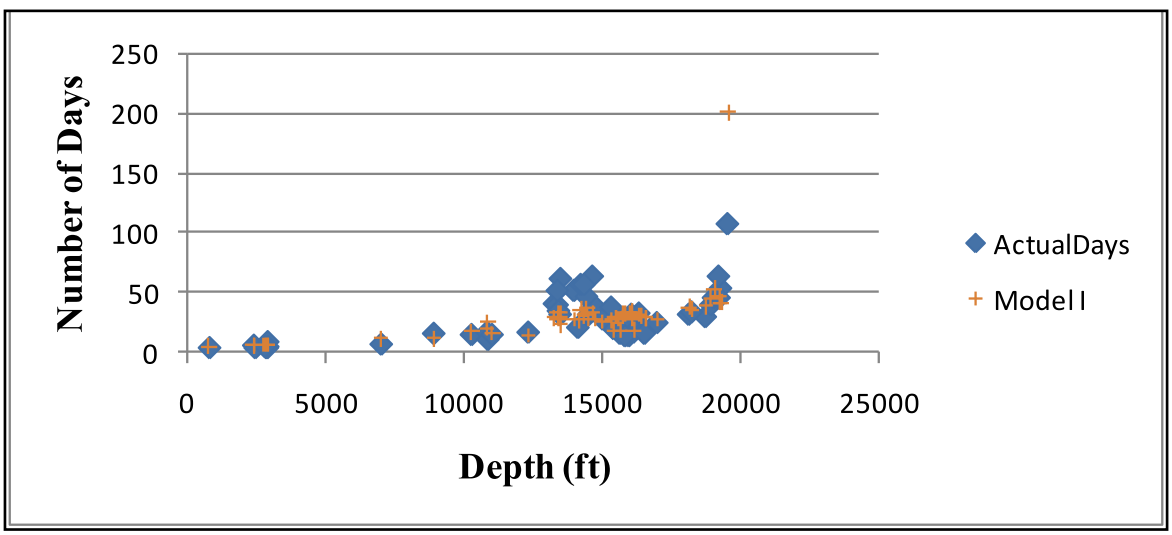


Fig. C.23–History Match between Actual and Predicted Days for Model I

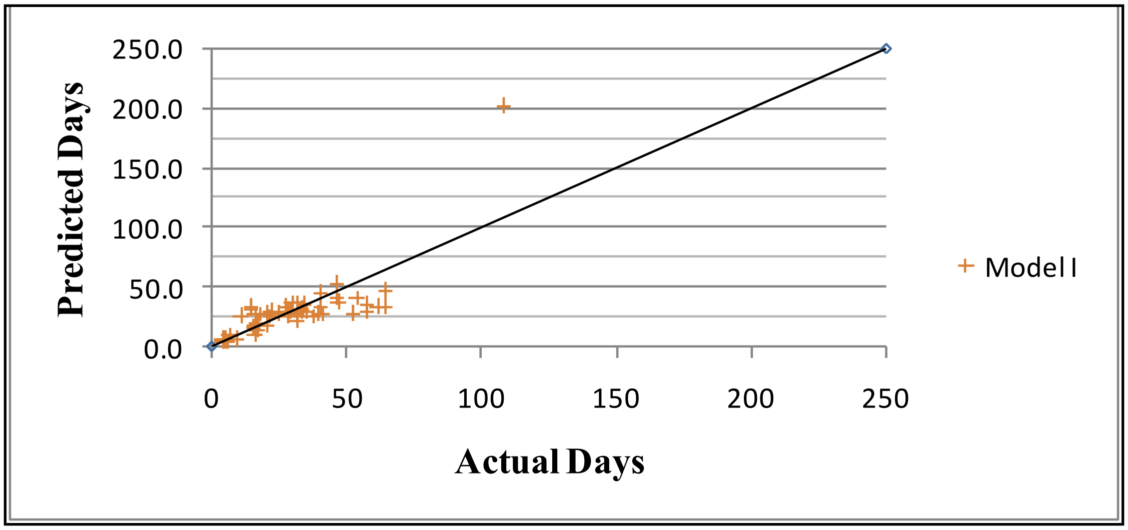


Fig. C.24–History Mach, Predicted vs Actual Days for Model I

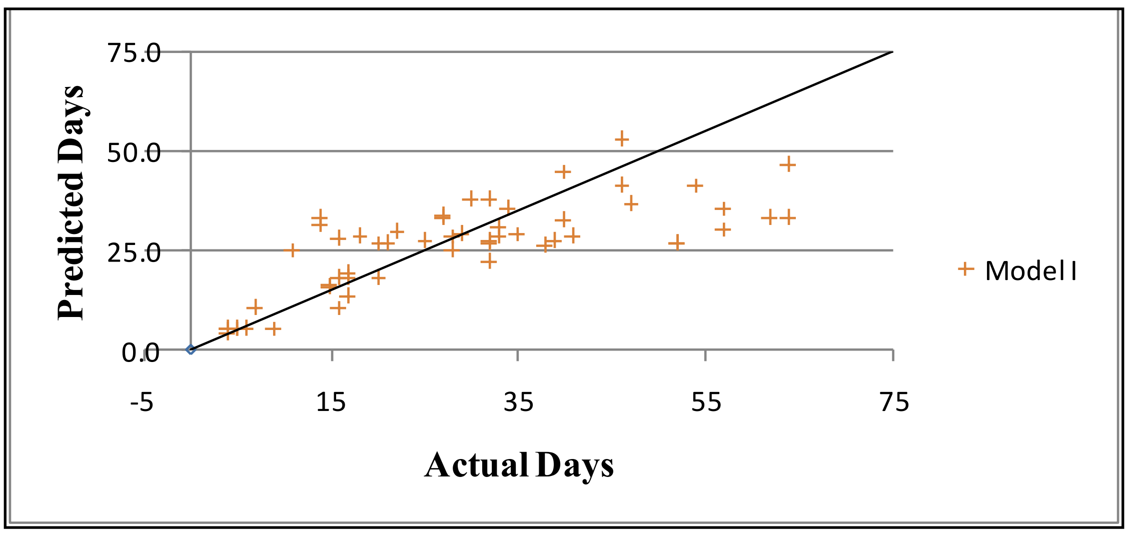


Fig. C.25–History Mach, Predicted vs Actual Days for Model I Zoomed In

$$\ln(y_J) = -4.1396 + (0.02007 \times Te) + (0.72552 \times \ln(D))\text{........................}(7.10)$$

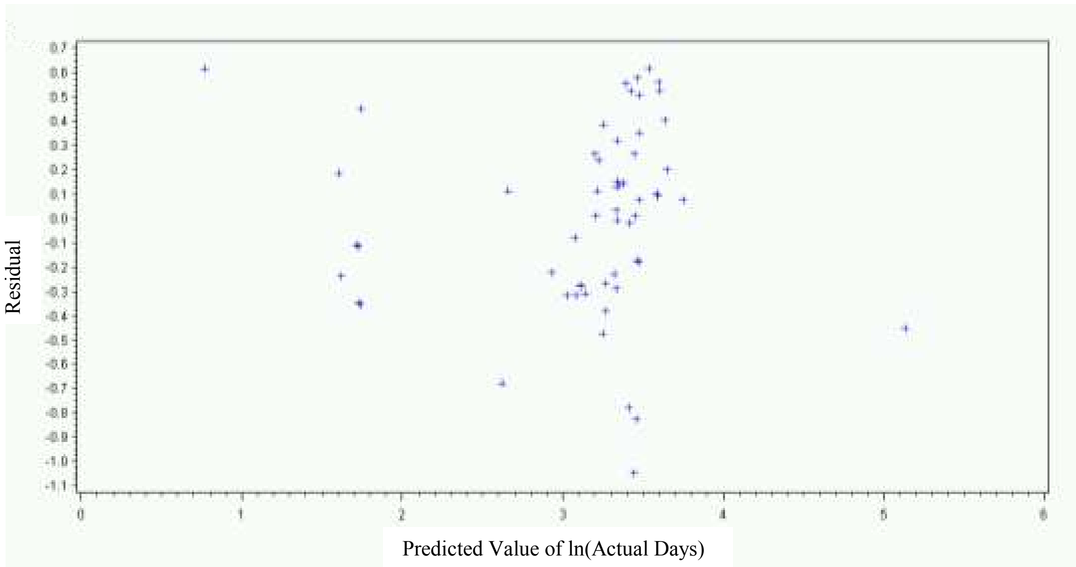


Fig. C.26–Residual Plot for Model J

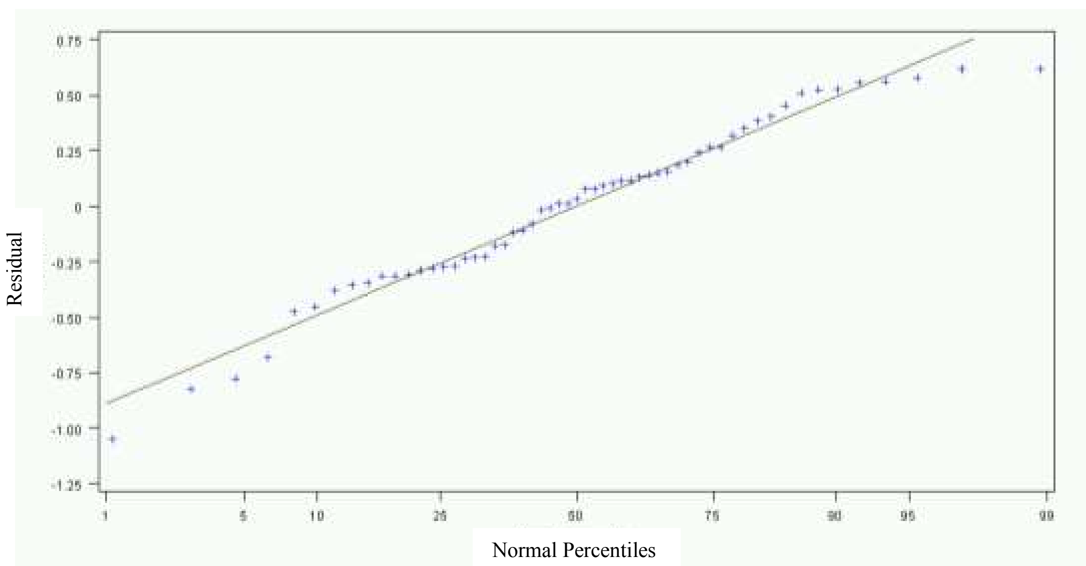


Fig. C.27–QQ Plot for Model J

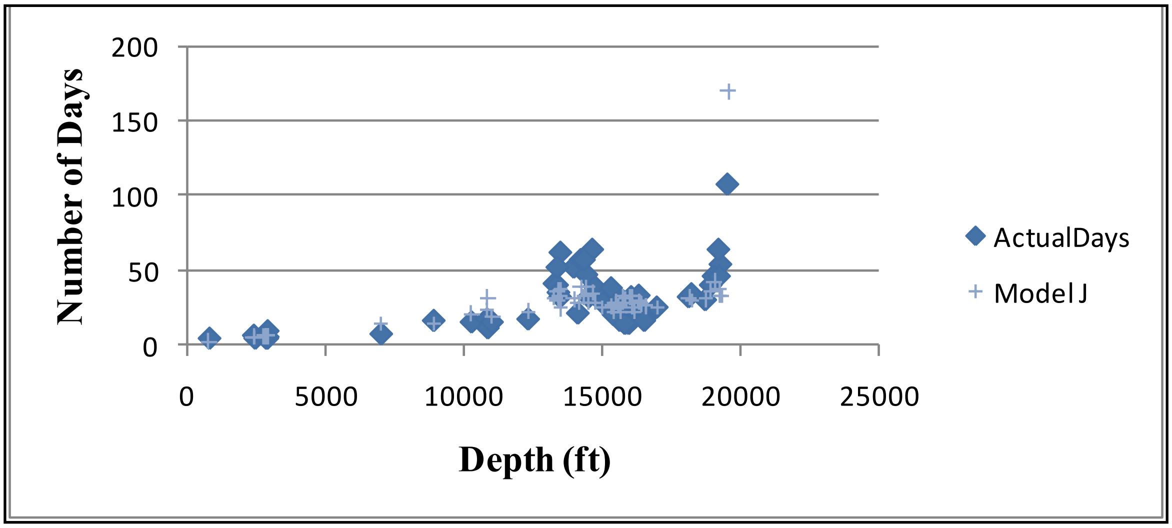


Fig. C.28–History Match between Actual and Prediced Days for Model J

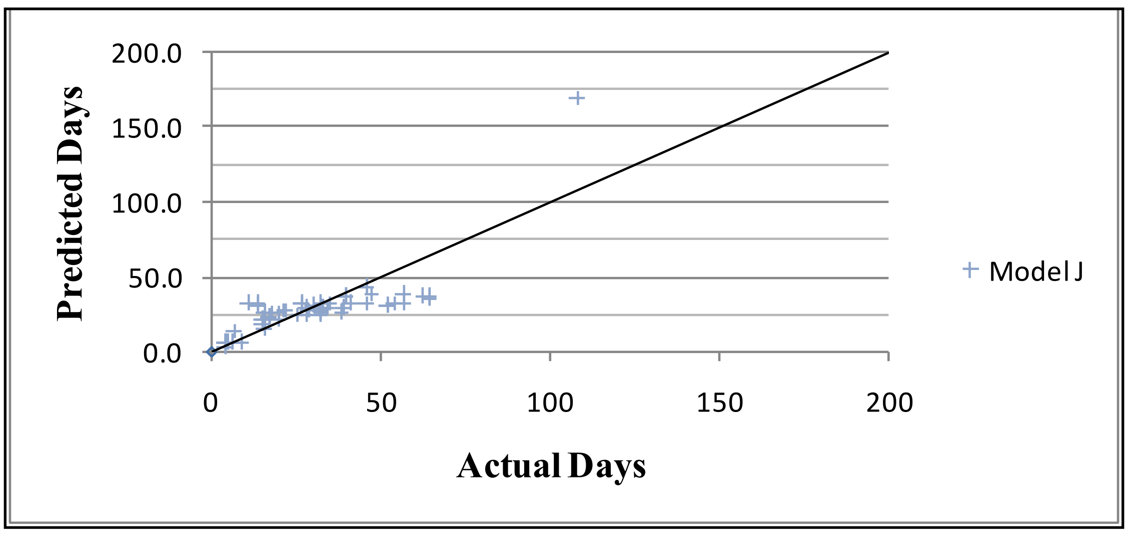


Fig. C29–History Match, Predicted vs Actual Days for Model J

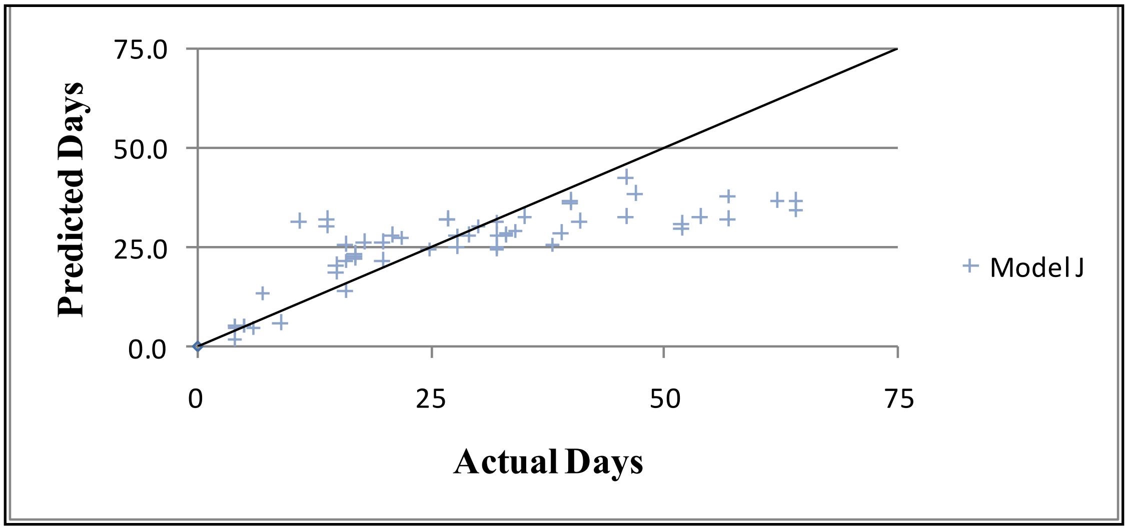


Fig. C.30–History Match, Predicted vs Actual Days for Model J Zoomed In

$$\ln(y_K) = -4.98991 + (0.01828 \times Te) + (1.36169 \times \ln(Tbh)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots(7.11)$$

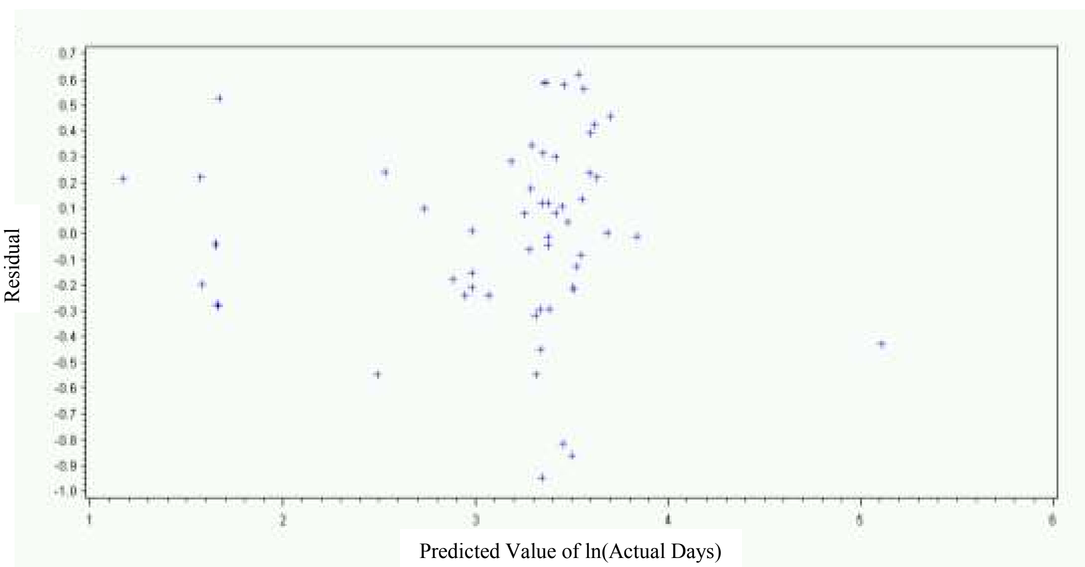


Fig. C.31–Residual Plot for Model K

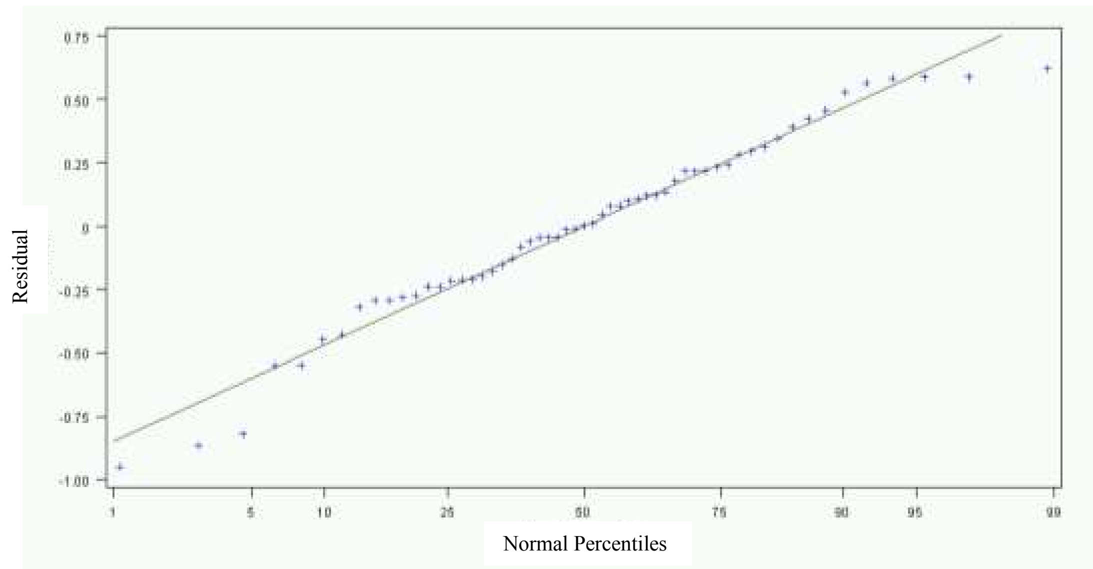


Fig C.32–QQ Plot for Model K

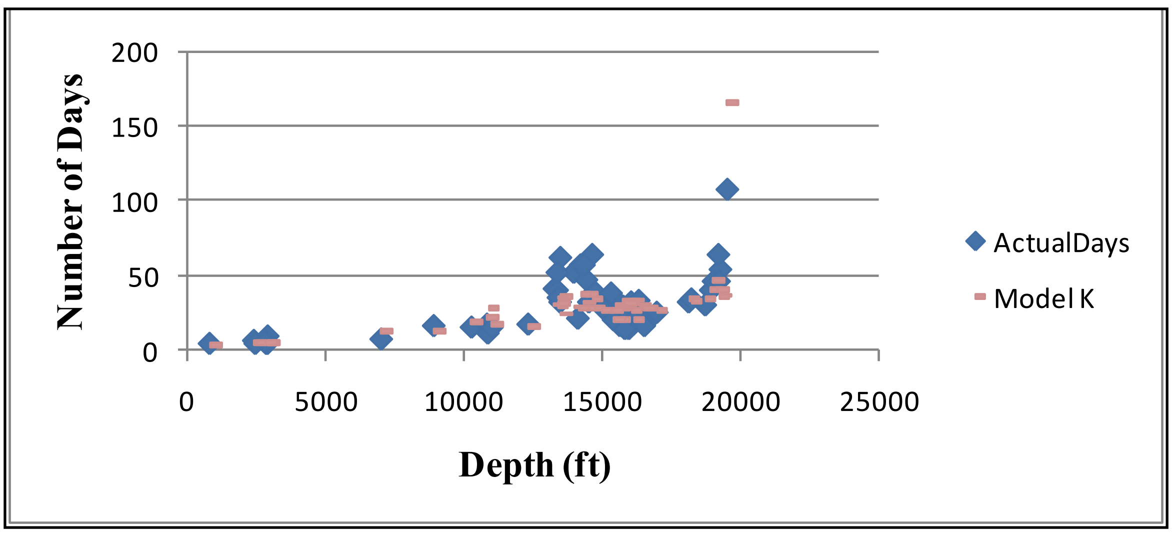


Fig C.33–History Match between Actual and Predicted Days for Model K

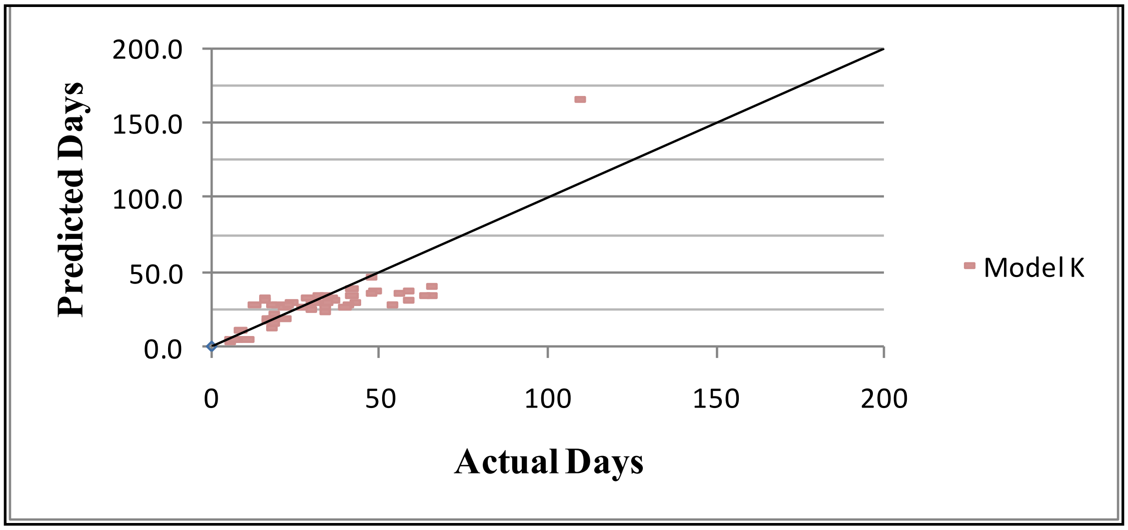


Fig C.34–History Match, Predicted Days vs Actual Days for Model K

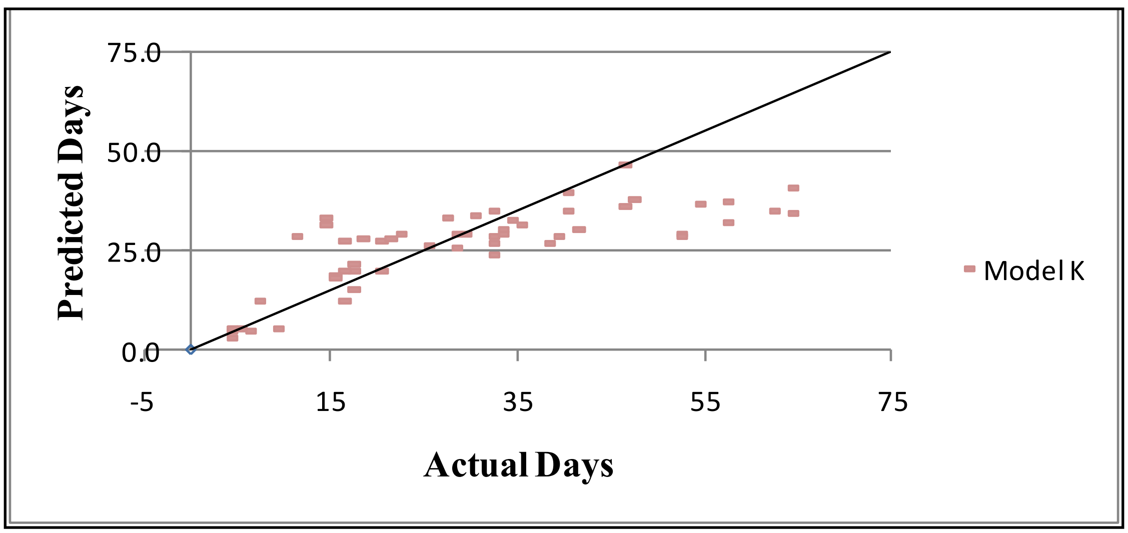


Fig. C.35–History Match, Predicted Days vs Actual Days for Model K

APPENDIX D

GRAPHICAL COMPARISON OF DEPENDENT VERSE INDEPENDENT VARIABLES

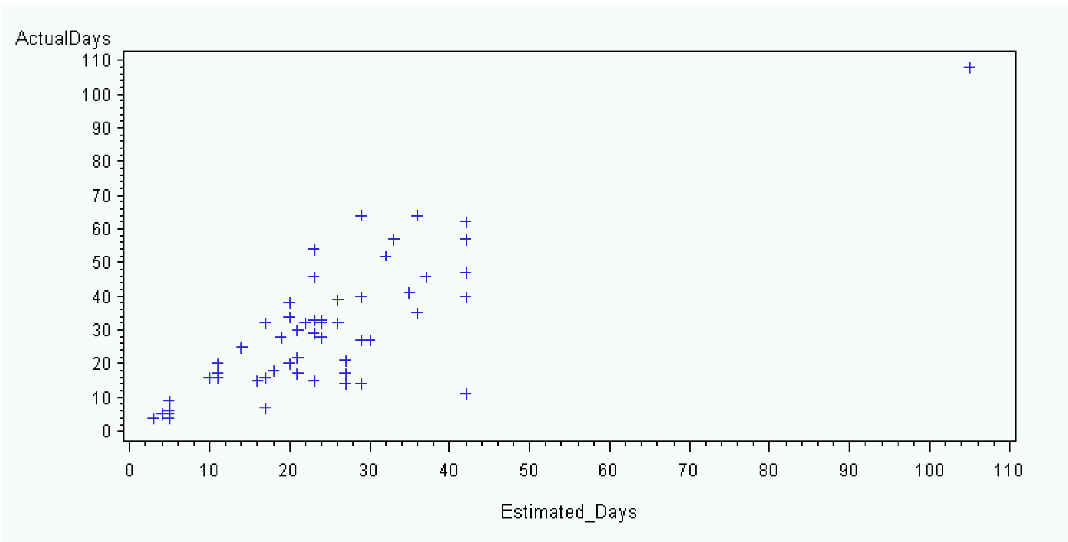


Fig. D.1–Actual Days vs Estimated Days

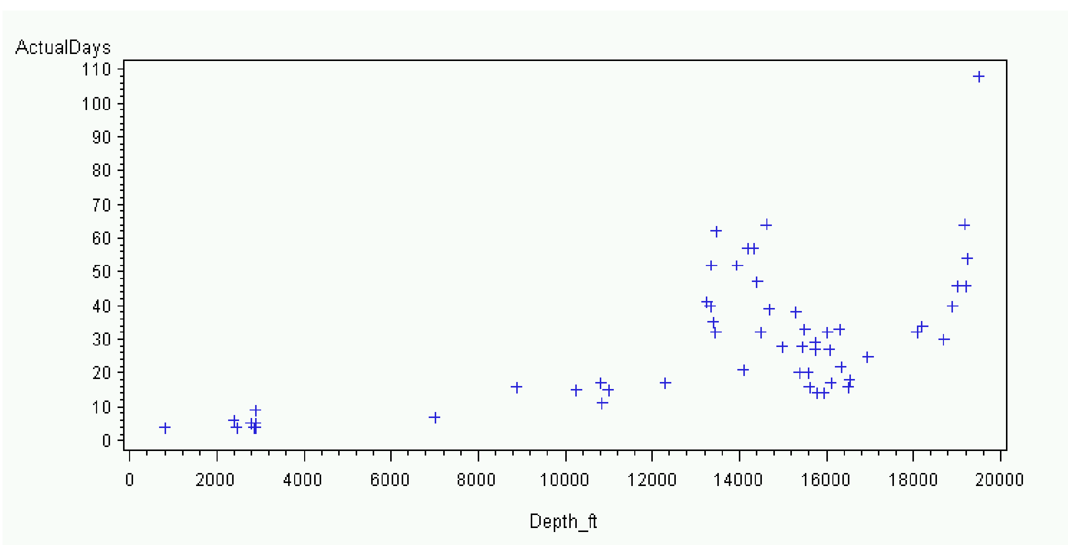


Fig. D.2–Actual Days vs Depth

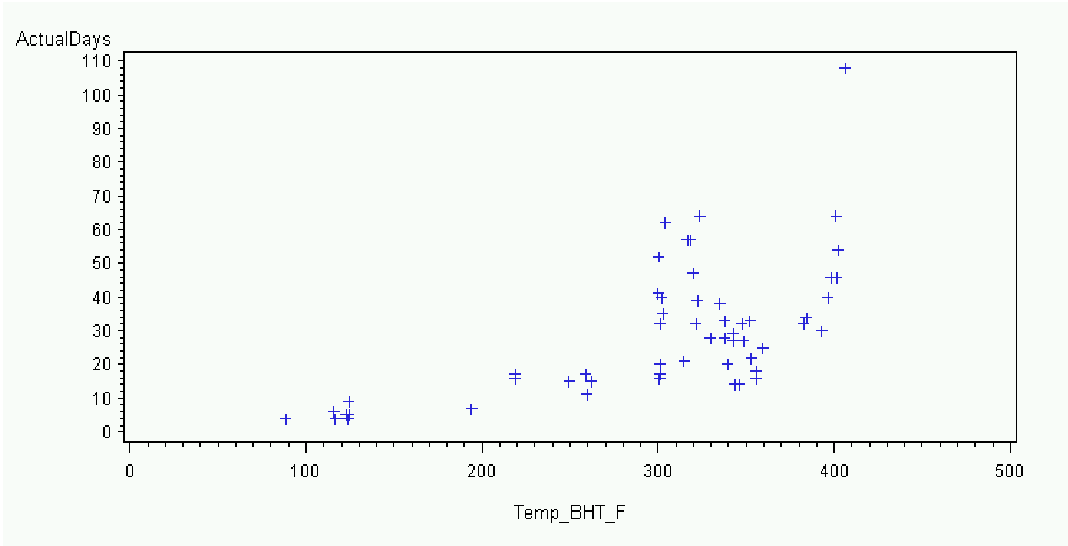


Fig. D.3–Actual Days vs. BHT

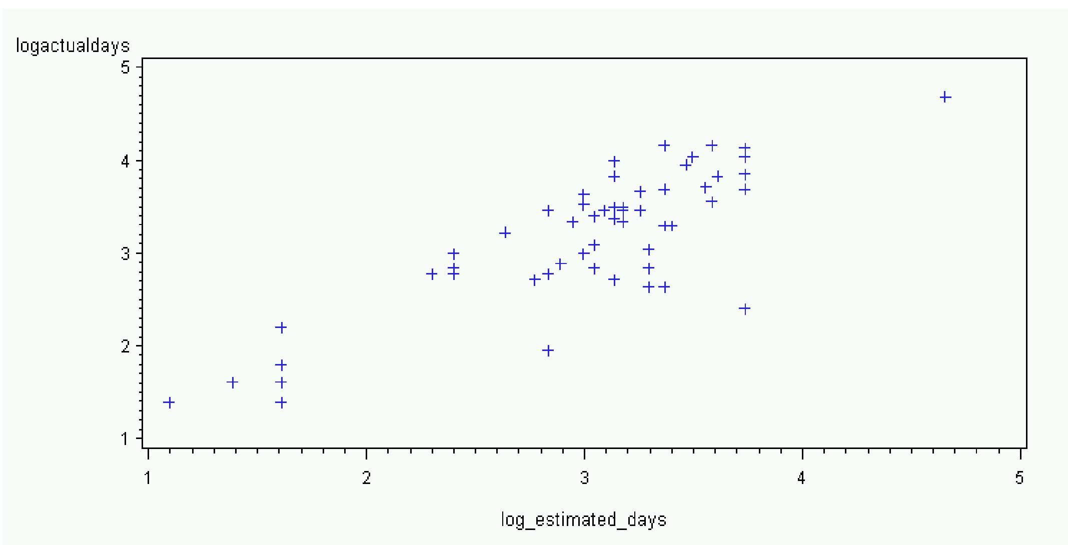


Fig. D.4–ln(Actual Days) vs. ln(Estimated Days)

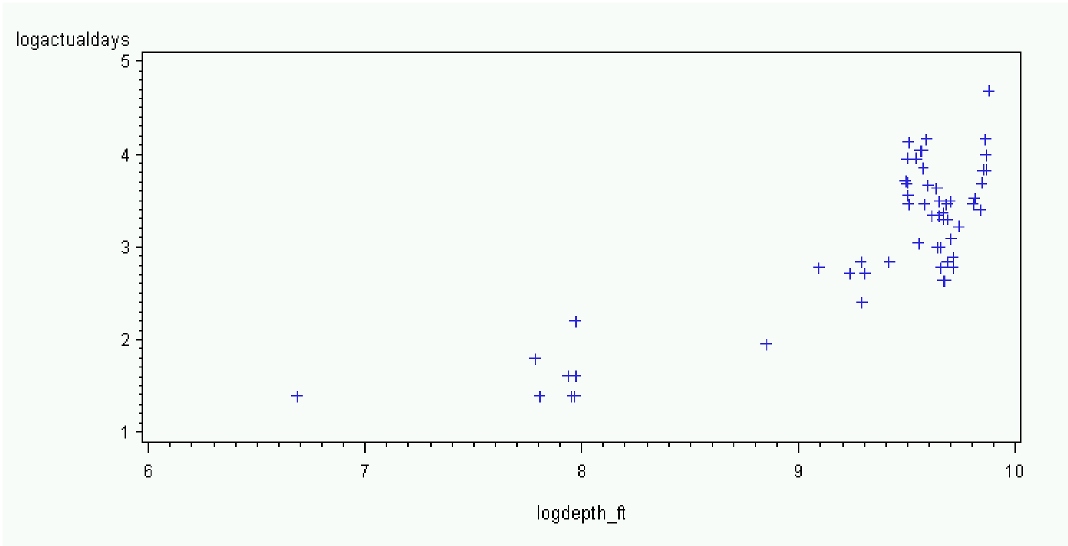


Fig. D.5–ln(Actual Days) vs. ln(Depth)

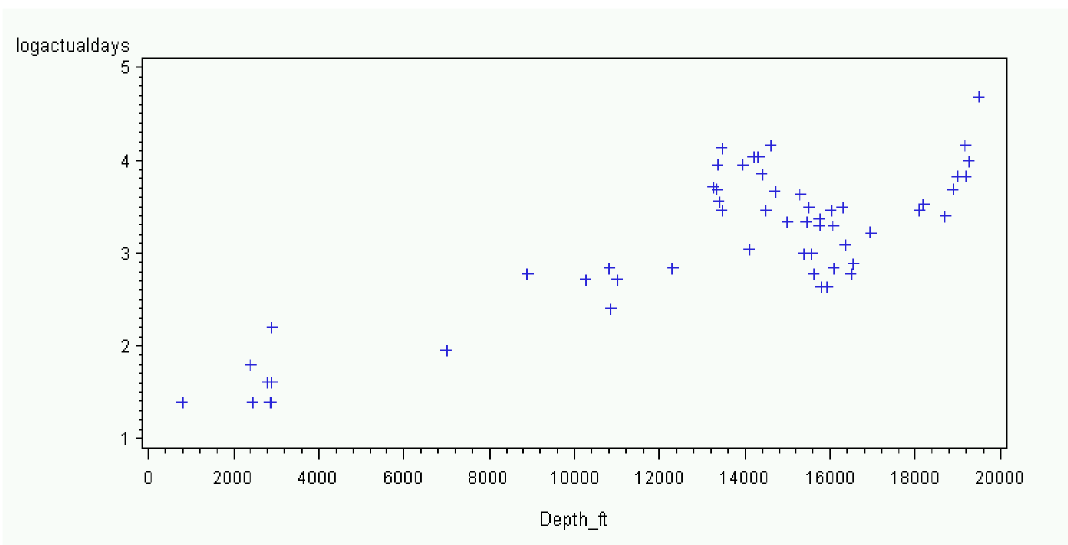


Fig. D.6–ln(Actual Days) vs. Depth

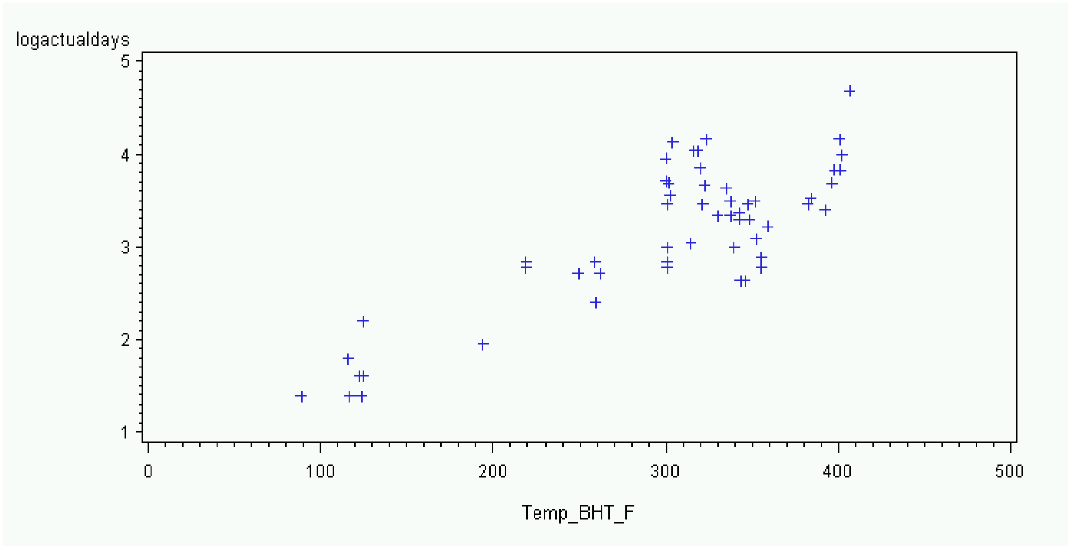


Fig. D.7– ln(Actual Days) vs. BHT

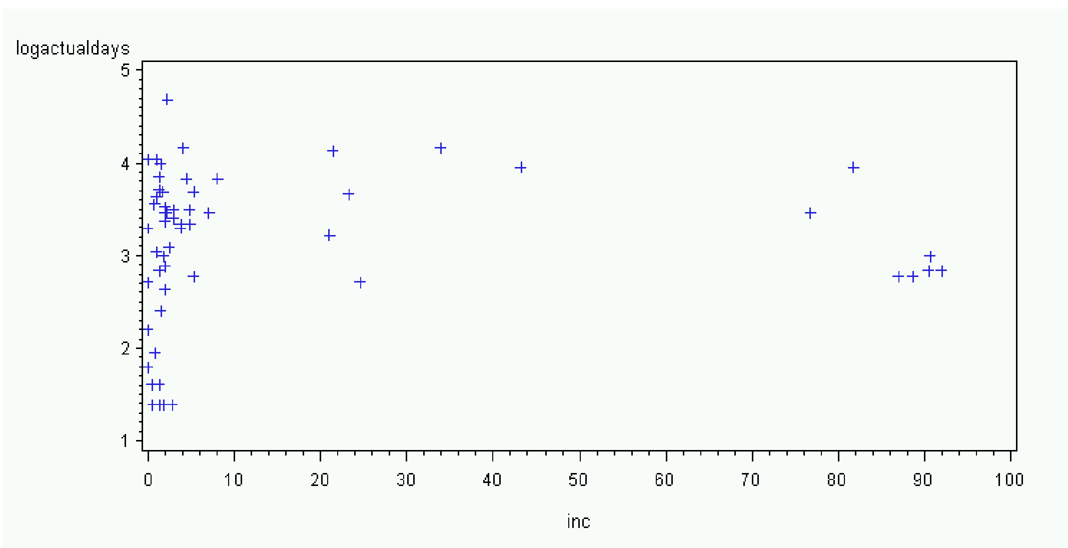


Fig. D.8– ln(Actual Days) vs. inc

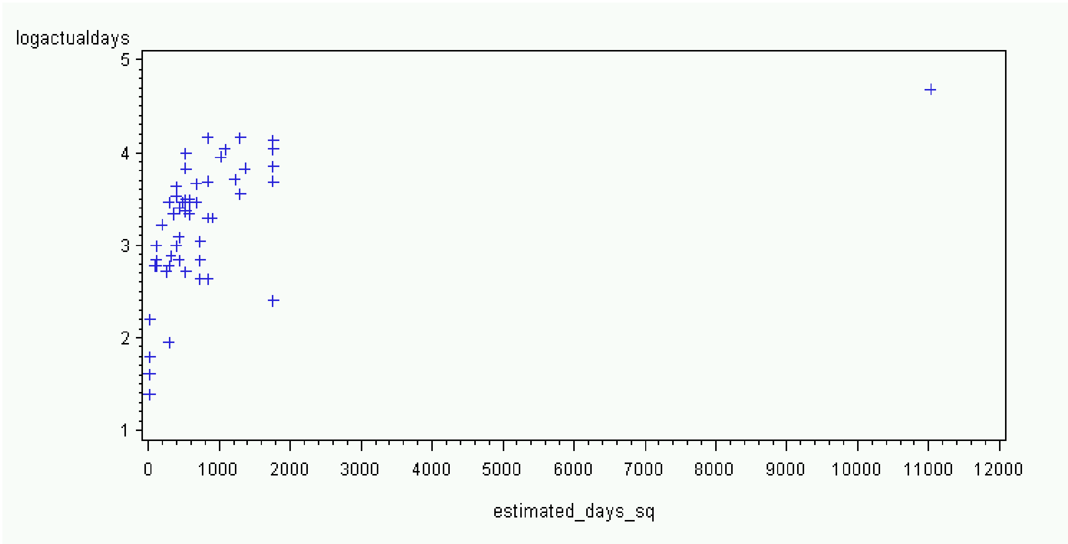


Fig. D.9–ln(Actual Days) vs. (Estimated Days)^2

APPENDIX E

SAS OUTPUT FOR ALL REGRESSIONS AND UNIVARIATE CALCULATIONS

```
                                        The SAS System      10:08 Thursday, August 12,
2010   1

                                    The CONTENTS Procedure

     Data Set Name        WORK.DRILLING                             Observations
58
     Member Type          DATA                                      Variables
6
     Engine               V9                                        Indexes
0
     Created              Thursday, August 12, 2010 10:13:10 AM    Observation Length
56
     Last Modified        Thursday, August 12, 2010 10:13:10 AM    Deleted Observations
0
     Protection                                                     Compressed
NO
     Data Set Type                                                  Sorted
NO
     Label
     Data Representation  WINDOWS_64
     Encoding             wlatin1  Western (Windows)


                              Engine/Host Dependent Information

Data Set Page Size          8192
Number of Data Set Pages    1
First Data Page             1
Max Obs per Page            145
Obs in First Data Page      58
Number of Data Set Repairs  0
Filename                    C:\Users\JDEALM~1\AppData\Local\Temp\SAS
                            Temporary Files\_TD3960\drilling.SAS7bdat
Release Created             9.0202M3
Host Created                X64_VSPRO


                          Alphabetic List of Variables and Attributes

                   #    Variable          Type    Len    Format      Informat

                   2    ActualDays        Num       8    BEST12.     BEST32.
                   4    Depth_ft          Num       8    BEST12.     BEST32.
                   3    Estimated_Days    Num       8    BEST12.     BEST32.
                   5    Temp_BHT_F        Num       8    BEST12.     BEST32.
                   1    Well              Char      9    $9.         $9.
                   6    inc               Num       8    BEST12.     BEST32.
```

Model A

```
                                 The SAS System      10:08 Thursday, August 12,
2010   2

                               The REG Procedure
                                 Model: MODEL1
                        Dependent Variable: ActualDays

                    Number of Observations Read          58
                    Number of Observations Used          58

                            Stepwise Selection: Step 1


        Variable Estimated_Days Entered: R-Square = 0.4218 and C(p) = 6.1922


                             Analysis of Variance

                                      Sum of           Mean
         Source                DF        Squares         Square    F Value    Pr > F

         Model                  1          18023          18023      40.85    <.0001
         Error                 56          24708      441.20679
         Corrected Total       57          42731


                         Parameter     Standard
             Variable     Estimate        Error   Type II SS  F Value  Pr > F

             Intercept     4.01466      5.17256    265.78388     0.60  0.4409
             Estimated_Days 1.15868     0.18129        18023    40.85  <.0001

                        Bounds on condition number: 1, 1
-----------------------------------------------------------------------------------------
-------

                            Stepwise Selection: Step 2


          Variable Temp_BHT_F Entered: R-Square = 0.4829 and C(p) = 1.8317


                             Analysis of Variance

                                      Sum of           Mean
         Source                DF        Squares         Square    F Value    Pr > F

         Model                  2          20634          10317      25.68    <.0001
         Error                 55          22097      401.75946
         Corrected Total       57          42731

                                 The SAS System      10:08 Thursday, August 12,
2010   3

                               The REG Procedure
                                 Model: MODEL1
                        Dependent Variable: ActualDays

                            Stepwise Selection: Step 2

                         Parameter     Standard
             Variable     Estimate        Error   Type II SS  F Value  Pr > F

             Intercept   -16.84055      9.55474   1248.07502     3.11  0.0835
             Estimated_Days 0.87604     0.20547   7303.17586    18.18  <.0001
             Temp_BHT_F    0.09255      0.03630   2610.80963     6.50  0.0136
```

Bounds on condition number: 1.4108, 5.643

All variables left in the model are significant at the 0.1500 level.

No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Estimated_Days		1	0.4218	0.4218	6.1922	40.85	<.0001
2	Temp_BHT_F		2	0.0611	0.4829	1.8317	6.50	0.0136

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Number of Observations Read	58
Number of Observations Used	58

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	20634	10317	25.68	<.0001
Error	55	22097	401.75946		
Corrected Total	57	42731			

Root MSE	20.04394	R-Square	0.4829
Dependent Mean	31.98276	Adj R-Sq	0.4641
Coeff Var	62.67107		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-16.84055	9.55474	-1.76	0.0835	0
Estimated_Days	1	0.87604	0.20547	4.26	<.0001	1.41076
Temp_BHT_F	1	0.09255	0.03630	2.55	0.0136	1.41076

The REG Procedure

Model: MODEL1
Dependent Variable: ActualDays

Test of First and Second
Moment Specification

DF	Chi-Square	Pr > ChiSq
5	3.48	0.6266

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Number of Observations Read	58
Number of Observations Used	58

Forward Selection: Step 1

Variable Estimated_Days Entered: R-Square = 0.4218 and C(p) = 6.1922

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	18023	18023	40.85	<.0001
Error	56	24708	441.20679		
Corrected Total	57	42731			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	4.01466	5.17256	265.78388	0.60	0.4409
Estimated_Days	1.15868	0.18129	18023	40.85	<.0001

Bounds on condition number: 1, 1

Forward Selection: Step 2

Variable Temp_BHT_F Entered: R-Square = 0.4829 and C(p) = 1.8317

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	20634	10317	25.68	<.0001
Error	55	22097	401.75946		
Corrected Total	57	42731			

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Forward Selection: Step 2

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-16.84055	9.55474	1248.07502	3.11	0.0835
Estimated_Days	0.87604	0.20547	7303.17586	18.18	<.0001
Temp_BHT_F	0.09255	0.03630	2610.80963	6.50	0.0136

Bounds on condition number: 1.4108, 5.643

No other variable met the 0.5000 significance level for entry into the model.

Summary of Forward Selection

Step	Variable Entered	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	Estimated_Days	1	0.4218	0.4218	6.1922	40.85	<.0001
2	Temp_BHT_F	2	0.0611	0.4829	1.8317	6.50	0.0136

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Number of Observations Read 58
Number of Observations Used 58

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	20634	10317	25.68	<.0001
Error	55	22097	401.75946		
Corrected Total	57	42731			

Root MSE	20.04394	R-Square	0.4829
Dependent Mean	31.98276	Adj R-Sq	0.4641
Coeff Var	62.67107		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-16.84055	9.55474	-1.76	0.0835	0
Estimated_Days	1	0.87604	0.20547	4.26	<.0001	1.41076
Temp_BHT_F	1	0.09255	0.03630	2.55	0.0136	1.41076

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Test of First and Second
Moment Specification

DF	Chi-Square	Pr > ChiSq
5	3.48	0.6266

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Number of Observations Read 58
Number of Observations Used 58

Backward Elimination: Step 0

All Variables Entered: R-Square = 0.4909 and C(p) = 5.0000

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	20976	5243.90663	12.78	<.0001
Error	53	21755	410.47842		
Corrected Total	57	42731			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-40.20190	28.46162	818.96294	2.00	0.1636
Depth_ft	-0.00517	0.00607	298.12846	0.73	0.3979
Estimated_Days	0.87268	0.21013	7079.57568	17.25	0.0001
inc	0.13626	0.15641	311.54542	0.76	0.3876
Temp_BHT_F	0.39575	0.35804	501.49284	1.22	0.2740

Bounds on condition number: 134.3, 1085.4

Backward Elimination: Step 1

Variable Depth_ft Removed: R-Square = 0.4839 and C(p) = 3.7263

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Backward Elimination: Step 1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	20677	6892.49935	16.88	<.0001
Error	54	22053	408.39786		
Corrected Total	57	42731			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-17.43942	9.80741	1291.33397	3.16	0.0810
Estimated_Days	0.88525	0.20908	7321.09539	17.93	<.0001
inc	0.03131	0.09619	43.28578	0.11	0.7460
Temp_BHT_F	0.09222	0.03662	2590.80623	6.34	0.0148

Bounds on condition number: 1.437, 11.612

Backward Elimination: Step 2

```
             Variable inc Removed: R-Square = 0.4829 and C(p) = 1.8317

                                 Analysis of Variance

                                        Sum of           Mean
         Source                   DF        Squares         Square    F Value    Pr > F

         Model                     2          20634          10317      25.68    <.0001
         Error                    55          22097      401.75946
         Corrected Total          57          42731


                                   The SAS System      10:08 Thursday, August 12,
2010  12

                                  The REG Procedure
                                    Model: MODEL1
                           Dependent Variable: ActualDays

                            Backward Elimination: Step 2

                          Parameter     Standard
             Variable           Estimate        Error   Type II SS  F Value  Pr > F

             Intercept         -16.84055      9.55474   1248.07502     3.11  0.0835
             Estimated_Days      0.87604      0.20547   7303.17586    18.18  <.0001
             Temp_BHT_F          0.09255      0.03630   2610.80963     6.50  0.0136

                       Bounds on condition number: 1.4108, 5.643
-------------------------------------------------------------------------------------------
-------


             All variables left in the model are significant at the 0.1000 level.



                           Summary of Backward Elimination

        Variable          Number     Partial      Model
  Step    Removed           Vars In    R-Square    R-Square     C(p)      F Value    Pr
> F

    1     Depth_ft             3       0.0070      0.4839      3.7263       0.73
0.3979
    2     inc                  2       0.0010      0.4829      1.8317       0.11
0.7460

                                    The SAS System      10:08 Thursday, August 12,
2010  13

                                  The REG Procedure
                                    Model: MODEL1
                           Dependent Variable: ActualDays

                      Number of Observations Read          58
                      Number of Observations Used          58


                                 Analysis of Variance

                                        Sum of           Mean
         Source                   DF        Squares         Square    F Value    Pr > F

         Model                     2          20634          10317      25.68    <.0001
         Error                    55          22097      401.75946
```

Corrected Total	57	42731

Root MSE	20.04394	R-Square	0.4829
Dependent Mean	31.98276	Adj R-Sq	0.4641
Coeff Var	62.67107		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-16.84055	9.55474	-1.76	0.0835	0
Estimated_Days	1	0.87604	0.20547	4.26	<.0001	1.41076
Temp_BHT_F	1	0.09255	0.03630	2.55	0.0136	1.41076

```
                              The SAS System      10:08 Thursday, August 12,
2010  14

                             The REG Procedure
                               Model: MODEL1
                      Dependent Variable: ActualDays

                          Test of First and Second
                            Moment Specification

                         DF    Chi-Square    Pr > ChiSq

                          5          3.48        0.6266
```

```
                              The SAS System      10:08 Thursday, August 12,
2010  15

                             The REG Procedure
                               Model: MODEL1
                      Dependent Variable: ActualDays

                  Number of Observations Read          58
                  Number of Observations Used          58


                            Analysis of Variance

                                    Sum of           Mean
         Source                DF         Squares         Square    F Value    Pr > F

         Model                  2           20634          10317      25.68    <.0001
         Error                 55           22097      401.75946
         Corrected Total       57           42731


                      Root MSE             20.04394    R-Square     0.4829
                      Dependent Mean       31.98276    Adj R-Sq     0.4641
                      Coeff Var            62.67107


                            Parameter Estimates

                           Parameter       Standard
Variance
    Variable           DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept           1      -16.84055        9.55474      -1.76      0.0835
0
    Temp_BHT_F          1        0.09255        0.03630       2.55      0.0136
1.41076
    Estimated_Days      1        0.87604        0.20547       4.26      <.0001
1.41076
```

```
                              The SAS System      10:08 Thursday, August 12,
2010  16

                             The REG Procedure
                               Model: MODEL1
                      Dependent Variable: ActualDays

                          Test of First and Second
                            Moment Specification

                         DF    Chi-Square    Pr > ChiSq

                          5          3.48        0.6266
```

Q-Q Plot: Actualdays = TEMP_BHT_F Estimated_Days
17
10:08 Thursday, August
12, 2010

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	58	Sum Weights	58
Mean	0	Sum Observations	0
Std Deviation	19.6891503	Variance	387.66264
Skewness	4.27757171	Kurtosis	26.9234937
Uncorrected SS	22096.7705	Corrected SS	22096.7705
Coeff Variation	.	Std Error Mean	2.58531209

Basic Statistical Measures

Location		Variability	
Mean	0.00000	Std Deviation	19.68915
Median	-2.72978	Variance	387.66264
Mode	.	Range	155.99533
		Interquartile Range	14.01188

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	-6	Pr >= |M|	0.1480
Signed Rank	S	-133.5	Pr >= |S|	0.3054

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.631467	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.174238	Pr > D	<0.0100
Cramer-von Mises	W-Sq	0.619197	Pr > W-Sq	<0.0050
Anderson-Darling	A-Sq	3.965366	Pr > A-Sq	<0.0050

Quantiles (Definition 5)

Quantile	Estimate
100% Max	123.03080
99%	123.03080
95%	18.32326
90%	13.46468

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	6.11412
50% Median	-2.72978
25% Q1	-7.89776
10%	-14.16112
5%	-24.61165
1%	-32.96453
0% Min	-32.96453

Extreme Observations

------Lowest-----		------Highest-----	
Value	Obs	Value	Obs
-32.9645	29	13.9134	8
-26.5824	26	15.4590	56
-24.6116	57	18.3233	35
-14.9525	46	19.3604	5
-14.9371	52	123.0308	39

Model B

```
                     Residual Plot: Actualdays = TEMP_BHT_F  Estimated_Days
19
                                                          10:08 Thursday, August
12, 2010

                                  The REG Procedure
                                    Model: MODEL1
                             Dependent Variable: ActualDays

                         Number of Observations Read          58
                         Number of Observations Used          58


                                  Analysis of Variance

                                         Sum of           Mean
         Source                   DF        Squares         Square    F Value    Pr > F

         Model                     2          20474          10237      25.30    <.0001
         Error                    55          22257      404.67104
         Corrected Total          57          42731


                      Root MSE             20.11644    R-Square     0.4791
                      Dependent Mean       31.98276    Adj R-Sq     0.4602
                      Coeff Var            62.89775


                                  Parameter Estimates

                              Parameter       Standard
Variance
    Variable          DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept          1       -9.88984        7.51429      -1.32      0.1936
0
    Depth_ft           1        0.00150     0.00061002       2.46      0.0170
1.36323
    Estimated_Days     1        0.90118        0.20271       4.45      <.0001
1.36323

                     Residual Plot: Actualdays = TEMP_BHT_F  Estimated_Days
20
                                                          10:08 Thursday, August
12, 2010

                                  The REG Procedure
                                    Model: MODEL1
                             Dependent Variable: ActualDays

                               Test of First and Second
                                 Moment Specification

                                DF    Chi-Square    Pr > ChiSq

                                 5          3.45        0.6307

                         Q-Q Plot: Actualdays = Depth_ft Estimated_Days
21
                                                          10:08 Thursday, August
12, 2010

                               The UNIVARIATE Procedure
                             Variable:  resid  (Residual)
```

Moments

N	58	Sum Weights	58
Mean	0	Sum Observations	0
Std Deviation	19.7603657	Variance	390.472053
Skewness	4.29124048	Kurtosis	26.9643936
Uncorrected SS	22256.907	Corrected SS	22256.907
Coeff Variation	.	Std Error Mean	2.59466313

Basic Statistical Measures

Location		Variability	
Mean	0.00000	Std Deviation	19.76037
Median	-2.85754	Variance	390.47205
Mode	.	Range	156.77331
		Interquartile Range	14.34040

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	-6	Pr >= |M|	0.1480
Signed Rank	S	-136.5	Pr >= |S|	0.2946

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.630373	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.178141	Pr > D	<0.0100
Cramer-von Mises	W-Sq	0.617013	Pr > W-Sq	<0.0050
Anderson-Darling	A-Sq	3.974491	Pr > A-Sq	<0.0050

Quantiles (Definition 5)

Quantile	Estimate
100% Max	123.52585
99%	123.52585
95%	18.96744
90%	13.81943

Q-Q Plot: Actualdays = Depth_ft Estimated_Days

22

10:08 Thursday, August

12, 2010

The UNIVARIATE Procedure

Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	6.33997
50% Median	-2.85754
25% Q1	-8.00043
10%	-13.78917
5%	-24.16070
1%	-33.24746

0% Min -33.24746

Extreme Observations

------Lowest-----		------Highest-----	
Value	Obs	Value	Obs
-33.2475	29	14.2649	4
-26.1717	26	15.6525	56
-24.1607	57	18.9674	35
-14.6087	52	19.5001	5
-14.1998	46	123.5259	39

Model C

```
                      Residual Plot: Actualdays = Depth_ft Estimated_Days
23
                                                                   10:08 Thursday, August
12, 2010

                                     The REG Procedure
                                      Model: MODEL1
                               Dependent Variable: ActualDays

                            Number of Observations Read          57
                            Number of Observations Used          57


                                    Analysis of Variance

                                           Sum of           Mean
         Source                   DF      Squares         Square    F Value    Pr > F

         Model                     2        15850     7925.04348      67.31    <.0001
         Error                    54   6358.15865      117.74368
         Corrected Total          56        22208


                      Root MSE             10.85098    R-Square     0.7137
                      Dependent Mean       29.49123    Adj R-Sq     0.7031
                      Coeff Var            36.79391


                                    Parameter Estimates

                              Parameter       Standard
Variance
    Variable          DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept          1       -5.28257        4.07262      -1.30      0.2001
0
    Depth_ft           1        0.00104     0.00033148       3.12      0.0029
1.35154
    Estimated_Days     1        0.87691        0.10936       8.02      <.0001
1.35154

                      Residual Plot: Actualdays = Depth_ft Estimated_Days
24
                                                                   10:08 Thursday, August
12, 2010

                                     The REG Procedure
                                      Model: MODEL1
                               Dependent Variable: ActualDays

                                  Test of First and Second
                                    Moment Specification

                                 DF    Chi-Square    Pr > ChiSq

                                  5         10.41        0.0643

                         Q-Q Plot: Actualdays = Depth_ft Estimated_Days
25
                                                                   10:08 Thursday, August
12, 2010

                                  The UNIVARIATE Procedure
                                Variable:  resid  (Residual)
```

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	10.6554468	Variance	113.538547
Skewness	-0.1558503	Kurtosis	0.94301366
Uncorrected SS	6358.15865	Corrected SS	6358.15865
Coeff Variation	.	Std Error Mean	1.41134841

Basic Statistical Measures

Location		Variability	
Mean	0.000000	Std Deviation	10.65545
Median	0.529895	Variance	113.53855
Mode	.	Range	55.77660
		Interquartile Range	9.78507

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	2.5	Pr >= |M|	0.5966
Signed Rank	S	10.5	Pr >= |S|	0.9344

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.972431	Pr < W	0.2173
Kolmogorov-Smirnov	D	0.093778	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.099368	Pr > W-Sq	0.1145
Anderson-Darling	A-Sq	0.59442	Pr > A-Sq	0.1202

Quantiles (Definition 5)

Quantile	Estimate
100% Max	23.993124
99%	23.993124
95%	19.178971
90%	15.385281

Q-Q Plot: Actualdays = Depth_ft Estimated_Days

26

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The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	4.412667
50% Median	0.529895
25% Q1	-5.372400
10%	-10.711766
5%	-20.755939
1%	-31.783474

0% Min -31.783474

Extreme Observations

------Lowest-----		-----Highest-----	
Value	Obs	Value	Obs
-31.7835	29	16.5033	8
-22.6537	26	18.5142	55
-20.7559	56	19.1790	4
-12.5988	11	22.5739	5
-11.9955	51	23.9931	35

Model D

Residual Plot: Actualdays = Depth_ft Estimated_Days
27
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Number of Observations Read	57
Number of Observations Used	57

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	15907	7953.54216	68.16	<.0001
Error	54	6301.16130	116.68817		
Corrected Total	56	22208			

Root MSE	10.80223	R-Square	0.7163
Dependent Mean	29.49123	Adj R-Sq	0.7058
Coeff Var	36.62862		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-9.98231	5.18294	-1.93	0.0594	0
Temp_BHT_F	1	0.06342	0.01972	3.22	0.0022	1.39833
Estimated_Days	1	0.86113	0.11074	7.78	<.0001	1.39833

Residual Plot: Actualdays = Depth_ft Estimated_Days
28
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: ActualDays

Test of First and Second
Moment Specification

DF	Chi-Square	Pr > ChiSq
5	10.60	0.0600

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	10.6075792	Variance	112.520738
Skewness	-0.190869	Kurtosis	0.97192839
Uncorrected SS	6301.1613	Corrected SS	6301.1613
Coeff Variation	.	Std Error Mean	1.40500819

Basic Statistical Measures

Location		Variability	
Mean	0.000000	Std Deviation	10.60758
Median	0.693429	Variance	112.52074
Mode	.	Range	55.21750
		Interquartile Range	9.66674

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	2.5	Pr >= |M|	0.5966
Signed Rank	S	11.5	Pr >= |S|	0.9282

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.969891	Pr < W	0.1659
Kolmogorov-Smirnov	D	0.095845	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.113858	Pr > W-Sq	0.0753
Anderson-Darling	A-Sq	0.662165	Pr > A-Sq	0.0833

Quantiles (Definition 5)

Quantile	Estimate
100% Max	23.579001
99%	23.579001
95%	18.667073
90%	15.385396

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	4.333042
50% Median	0.693429
25% Q1	-5.333699
10%	-11.201434
5%	-21.058065
1%	-31.638498
0% Min	-31.638498

Extreme Observations

------Lowest-----		-----Highest-----	
Value	Obs	Value	Obs
-31.6385	29	16.5369	8
-22.9302	26	18.3696	55
-21.0581	56	18.6671	4
-12.6892	11	22.4639	5
-12.2253	51	23.5790	35

Model E

logactualdays*logDepth_ft
31
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read 57
Number of Observations Used 57

Stepwise Selection: Step 1

Variable log_estimated_days Entered: R-Square = 0.7232 and C(p) = 29.5573

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	26.45166	26.45166	143.70	<.0001
Error	55	10.12436	0.18408		
Corrected Total	56	36.57601			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	0.25572	0.24557	0.19961	1.08	0.3023
log_estimated_days	0.96484	0.08049	26.45166	143.70	<.0001

Bounds on condition number: 1, 1

Stepwise Selection: Step 2

Variable Depth_ft Entered: R-Square = 0.7995 and C(p) = 8.7999

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	29.24250	14.62125	107.66	<.0001
Error	54	7.33352	0.13581		
Corrected Total	56	36.57601			

logactualdays*logDepth_ft
32
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Stepwise Selection: Step 2

Parameter Standard

```
          Variable              Estimate       Error   Type II SS  F Value  Pr > F

          Intercept               0.44017     0.21481      0.57021     4.20  0.0453
          Depth_ft             0.00006721  0.00001483      2.79084    20.55  <.0001
          log_estimated_days      0.60152     0.10584      4.38632    32.30  <.0001

                          Bounds on condition number: 2.3439, 9.3758
-----------------------------------------------------------------------------------------
-------


             All variables left in the model are significant at the 0.1500 level.

        No other variable met the 0.1500 significance level for entry into the model.


                                  Summary of Stepwise Selection

      Variable           Variable           Number  Partial   Model
  Step Entered           Removed            Vars In R-Square R-Square   C(p)   F Value Pr
> F

    1  log_estimated_days                       1    0.7232   0.7232  29.5573  143.70
<.0001
    2  Depth_ft                                 2    0.0763   0.7995   8.7999   20.55
<.0001

                                    logactualdays*logDepth_ft
33
                                                                  10:08 Thursday, August
12, 2010

                                          The REG Procedure
                                            Model: MODEL1
                                   Dependent Variable: logactualdays

                            Number of Observations Read          57
                            Number of Observations Used          57


                                         Analysis of Variance

                                              Sum of           Mean
         Source                   DF         Squares         Square    F Value    Pr > F

         Model                     2        29.24250       14.62125     107.66    <.0001
         Error                    54         7.33352        0.13581
         Corrected Total          56        36.57601


                      Root MSE              0.36852    R-Square     0.7995
                      Dependent Mean        3.11950    Adj R-Sq     0.7921
                      Coeff Var            11.81338


                                         Parameter Estimates

                                   Parameter       Standard
Variance
  Variable               DF        Estimate          Error    t Value    Pr > |t|
Inflation

  Intercept               1         0.44017        0.21481       2.05      0.0453
0
  Depth_ft                1      0.00006721     0.00001483       4.53      <.0001
2.34394
```

```
  log_estimated_days     1        0.60152        0.10584       5.68      <.0001
2.34394

                                   logactualdays*logDepth_ft
34
                                                                 10:08 Thursday, August
12, 2010

                                       The REG Procedure
                                         Model: MODEL1
                                Dependent Variable: logactualdays

                                     Test of First and Second
                                       Moment Specification

                                   DF    Chi-Square    Pr > ChiSq

                                    5          8.26        0.1423
```

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	10.6075792	Variance	112.520738
Skewness	-0.190869	Kurtosis	0.97192839
Uncorrected SS	6301.1613	Corrected SS	6301.1613
Coeff Variation	.	Std Error Mean	1.40500819

Basic Statistical Measures

Location		Variability	
Mean	0.000000	Std Deviation	10.60758
Median	0.693429	Variance	112.52074
Mode	.	Range	55.21750
		Interquartile Range	9.66674

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	2.5	Pr >= |M|	0.5966
Signed Rank	S	11.5	Pr >= |S|	0.9282

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.969891	Pr < W	0.1659
Kolmogorov-Smirnov	D	0.095845	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.113858	Pr > W-Sq	0.0753
Anderson-Darling	A-Sq	0.662165	Pr > A-Sq	0.0833

Quantiles (Definition 5)

Quantile	Estimate
100% Max	23.579001
99%	23.579001
95%	18.667073
90%	15.385396

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	4.333042
50% Median	0.693429
25% Q1	-5.333699
10%	-11.201434
5%	-21.058065
1%	-31.638498
0% Min	-31.638498

Extreme Observations

------Lowest-----		-----Highest-----	
Value	Obs	Value	Obs
-31.6385	29	16.5369	8
-22.9302	26	18.3696	55
-21.0581	56	18.6671	4
-12.6892	11	22.4639	5
-12.2253	51	23.5790	35

Model F

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
37
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read 57
Number of Observations Used 57

Forward Selection: Step 1

Variable log_estimated_days Entered: R-Square = 0.7232 and C(p) = 29.5573

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	26.45166	26.45166	143.70	<.0001
Error	55	10.12436	0.18408		
Corrected Total	56	36.57601			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	0.25572	0.24557	0.19961	1.08	0.3023
log_estimated_days	0.96484	0.08049	26.45166	143.70	<.0001

Bounds on condition number: 1, 1

Forward Selection: Step 2

Variable Depth_ft Entered: R-Square = 0.7995 and C(p) = 8.7999

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	29.24250	14.62125	107.66	<.0001
Error	54	7.33352	0.13581		
Corrected Total	56	36.57601			

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
38
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Forward Selection: Step 2

Parameter Standard

Variable	Estimate	Error	Type II SS	F Value	Pr > F
Intercept	0.44017	0.21481	0.57021	4.20	0.0453
Depth_ft	0.00006721	0.00001483	2.79084	20.55	<.0001
log_estimated_days	0.60152	0.10584	4.38632	32.30	<.0001

Bounds on condition number: 2.3439, 9.3758

Forward Selection: Step 3

Variable inc Entered: R-Square = 0.8052 and C(p) = 9.1051

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	29.45033	9.81678	73.02	<.0001
Error	53	7.12568	0.13445		
Corrected Total	56	36.57601			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	0.37856	0.21940	0.40026	2.98	0.0903
Depth_ft	0.00006371	0.00001502	2.42031	18.00	<.0001
log_estimated_days	0.62660	0.10723	4.59127	34.15	<.0001
inc	0.00219	0.00177	0.20784	1.55	0.2192

Bounds on condition number: 2.43, 17.702

Forward Selection: Step 4

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
39
10:08 Thursday, August 12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Forward Selection: Step 4

Variable Temp_BHT_F Entered: R-Square = 0.8257 and C(p) = 5.0000

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	30.19903	7.54976	61.56	<.0001
Error	52	6.37699	0.12263		
Corrected Total	56	36.57601			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F

Intercept	-0.72931	0.49492	0.26629	2.17	0.1466
Depth_ft	-0.00019360	0.00010512	0.41594	3.39	0.0712
log_estimated_days	0.57459	0.10455	3.70414	30.20	<.0001
inc	0.00743	0.00271	0.92345	7.53	0.0083
Temp_BHT_F	0.01549	0.00627	0.74869	6.11	0.0168

Bounds on condition number: 134.39, 1080.4

All variables have been entered into the model.

Summary of Forward Selection

Step	Variable Entered	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	log_estimated_days	1	0.7232	0.7232	29.5573	143.70	<.0001
2	Depth_ft	2	0.0763	0.7995	8.7999	20.55	<.0001
3	inc	3	0.0057	0.8052	9.1051	1.55	0.2192
4	Temp_BHT_F	4	0.0205	0.8257	5.0000	6.11	0.0168

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
40
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read 57
Number of Observations Used 57

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	30.19903	7.54976	61.56	<.0001
Error	52	6.37699	0.12263		
Corrected Total	56	36.57601			

Root MSE	0.35019	R-Square	0.8257
Dependent Mean	3.11950	Adj R-Sq	0.8122
Coeff Var	11.22590		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.72931	0.49492	-1.47	0.1466	0

```
  Depth_ft              1    -0.00019360     0.00010512      -1.84      0.0712
130.50124
  log_estimated_days    1        0.57459        0.10455       5.50      <.0001
2.53265
  inc                   1        0.00743        0.00271       2.74      0.0083
2.68749
  Temp_BHT_F            1        0.01549        0.00627       2.47      0.0168
134.39072

                  Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
41
                                                                  10:08 Thursday, August
12, 2010

                                       The REG Procedure
                                         Model: MODEL1
                                 Dependent Variable: logactualdays

                                    Test of First and Second
                                      Moment Specification

                                   DF    Chi-Square    Pr > ChiSq

                                   14         12.71        0.5495
```

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
42
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read 57
Number of Observations Used 57

Backward Elimination: Step 0

All Variables Entered: R-Square = 0.8257 and C(p) = 5.0000

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	30.19903	7.54976	61.56	<.0001
Error	52	6.37699	0.12263		
Corrected Total	56	36.57601			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	-0.72931	0.49492	0.26629	2.17	0.1466
Depth_ft	-0.00019360	0.00010512	0.41594	3.39	0.0712
log_estimated_days	0.57459	0.10455	3.70414	30.20	<.0001
inc	0.00743	0.00271	0.92345	7.53	0.0083
Temp_BHT_F	0.01549	0.00627	0.74869	6.11	0.0168

Bounds on condition number: 134.39, 1080.4

All variables left in the model are significant at the 0.1000 level.

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
43
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read 57
Number of Observations Used 57

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	30.19903	7.54976	61.56	<.0001
Error	52	6.37699	0.12263		
Corrected Total	56	36.57601			

Root MSE	0.35019	R-Square	0.8257
Dependent Mean	3.11950	Adj R-Sq	0.8122
Coeff Var	11.22590		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.72931	0.49492	-1.47	0.1466	0
Depth_ft	1	-0.00019360	0.00010512	-1.84	0.0712	130.50124
log_estimated_days	1	0.57459	0.10455	5.50	<.0001	2.53265
inc	1	0.00743	0.00271	2.74	0.0083	2.68749
Temp_BHT_F	1	0.01549	0.00627	2.47	0.0168	134.39072

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days 44

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The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Test of First and Second
Moment Specification

DF	Chi-Square	Pr > ChiSq
14	12.71	0.5495

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	10.6075792	Variance	112.520738
Skewness	-0.190869	Kurtosis	0.97192839
Uncorrected SS	6301.1613	Corrected SS	6301.1613
Coeff Variation	.	Std Error Mean	1.40500819

Basic Statistical Measures

Location		Variability	
Mean	0.000000	Std Deviation	10.60758
Median	0.693429	Variance	112.52074
Mode	.	Range	55.21750
		Interquartile Range	9.66674

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	2.5	Pr >= |M|	0.5966
Signed Rank	S	11.5	Pr >= |S|	0.9282

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.969891	Pr < W	0.1659
Kolmogorov-Smirnov	D	0.095845	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.113858	Pr > W-Sq	0.0753
Anderson-Darling	A-Sq	0.662165	Pr > A-Sq	0.0833

Quantiles (Definition 5)

Quantile	Estimate
100% Max	23.579001
99%	23.579001
95%	18.667073
90%	15.385396

Q-Q Plot:log Actual Days = Depth_ft log_Estimated_Days Temp_BHT_F inc 46
10:08 Thursday, August 12, 2010

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	4.333042
50% Median	0.693429
25% Q1	-5.333699
10%	-11.201434
5%	-21.058065
1%	-31.638498
0% Min	-31.638498

Extreme Observations

------Lowest-----		-----Highest-----	
Value	Obs	Value	Obs
-31.6385	29	16.5369	8
-22.9302	26	18.3696	55
-21.0581	56	18.6671	4
-12.6892	11	22.4639	5
-12.2253	51	23.5790	35

Model G

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days Temp_BHT_F inc
47
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read	57
Number of Observations Used	57

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	29.24001	14.62000	107.62	<.0001
Error	54	7.33601	0.13585		
Corrected Total	56	36.57601			

Root MSE	0.36858	R-Square	0.7994
Dependent Mean	3.11950	Adj R-Sq	0.7920
Coeff Var	11.81539		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.18264	0.21158	0.86	0.3918	0
Temp_BHT_F	1	0.00408	0.00090007	4.53	<.0001	2.50092
log_estimated_days	1	0.58106	0.10935	5.31	<.0001	2.50092

Residual Plot: log Actual Days = Depth_ft log_Estimated_Days Temp_BHT_F inc
48
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Test of First and Second
Moment Specification

DF	Chi-Square	Pr > ChiSq
5	7.69	0.1744

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	0.36193941	Variance	0.13100014
Skewness	-0.7239985	Kurtosis	0.67582857
Uncorrected SS	7.33600764	Corrected SS	7.33600764
Coeff Variation	.	Std Error Mean	0.04794005

Basic Statistical Measures

Location		Variability	
Mean	0.000000	Std Deviation	0.36194
Median	0.037210	Variance	0.13100
Mode	.	Range	1.58922
		Interquartile Range	0.45505

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	2.5	Pr >= |M|	0.5966
Signed Rank	S	64.5	Pr >= |S|	0.6127

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.954123	Pr < W	0.0303
Kolmogorov-Smirnov	D	0.084488	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.06938	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.566471	Pr > A-Sq	0.1405

Quantiles (Definition 5)

Quantile	Estimate
100% Max	0.5746979
99%	0.5746979
95%	0.5330984
90%	0.5299825

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	0.2201254
50% Median	0.0372096
25% Q1	-0.2349214
10%	-0.4220720
5%	-0.8597671
1%	-1.0145186
0% Min	-1.0145186

Extreme Observations

------Lowest------		------Highest-----	
Value	Obs	Value	Obs
-1.014519	29	0.530152	55
-0.910925	26	0.530468	40
-0.859767	56	0.533098	8
-0.674074	50	0.572543	32
-0.505949	45	0.574698	5

Model H

```
                 Residual Plot: log Actual Days = TEMP_BHT_F log_Estimated_Days
51
                                                                 10:08 Thursday, August
12, 2010

                                  The REG Procedure
                                    Model: MODEL1
                           Dependent Variable: logactualdays

                        Number of Observations Read          57
                        Number of Observations Used          57


                                 Analysis of Variance

                                        Sum of           Mean
         Source                   DF       Squares         Square    F Value    Pr > F

         Model                     2      28.80412       14.40206     100.07    <.0001
         Error                    54       7.77190        0.14392
         Corrected Total          56      36.57601


                      Root MSE              0.37937    R-Square     0.7875
                      Dependent Mean        3.11950    Adj R-Sq     0.7796
                      Coeff Var            12.16135


                                 Parameter Estimates

                              Parameter       Standard
Variance
    Variable          DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept          1        1.30916        0.14239       9.19      <.0001
0
    Depth_ft           1     0.00010005     0.00001159       8.63      <.0001
1.35154
    Estimated_Days     1        0.02003        0.00382       5.24      <.0001
1.35154

\                 Residual Plot: log Actual Days = TEMP_BHT_F log_Estimated_Days
52
                                                                 10:08 Thursday, August
12, 2010

                                  The REG Procedure
                                    Model: MODEL1
                           Dependent Variable: logactualdays

                              Test of First and Second
                                Moment Specification

                             DF    Chi-Square    Pr > ChiSq

                              5          9.81        0.0807
```

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	0.37253708	Variance	0.13878388
Skewness	-0.2070043	Kurtosis	-0.1638041
Uncorrected SS	7.77189712	Corrected SS	7.77189712
Coeff Variation	.	Std Error Mean	0.04934374

Basic Statistical Measures

Location		Variability	
Mean	0.00000	Std Deviation	0.37254
Median	-0.06298	Variance	0.13878
Mode	.	Range	1.51161
		Interquartile Range	0.47422

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	-3.5	Pr >= |M|	0.4270
Signed Rank	S	11.5	Pr >= |S|	0.9282

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.973903	Pr < W	0.2536
Kolmogorov-Smirnov	D	0.075896	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.045614	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.347221	Pr > A-Sq	>0.2500

Quantiles (Definition 5)

Quantile	Estimate
100% Max	0.6660560
99%	0.6660560
95%	0.6402173
90%	0.4977924

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	0.2581751
50% Median	-0.0629803
25% Q1	-0.2160444
10%	-0.4350841
5%	-0.7915949
1%	-0.8455539
0% Min	-0.8455539

Extreme Observations

------Lowest------		------Highest-----	
Value	Obs	Value	Obs
-0.845554	26	0.605254	14
-0.837898	29	0.629209	8
-0.791595	56	0.640217	55
-0.680735	24	0.664484	40
-0.527839	45	0.666056	5

Model I

```
                   Residual Plot: Log Actual Days = Depth_ft Estimated_Days
55
                                                             10:08 Thursday, August
12, 2010

                                   The REG Procedure
                                     Model: MODEL1
                             Dependent Variable: logactualdays

                          Number of Observations Read          57
                          Number of Observations Used          57


                                  Analysis of Variance

                                        Sum of           Mean
         Source                DF        Squares         Square    F Value    Pr > F

         Model                  2       28.81429       14.40715     100.23    <.0001
         Error                 54        7.76172        0.14374
         Corrected Total       56       36.57601


                      Root MSE              0.37912    R-Square     0.7878
                      Dependent Mean        3.11950    Adj R-Sq     0.7799
                      Coeff Var            12.15338


                                  Parameter Estimates

                              Parameter       Standard
Variance
    Variable          DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept          1        0.88750        0.18191       4.88      <.0001
0
    Temp_BHT_F         1        0.00598     0.00069228       8.64      <.0001
1.39833
    Estimated_Days     1        0.01893        0.00389       4.87      <.0001
1.39833

                    Residual Plot: Log Actual Days = Depth_ft Estimated_Days
56
                                                             10:08 Thursday, August
12, 2010

                                   The REG Procedure
                                     Model: MODEL1
                             Dependent Variable: logactualdays

                                Test of First and Second
                                  Moment Specification

                               DF    Chi-Square    Pr > ChiSq

                                5         10.06        0.0734
```

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	0.3722931	Variance	0.13860216
Skewness	-0.248246	Kurtosis	-0.0810346
Uncorrected SS	7.76172071	Corrected SS	7.76172071
Coeff Variation	.	Std Error Mean	0.04931143

Basic Statistical Measures

Location		Variability	
Mean	0.00000	Std Deviation	0.37229
Median	-0.03973	Variance	0.13860
Mode	.	Range	1.52890
		Interquartile Range	0.47775

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	-2.5	Pr >= |M|	0.5966
Signed Rank	S	28.5	Pr >= |S|	0.8232

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.975171	Pr < W	0.2890
Kolmogorov-Smirnov	D	0.059124	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.037815	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.306774	Pr > A-Sq	>0.2500

Quantiles (Definition 5)

Quantile	Estimate
100% Max	0.6614564
99%	0.6614564
95%	0.6540181
90%	0.4713515

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	0.2530500
50% Median	-0.0397291
25% Q1	-0.2247016
10%	-0.4659558
5%	-0.8154419
1%	-0.8674445
0% Min	-0.8674445

Extreme Observations

------Lowest------		------Highest-----	
Value	Obs	Value	Obs
-0.867444	26	0.625395	55
-0.837098	29	0.625649	8
-0.815442	56	0.654018	5
-0.625418	24	0.660744	14
-0.563790	45	0.661456	40

Model J

```
                   Residual Plot:Log Actual Days = TEMP_BHT_F  Estimated_Days
59
                                                                 10:08 Thursday, August
12, 2010

                                       The REG Procedure
                                         Model: MODEL1
                               Dependent Variable: logactualdays

                            Number of Observations Read          57
                            Number of Observations Used          57


                                      Analysis of Variance

                                             Sum of           Mean
         Source                   DF        Squares         Square    F Value    Pr > F

         Model                     2       28.37448       14.18724      93.41    <.0001
         Error                    54        8.20153        0.15188
         Corrected Total          56       36.57601


                      Root MSE              0.38972    R-Square     0.7758
                      Dependent Mean        3.11950    Adj R-Sq     0.7675
                      Coeff Var            12.49297


                                      Parameter Estimates

                              Parameter       Standard
Variance
    Variable          DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept          1       -4.13960        0.78034      -5.30      <.0001
0
    logdepth_ft        1        0.72552        0.08811       8.23      <.0001
1.36426
    Estimated_Days     1        0.02007        0.00395       5.09      <.0001
1.36426

                   Residual Plot:Log Actual Days = TEMP_BHT_F  Estimated_Days
60
                                                                 10:08 Thursday, August
12, 2010

                                       The REG Procedure
                                         Model: MODEL1
                               Dependent Variable: logactualdays

                                    Test of First and Second
                                      Moment Specification

                                   DF    Chi-Square    Pr > ChiSq

                                    5          6.63        0.2500
```

Q-Q Plot: log Actual Days = logDepth_ft Estimated_Days
61
10:08 Thursday, August
12, 2010

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	0.38269556	Variance	0.14645589
Skewness	-0.4134658	Kurtosis	-0.0197204
Uncorrected SS	8.20152993	Corrected SS	8.20152993
Coeff Variation	.	Std Error Mean	0.05068927

Basic Statistical Measures

Location		Variability	
Mean	0.000000	Std Deviation	0.38270
Median	0.033453	Variance	0.14646
Mode	.	Range	1.66504
		Interquartile Range	0.53982

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	2.5	Pr >= |M|	0.5966
Signed Rank	S	26.5	Pr >= |S|	0.8354

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.969709	Pr < W	0.1627
Kolmogorov-Smirnov	D	0.071677	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.047175	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.385826	Pr > A-Sq	>0.2500

Quantiles (Definition 5)

Quantile	Estimate
100% Max	0.6181359
99%	0.6181359
95%	0.5775079
90%	0.5254011

Q-Q Plot: log Actual Days = logDepth_ft Estimated_Days
62
10:08 Thursday, August
12, 2010

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	0.2640075
50% Median	0.0334534
25% Q1	-0.2758166
10%	-0.4524619
5%	-0.7773676
1%	-1.0469089
0% Min	-1.0469089

Extreme Observations

------Lowest------		------Highest-----	
Value	Obs	Value	Obs
-1.046909	29	0.556112	40
-0.823864	26	0.561783	35
-0.777368	56	0.577508	55
-0.679165	50	0.615893	49
-0.474580	45	0.618136	5

Model K

```
                  Residual Plot: log Actual Days = logDepth_ft Estimated_Days
63
                                                                 10:08 Thursday, August
12, 2010

                                     The REG Procedure
                                       Model: MODEL1
                              Dependent Variable: logactualdays

                           Number of Observations Read          57
                           Number of Observations Used          57


                                    Analysis of Variance

                                          Sum of           Mean
         Source                   DF     Squares         Square    F Value    Pr > F

         Model                     2    29.17926       14.58963     106.51    <.0001
         Error                    54     7.39676        0.13698
         Corrected Total          56    36.57601


                      Root MSE              0.37010    R-Square     0.7978
                      Dependent Mean        3.11950    Adj R-Sq     0.7903
                      Coeff Var            11.86421


                                    Parameter Estimates

                              Parameter       Standard
Variance
    Variable          DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept          1       -4.98991        0.80789      -6.18      <.0001
0
    logTEMP_BHT_F      1        1.36169        0.15125       9.00      <.0001
1.41380
    Estimated_Days     1        0.01828        0.00382       4.79      <.0001
1.41380

                  Residual Plot: log Actual Days = logDepth_ft Estimated_Days
64
                                                                 10:08 Thursday, August
12, 2010

                                     The REG Procedure
                                       Model: MODEL1
                              Dependent Variable: logactualdays

                                  Test of First and Second
                                    Moment Specification

                                 DF    Chi-Square    Pr > ChiSq

                                  5          8.88        0.1138
```

Q-Q Plot: log Actual Days = logTEMP_BHT_F Estimated_Days
65
10:08 Thursday, August
12, 2010

The UNIVARIATE Procedure
Variable: resid (Residual)

Moments

N	57	Sum Weights	57
Mean	0	Sum Observations	0
Std Deviation	0.36343491	Variance	0.13208493
Skewness	-0.4378214	Kurtosis	0.18934783
Uncorrected SS	7.39675609	Corrected SS	7.39675609
Coeff Variation	.	Std Error Mean	0.04813813

Basic Statistical Measures

Location		Variability	
Mean	0.000000	Std Deviation	0.36343
Median	0.002799	Variance	0.13208
Mode	.	Range	1.57006
		Interquartile Range	0.44930

Tests for Location: Mu0=0

Test	-Statistic-		-----p Value------	
Student's t	t	0	Pr > |t|	1.0000
Sign	M	0.5	Pr >= |M|	1.0000
Signed Rank	S	37.5	Pr >= |S|	0.7687

Tests for Normality

Test	--Statistic---		-----p Value------	
Shapiro-Wilk	W	0.971689	Pr < W	0.2009
Kolmogorov-Smirnov	D	0.071257	Pr > D	>0.1500
Cramer-von Mises	W-Sq	0.030583	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq	0.30949	Pr > A-Sq	>0.2500

Quantiles (Definition 5)

Quantile	Estimate
100% Max	0.62106691
99%	0.62106691
95%	0.58773308
90%	0.52869277

The UNIVARIATE Procedure
Variable: resid (Residual)

Quantiles (Definition 5)

Quantile	Estimate
75% Q3	0.23482423
50% Median	0.00279929
25% Q1	-0.21447374
10%	-0.44734575
5%	-0.81615983
1%	-0.94898981
0% Min	-0.94898981

Extreme Observations

------Lowest------		------Highest-----	
Value	Obs	Value	Obs
-0.948990	29	0.564515	8
-0.862051	26	0.581635	55
-0.816160	56	0.587733	14
-0.548144	50	0.588273	40
-0.546199	45	0.621067	5

Testing Chosen Models with a New Variable that equals the Chosen Regressor Variables Multiplied Together (No Additional Significance was Found)

```
                 Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days
67
                                                              10:08 Thursday, August
12, 2010

                                      The REG Procedure
                                        Model: MODEL1
                                Dependent Variable: ActualDays

                            Number of Observations Read          57
                            Number of Observations Used          57


                                     Analysis of Variance

                                            Sum of           Mean
         Source                   DF       Squares         Square    F Value    Pr > F

         Model                     3         16189     5396.18685      47.51    <.0001
         Error                    53    6019.68506      113.57896
         Corrected Total          56         22208


                      Root MSE             10.65734    R-Square     0.7289
                      Dependent Mean       29.49123    Adj R-Sq     0.7136
                      Coeff Var            36.13733


                                     Parameter Estimates

                              Parameter       Standard
Variance
   Variable           DF       Estimate          Error    t Value    Pr > |t|
Inflation

   Intercept           1        0.18262        5.10120       0.04      0.9716
0
   Depth_ft            1     0.00075006     0.00036517       2.05      0.0449
1.70032
   Estimated_Days      1        0.26043        0.37292       0.70      0.4880
16.29040
   DepthbyEst_days     1     0.00003660     0.00002120       1.73      0.0901
18.61595

                 Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days
68
                                                              10:08 Thursday, August
12, 2010

                                      The REG Procedure
                                        Model: MODEL1
                                Dependent Variable: ActualDays

                                    Test of First and Second
                                      Moment Specification

                                   DF    Chi-Square    Pr > ChiSq

                                    8         13.29        0.1024

                 Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days
69
```

The REG Procedure

Number of Observations Read	57
Number of Observations Used	0
Number of Observations with Missing Values	57

Residual Plot: log Actual Days = logTEMP_BHT_F Estimated_Days
70
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read	57
Number of Observations Used	57

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	28.49568	9.49856	62.30	<.0001
Error	53	8.08033	0.15246		
Corrected Total	56	36.57601			

Root MSE	0.39046	R-Square	0.7791
Dependent Mean	3.11950	Adj R-Sq	0.7666
Coeff Var	12.51675		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-3.69290	0.92858	-3.98	0.0002	0
logdepth_ft	1	0.68257	0.10057	6.79	<.0001	1.77043
Estimated_Days	1	-0.07912	0.11132	-0.71	0.4804	1081.45512
logdepthbyEstDays	1	0.01017	0.01140	0.89	0.3766	1103.14258

Residual Plot: log Actual Days = logTEMP_BHT_F Estimated_Days
71
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Test of First and Second
Moment Specification

DF	Chi-Square	Pr > ChiSq
8	11.14	0.1940

Residual Plot: log Actual Days = logTEMP_BHT_F Estimated_Days
72
10:08 Thursday, August
12, 2010

The REG Procedure
Model: MODEL1

Dependent Variable: logactualdays

Number of Observations Read 57
Number of Observations Used 57

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	29.18034	9.72678	69.71	<.0001
Error	53	7.39568	0.13954		
Corrected Total	56	36.57601			

Root MSE	0.37355	R-Square	0.7978
Dependent Mean	3.11950	Adj R-Sq	0.7864
Coeff Var	11.97474		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-5.04516	1.02928	-4.90	<.0001	0
logTEMP_BHT_F	1	1.37080	0.18444	7.43	<.0001	2.06368
Estimated_Days	1	0.02819	0.11266	0.25	0.8034	1210.24741
logdepthbyEstDays	1	-0.00102	0.01157	-0.09	0.9302	1240.81068

Residual Plot: log Actual Days = logTEMP_BHT_F Estimated_Days 73
10:08 Thursday, August 12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Test of First and Second
Moment Specification

DF	Chi-Square	Pr > ChiSq
9	11.73	0.2290

Residual Plot: log Actual Days = logTEMP_BHT_F Estimated_Days 74
10:08 Thursday, August 12, 2010

The REG Procedure
Model: MODEL1
Dependent Variable: logactualdays

Number of Observations Read 57
Number of Observations Used 57

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	29.27033	9.75678	70.78	<.0001
Error	53	7.30569	0.13784		
Corrected Total	56	36.57601			

Root MSE	0.37127	R-Square	0.8003
Dependent Mean	3.11950	Adj R-Sq	0.7890
Coeff Var	11.90166		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.10633	0.17771	6.23	<.0001	0
Depth_ft	1	0.00011065	0.00001272	8.70	<.0001	1.70032
Estimated_Days	1	0.04291	0.01299	3.30	0.0017	16.29040
DepthbyEst_days	1	-0.00000136	7.385924E-7	-1.84	0.0715	18.61595

```
                Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days
75
                                                                  10:08 Thursday, August
12, 2010

                                      The REG Procedure
                                        Model: MODEL1
                              Dependent Variable: logactualdays

                                   Test of First and Second
                                     Moment Specification

                                  DF    Chi-Square    Pr > ChiSq

                                   8          6.88        0.5495

                Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days
76
                                                                  10:08 Thursday, August
12, 2010

                                      The REG Procedure

                    Number of Observations Read                        57
                    Number of Observations Used                         0
                    Number of Observations with Missing Values         57

                Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days
77
                                                                  10:08 Thursday, August
12, 2010

                                      The REG Procedure
                                        Model: MODEL1
                              Dependent Variable: logactualdays

                           Number of Observations Read          57
                           Number of Observations Used          57


                                     Analysis of Variance

                                            Sum of           Mean
         Source                   DF       Squares         Square    F Value    Pr > F

         Model                     2      29.17926       14.58963     106.51    <.0001
         Error                    54       7.39676        0.13698
         Corrected Total          56      36.57601


                      Root MSE              0.37010    R-Square     0.7978
                      Dependent Mean        3.11950    Adj R-Sq     0.7903
                      Coeff Var            11.86421


                                     Parameter Estimates

                              Parameter       Standard
Variance
    Variable           DF       Estimate          Error    t Value    Pr > |t|
Inflation

    Intercept           1       -4.98991        0.80789      -6.18      <.0001
0
    logTEMP_BHT_F       1        1.36169        0.15125       9.00      <.0001
1.41380
```

```
    Estimated_Days     1        0.01828        0.00382       4.79      <.0001
1.41380

                 Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days
78
                                                                  10:08 Thursday, August
12, 2010

                                       The REG Procedure
                                         Model: MODEL1
                                Dependent Variable: logactualdays

                                    Test of First and Second
                                      Moment Specification

                                   DF    Chi-Square    Pr > ChiSq

                                    5          8.88        0.1138
```

APPENDIX F

SAS CODE NECESSARY FOR REGRESSIONS AND UNIVARIATE CALCULATIONS

```
proc contents data=drilling;
run;

proc reg data=drilling;
model actualdays = Depth_ft Estimated_Days inc TEMP_BHT_F
/selection=stepwise spec vif;
run;
quit;

proc reg data=drilling;
model actualdays = Depth_ft Estimated_Days inc TEMP_BHT_F
/selection=forward spec vif;
run;
quit;

proc reg data=drilling;
model actualdays = Depth_ft Estimated_Days inc TEMP_BHT_F
/selection=backward spec vif;
run;
quit;

proc reg data=drilling;
model actualdays = TEMP_BHT_F  Estimated_Days/spec vif  ;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: Actualdays = TEMP_BHT_F  Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: Actualdays = TEMP_BHT_F  Estimated_Days';
plot resid*fits;
run;

proc reg data=drilling;
model actualdays = Depth_ft Estimated_Days/spec vif;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
```

```
title 'Q-Q Plot: Actualdays = Depth_ft Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: Actualdays = Depth_ft Estimated_Days';
plot resid*fits;
run;
/* removal of outlier */
data drilling2;
set drilling;
where actualdays ne 174;
run;

proc reg data=drilling2;
model actualdays = Depth_ft Estimated_Days /spec vif;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: Actualdays = Depth_ft Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: Actualdays = Depth_ft Estimated_Days';
plot resid*fits;
run;

proc reg data=drilling2;
model actualdays = TEMP_BHT_F  Estimated_Days /spec vif ;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: Actualdays = TEMP_BHT_F  Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: Actualdays = TEMP_BHT_F  Estimated_Days';
plot resid*fits;
run;

proc gplot data=drilling2;
title 'Actual Days vs. Estimated Days';
plot actualdays*estimated_days;
run;
proc gplot data=drilling2;
title 'Actual Days vs. Depth_ft';
```

```
plot actualdays*depth_ft;
run;
proc gplot data=drilling2;
title 'Actual Days vs. TEMP_BHT_F';
plot actualdays*TEMP_BHT_F;
run;

data drilling3;
set drilling2;
logactualdays=log(actualdays);
exp_estimated_days=exp(estimated_days);
estimated_days_sq=estimated_days**2;
log_estimated_days=log(estimated_days);
logdepth_ft=log(Depth_ft);
logTEMP_BHT_F=log(TEMP_BHT_F);
run;

proc gplot data=drilling3;
title 'logactualdays*log_estimated_days';
plot logactualdays*log_estimated_days;
run;
proc gplot data=drilling3;
title 'logactualdays*estimated_days_sq';
plot logactualdays*estimated_days_sq;
run;
title 'logactualdays*depth_ft';
plot logactualdays*depth_ft;
proc gplot data=drilling3;
title 'logactualdays*TEMP_BHT_F';
plot logactualdays*TEMP_BHT_F;
run;
proc gplot data=drilling3;
title 'logactualdays*inc';
plot logactualdays*inc;
run;
proc gplot data=drilling3;
title 'logactualdays*logDepth_ft';
plot logactualdays*logDepth_ft;
run;

proc reg data=drilling3;
model logactualdays = Depth_ft log_Estimated_Days inc TEMP_BHT_F
/selection=stepwise spec vif;
run;
quit;
proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot:log Actual Days = Depth_ft log_Estimated_Days' ;
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: log Actual Days = Depth_ft log_Estimated_Days';
plot resid*fits;
```

```
run;
proc reg data=drilling3;
model logactualdays = Depth_ft log_Estimated_Days inc TEMP_BHT_F
/selection=forward spec vif;
run;
quit;

proc reg data=drilling3;
model logactualdays = Depth_ft log_Estimated_Days inc TEMP_BHT_F
/selection=backward spec vif;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot:log Actual Days = Depth_ft log_Estimated_Days
Temp_BHT_F inc';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: log Actual Days = Depth_ft log_Estimated_Days
Temp_BHT_F inc';
plot resid*fits;
run;

proc reg data=drilling3;
model logactualdays = TEMP_BHT_F  log_Estimated_Days /spec vif ;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot:log Actual Days = TEMP_BHT_F  log_Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: log Actual Days = TEMP_BHT_F log_Estimated_Days';
plot resid*fits;
run;

proc reg data=drilling3;
model logactualdays = depth_ft Estimated_Days /spec  vif;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: Log Actual Days = Depth_ft Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;
```

```
proc gplot data=results;
title 'Residual Plot: Log Actual Days = Depth_ft Estimated_Days';
plot resid*fits;
run;
proc reg data=drilling3;
model logactualdays = TEMP_BHT_F  Estimated_Days /spec vif ;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest;
var resid;
title 'Q-Q Plot: Log Actual Days = TEMP_BHT_F  Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot:Log Actual Days = TEMP_BHT_F  Estimated_Days';
plot resid*fits;
run;

proc reg data=drilling3;
model logactualdays = logDepth_ft Estimated_Days /spec vif;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: log Actual Days = logDepth_ft Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: log Actual Days = logDepth_ft Estimated_Days';
plot resid*fits;
run;

proc reg data=drilling3;
model logactualdays = logTEMP_BHT_F  Estimated_Days /spec vif ;
output out=results r=resid p=fits;
run;
quit;

proc univariate data=results normaltest ;
var resid;
title 'Q-Q Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days';
probplot resid / normal(mu=est sigma=est);
run;

proc gplot data=results;
title 'Residual Plot: log Actual Days = logTEMP_BHT_F  Estimated_Days';
plot resid*fits;
```

```
run;

data drilling3wint;
set drilling3;
DepthbyEst_days=Depth_ft*Estimated_Days;
EstDaysbyBHT=Estimated_Days*Temp_bht_;
logTempBHTbyEst=logTEMP_BHT_F*Estimated_Days;
logdepthbyEstDays=logDepth_ft*Estimated_Days;
run;

proc reg data=drilling3wint;
model actualdays = Depth_ft Estimated_Days DepthbyEst_days/spec vif;
output out=results r=resid p=fits;
run;
quit;

proc reg data=drilling3wint;
model actualdays = TEMP_BHT_F  Estimated_Days EstDaysbyBHT /spec vif  ;
output out=results r=resid p=fits;
run;
quit;

proc reg data=drilling3wint;
model logactualdays = logDepth_ft Estimated_Days logdepthbyEstDays/spec
vif;
output out=results r=resid p=fits;
run;
quit;

proc reg data=drilling3wint;
model logactualdays = logTEMP_BHT_F  Estimated_Days
logdepthbyEstDays/spec vif ;
output out=results r=resid p=fits;
run;
quit;

proc reg data=drilling3wint;
model logactualdays = depth_ft Estimated_Days DepthbyEst_days/spec
vif;
output out=results r=resid p=fits;
run;
quit;

proc reg data=drilling3wint;
model logactualdays = TEMP_BHT_F  Estimated_Days EstDaysbyBHT/spec vif
;
output out=results r=resid p=fits;
run;
quit;

proc reg data=drilling3wint;
model logactualdays = logTEMP_BHT_F  Estimated_Days /spec vif ;
output out=results r=resid p=fits;
run;
```

```
ods graphics on;

proc corr data=drilling plots=matrix;
var actualdays estimated_days TEMP_bht_f Depth_ft inc;
run;
```

APPENDIX G

AN EXAMPLE OF R'S CODE AND OUTPUT FOR REGRESSIONS AND UNIVARIATE CALCULATIONS

```
> drilling = read.csv(file.choose(), header=T)
> attach(drilling)
>
> Reg1<-lm(ActualDays~Estimated.Days+Depth.ft,drilling)
> full<-lm(ActualDays~.,drilling)
> Reg2=step(full)
Start:  AIC=353.78
ActualDays ~ Estimated.Days + Depth.ft + Temp.BHT.F + inc

                 Df Sum of Sq   RSS    AIC
- Depth.ft        1     298.1 22054 352.57
- inc             1     311.5 22067 352.60
- Temp.BHT.F      1     501.5 22257 353.10
<none>                        21755 353.78
- Estimated.Days  1    7079.6 28835 368.12

Step:  AIC=352.57
ActualDays ~ Estimated.Days + Temp.BHT.F + inc

                 Df Sum of Sq   RSS    AIC
- inc             1      43.3 22097 350.68
<none>                        22054 352.57
- Temp.BHT.F      1    2590.8 24644 357.01
- Estimated.Days  1    7321.1 29375 367.19

Step:  AIC=350.68
ActualDays ~ Estimated.Days + Temp.BHT.F

                 Df Sum of Sq   RSS    AIC
<none>                        22097 350.68
- Temp.BHT.F      1    2610.8 24708 355.16
- Estimated.Days  1    7303.2 29400 365.24
> null<-lm(ActualDays~1,drilling)
> Reg3=step(null,scope=list(lower=null,upper=full,direction="forward"))
Start:  AIC=384.93
ActualDays ~ 1
```

```
               Df Sum of Sq   RSS    AIC
+ Estimated.Days  1     18023 24708 355.16
+ Temp.BHT.F      1     13331 29400 365.24
+ Depth.ft        1     12476 30255 366.90
<none>                        42731 384.93
+ inc             1       129 42602 386.75

Step:  AIC=355.16
ActualDays ~ Estimated.Days

               Df Sum of Sq   RSS    AIC
+ Temp.BHT.F      1    2610.8 22097 350.68
+ Depth.ft        1    2450.7 22257 351.10
<none>                        24708 355.16
+ inc             1      63.3 24644 357.01
- Estimated.Days  1   18023.4 42731 384.93

Step:  AIC=350.68
ActualDays ~ Estimated.Days + Temp.BHT.F

               Df Sum of Sq   RSS    AIC
<none>                        22097 350.68
+ inc             1      43.3 22054 352.57
+ Depth.ft        1      29.9 22067 352.60
- Temp.BHT.F      1    2610.8 24708 355.16
- Estimated.Days  1    7303.2 29400 365.24
> Reg4=step(full,direction="backward")
Start:  AIC=353.78
ActualDays ~ Estimated.Days + Depth.ft + Temp.BHT.F + inc

               Df Sum of Sq   RSS    AIC
- Depth.ft        1     298.1 22054 352.57
- inc             1     311.5 22067 352.60
- Temp.BHT.F      1     501.5 22257 353.10
<none>                        21755 353.78
- Estimated.Days  1    7079.6 28835 368.12

Step:  AIC=352.57
ActualDays ~ Estimated.Days + Temp.BHT.F + inc

               Df Sum of Sq   RSS    AIC
- inc             1      43.3 22097 350.68
<none>                        22054 352.57
- Temp.BHT.F      1    2590.8 24644 357.01
```

```
- Estimated.Days  1    7321.1 29375 367.19

Step:  AIC=350.68
ActualDays ~ Estimated.Days + Temp.BHT.F

               Df Sum of Sq   RSS    AIC
<none>                      22097 350.68
- Temp.BHT.F      1    2610.8 24708 355.16
- Estimated.Days  1    7303.2 29400 365.24
>
> Reg5=step(full,scale=(summary(full)$sigma)^2)
Start:  AIC=5
ActualDays ~ Estimated.Days + Depth.ft + Temp.BHT.F + inc

               Df Sum of Sq   RSS      Cp
- Depth.ft        1     298.1 22054  3.7263
- inc             1     311.5 22067  3.7590
- Temp.BHT.F      1     501.5 22257  4.2217
<none>                      21755  5.0000
- Estimated.Days  1    7079.6 28835 20.2471

Step:  AIC=3.73
ActualDays ~ Estimated.Days + Temp.BHT.F + inc

               Df Sum of Sq   RSS      Cp
- inc             1      43.3 22097  1.8317
<none>                      22054  3.7263
- Temp.BHT.F      1    2590.8 24644  8.0380
- Estimated.Days  1    7321.1 29375 19.5618

Step:  AIC=1.83
ActualDays ~ Estimated.Days + Temp.BHT.F

               Df Sum of Sq   RSS      Cp
<none>                      22097  1.8317
- Temp.BHT.F      1    2610.8 24708  6.1922
- Estimated.Days  1    7303.2 29400 17.6236
>
Reg6=step(null,scope=list(lower=null,upper=full,direction="forward"),scale=(summary(
full)$sigma)^2)
Start:  AIC=48.1
ActualDays ~ 1

               Df Sum of Sq   RSS      Cp
```

```
+ Estimated.Days  1     18023 24708  6.1922
+ Temp.BHT.F      1     13331 29400 17.6236
+ Depth.ft        1     12476 30255 19.7055
<none>                        42731 48.1004
+ inc             1       129 42602 49.7862

Step:  AIC=6.19
ActualDays ~ Estimated.Days

               Df Sum of Sq   RSS      Cp
+ Temp.BHT.F      1    2610.8 22097  1.8317
+ Depth.ft        1    2450.7 22257  2.2219
<none>                        24708  6.1922
+ inc             1      63.3 24644  8.0380
- Estimated.Days  1   18023.4 42731 48.1004

Step:  AIC=1.83
ActualDays ~ Estimated.Days + Temp.BHT.F

               Df Sum of Sq   RSS      Cp
<none>                        22097  1.8317
+ inc             1      43.3 22054  3.7263
+ Depth.ft        1      29.9 22067  3.7590
- Temp.BHT.F      1    2610.8 24708  6.1922
- Estimated.Days  1    7303.2 29400 17.6236
> Reg7=step(full,direction="backward",scale=(summary(full)$sigma)^2)
Start:  AIC=5
ActualDays ~ Estimated.Days + Depth.ft + Temp.BHT.F + inc

               Df Sum of Sq   RSS      Cp
- Depth.ft        1     298.1 22054  3.7263
- inc             1     311.5 22067  3.7590
- Temp.BHT.F      1     501.5 22257  4.2217
<none>                        21755  5.0000
- Estimated.Days  1    7079.6 28835 20.2471

Step:  AIC=3.73
ActualDays ~ Estimated.Days + Temp.BHT.F + inc

               Df Sum of Sq   RSS      Cp
- inc             1      43.3 22097  1.8317
<none>                        22054  3.7263
- Temp.BHT.F      1    2590.8 24644  8.0380
- Estimated.Days  1    7321.1 29375 19.5618
```

```
Step:  AIC=1.83
ActualDays ~ Estimated.Days + Temp.BHT.F

                Df Sum of Sq   RSS      Cp
<none>                       22097  1.8317
- Temp.BHT.F      1    2610.8 24708  6.1922
- Estimated.Days  1    7303.2 29400 17.6236
>
> par(mfrow=c(2,2))
> plot.lm(Reg7)
> plot(Reg7$res,ylab="Residual",xlab="Predicted value of ActualDays",main="Residual
Plot: ActualDays = Depth_ft Estimated_Days")
>
> a<-Reg7$res
> u<-(1:length(a)-.5)/length(a)
> Q<-quantile(a,u,type=5)
> plot(qnorm(u),Q)
> abline(lm(Q~qnorm(u)))
>
> SWReg7=shapiro.test(Reg7$res)
> SWReg7

        Shapiro-Wilk normality test

data:  Reg7$res
W = 0.6315, p-value = 8.311e-11

> PTReg7=pearson.test(Reg7$res)
> PTReg7

        Pearson chi-square normality test

data:  Reg7$res
P = 34.1724, p-value = 3.781e-05

>
> summary(Reg7)

Call:
lm(formula = ActualDays ~ Estimated.Days + Temp.BHT.F, data = drilling)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-32.965  -7.853  -2.730   6.002 123.031

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)    -16.84055    9.55474  -1.763   0.0835 .
Estimated.Days   0.87604    0.20547   4.264 7.96e-05 ***
Temp.BHT.F       0.09255    0.03630   2.549   0.0136 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 20.04 on 55 degrees of freedom
Multiple R-squared: 0.4829,     Adjusted R-squared: 0.4641
F-statistic: 25.68 on 2 and 55 DF,  p-value: 1.329e-08

>
> plot(Depth.ft,ActualDays)
> lndepth<-log(Depth.ft)
> logdepth<-log10(Depth.ft)
> depthsqr<-(Depth.ft)^2
>
> drilling2<-(cbind(drilling,lndepth))
> drilling2
   ActualDays Estimated.Days Depth.ft Temp.BHT.F       inc  lndepth
1          15             23    10260    249.420 24.600000 9.236008
2          32             26    14496    321.432  2.150000 9.581628
3          32             17    16025    347.425  2.000000 9.681905
4          54             23    19250    402.250  1.500000 9.865266
5          64             36    14620    323.540 33.850000 9.590146
6          22             21    16350    352.950  2.500000 9.701983
7          30             21    18700    392.900  2.990000 9.836279
8          62             42    13470    303.990 21.370000 9.508220
9          28             24    15449    337.633  3.750000 9.645300
10         32             24    18100    382.700  7.000000 9.803667
11         17             27    10820    258.940  1.250000 9.289152
12         32             22    13460    301.066 76.800000 9.507478
13         17             11    16102    301.236 92.070000 9.686699
14         52             32    13953    300.369 81.780000 9.543450
15         16             11    15618    300.811 88.720000 9.656179
16         41             35    13255    299.995  1.250000 9.492130
17         33             24    15499    337.820  3.000000 9.648531
18         18             18    16550    355.670  2.000000 9.714141
19         39             26    14700    322.537 23.210000 9.595603
20         25             14    16950    359.410 21.020000 9.738023
21         40             42    13350    301.950  1.700000 9.499272
```

```
22        20           20   15573    339.741  1.750000 9.653294
23        34           20   18200    384.400  2.000000 9.809177
24       108          105    19500    406.500  2.184211 9.878170
25        47           42   14410    319.970  1.250000 9.575678
26        14           29   15939    345.963  2.000000 9.676524
27        40           29   18900    396.300  5.250000 9.846917
28         4            5   2885   124.045  1.750000 7.967280
29        11           42   10850    259.450  1.500000 9.291920
30        29           23   15750    342.750  2.000000 9.664596
31        46           37   19000    398.000  4.440000 9.852194
32         9            5   2900   124.300  0.000000 7.972466
33        57           42   14200    316.400  0.000000 9.560997
34        27           29   16077    348.309  3.780000 9.685145
35        64           29   19177    401.009  4.030000 9.861467
36         5            4   2900   124.300  0.500000 7.972466
37        15           16   11000    262.000  0.000000 9.305651
38        27           30   15750    342.750  0.000000 9.664596
39       174           35    19200    401.400  2.510000 9.862666
40         6            5   2400   115.800  0.000000 7.783224
41        52           32   13361    300.250 43.180000 9.500095
42        20           11   15388    300.930 90.660000 9.641343
43         4            5   2450   116.650  0.530000 7.803843
44        35           36   13400    302.800  0.700000 9.503010
45        28           19   15000    330.000  4.840000 9.615805
46        16           17   16500    355.500  5.250000 9.711116
47         4            5   2850   123.450  2.810000 7.955074
48        16           10    8896    219.092 86.960000 9.093357
49        17           21   12306    219.092 90.460000 9.417842
50         4            3    800    88.600  1.250000 6.684612
51         7           17    7000    194.000  0.750000 8.853665
52        21           27   14100    314.700  1.000000 9.553930
53        38           20   15300    335.100  1.000000 9.635608
54        33           23   16300    352.100  4.800000 9.698920
55         5            5   2800   122.600  1.250000 7.937375
56        57           33   14321    318.457  1.000000 9.569482
57        14           27   15800    343.600  2.000000 9.667765
58        46           23   19200    401.400  8.000000 9.862666
> drilling3<-drilling2[which(ActualDays!=174),]
> drilling3
   ActualDays Estimated.Days Depth.ft Temp.BHT.F       inc  lndepth
1         15             23    10260    249.420 24.600000 9.236008
2         32             26    14496    321.432  2.150000 9.581628
3         32             17    16025    347.425  2.000000 9.681905
4         54             23    19250    402.250  1.500000 9.865266
```

5	64	36	14620	323.540	33.850000	9.590146
6	22	21	16350	352.950	2.500000	9.701983
7	30	21	18700	392.900	2.990000	9.836279
8	62	42	13470	303.990	21.370000	9.508220
9	28	24	15449	337.633	3.750000	9.645300
10	32	24	18100	382.700	7.000000	9.803667
11	17	27	10820	258.940	1.250000	9.289152
12	32	22	13460	301.066	76.800000	9.507478
13	17	11	16102	301.236	92.070000	9.686699
14	52	32	13953	300.369	81.780000	9.543450
15	16	11	15618	300.811	88.720000	9.656179
16	41	35	13255	299.995	1.250000	9.492130
17	33	24	15499	337.820	3.000000	9.648531
18	18	18	16550	355.670	2.000000	9.714141
19	39	26	14700	322.537	23.210000	9.595603
20	25	14	16950	359.410	21.020000	9.738023
21	40	42	13350	301.950	1.700000	9.499272
22	20	20	15573	339.741	1.750000	9.653294
23	34	20	18200	384.400	2.000000	9.809177
24	108	105	19500	406.500	2.184211	9.878170
25	47	42	14410	319.970	1.250000	9.575678
26	14	29	15939	345.963	2.000000	9.676524
27	40	29	18900	396.300	5.250000	9.846917
28	4	5	2885	124.045	1.750000	7.967280
29	11	42	10850	259.450	1.500000	9.291920
30	29	23	15750	342.750	2.000000	9.664596
31	46	37	19000	398.000	4.440000	9.852194
32	9	5	2900	124.300	0.000000	7.972466
33	57	42	14200	316.400	0.000000	9.560997
34	27	29	16077	348.309	3.780000	9.685145
35	64	29	19177	401.009	4.030000	9.861467
36	5	4	2900	124.300	0.500000	7.972466
37	15	16	11000	262.000	0.000000	9.305651
38	27	30	15750	342.750	0.000000	9.664596
40	6	5	2400	115.800	0.000000	7.783224
41	52	32	13361	300.250	43.180000	9.500095
42	20	11	15388	300.930	90.660000	9.641343
43	4	5	2450	116.650	0.530000	7.803843
44	35	36	13400	302.800	0.700000	9.503010
45	28	19	15000	330.000	4.840000	9.615805
46	16	17	16500	355.500	5.250000	9.711116
47	4	5	2850	123.450	2.810000	7.955074
48	16	10	8896	219.092	86.960000	9.093357
49	17	21	12306	219.092	90.460000	9.417842

50	4	3	800	88.600	1.250000	6.684612
51	7	17	7000	194.000	0.750000	8.853665
52	21	27	14100	314.700	1.000000	9.553930
53	38	20	15300	335.100	1.000000	9.635608
54	33	23	16300	352.100	4.800000	9.698920
55	5	5	2800	122.600	1.250000	7.937375
56	57	33	14321	318.457	1.000000	9.569482
57	14	27	15800	343.600	2.000000	9.667765
58	46	23	19200	401.400	8.000000	9.862666

APPENDIX H

A TEMPLATE OF R's CODE FOR REGRESSION AND UNIVARIATE CALCULATIONS

```
drilling = read.csv(file.choose(), header=T)
attach(drilling)

Reg1<-lm(ActualDays~Estimated.Days+Depth.ft,drilling)
full<-lm(ActualDays~.,drilling)
Reg2=step(full)
null<-lm(ActualDays~1,drilling)
Reg3=step(null,scope=list(lower=null,upper=full,direction="forward"))
Reg4=step(full,direction="backward")

Reg5=step(full,scale=(summary(full)$sigma)^2)
Reg6=step(null,scope=list(lower=null,upper=full,direction="forward"),scale=(summary(
full)$sigma)^2)
Reg7=step(full,direction="backward",scale=(summary(full)$sigma)^2)

par(mfrow=c(2,2))
plot.lm(Reg7)
plot(Reg7$res,ylab="Residual",xlab="Predicted value of ActualDays",main="Residual
Plot: ActualDays = Depth_ft Estimated_Days")

a<-Reg7$res
u<-(1:length(a)-.5)/length(a)
Q<-quantile(a,u,type=5)
plot(qnorm(u),Q)
abline(lm(Q~qnorm(u)))

SWReg7=shapiro.test(Reg7$res)
SWReg7
PTReg7=pearson.test(Reg7$res)
PTReg7

summary(Reg7)

plot(Depth.ft,ActualDays)
lndepth<-log(Depth.ft)
logdepth<-log10(Depth.ft)
depthsqr<-(Depth.ft)^2
```

```
drilling2<-(cbind(drilling,lndepth))
drilling2
drilling3<-drilling2[which(ActualDays!=174),]
drilling3
```

VITA

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