Creep-Fatigue Life Prediction of Low Alloy Steels

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ABSTRACT

The creep-fatigue behavior of Cr-Mo steels has been examined from published data. The published data were compiled in an earlier effort and used in this paper to develop a multivariate best-fit equation to predict the low cycle fatigue life. The fatigue test temperatures were representative of temperatures experienced in nuclear power plants, which varied from room temperature to 600°C. Within this temperature range, depending upon the test parameters used, creep and fatigue processes interact and failure occurs in the low-cycle fatigue regime.

INTRODUCTION

The components of engineering applications such as gas turbines, steam turbines, rocket motors, space shuttle main engine, and other sub-systems operate under near steady conditions for an extended period of time at peak operating conditions. Under these steady state loading situations deformations in a material accrue by creep, fatigue, and other interactive mechanisms. Therefore, under such conditions the material of construction suffers not only from the rapidly induced damage from the start-up and shutdown cycles, but also from the creep damage under sustained loading periods. The extent of the creep damage depends on the operating parameters such as temperature, stress, loading waveform, material parameters, and dwell time. Since a number of parameters control the behavior of a material, those variables are neglected and only independent variables such as strain range, strain rate, hold time and temperature were used in deriving a best-fit equation relating to the cyclic fatigue life.

High-temperature low-cycle fatigue (HTLCF) is a failure mechanism of engineering components that operate at high temperature and experience plastic as well as creep strain accumulation due to applied loads. Failures by low-cycle fatigue mode were experienced in the power as well as aviation industries and documented from the early 1950s. While the commercial aviation industry experienced distinct failures, disk bursts due to dwell effects creep-fatigue interaction was the cause of failures in power plant components. Therefore, damage mechanisms are studied under different test parameters such as dwell time to simulate the failure of power and aviation engine components. The low cycle fatigue life depends upon a number of factors including temperatures, alloy composition, processing heat treatment and test parameters such as temperature, strain rate, dwell time and environment. The objective of this research is to compile a database of HTLCF behavior of Cr-Mo steels and develop a multivariate equation from the compiled data that will predict the life of the components.

A multivariate equation was derived using the method of multi-linear regression with strain rate, strain range, temperature, dwell-time as the independent variables and number of cycles to failure as the dependent variable allowing some assumptions to simplify the analysis. The quality of the model to predict cycles to failure was evaluated using the R^2 value. Four different software packages were used to derive the multivariate equation each conducting a multi-linear regression.

DATA COLLECTION

The data used has been collected from various published and unpublished sources and was produced by laboratories in the USA, Europe, and Asia and presented in an earlier work by Solomon and Goswami /1/. A summary of the Cr-Mo steel data used is given in Table 1.

Table 1

Summary of Range of Data Collected

Material	Number of Data Points	Temperature (Celcius)	Hold time (hours)	Total Strain Range	Strain Rate	No. cycles to Failure
Cr-M0	450	Room to 600	0 -48	0.001 -0.024	0.001 - 1.48	62 - 155000

METHODOLOGY

An attempt was made to develop a regression equation using Excel. Excel was limited to only 16 terms and was very time consuming. In Excel all variables had to be entered into the equation without any evaluation of the variable. Each variable and combination had to be added to the equation to determine the R^2 value; this led to approximately 8000 cases to be studied. Instead of studying each of the cases an educated guess was used to determine 10 combinations of the 16 terms that would provide the highest R^2 value. This educated guess was determined using the residual plots. Residual plots helped to determine value of the parameters by defining trends. Some examples of the trend types are shown in Figure 1 through Figure 3. This process was very time consuming and provided only a 16-term equation, which produced a low R^2 value of 45% from Equation 3.

$$N_f = 25413.21 + (-1768576 * S) + (-23.163 * T) + (50868125 * S^2) + (-69528.5 * SR^4) + (-793.477 * SH) + (11.700 * RT) + (-.00595 * RT^2) + (39354.9 * HS^2) + (47.799 * HR^2) + (-.0052 * R^2T^2) + (.0156 * R^2H^2) + (-8.8E\text{-}11 * R^2H^4) + (.0031 * R^4T^2) + (-.0268 * R^4H^2) + (1.34E\text{-}8 * T^2H^2) + (-4.5E\text{-}14 * T^4H^2), \quad (1)$$

A custom Mat Lab program was designed to use the same data set used for the Excel evaluation. The R^2 value of each 18-20 term combination of variables was determined. The maximum R^2 value was then identified and the coefficients and variables associated with this value were recorded. Residual plots of each of these variables, the program, and the output from this program are documented. The Mat Lab code uses every variable and their combinations without ranking them and therefore created an intensive analysis which was time consuming. When the equation exceeded 20 variables the program would take approximately 15 hours to run on a Dell Inspiron Laptop with 512 MB of Ram and a 20 GB hard drive.

The next multivariate equation was developed with Simstat. Simstat is a computational software developed by the Provalis Corporation®. Simstat has three methods of generating multi-linear regression equations: step-wise entry, backward elimination, and forward elimination. The step-wise method is the most commonly used and was chosen for this study to develop a multi-variate equation. In step-wise the p-value is used to calculate the F-statistic, which determines the variables with the highest confidence level. A p_{min} and p_{max} of .7 and .77 respectively were used for all analysis conducted.

$$F_j = [SS_R(x_j, x_1) - SS_R(x_0)] / [MS_e(x_j, x_1)] \quad (2)$$

F_j - F-Statistic
SS_R – Sum of the Squares of the Regression
MS_e – Sum of the Squares of the Error

The Simstat program is limited to 40 terms for each analysis and therefore 7 analyses had to be performed to obtain the equation of 40 terms that yielded the best R^2 value from the expanded data set of 102 variables. In each of the analyses the variables that did not meet the p-value criteria were omitted from the equation and were replaced with an equal amount of variables that had not been tried in the equation and then another analysis was performed. This procedure was repeated until all combinations of 40 terms had been completed. The 40 term equation was then evaluated to see how many terms were needed by plotting R^2 versus number of terms and observing where the knee of the curve started (Fig. 1).

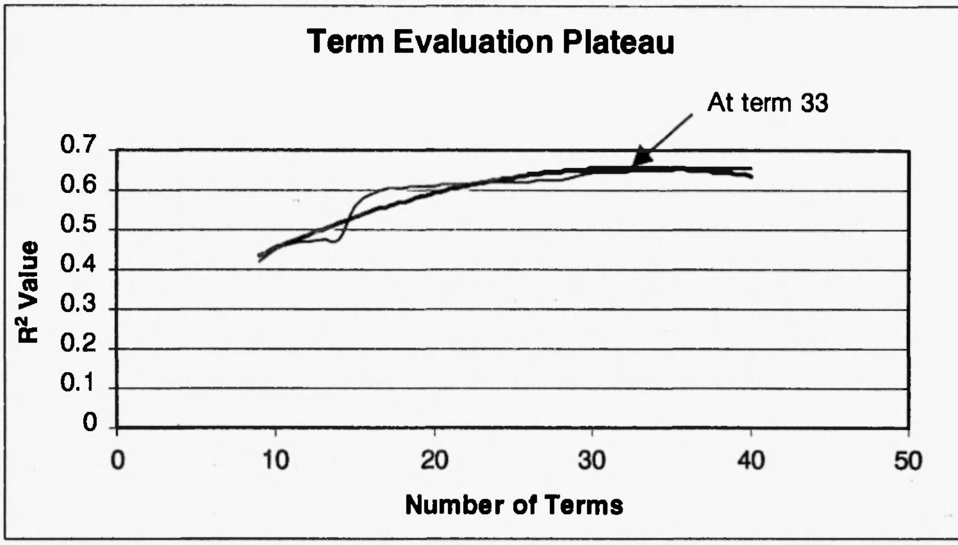

Fig. 1: Term Evaluation Plateau

After observing the residual plots (see Fig. 2 and Fig. 3) of the initial analysis, it was determined that transformations to the dependent and independent variables were needed to reduce the residuals and increase the R^2 value. The following transformations were applied and then the procedure above was carried out once again.

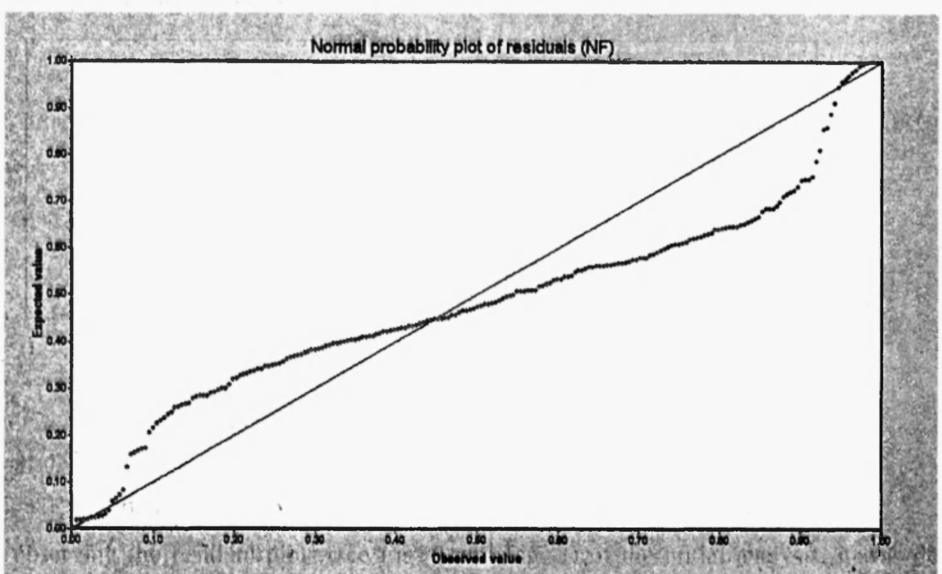

Fig. 2: Probability Plot from Simstat without Transformations

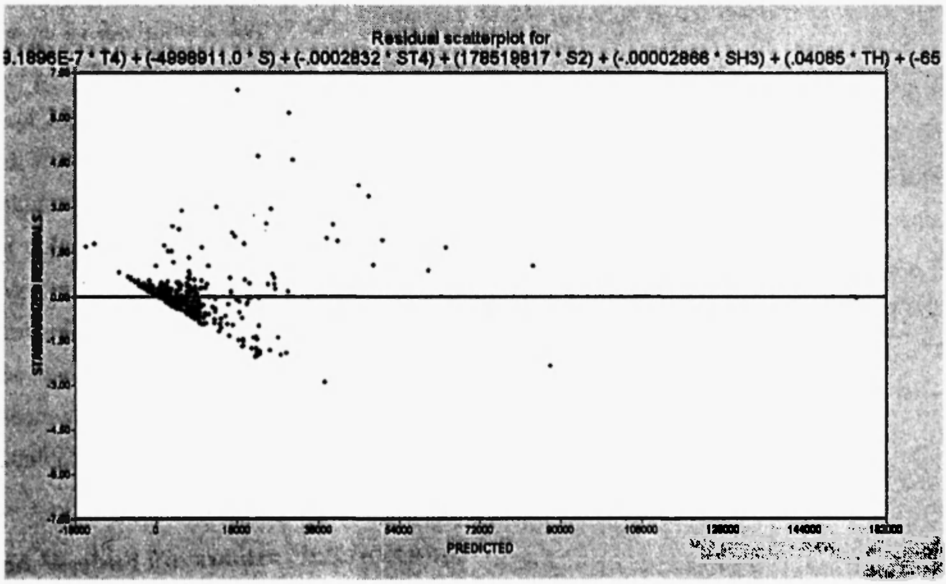

Fig. 3: Residual Plot from Simstat without Transformations

$$S = \text{Log}\,(\text{De}/\,100) \tag{3}$$

$$R = \text{Log}\,(\dot{e}) \tag{4}$$

$$T = T\,/\,100 \tag{5}$$

$$H = \text{Log}\,(t_h + 1) \tag{6}$$

$$N_f = \sqrt{(\text{Log}\,(N_f))} \tag{7}$$

The transformations were successful in the attempt to increase the R^2 value and reduce the residuals. A plot of the R^2 value versus number of terms was once again plotted (Fig. 4) to observe the plateau area so that the number of terms critical to the equation could be determined.

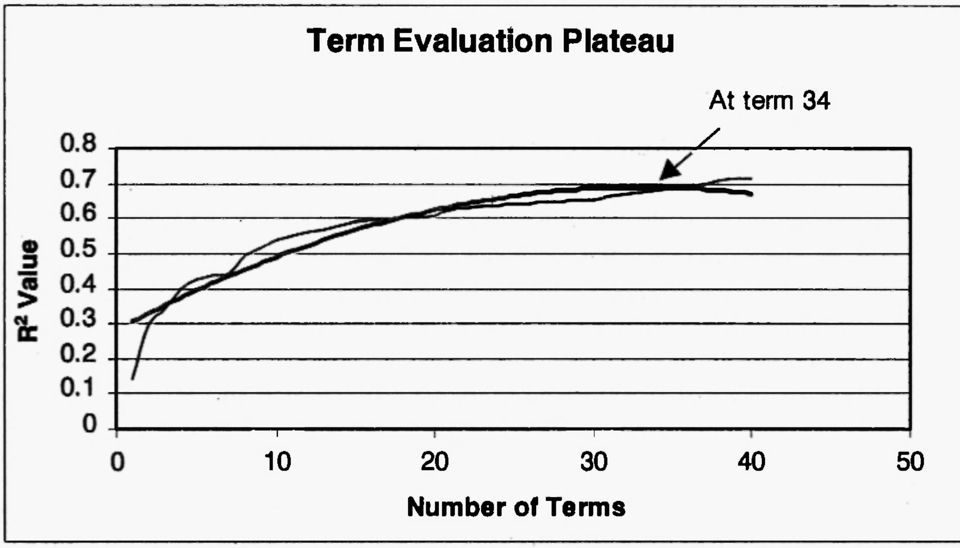

Fig. 4: Term Evaluation Plateau

The best fit equation was determined to be:

$$
\begin{aligned}
NF = {} & 26.4921 + (-.09054 * RT^2) + (18.8290 * S) + (.8171 * H) + (.009558 * HS^3) \\
& + (-.04042 * S^4) + (-.002473 * S^3H^2) + (2.1374 * R^2H^2) + (3.6811 * S^2) + (-.7903 * R^2H^3) + (.01711 * S^4R^2) \\
& + (.09170 * R^2H^4) + (-.0004657 * S^4R^4) + (1.7295 * SR) + (1.0723 * R^3H^2) \\
& + (.04939 * R^3H^4) + (-.4344 * R^3H^3) + (.1357 * S^3R^2) + (-.1123 * S^2R^3) + (.005630 * T^4) \\
& + (-.02100 * ST^3) + (.04853 * RT^3) + (.000004218 * S^4T^4) + (.003130 * ST^4) + (.01137 * R^2T^4) \\
& + (.09528 * R^3T^2) + (.07471 * ST^2) + (-.09562 * ST) + (.004706 * R^4T^4) + (-.03680 * R^2T^3) + (-2.2496 * R^2) \\
& + (.4469 * RH^2) + (-.08484 * R^3T^3) + (.07945 * R^4T^2) + (-.07468 * TH) + (.01295 * R^3T^4) + (-.04087 * R^4T^3) \\
& + (.004230 * TH^2),
\end{aligned}
$$

The above equation yielded an R^2 value of 72% and is weighted to the *conservative* side of prediction.

The final multivariate equation was developed with Statistical Analysis System (SAS) software. SAS was used because it did not limit the amount of terms for each analysis. The only analysis conducted with SAS was on the data with transformations since trends had already been established in the data. By entering all variables into a single analysis and returning the combination that yielded the R^2 value, the following equation was derived:

$$NF = 20.55 + (-42.48 * S) + (214.16 * R) + (-1.677 * T) + (-114.004 * H)$$
$$+ (-11.00 * S^2) + (-.922 * S^3) + (96.436 * R^2) + (-70.29 * R^3) + (-33.33 * R^4) + (2.54 * T^3) + (56.745 * H^2)$$
$$+ (4.124 * H^4) + (5.982 * SR) + (1.331 * SR^3) + (-.797 * SR^4) + (-.324 * ST) + (8.327 * ST^2)$$
$$+ (.218 * ST^4) + (-4.148 * SH^3) + (.711 * RT) + (52.065 * RT^2) + (14.356 * RT^3) + (-1.091 * RT^4)$$
$$+ (-200.298 * RH) + (215.113 * RH^2) + (-76.724 * RH^3) + (9.018 * RH^4) + (25.707 * TH) + (-.394 * TH^4)$$
$$+ (2.632 * HS^2) + (.661 * HS^3) + (.0394 * HS^4) + (-321.685 * HR^2) + (-116.073 * HR^3) + (12.054 * HR^4)$$
$$+ (-2.348 * HT^2) + (-2.774 * S^2R^2) + (-.1578 * S^2R^4) + (.724 * S^2T^3) + (.039 * S^2T^4) + (-1.062 * S^2H^2)$$
$$+ (-.331 * S^2H^4) + (-.6011 * S^3R^2) + (-.485 * S^3T^2) + (.232 * S^3T^3) + (.093 * S^3H^3) + (-.089 * S^3H^4)$$
$$+ (-.055 * S^4R^2) + (-.008 * S^4R^3) + (-.058 * S^4T^2) + (.021 * S^4T^3) + (.035 * S^4H^2) + (-36.576 * R^2T^2),$$

The R^2 value of 77% was obtained by the above equation. As expected the R^2 value was increased and the probability plot and residual plot did not represent any trends as seen in Fig. 5 and Fig. 6.

CONCLUSIONS:

An evaluation of software packages was conducted and SAS was determined to provide the best results exhibited by high R^2 value. A best-fit equation was developed and recommended for use to determine the tentative low cycle behavior of Cr-Mo steels. Future work will include gathering more data that was not used in the development of this equation and assessing the confidence level of the equation in predicting the creep-fatigue behavior.

REFERENCES

1. Solomon, M. and Goswami, T. "Low cycle fatigue behavior of pressure vessel steel alloys," Arkansas Center for Energy, Natural Resources and Environmental Studies, ACENRES 01-00-014, April 2001.

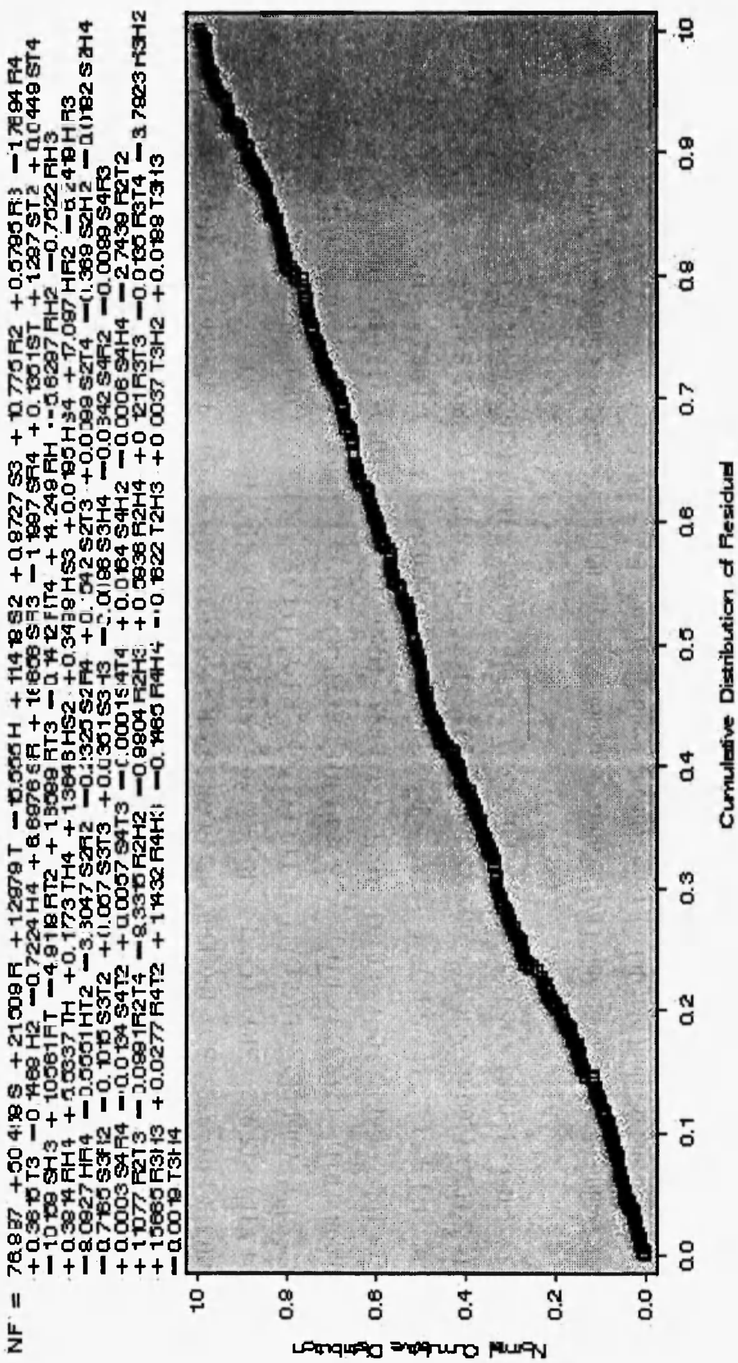

Fig. 5: Probability Plot from SAS with Transformations

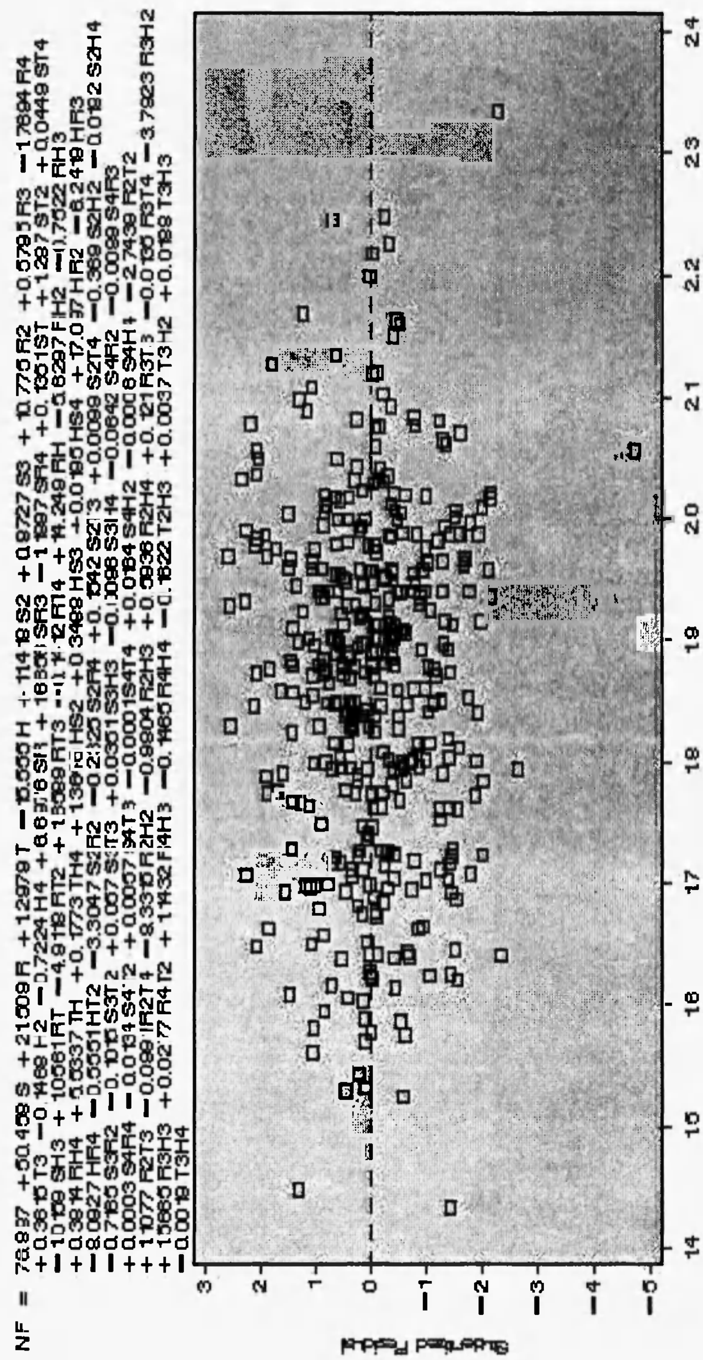

Fig. 6: Residual Plot from SAS with Transformations