Paper I

Effect of short-term data on predicted creep rupture life – pivoting effect and optimized censoring

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Effect of short-term data on predicted creep rupture life – pivoting effect and optimized censoring

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ABSTRACT

Fitting data to classical creep rupture models can result in unrealistically high extrapolated long-term strength. As a consequence, the standard strength values for new steel grades have frequently needed downward correction after obtaining more long-term test data. The reasons for non-conservative extrapolation include the influence of short-term data, which are easiest to produce but tend to pivot upwards the extrapolated values of creep rupture strength. Improvement in extrapolation could be expected by reducing this effect through model rigidity correction and censoring of very short-term data, but it may not be immediately clear how to justify the correction of particular models or censoring.

Analogously to the instability parameter in the minimum commitment model for creep rupture, a rigidity parameter correction (RPC) is introduced to assess the pivoting effect of creep rupture models for the purpose of reducing potential to non-conservativeness in extrapolation. The RPC approach can be used with any creep rupture model for comparing the model rigidity and the potential benefit from censoring short-term data. The correction itself will never introduce non-conservatism, regardless of the model. The RPC approach is demonstrated by analyzing an ECCC data set for cross-welded 9%Cr steel (E911).

Keywords: short-term data, creep rupture life, pivoting effect, optimized censoring

1. INTRODUCTION

The creep rupture data used for evaluating the representative creep strength typically spans over several orders of magnitude in time. As relatively short-term tests are obviously fastest and cheapest to perform, they are better represented than long-term tests in the data sets. In addition, the damage and failure mechanisms in the short-term tests tend to differ from those in the long-term tests, which may better represent the foreseen service conditions. Although the fitted creep rupture models can accommodate much of the resulting curvature in the creep rupture strength vs. time curves, some residual curvature is not included. This has often resulted in overestimated values of new material strength, so that standard values had to be later reduced when additional long-term data have become available. The reasons for the overestimates can include long-term degradation and bias in material sampling, for example. However, the common reasons can also include the pivoting effect by ‘‘over-represented’’ short-term tests, which may unduly increase the extrapolated creep rupture strength (and life) unless at least partially censored for fitting. This effect also depends on the rigidity or the creep rupture model, or its inherent ability to describe both the short and the long duration data. The main interest in most cases is in extrapolation towards long-term service conditions, and therefore the effect of pivoting and data censoring are of interest for extrapolation accuracy.

The rigidity parameter correction (RPC) method presented here is a tool for quantifying the rigidity of creep rupture models and the likely extrapolation error due to pivoting, and for optimized data censoring. As an example, an ECCC data set with cross-welded 9%Cr material (E911) data is analyzed using RPC. First a series of models are compared for rigidity and likely extrapolation error due to pivoting. For this data set it is known that the fracture location is changing from base material fractures to fractures in the heat affected zone (HAZ), leading to a change in the curvature. Most creep rupture models are expected to show pivoting problems with such data sets. Finally, some data-censoring options are tested for this data set.

2. METHODS, APPLIED MODELS AND TEST DATA

The RPC approach applies a similar non-linearity formulation as the master curve equation of the Manson’s [1] minimum commitment method (MCM):

$$\log(tr^*) = \frac{G(\sigma) - P(T)}{1 + A \cdot P(T)} \qquad (1)$$

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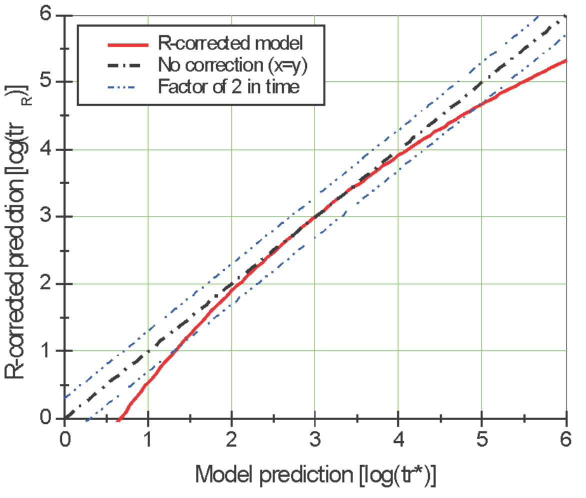

Figure 1 *R*-parameter corrected vs. uncorrected predicted rupture life (in h). $R = 0.089$ halves the predicted rupture time from 100 000 h when the pivot point is set at 1000 h.

where tr^* is the predicted time to rupture, *P(T)* and $G(\sigma)$ are respectively the temperature and stress functions of the expression, and A is a constant called the instability parameter. Increasing negative values of the instability parameter A will reduce the predicted life (and creep strength) in extrapolation. MCM is not included in standard PD6605 [2] models for creep rupture data fitting (except as a simplified linear MC model with $A = 0$), but is used below as one of the creep rupture models for rigidity testing.

Analogously to Eqn (1), a rigidity parameter R can be defined to correct the predicted rupture time by bending any creep model prediction to the conservative side over a pivot point in time (Figure 1). The corresponding corrected time to rupture is defined as

$$\log(tr_R) = \frac{\log(tr_m) - \log(t_p)}{1 + R \cdot (\log(tr_m) - \log(t_p))} + \log(t_p) \quad (2)$$

where tr_R is the rigidity corrected time to rupture, tr_m the uncorrected (model predicted) time to rupture and t_p the pivot point in time. The correction is zero at the pivot point and reduces the predicted life elsewhere. Any creep model can be R-parameter corrected by minimising the root mean square error (RMS, Eqn (3)) or the standard error of estimate (see Eqn (4) [3]) by optimizing the value of R.

RMS is defined as

$$RMS = \sqrt{\frac{\Sigma(\log(tr) - \log(tr^*))^2}{n - 1}} \quad (3)$$

where tr is the observed rupture time, tr^* the corresponding rupture time predicted by the model, and n the number of data points.

SEE is defined as

$$SEE = \sqrt{\frac{\Sigma(\log(tr) - \log(tr^*))^2}{n - k - 1 - m}} \quad (4)$$

where k the degree of regression and m the number of constants in the model. The ECCC recommendations [4,5] further define a convenient fitting efficiency parameter or scatter factor as

$$Z_{PARAM} = 10^{2.5 \cdot PARAM} \quad (5)$$

where the PARAM = RMS or SEE.

The pivot point could be similarly selected as a part of the fitting procedure. As most creep rupture data points are concentrated in the mid-region in logarithmic time, where any model could be expected to give similar prediction, the pivot point could be also defined as the logarithmic mean of the testing times. However, since most of the pivoting effect can be expected from the extreme values in time, the pivot point can be taken as the average of the shortest and longest test duration.

For example, a pivot point of 1000 h and $R = 0.089$ will shorten the uncorrected 100 000 h prediction by a factor of 2, independently of the applied creep rupture model, as seen in Figure 1. To estimate the likely error in extrapolated time, optimization is below however only done for data with rupture times longer than the pivot point.

Table 1 Creep rupture models of PD6605

Soviet model 1 (SM1)	Soviet model 2 (SM2)
$\log(t_r) = \beta_0 + \beta_1 \cdot \log[T] + \beta_2 \cdot \log[\sigma_0] + \beta_3/T + \beta_4 \cdot \sigma_0/T$	$\ln(t_r) = \beta_0 + \beta_1 \cdot \log[T] + \beta_2 \cdot \log[\sigma_0]/T + \beta_3/T + \beta_4 \cdot \sigma_0/T$
Simplified minimum commitment method (MC)	Simplified Mendelson–Roberts-Manson (MRn)[a]
$\ln(t_r) = \beta_0 + \beta_1 \cdot \log[\sigma_0] + \beta_2 \cdot \sigma_0 + \beta_3 \cdot \sigma_0^2 + \beta_4 \cdot T + \beta_5/T$	$\ln(t_r) = \left\{\sum_{k=0}^{n} \beta_k \cdot (\log[\sigma_0])^k\right\}/(T - T_0)^r + \beta_5$
Larson-Miller (LMn)[1)] (MRn with $T_0 = 0$, $r = 1$)	Manson-Haferd (MHn)[a]
$\ln(t_r) = \left\{\sum_{k=0}^{n} \beta_k \cdot (\log[\sigma_0])^k\right\}/T + \beta_5$	$\ln(t_r) = \left\{\sum_{k=0}^{n} \beta_k \cdot (\log[\sigma_0])^k\right\} \cdot (T - T_0) + \beta_5$
Manson-Haferd with $T_0 = 0$ (MH0n)[a]	Orr-Sherby-Dorn (OSDn)[a]
$\ln(t_r) = \left\{\sum_{k=0}^{n} \beta_k \cdot (\log[\sigma_0])^k\right\} \cdot T + \beta_5$	$\ln(t_r) = \left\{\sum_{k=0}^{n} \beta_k \cdot (\log[\sigma_0])^k\right\} + \beta_5/T$

[a] For $n = 2$, 3 or 4.

Table 2 Calculated values of *R* and *Z* for selected creep rupture models, optimized on all data. The model scatter factors (both RMS and SEE Z-values) are presented before and after RPC. The pivot point is set to 1000 h

Model	Z_{RMS} (uncorrected/*R*-corrected)	Z_{SEE} (uncorrected/*R*-corrected)	*R*-parameter
MC	4.95/4.68	5.11/4.87	0.095
OSD3	4.90/4.27	5.03/4.42	0.165
MH03	4.85/4.23	4.97/4.37	0.159
MR03	5.16/4.47	5.30/4.62	0.181
SM1	5.76/5.07	5.92/5.26	0.179
SM2	5.75/5.04	5.91/5.23	0.182
MR02	7.99/7.15	8.21/7.43	0.197
MH02	9.23/8.26	9.49/8.61	0.185
OSD2	9.07/7.96	9.34/8.29	0.219
MCM (A = −0.155)	3.82/3.69	3.95/3.85	0.052

In this work the non-linear MCM model was tested together with a selection of PD6605 [2] creep rupture models. The PD6605 supported models (18 model variants in total, see Table 1) apply maximum likelihood linear fitting to the rupture test data. An advantage of this approach is the possibility of using unfailed data (ongoing or interrupted tests) in the assessment.

Applying RPC for models selected by ECCC post assessment testing (PAT) will further characterise their suitability for extrapolation. A rigid model or a ''difficult'' data set might require left censoring (in time) or stress censoring (isothermal) for improved reliability. Optimizing *R* on data with longer rupture times than the pivot point again quantifies the likely error in the extrapolated life. A large positive value of *R* would suggest a model (and/or data) susceptible to pivoting errors, and non-conservative (uncorrected) predicted life.

To show the potential of RPC, an ECCC data set of cross-welded 9%Cr material (E911) is fitted to the selected creep ruptured models. A series of models are compared for their fitting efficiency with and without RPC, and then their likely extrapolation error due to pivoting is quantified. Finally, data censoring options are tested for potential improvement in extrapolation. For this data set it is known that the fracture location is changing from the base material to the heat affected zone (HAZ). Such a data set can be expected to show pivoting problems with most creep rupture models. The full data set consists of 159 ruptured and 36 unfailed data points including specimens ruptured in the parent material, weld metal and in the heat affected zone (HAZ). The data covers a temperature range of 550–690°C and stress range of 26–230 MPa, with the longest ruptured test about 32 000 h and the longest unfailed test about 65 000 h in duration. In addition to the full data set, subsets of data are analyzed on HAZ failures without censoring and with left censoring up to 1000 h. A source for error in the PD6605 models is possible when assessing HAZ data only; caused by the fact that there are unfailed data in isotherms (550 and 575°C) where there are no failed data. The impact of this situation on the models should be clarified in future work.

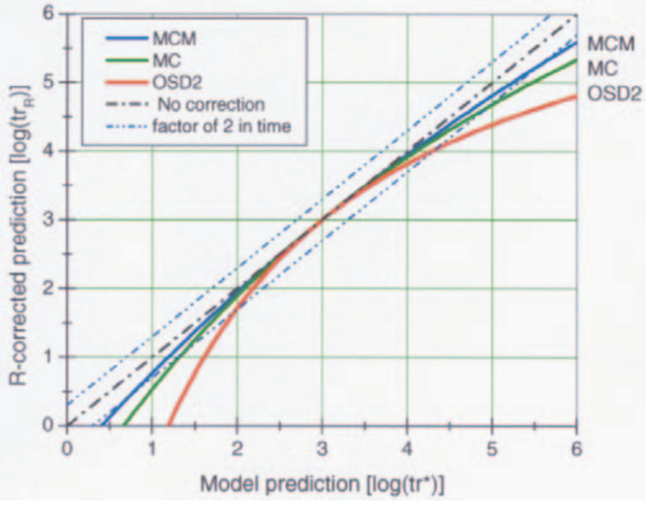

Figure 2 RPC fits of the two best performing models (MCM, MC) and the worst performing OSD model, with a pivot point at 1000 h.

3. COMPARISON OF CREEP MODELS WITH RPC FOR CROSS-WELDED 9Cr STEEL

Nine best-fitting PD6605 models and the MCM model were selected for RPC applied to the ECCC data set on cross-welded 9Cr steel. The RPC optimization results on all data are shown in Table 2, when the pivot point is set at 1000 h. For all models it can be noted that the RPC reduces the scatter factor Z_{SEE} by 5–13%.

Rating the models according to the result of the RPC (the smaller the *R*-parameter the better), the best (MCM and MC) and worst (OSD2) performing models are compared with uncorrected models in Figure 2.

For comparison, the same data set was RPC optimized on data longer than the pivot point. The resulting values of *R* and *Z* for the models before and after RPC are presented in Table 3, and a comparison of uncorrected and corrected best and worst performing models is shown in Figure 3. The time ratio tr_R/tr_m at longest observed rupture time (about 30 000 h) and at 100 000 h are also listed to characterise the effect of optimized RPC. Again, Z_{SEE} is systematically reduced by RPC but the reduction is now between 0.4 and 4.1%. The predicted life at 30 000 h (uncorrected) is reduced by about 15–30% depending on model. Of the PD6605 models, the MC model showed smallest value of *Z* and *R* (and largest time ratio), while OSD2 showed the largest *Z* and *R*. The non-linear MCM gave no more obvious improvement in this case in comparison with the simplified minimum commitment model (MC).

Table 3 Calculated values of R and Z for the same creep rupture models as in Table 2, optimized on all rupture data above the pivot point (1000 h). The scatter factors (Z) are shown with and without RPC. The models shown in bold are further applied to the data points of HAZ failures

Model	Z_{RMS} (uncorrected/R-corrected)	Z_{SEE} (uncorrected/R-corrected)	R	Time ratio tr_R/tr_m at 30 000 h/100 000 h
MC	**2.40/2.37**	**2.45/2.44**	**0.032**	**0.858/0.758**
OSD3	2.59/2.48	2.64/2.55	0.055	0.774/0.634
MH03	2.60/2.49	2.65/2.56	0.057	0.768/0.624
MR03	2.62/2.50	2.68/2.57	0.058	0.765/0.620
SM1	2.93/2.83	3.0/2.91	0.057	0.768/0.624
SM2	2.95/2.83	3.01/2.92	0.058	0.765/0.620
MR02	3.46/3.34	3.54/3.45	0.061	0.755/0.606
MH02	3.78/3.62	3.86/3.74	0.071	0.724/0.564
OSD2	**3.89/3.72**	**3.98/3.84**	**0.074**	**0.715/0.552**
MCM (A = − 0.155)	**2.48/2.42**	**2.56/2.51**	**0.045**	**0.809/0.684**

Note that here the usually well behaving SM1 model appears to behave rigidly, giving inferior results in comparison with MC and MCM.

Table 4 Calculated values of R and Z for MC, OSD2 and the MCM models, fitted and RPC optimized on uncensored data of HAZ failures (pivot point at 3000 h)

Model	Z_{RMS} (uncorrected/R-corrected)	Z_{SEE} (uncorrected/R-corrected)	R
MC	2.20/2.09	2.26/2.16	0.166
OSD2	2.21/2.11	2.25/2.17	0.145
MCM (A = − 0.13)	2.09/2.09	2.17/2.18	0.028

Table 5 Calculated values of R and Z for best and worst performing PD6605 models and MCM model on the full data set, optimized on HAZ data with longer durations than 3000 h (pivot point)

Model	Z_{RMS} (uncorrected/R-corrected)	Z_{SEE} (uncorrected/R-corrected)	R	Time ratio at time of 30 000 h/100 000 h
MC	2.22/2.12	2.31/2.23	0.134	0.762/0.552
OSD2	2.26/2.16	2.32/2.24	0.133	0.763/0.554
MCM (A = − 0.13)	2.15/2.14	2.26/2.29	0.019	0.958/0.906

4. OPTIMAL CENSORING OF 9Cr CROSS-WELD DATA USING RPC

Three cross-weld data subsets of the 9Cr material were tested for optimal performance by left censoring. The first subset included HAZ failures only, the second the same data set censored up to 300 hours and the third subset the same data set censored up to 1000 hours. In all cases the pivot point is set at 3000 h (mid-range of data with HAZ failures).

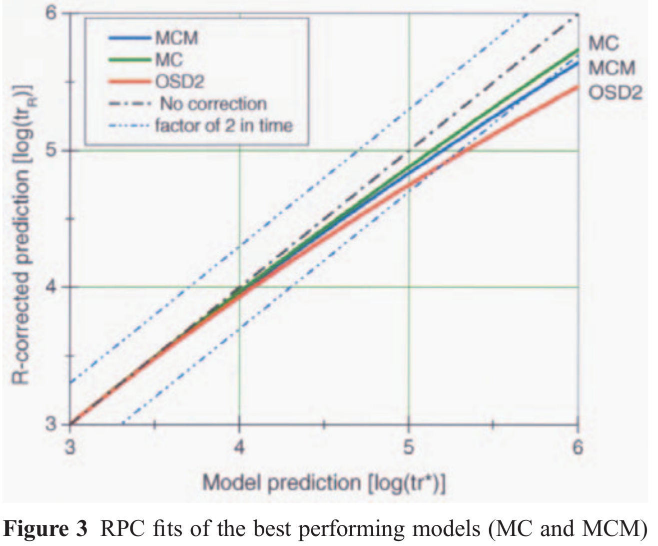

Figure 3 RPC fits of the best performing models (MC and MCM) and the worst performing (OSD2) model. The models are optimized on data above the pivot point (1000 h).

4.1 HAZ failures, no censoring

With RPC, the predicted life is shortened by a factor of two in time from 100 000 h with $R = 0.1618$, when the pivot point is set at 3000 h. The RPC optimization results with all data are shown for the MC, MCM and the ODS2 models in Table 4, and the corresponding results for data above pivot point in Table 5.

The removal of data not failing in the HAZ changes the order of the MC and OSD2 models indicating that the MC behaves more rigidly for these data. However, the MCM model hardly changes at all by RPC, in fact the Z_{SEE} is getting worse which indicate that the RPC does not represent a true improvement for this model.

From the extrapolation point of view the two PD6605 models perform very similarly, and both MC and OSD2 models seem to suffer from the pivoting effect in extrapolation. The MCM model again shows decline in the Z_{SEE} scatter factor by RPC. The MCM is thereby nearly optimal without further correction, and would be selected as preferred model for the HAZ failure data assuming it also passes all PAT tests. However, again one has to remember

Table 6 Calculated values of R and Z for best and worst performing PD6605 models on all HAZ failure data, left censored at 300 h

Model	ZRMS (uncorrected/R-corrected)	ZSEE (uncorrected/R-corrected)	R
MC	2.19/2.09	2.25/2.17	0.152
OSD2	2.20/2.12	2.24/2.18	0.135

Table 8 Calculated values of R and Z for best and worst performing PD6605 models on the full HAZ data set, optimized on data left censored at 1000 h

Model	Z_{RMS} (uncorrected/R-corrected)	Z_{SEE} (uncorrected/R-corrected)	R
MC	2.18/2.08	2.22/2.16	0.131
OSD2	2.18/2.14	2.23/2.20	0.108

that the MCM model has not utilised the unfailed data and might therefore show better fits.

4.2 HAZ failures, left censoring at 300 h

It is to be noted that the difference from the uncensored data set is only one failed data point at 262 hours ($\log(t_r) = 2.4$); the next shortest test has a logarithmic rupture time of 2.8 (630 h). The RPC optimization results are shown here for the MC and OSD2 models in Table 6 for the whole data range and in Table 7 for the data above the pivot point. The pivoting point is still kept at 3000 h.

The OSD2 model seems to behave more flexibly than the MC model. From the extrapolation point of view the MC model shows no change in the R-parameter as an effect of the left censoring (in comparison to the uncensored HAZ data set), indicating that the culling does not affect this model. The OSD2 model shows some decrease in the value of R, suggesting an improvement.

4.3 HAZ failures only, left censoring at 1000 h

The pivot point is still kept at 3000 hours for comparison reasons and to avoid a too short bending range for the long-term data. The RPC optimization is performed on the left censored HAZ data using the same MC and OSD2 models as before. The RPC results are presented in Table 8 for optimized R-parameter on the whole range and in Table 9 on the data above the pivoting point.

From the rigidity point of view both the MC and the OSD2 show only slight improvement in the R-parameter (in comparison to the less culled and un-culled data sets). The location of the pivoting point closer to the short duration end (due to culling) emphasizes the long duration end, which can be seen comparing Table 8 and Table 9 (which are nearly identical). This indicates that any pivoting due to the shorter test data (1000 to 3000 h) can be ruled out.

The OSD2 performs better the more left-censoring is applied whereas the MC show no clear improvement in the R-parameter. This suggests that the uncensored HAZ data is already the optimal data set for MC to perform the assessment, and that further censoring only favours relatively simple models such as the OSD2.

5. DISCUSSION AND CONCLUSIVE REMARKS

The RPC approach is available to supplement any classical creep rupture model, including those supported by PD6605. RPC will typically reduce the common inherent non-conservatism in predicted life, because it can justify additional downward curvature to the (*e.g.* isothermal) extrapolated creep rupture curves. As the correction is zero at the selected pivot point and reduces life elsewhere, RPC itself is not likely to be non-conservative. In the example case of cross-welded 9Cr steel, the data fits were improved by RPC (improvement in scatter factor) for all tested PD6605 creep models, and in each case by additional curvature towards the non-conservative side. This suggests good potential in reducing the commonly observed non-conservatism in extrapolated creep rupture life. In the example data set for cross-welded 9Cr steel, the resulting reduction in predicted life was 15–25% at 30 000 h and 24–45% at 100 000 h for the tested models, which corresponds to the maximum observed failure time and maximum target extrapolation time.

For the full data set the MC and MCM models were least affected by pivoting (see Figure 4). The relatively inflexible SM1 and SM2 models require more correction, and should be RPC tested when post assessment tests (PAT) suggest these as preferred models.

Table 7 Calculated values of R and Z for best and worst performing PD6605 models on HAZ failure data, left censored at 300 h and above the pivot point

Model	Z_{RMS} (uncorrected/R-corrected)	Z_{SEE} (uncorrected/R-corrected)	R	Time ratio at max rupture time (30 000 h/100 000 h)
MC	2.22/2.11	2.31/2.22	0.134	0.762/0.552
OSD2	2.24/2.15	2.30/2.24	0.125	0.774/0.571

Table 9 Values of R and Z as in Table 8 but for failures above the pivot point

Model	Z_{RMS} (uncorrected/R-corrected)	Z_{SEE} (uncorrected/R-corrected)	R	Time ratio at max rupture time (30 000 h/100 000 h)
MC	2.18/2.09	2.27/2.19	0.130	0.767/0.560
OSD2	2.19/2.13	2.25/2.21	0.107	0.800/0.612

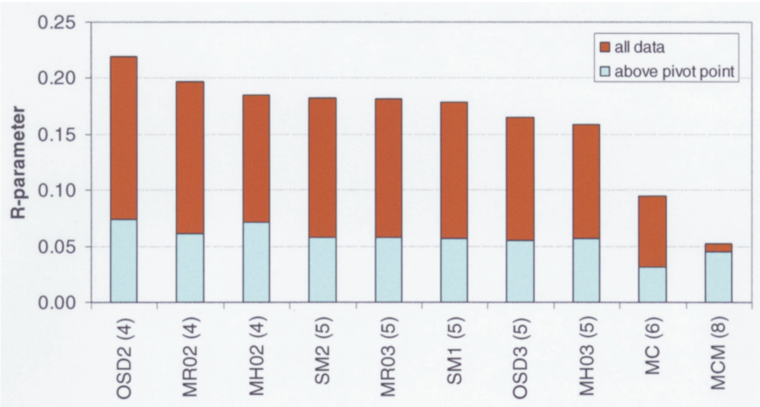

Figure 4 The optimized value of *R* for 10 rupture models (in the order of least to most flexible model, *i.e.* order of *R*) using either all data or data above the pivoting point. The numbers in brackets refer to the numbers of free fitting variables in each model.

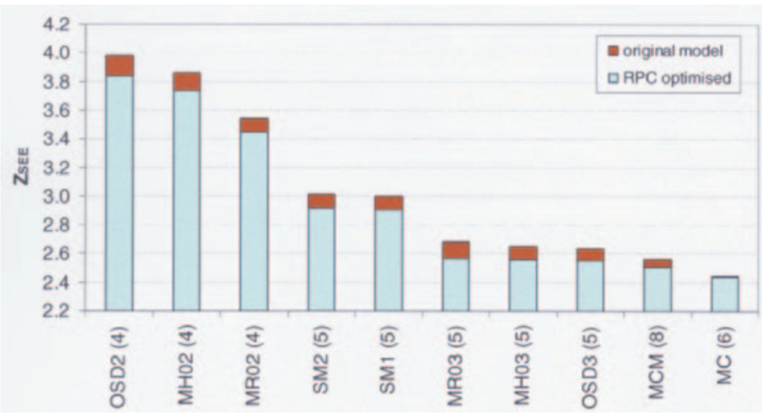

Figure 5 The RPC optimization impact on Z_{SEE} (in the order of worst to best fitting models above pivoting point). The improvement in Z appears to be unrelated to the initial model performance, *i.e.* initially poorly fitting models do not improve more than good ones.

Looking at the improvement of fit above the pivoting point (see Figure 5), it appears that the RPC does not improve badly fitting models (in expected time scatter) more than the initially better ones.

Plotting the corrected and uncorrected models (all data case, see Figure 6) it can be seen that for this data set the 625°C isotherm is improved the most from the RPC.

For the subsets on HAZ failures it was shown that left censoring does not improve the MC model performance from the flexibility point of view, whereas the OSD2 benefits from more left censoring (Figure 7). The Z_{SEE} for the MCM model became worse by RPC for the uncensored HAZ data set, suggesting that it is already close to the optimum fit.

The HAZ failures data set without censoring was hence the best data set in this assessment for both the MCM and the MC model. Left censoring the HAZ data only improves the flexibility performance of simple models such as the OSD2 model. All the PD6605 models, however, show some improved fitting by RPC suggesting that none of the uncorrected models are optimal. The nonlinear MCM and the MC models show considerably less change by RPC than the others, not perhaps surprisingly for the MCM since it already includes a similar non-linearity formulation comparable to RPC. However, MCM fitting does not take unfailed data into account.

Model rigidity, however, is a double-edged sword. A model with numerous fitting parameters can be more flexible than one with only few, but a good fit to the existing data (in interpolation) does not guarantee good performance in extrapolation. The number of fitting constants to be optimized in the models considered above varies from 4 (LM2) to 8 (full MCM). This variation involves a part of the inherent rigidity, and conventional fitting efficiency is therefore better described by the Z_{SEE} than the Z_{RMS}. However, provided that the fitted data set is reasonably large in comparison with the number of fitting parameters, the inherent rigidity of the models is bound by their phenomenological description of the underlying creep (rupture) process. In this respect the models rather similarly apply a temperature dependence

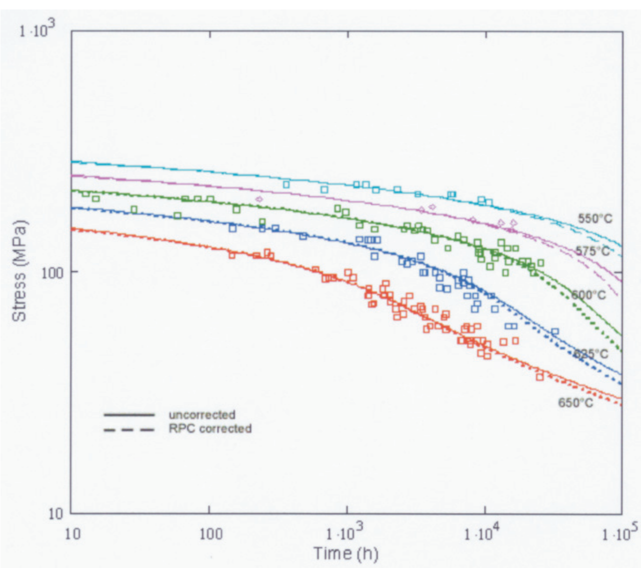

Figure 6 RPC fit of the full data set using the MC model (pivot point = 1000 h, $R = 0.032$). The main improvement appears to be in the 625°C isotherm. The stress ratio (uncorrected/corrected) at 600°C and 100 000 h is 0.86.

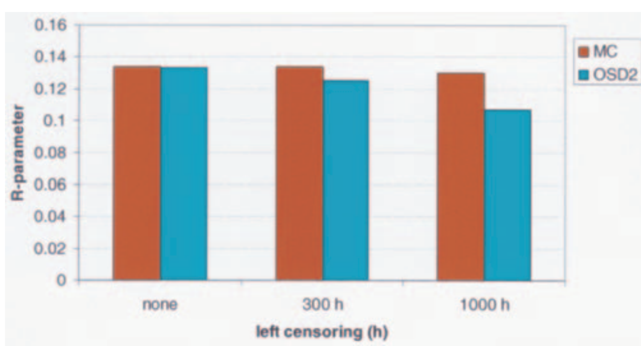

Figure 7 Influence of left censoring on the optimized value of *R* (above pivoting point) for the MC and OSD2 models.

related to the Arrhenius rate expression. In contrast, the stress dependence is given by a polynomial without real theoretical background, except for the SM models which assume a stress activation term for creep [6]. Not surprisingly, the SM1 and SM2 models may then appear relatively rigid, as was found above in RPC testing of the example data set. None of the PD6605 models explicitly include terms for thermal degradation or creep damage, and the expected additional downward curvature in isothermal creep rupture curves is only accommodated to the extent allowed by the (mostly polynomial) stress expressions. MCM, however, includes the instability parameter to model for additional ‘‘damage’’, and a similar approach has been adopted for RPC. The observed improvement in the fitting capability of MCM and all rigidity corrected PD6605 models suggests that some of the non-conservatism in extrapolation is due to models rather than the data not yet reflecting long term degradation. The potential benefit of the RPC approach should be investigated with a wider range of data sets.

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