



ECCC RECOMMENDATIONS - VOLUME 5 Part Ia [Issue 6]

**GENERIC RECOMMENDATIONS AND
GUIDANCE FOR THE ASSESSMENT
OF FULL SIZE CREEP RUPTURE
DATASETS**

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ABSTRACT

ECCC Recommendations Volume 5 Part Ia provides guidance for the assessment of large creep rupture data sets. It recognises that it is not practical at the present time to recommend a single European creep rupture data assessment (CRDA) procedure and promotes the innovative use of post assessment acceptability criteria to independently test the effectiveness and credibility of creep rupture strength predictions.

The guidance is based on the outcome of a four year work programme involving the evaluation of a number of assessment procedures by several analysts using large working data sets. The results of this exercise highlight the risk of unacceptable levels of uncertainty in predicted strength values without the implementation of well defined assessment strategies including critical checks during the course of analysis. The findings of this work programme are detailed in appendices to the document.

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1. INTRODUCTION

ECCC Recommendations Volume 5 Part Ia provides guidance for the assessment of creep rupture data. Emphasis is placed on pre-assessment and the use of post assessment acceptability criteria to independently test the effectiveness and credibility of the main assessment model equation(s) in characterising material behaviour on the basis of the available data. The use of post assessment tests (PATs) is an original concept.

The PATs were developed during a four year WG1 work programme during the period 1992 to 1996¹ which involved the assessment of large international working data sets by a number of analysts using a range of procedures. This was the first time that the reproducibility of various assessment methods had been evaluated on major data sets, and the exercise provided important information on which to base the ECCC-WG1 recommendations. Details of the working data sets are given in Appendix A1. The assessment methods evaluated (and others) are reviewed in Appendix B1. The results from this first WG1 activity are described in Appendix C1. Since, 1996 there have been a number of minor amendments but no major changes to the original procedures (up to Issue 5). Nevertheless, a large number of full-sized datasets have been analysed over the last 18 years using the ECCC Recommendations and the assessed strength values have been used in European Design and Product Standards and within the industrial members of ECCC for the purpose of design and life assessment. However, over the last 18 years there have been many changes to both the software which can be used to fit creep rupture data and to the membership of ECCC WG1 and in addition many observations have been made regarding the effectiveness of the procedures in Volume 5 Part Ia. Recently the effectiveness of the original procedures have been re-evaluated by the current members of WG1 using the most up-to data methods for Creep Rupture Data Assessment (CRDA) and Volume 5 Part Ia has been reissued. The results of the re-evaluation activity are described in Appendix C2 and form the basis of a simple revision to PATs 2.1 and 2.2, which has been updated in the following main text, as Issue 6. This simple revision now plots the observed logarithm of the rupture time (as the y-value) versus the predicted logarithm of the rupture time (as the x-value). It has been shown that the application of the full range of ECCC post assessment tests including the Revised PAT 2.1 and 2.2, allows the assessor to discriminate between unreliable and reliable creep rupture data assessments, and models. In particular, the shortlisted models produce similar mean fits and rupture strength values (Appendix C2).

2. CREEP RUPTURE DATA ASSESSMENT

2.1 Overview

ECCC recommendations for the assessment of creep rupture data are based on a comprehensive review of CRDA procedures (App. B1) and an extensive evaluation of their effectiveness (App. C1 and C2). The evaluation programme was performed by members of ECCC-WG1 using four large, inhomogeneous, multi-cast, multi-temperature working data sets, especially compiled for the exercise (App. A1). The four alloys were 2¼CrMo, 11CrMoVNb, 18Cr11Ni and 31Ni20CrAlTi (Incoloy 800), and were selected to represent the spectrum of materials covered by ECCC-WG3x working groups. The results of the evaluation programme have strongly influenced the recommendations listed in Sect. 2.2.

It is not practical at the present time to recommend a single CRDA methodology for use by ECCC. Consequently, the recommendations do not impose restrictions on the use of any procedure, provided that the results determined satisfy certain conditions and a set of post assessment acceptability criteria (Sect. 2.4). The post assessment acceptability criteria are the key to the ECCC CRDA recommendations and have been devised to give the user maximum confidence in the strength predictions derived through a series of independent tests (PATs) on the results of the analysis.

¹ The success of this WG1 activity is attributed to the support of the BRITE-EURAM Concerted Action BE 5524 (1992-6) and the in-kind contribution provided by WG1 participant organisations during this period.

Implementation of the ECCC recommendations require significant additional effort. However, this is regarded as entirely justified. The evidence from the CRDA evaluation exercise clearly demonstrates that, without pre-assessment, repeat main assessments and post assessment tests, the uncertainty associated with predicted strength values (in particular extrapolated strength values) is unacceptably high (Tables C1.2a-d and Figs.C1.1a-4c and Table C2.2 and Figs. C2.13 to C2.16).

A laudable goal for the future is the development of a European state-of-the-art CRDA procedure, and a number of target requirements for such a methodology are identified in Table 1.

2.2 Recommendations for the Assessment of Creep Rupture Data

The ECCC-WG1 CRDA evaluation exercise highlighted the risk of unacceptable levels of uncertainty in predicted strength values without the implementation of certain precautionary checks during the course of assessment (Apps. C1,C2). The findings of these investigations have led to the following recommendations.

- 1) At least two CRDAs should be performed by two independent metallurgical specialists using their favoured proven methodology.
- 2) At least one of the CRDAs should be performed using a method for which there is an ECCC procedure document detailed in App. D. These are referred to as ECCC-CRDAs².
- 3) Prior to the main-assessment of the CRDA, a pre-assessment should be performed which takes cognisance of the guidance given in Sect. 2.3.
- 4) The results of the main-assessment of the CRDA should satisfy the requirements of the ECCC post assessment acceptability criteria (Sect. 2.4).
- 5) The results of the two CRDAs should predict $R_{u/100kh/T}$ strength levels to within 10% at $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$ ^{3,4}. $R_{u/300kh/T}$ strength levels should be predicted to within 20% at the same temperatures.

If the maximum test duration is less than 100,000h, the predicted strength comparisons should be made for test durations of $t_{u[\max]}$ and $3.t_{u[\max]}$.

- 6) If the results of the two CRDAs meet the requirements defined in 5) and only one is an ECCC-CRDA, the results of the ECCC-CRDA should be adopted. If both assessments have been performed according to ECCC-CRDA procedures, the results of the ECCC-CRDA giving the minimum $R_{u/100kh}$ strength values at T_{main} should be adopted, unless ECCC-WG3x agree otherwise.

An important deliverable from each individual assessment is a master equation defining time as a function of stress and temperature. Consequently, the results from only one ECCC-CRDA should be adopted to construct the final table of strength values.

- 7) If the results of the two CRDAs do not meet the requirements of 5), up to two repeat independent CRDAs should be performed until the defined conditions are satisfied. However, repeat assessment should be unnecessary if the material has been sensibly specified and pre-assessment has confirmed that (i) all casts making up the dataset

² An ECCC-CRDA is one for which there is a comprehensive procedure document, approved by ECCC-WG1 and included in App. D.

³ $T_{\min[10\%]}$ and $T_{\max[10\%]}$ refer to the minimum and maximum temperatures at which there are greater than 10% data points. T_{main} is the temperature with the highest number of data points.

⁴ For information on ECCC terms and terminology, the reader is referred to [1].

conform to the specification, (ii) the distribution of the data is not impractical for the purpose, and (iii) there are no sub-populations which may influence the uncertainty of the analysis result. It is therefore strongly recommended that these aspects are considered by ECCC-WG3x prior to repeat assessment.

- 8) The results of all assessments should be reported according to the prescribed ECCC format (App. E1, a CRDA check list file is contained on the Volumes CD).

A copy of the reporting package should be sent to the ECCC-WG1 Convenor to provide the working group with essential feedback on the effectiveness of their recommendations.

- 9) During subsequent use of the master equation derived from the CRDA, strength predictions based on extended time extrapolations and extended stress extrapolations as defined by [2]⁵ must be identified.

Quantification of the uncertainties associated with extrapolated strength values and those involving extended extrapolations should be a goal for the future.

- 10) The reliability of CRDA predictions is dependent on both the quality and quantity of the data available for the analysis. Interim-minimum and target-minimum dataset sizes for the determination of creep rupture strength values for standards are recommended in Table 2.

It is recommended that the original ECCC recommendation concerning the requirements for a target-minimum dataset continues to be acknowledged as an ideal, i.e. TM1 (in Table 2). A well organised testing strategy can provide a dataset to meet these requirements with 90 tests. However, it is now recognised that large datasets comprised of $t_u(T, \sigma_o)$ observations from a significant number of casts may also be acceptable while failing to meet TM1 requirements (App. F). Hence, a target-minimum requirement based on TM2 (in Table 2) is acceptable. Moreover, for very large datasets which do not meet either the TM1 or TM2 requirements, a target-minimum requirement based on TM3 (in Table 2) is also acceptable.

- 11) To improve the reliability of CRDA predictions in the future, greater emphasis should be placed on the generation of homogeneously distributed datasets during the planning of creep testing programmes, in particular those activities forming part of large collaborative actions.

- 12) The use of post service exposure test data for the derivation of design strength values is not recommended.

The creep rupture data assessment philosophy presented in this section is summarised in Fig. 1.

2.3 Pre-Assessment

Pre-assessment is an important step in the analysis of creep rupture data. It involves (a) characterisation of the data in terms of its pedigree, distribution and scatter (random and systematic), and (b) data re-organisation (if deemed necessary by the findings of (a)). In certain CRDAs it includes pre-conditioning/data reduction as routine (eg. App. D1). However, since such steps are method dependent, they are not considered further as part of this section. An

⁵ According to reference 2, extended time extrapolations are those beyond x3 the test duration exceeded by data points from 5 casts at temperatures within 25°C of that specified. Results from tests in progress may be included when above the -20% scatterband limit at the appropriate duration. Extended time extrapolations are not permitted at temperatures which do not meet this criterion. Extended stress extrapolations are those in the ranges $(0.9 \cdot \sigma_{o[\min]} - \sigma_{o[\min]})$ and $(1.1 \cdot \sigma_{o[\max]} - \sigma_{o[\max]})$, where $\sigma_{o[\min]}$ and $\sigma_{o[\max]}$ are the minimum and maximum stress value used in the derivation of the master curve.

important by-product from pre-assessment data distribution analyses is information which could be influential in the planning of future creep testing programmes⁶.

The precise boundary between the end of pre-assessment and the start of the main-assessment may be unclear and in certain CRDAs, the final assessment is only performed after a number of iterative steps back into pre-assessment. At least one analysis is usual as part of pre-assessment, in order to characterise the trends and scatter in the data.

Pre-assessment should include:

- (i) confirmation that the data meet the material pedigree and testing information requirements recommended in ECCC Recommendations Volume 3 [3],
- (ii) confirmation that the material pedigrees of all casts meet the specification set by the instigator(s) of the assessment (eg. Table A1.1),
- (iii) an evaluation of the distribution of broken and unbroken testpiece data points with respect to temperature and time (eg. Tables A1.2a-5a); identifying $t_{u[\max]}$, $\sigma_{o[\min]}$, and the temperatures for which there are (a) $\geq 5\%$ broken specimen test data conditions ($T_{[5\%]}$) and (b) $\geq 10\%$ broken specimen test data conditions ($T_{[10\%]}$),

[The $T_{[5\%]}$ and $T_{[10\%]}$ information is needed for the identification of best-tested casts in (iv) and to perform the post assessment tests (Sect. 2.4). Checks for duplicate entries in the dataset should be made at this stage.]

It is acceptable to consider data for temperatures within $\pm 2^\circ\text{C}$ of principal test temperatures to be part of the dataset for that principal test temperature (eg. test data available for 566°C may be considered together with data for 565°C).

- (iv) an analysis of the distribution of casts at each temperature, specifically identifying (a) the main cast, ie. the cast having the most data points at the most temperatures, and (b) the best-tested casts⁷,

[The best-tested cast information is required to perform the post assessment tests (eg. PAT 2.2, Sect. 2.4).]

- (v) a visual examination of isothermal $\log \sigma_o$ versus $\log t_u$ plots (containing broken and unbroken data points) and a first assessment to characterise the trends and scatter in the data,

[The first assessment will indicate the presence of metallurgical instabilities, and thereby allow the analyst to take the necessary steps to account for these in the main-assessment. It will also identify excessive scatter, a useful indicator being the presence of data points outside the isothermal mean $\pm 20\%$ lines. Excessive scatter may be due to individual outliers or sub-populations resulting from systematic variations, eg. chemical composition, product form. The cause(s) of excessive scatter should be identified]

- (vi) a re-organisation of the data, if the results of the first assessment identify the need.

[As an example, analysis of variance may indicate that there is a product form related sub-population in the data-set. One solution would be to make the material specification more specific]

⁶ For example, gaps in the data at critical positions in the dataset.

⁷ As a guide, best-tested casts are those for which there are ≥ 5 broken testpiece data points at each of at least three $T_{[5\%]}$ temperatures (with ≥ 2 /temperature having rupture durations $> 10,000\text{h}$). A cast which just fails to meet this criterion, may still be regarded as a best-tested cast if there are ≥ 16 broken testpiece data points total (eg. Tables A2b-5b). For practical reasons, it is recommended that a maximum of 10 best tested casts are selected.

in terms of product form, with the consequence that certain data would have to be removed from the original data set]

The reason(s) for excluding any individual data points which are acceptable in terms of (i) and (ii) above, should be fully documented. In practice, it should not usually be necessary to remove data meeting the requirements of ECCC Recommendations Volume 3, providing the material specification is realistic.

2.4 Post Assessment Acceptability Criteria

The CRDA post assessment acceptability criteria fall into three main categories, evaluating:

- the physical realism of the predicted isothermal lines,
- the effectiveness of the model prediction within the range of the input data, and
- the repeatability and stability of the extrapolations⁸.

These are investigated in the following post assessment tests⁹.

Physical Realism of Predicted Isothermal Lines

PAT-1.1 Visually check the credibility of the fit of the isothermal $\log \sigma_o$ versus $\log t_u^*$ lines to the individual $\log \sigma_o, \log t_u$ data points over the range of the data (eg. Fig. C2.1).

[σ_o is the initial applied stress, t_u is the observed time to rupture and t_u^ is predicted time to rupture⁴]*

PAT-1.2 Produce isothermal curves of $\log \sigma_o$ versus $\log t_u^*$ at 25°C intervals from 25°C below the minimum test temperature, to 25°C above the maximum application temperature¹⁰ (eg. Fig. C2.2).

For times between 10 and 1,000,000h and stresses $\geq 0.8 \cdot \sigma_{o[\min]}$, predicted isothermal lines must not (a) cross-over, (b) come-together, or (c) turn-back.

[$\sigma_{o[\min]}$ is the lowest stress to rupture in the assessed data set]

PAT-1.3 Plot the derivative $\partial \log t_u^* / \partial \log \sigma_o$ as a function of $\log \sigma_o$ with respect to temperature to show whether the predicted isothermal lines fall away too quickly at low stresses (ie. $\sigma_o \geq 0.8 \sigma_{o[\min]}$) (eg. Fig. C1.2.2b).

The values of $-\partial \log t_u^* / \partial \log \sigma_o$, ie. n_u in $t_u^* \propto \sigma_o^{n_u}$, should not be ≤ 1.5 ,

It is permissible for n_u to enter the range 1.0-1.5 if the assessor can demonstrate that this trend is due to the material exhibiting either sigmoidal behaviour or a creep mechanism for which $n = 1$, eg. diffusional flow.

⁸ The underlying background to the development of the post assessment tests for CRDA is given in App. C1 and a re-evaluation of the effectiveness in App. C2.

⁹ The post assessment tests may be conveniently performed in a spreadsheet such as Excel.

¹⁰ The maximum temperature for which predicted strength values are required

Effectiveness of Model Prediction within Range of Input Data

PAT-2.1 To assess the effectiveness of the model to represent the behaviour of the complete dataset, plot predicted time versus observed time for all input data (eg. Fig. C2.11).

The log t_u versus log t_u^* diagram¹¹ should show:

- the log $t_u = \log t_u^*$ line (ie. the ideal line),
- the log $t_u = \log t_u^* \pm 2.5 \cdot s_{[A-RLT]}$ boundary lines^{12,13},
- the log $t_u = \log t_u^* \pm \log 2$ boundary lines¹⁴, and
- the linear mean line fit through the log t_u versus log t_u^* data points between $t_u^* = 100h$ and $t_u^* = 3 \cdot t_{u[max]}$.

The model equation should be re-assessed:

- (a) if more than 1.5% of the log t_u^* , log t_u (x,y) data points fall outside one of the $\pm 2.5 \cdot s_{[A-RLT]}$ boundary lines,^{15,16}
- (b) if the slope of the mean line is less than 0.78 or greater than 1.22, and
- (c) if the mean line is not contained within the $\pm \log 2$ boundary lines between $t_u^* = 100h$ and $t_u^* = 100,000h$.¹⁷

It may also be informative to plot standardised residual log times for all input data (i.e. A-SRLTs¹⁸) as a function of (i) log t_u^* , (ii) temperature and (iii) log σ_o (e.g. Fig.C1.2.3).

¹¹ Plotting log t_u versus log t_u^* (y versus x) is an important requirement of this test as it is necessary for regression analysis to reliably fit the linear mean line through the data points. This is because regression analysis minimises the error in the y-value, with the assumption that there is no error in the x-value. Clearly, log t_u must be the y-value. Nevertheless, for comparison with Issue 5 of Volume 5 Part Ia the instigator has the option of also plotting log t_u^* versus log t_u to see how the two approaches differ. A considerable deviation between both approaches (for example passing one version and failing the other) indicates excessive scatter in the residual, which is influencing the outcome of the test when plotted as log t_u^* versus log t_u . Further investigation of the sources for this scatter is advised, for example re-examining the pre-assessment, the material pedigree and whether the model really is a good fit to the data are advised.

¹² $s_{[A-RLT]}$ is the standard deviation of the residual log times for all the data at all temperatures, ie. $s_{[A-RLT]} = \sqrt{\{\sum_i (\log t_{u_i} - \log t_{u_i}^*)^2 / (n_A - 1)\}}$, where $i = 1, 2, \dots, n_A$, and n_A is the total number of data points

¹³ for a log normal error distribution, 98.75% of the data points would be expected to lie within log $t_u = \log t_u^* \pm 2.5 \cdot s_{[A-RLT]}$ boundary lines

¹⁴ i.e. the $t_u = 2 \cdot t_u^*$ and $t_u = 0.5 \cdot t_u^*$ boundary lines

¹⁵ This test can help to identify any errors and outliers in the dataset which should be corrected or deleted before the dataset is re-assessed.

¹⁶ Experience suggests that the $\pm 2.5 \cdot s_{[A-RLT]}$ boundary lines typically intersect the $t_u = 100h$ grid line at $t_u^* \leq 1,000h$ and $t_u^* \geq 10h$ respectively (App. C1). The explanation for those which do not is either an imbalance in the model fit (and hence the PAT-2.1a criteria) or excessive variability in the dataset (eg. as in the Type 304 18Cr11Ni working dataset, Fig. C1.4.3). In the latter case, consideration should be given to the scope of the material specification (in conjunction with the assessment instigator, eg WG3.x).

¹⁷ Ideally, the mean line will lie within the $\pm \log 2$ boundary lines at $t_u^* = 3 \cdot t_{u[max]}$.

¹⁸ A-SRLT is residual log time (log $t_u - \log t_u^*$) divided by the standard deviation for all residuals at all temperatures, ie. $A-SRLT = \{(\log t_u - \log t_u^*)\} / s_{[A-RLT]}$

PAT-2.2 To assess the effectiveness of the model to represent the behaviour of individual casts, plot at temperatures for which there are $\geq 10\%$ data points (at least at $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$):

- (i) $\log \sigma_0$ versus $\log t_u$ with $\log \sigma_0$ versus $\log t_u^*$, and
- (ii) $\log t_u$ versus $\log t_u^*$, with:
 - the $\log t_u = \log t_u^*$ line (ie. the ideal line),
 - the $\log t_u = \log t_u^* \pm 2.5 \cdot s_{[I-RLT]}$ boundary lines¹⁹
 - the $\log t_u = \log t_u^* \pm \log 2$ boundary lines¹⁴, and
 - the linear mean line fit through the $\log t_u$ versus $\log t_u^*$ data points between $t_u^* = 100\text{h}$ and $t_u = 3 \cdot t_{u[\max]}$.

and identify the best-tested individual cast(s)²⁰ (e.g. Fig. C2.12).

- (a) $\log t_u$ versus $\log t_u^*$ plots for individual casts should have slopes close to unity and be contained within the $\pm 2.5 \cdot s_{[I-RLT]}$ boundary lines. The pedigree of casts with $\partial(\log t_u)/\partial(\log t_u^*)$ slopes ≤ 0.5 or ≥ 1.5 and/or which have a significant number of $\log t_u^*$, $\log t_u$ data points outside the $\pm 2.5 \cdot s_{[I-RLT]}$ boundary lines should be re-investigated.

If the material and testing pedigrees of the data satisfy the requirements of Reference 3 and the specification set by the assessment instigator (eg. WG3.x) [as recommended in Sects. 2.3(i),(ii)], the assessor should first consider with the instigator whether the scope of the alloy specification is too wide. If there is no metallurgical justification for modifying the alloy specification, the effectiveness of the model to predict individual cast behaviour should be questioned.

The distribution of $\log t_u^*$, $\log t_u$ (x,y) data points about the $\log t_u = \log t_u^*$ line reflects the homogeneity of the dataset and the effectiveness of the predictive capability of the model (eg. Fig. C2.12). Non-uniform distributions at key temperatures should be taken as a strong indication that the model does not effectively represent the specified material within the range of the data, in particular at longer times.

The model equation should be re-evaluated if at any temperature:

- (b) the slope of the mean line through the isothermal $\log t_u$ versus $\log t_u^*$ data points is less than 0.78 or greater than 1.22, and
- (c) the mean line is not contained within the $\pm \log 2$ boundary lines between $t_u^* = 100\text{h}$ and $t_u^* = 100,000\text{h}$ ¹⁷.

Repeatability and Stability of Extrapolations

PAT-3.1 and PAT-3.2 represent the most practical solution to the problem of evaluating the reliability of assessed strength values predicted by extrapolation. In reality, the only sure way to check extrapolation reliability is to perform long term tests. The culling tests simulate this situation by removing information from the long term data regime and checking extrapolation reliability and stability by re-assessment of the reduced data sets.

¹⁹ $s_{[I-RLT]}$ is the standard deviation for the n_i residual log times at the temperature of interest, ie. $s_{[I-RLT]} = \sqrt{\{\sum_j (\log t_{u_j} - \log t_{u^*_j})^2 / (n_i - 1)\}}$, where $j = 1, 2, \dots, n_i$.

²⁰ The best-tested casts are identified as part of pre-assessment, eg. Tables A2b-A5b (see Sect. 2.3(iv)).

PAT-3.1 Randomly cull 50% of data (failed and unfailed) between $t_{u[\max]}/10$ and $t_{u[\max]}$ and repeat the assessment to check the repeatability of the extrapolation to variations in the data set (e.g. Fig. C1.2.7).

If the CRDA $R_{u/300kh}$ strength predictions determined at $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$ are not reproduced to within 10%, PAT-3.1 may be repeated. However, if the acceptability criterion is not met after the second cull, the main assessment should be repeated using a different model equation or procedure.

If the maximum test duration is less than 100,000h, the predicted strength comparison should be made for a test duration of $3.t_{u[\max]}$, i.e. with $R_{u/3.tu[\max]}$ strength values.

PAT-3.2 Cull 10% of the data set by removing the lowest stress data points (failed and unfailed) from each of the main test temperatures (i.e. 10% from each) and repeat the assessment to check the sensitivity and stability of the extrapolation procedure (eg. Fig. C1.2.7).

If the CRDA $R_{u/300kh}$ strength predictions determined at $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$ are not reproduced to within 10%, the main assessment should be repeated using a different model or procedure.

If the maximum test duration is less than 100,000h, the predicted strength comparison should be made for a test duration of $3.t_{u[\max]}$ (ie. with $R_{u/3.tu[\max]}$ strength values).

Meeting the requirements of PAT-3.2 is not mandatory in circumstances where it can be shown that the material is metallurgically unstable and that the removal of low stress values at temperatures up to 50°C above the maximum application temperature¹⁰ prevent this mechanism change from being represented by the reduced dataset.

3. SUMMARY

ECCC Recommendations Volume 5 Part Ia provides guidance for the assessment of creep rupture data sets. The principal aim is to minimise the uncertainty associated with strength predictions by recommending pre-assessment, the implementation of post assessment acceptability criteria, the use of well documented CRDA procedures and the performance of duplicate assessments.

Implementation of the ECCC recommendations require significant additional effort on completion of the first main assessment. However, this is regarded as entirely justified by the demonstrated reduction in the level of uncertainty associated with predicted strength values, in particular those involving extrapolation beyond the range of the available experimental data.

Quantification of the uncertainties associated with extrapolated strength values and those involving extended extrapolations should be a goal for the future.

4. REFERENCES

- 1 ECCC Recommendations Volume 2 Part I, 2005, 'General terms and terminology and items specific to parent material', ECCC Document AC/MC/96 [Issue 9], eds: Morris, P.F. & Orr, J., August-2005.
- 2 PD6525:Part 1:1990, 'Elevated temperature properties for steels for pressure purposes; Part 1 - Stress rupture properties', [Issue 2], Feb-1994.

3 ECCC Recommendations Volume 3 Part I, 2001, 'Data acceptability criteria and data generation: Generic recommendations for creep, creep-rupture, stress-rupture and stress relaxation data', ECCC Document 5524/MC/30 [Issue 5], eds: Granacher, J. & Holdsworth, S.R., May-2001.

Table 1 Target Requirements for a State-of-the-Art CRDA Procedure

The target requirements for a modern state-of-the-art creep rupture data assessment procedure are:

- well defined acceptability criteria for input data and guidelines for the treatment of unfailed tests,
- the means of generating a predictive equation with time as the experimentally dependent variable,
- a sound statistical base,
- an assessment including cast by cast analysis which is capable of incorporating metallurgical effects (eg. composition, oxidation),
- validity checks for extrapolation (eg. credibility of extrapolations with respect to data sets for individual casts),
- guidelines to minimise subjectivity associated with 'metallurgical judgement',
- an indication of the reliability of creep rupture strength predictions for durations up to 350,000h, with associated confidence limits, and
- manpower efficiency, ie. maximising on the use of computer power in a user friendly way.

Statistical methods should be investigated to:

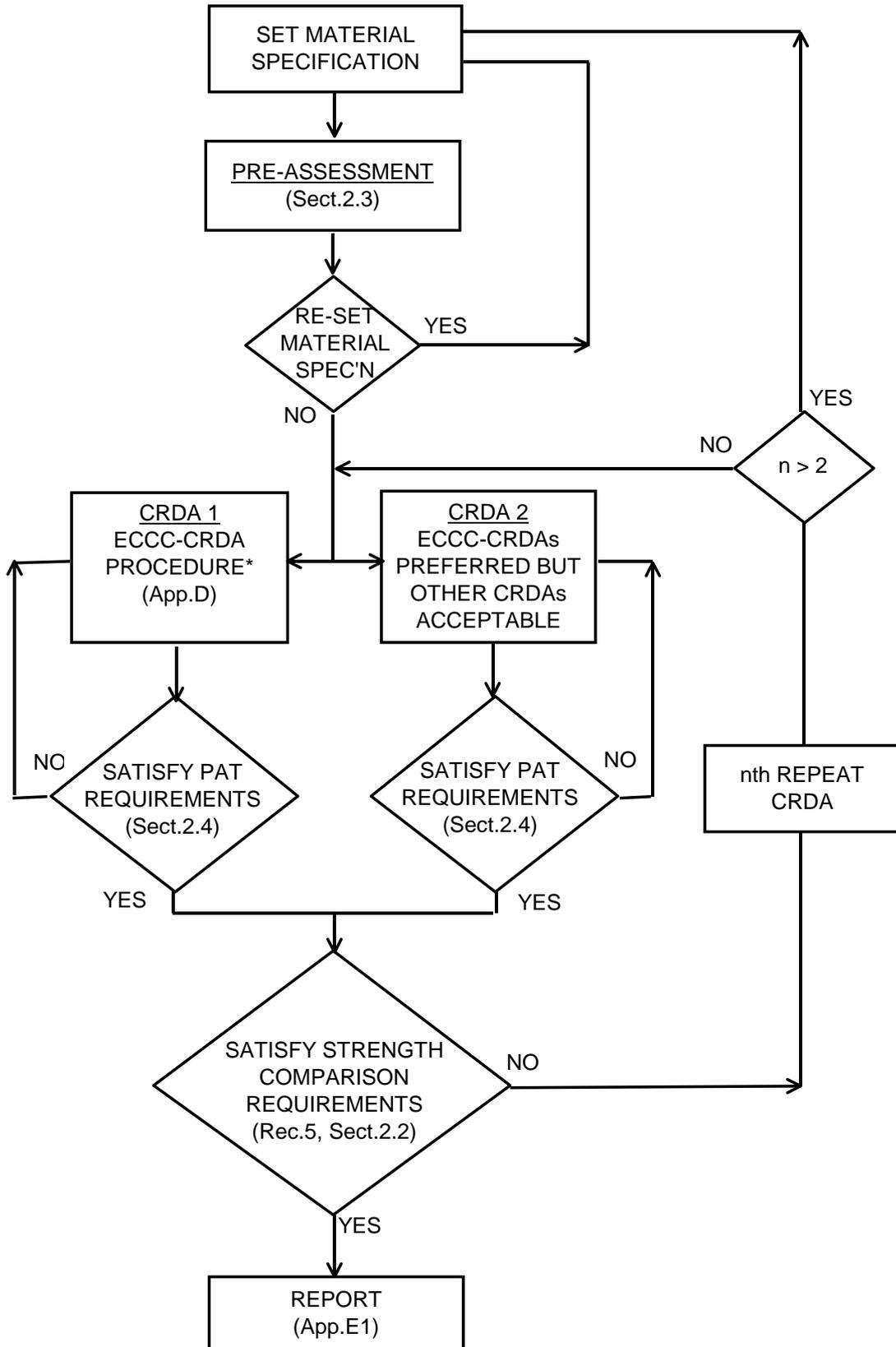
- establish a procedure for the treatment of unfailed tests,
- set guidelines for choosing the optimum distribution of the data set (ie. normal, log normal, log logistic etc.),
- establish tests of significance to minimise subjectivity where metallurgical judgement is required,
- produce an overall quotable value for errors, and
- produce a statistical confidence level for the preferred equation (ie. replacing the current empirical $\pm 20\%$ stress lines)

For the assessment of creep curves, there is the added requirement of a capability to fit curve families.

Table 2 Recommended Interim-Minimum and Target-Minimum CRDA Dataset Size Requirements for the Provision of Creep Rupture Strength Values for Standards

INTERIM-MINIMUM REQUIREMENTS	TARGET-MINIMUM REQUIREMENTS		
	Original (TM1)	TM2	TM3
		For datasets with ≥ 300 observations, originating from ≥ 10 casts, at ≥ 5 temperatures covering the range $T_{\text{MAIN}} \pm \geq 50^{\circ}\text{C}$	For datasets with ≥ 500 observations, originating from ≥ 20 casts, at ≥ 5 temperatures covering the range $T_{\text{MAIN}} \pm \geq 50^{\circ}\text{C}$
For ≥ 3 casts, there should be $t_u(T, \sigma_0)$ observations from: <ul style="list-style-type: none"> ➤ ≥ 3 tests at each of ≥ 3 temperatures, at intervals of 50 to 100°C - ≥ 3 tests per temperature (different σ_0) with $t_{u,\text{max}} \geq 10\text{kh}$ 	For ≥ 6 casts, there should be $t_u(T, \sigma_0)$ observations from: <ul style="list-style-type: none"> ➤ ≥ 5 tests at each of ≥ 3 temperatures in the design application range at intervals of 25 to 50°C - ≥ 4 tests per temperature (different σ_0) with $t_u \leq 40\text{kh}$ - ≥ 1 test per temperature with $t_{u,\text{max}} \geq 40\text{kh}$ 	For ≥ 5 casts, there should be $t_u(T, \sigma_0)$ observations from: <ul style="list-style-type: none"> ➤ ≥ 5 tests at each of ≥ 2 temperatures in the design application range at an interval(s) of 25 to 50°C - ≥ 4 tests per temperature (different σ_0) with $t_u \leq 35\text{kh}$ - ≥ 1 test per temperature with $t_{u,\text{max}} \geq 35\text{kh}$ 	For ≥ 5 casts, should be $t_u(T, \sigma_0)$ observations from: <ul style="list-style-type: none"> ➤ ≥ 5 tests at ≥ 1 temperature(s) in the design application range (at intervals of 25 to 50°C) - ≥ 4 tests per temperature (different σ_0) with $t_u \leq 35\text{kh}$ - ≥ 1 test per temperature with $t_{u,\text{max}} \geq 35\text{kh}$
<i>Predicted strength values determined from an Interim-minimum dataset shall be regarded as tentative until the data requirements defined in one of the Target-minimum columns are obtained</i>			

Note: this table does not cover the qualification of material manufacturers



* an ECCC-CRDA is one for which there is a procedure document (App.D)

Fig. 1 ECCC recommended creep rupture data assessment procedure

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APPENDIX A

WORKING DATA SETS FOR WG1 ASSESSMENT METHOD EVALUATION

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APPENDIX A1

WORKING DATA SETS FOR WG1 CRDA METHOD EVALUATION

S R Holdsworth [ALSTOM Power]

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APPENDIX A1

WORKING DATA SETS FOR WG1 CRDA METHOD EVALUATION

S R Holdsworth [ALSTOM Power]

Introduction

The guidelines given in the main text of ECCC-WG1 Volume 5 are based on the comprehensive evaluation of a number of multi-cast, multi-temperature working data sets collated specifically for the purpose.

A principal role of the ECCC-WG3.x groups is to perform assessments on typically, but not exclusively, large international data compilations. At least initially, these will not all be compiled from the results of well structured, co-ordinated test programmes, and will therefore be typically inhomogeneous. The WG1 working data sets were assembled to represent this situation. Their details are summarised in this and two following sub-appendices (Apps.A2,A3).

Creep Rupture Data Sets

Four working data sets were established for the creep rupture data assessment exercise. These were for the 2¼CrMo, 11CrMoVNb, 18Cr11Ni and 31Ni20CrAlTi. The alloys were selected to represent the spectrum of materials covered by the four ECCC-WG3.x working groups and specified to enable freely available data to be gathered from the majority of member countries. The specifications are summarised in Table A1.1. All the casts used in the CRDA assessment exercise met the requirements of the respective specifications.

The data sets were exchanged as EXCEL spreadsheet files.

The complexity and size of the data sets for the four alloys are apparent from Figs.A1.1-A1.4 and the tabulations summarising the distribution of the data as a function of test temperature and time to rupture (or test interruption) (Tables A1.2a-A1.5a).

Tables A1.2a to A1.5a also indicate the temperatures at which there are >5% and >10% broken testpiece data. This information is used to identify the dominant casts in Tables A1.2b to A1.5b.

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TABLE A1.1 SPECIFICATIONS FOR ECCC-WG1 WORKING DATASETS

2.25CrMo N+T (10 CrMo 9 10)

	C	Si	Mn	P	S	N	Al	B	Co	Cr	Cu	Mo	Nb	Ni	Ti	V	Harden	Temper	Rp _{0.2}	Rm
min	0.08	-	0.30	-	-	-	-	-	-	2.00	-	0.90	-	-	-	-	900	680	270	450
max	0.18	0.50	0.80	0.040	0.040	0.02	0.02	-	-	2.50	0.30	1.20	-	0.30	-	-	960	775	-	640

11CrMoVnb (X 19 CrMoVnbN 11 1)

	C	Si	Mn	P	S	N	Al	B	Co	Cr	Cu	Mo	Nb	Ni	Ti	V	Harden	Temper	Rp _{0.2}	Rm
min	0.12	0.20	0.40	-	-	0.03	-	-	-	10.00	-	0.50	0.20	0.30	-	0.18	1100	680	740	895
max	0.20	0.70	1.00	0.035	0.015	0.08	0.010	0.010	-	11.50	-	0.90	0.55	0.80	-	0.35	1170	720	-	1050

304H (X 6 CrNi 18 11)

	C	Si	Mn	P	S	N	Al	B	Co	Cr	Cu	Mo	Nb	Ni	Ti	V	Soln	Age	Rp _{0.2}	Rm
min	0.04	-	-	-	-	-	-	-	-	17.00	-	-	-	8.00	-	-	1000	-	230	490
max	0.10	1.00	2.00	0.040	0.030	-	-	-	-	19.00	-	0.50	-	11.00	-	-	1100	-	-	700

Incoloy 800 (X 5 NiCrAlTi 31 20, X 9 NiCrAlTi 32 21)

	C	Si	Mn	P	S	N	Al	B	Co	Cr	Cu	Mo	Nb	Ni	Ti	V	Soln	Age	Rp _{0.2}	Rm
min	-	-	-	-	-	-	0.15	-	-	19.00	-	-	-	30.00	0.15	-	1100	-	170	450
max	0.10	1.00	1.50	0.015	0.015	-	0.60	-	0.50	23.00	0.75	-	-	35.00	0.60	-	1200	-	-	-

TABLE A1.2a DISTRIBUTION OF STRESS RUPTURE DATA POINTS FOR 2.25CrMo AS A FUNCTION OF TEMPERATURE AND TIME

TEMP °C	TOTAL DATA		TEST DURATION, h																		COUNTRY					TOTAL	% BOF TOTAL
	B	UB	<10kh		10-20kh		20-30kh		30-50kh		50-70kh		70-100kh		>100kh		t _{r(max)}	(i)	(ii)	(iii)	(iv)	(v)					
			B	UB	B	UB	B	UB	B	UB	B	UB	B	UB	B	UB											
			B		UB		B		UB		B		UB		B								UB				
450	19	5	17	2	1	1	2	1	1	2							37.6	18		3	3		24	2			
454	3		2	1													10.1				3		3	0			
475	45	7	20	8	2	1	6	1	2	3							141.3		47	5		52	4				
482	3		3														1.5				3		3	0			
500	174	21	125	12	5	8	2	14	4	6	7	3	4	1	20	95	120.7	57	23	20		195	17				
510	1		1														0.9				1		1	0			
520	1		1														0.3			1		1		0			
525	73	9	48	3	8	2	3	7	9	2	2	3					77.8	10	69	3		82	7				
535	1		1														0.2			1		1		0			
538	10	4	8	1	2	1			1				1				21.9		14			14	1				
540	1		1														0.6			1		1		0			
550	230	24	156	4	19	18	4	14	2	13	7	8	4	7	3	118.3	67	23	58	106		254	23				
565	70	9	59	1	4	1	1	6	2	4							36.7		66		13	79	7				
575	71	11	43	7	10	3	8	7	2	1	6		1				131.7	17	65			82	7				
590	3		3														0.6			3		3		0			
593	35	1	25	2	1	4		2	2	2							54.4		27		9	36	3				
600	184	8	132	3	21	1	10	7	14	2	4	2	1	1	1	113.4	46	26	28	92		192	18				
615	2		2														0.7			2		2		0			
620	13		13														5.5		11		2	13	1				
625	10		10														6.9		10			10	1				
630	3		3														0.3		3			3	0				
635	1		1														2.7		1			1	0				
650	65		63	2													11.1		10	55		65	6				
TOTALS	1018	99																215	137	375	359	31	1117				

98 castis

% broken test points > 107%

% broken test points > 5%

TABLE A1.2b BEST-TESTED CAST ANALYSIS FOR 2.25CrMo WORKING DATA SET

CASTS	TEMPERATURE, °C								TOTALS
	475	500	525	550	565	575	600	650	
7R	4	7		9			6		26
7ZT		11	9	10		8	9		47
RG	5		5			5	4		19
MAA		6		8			5	4	23
MAB		6		5			5	4	20
MaB		6		6			7	3	22
MAC		8		12			6	4	30
MaC		5		6			6	3	20
/MaD		5		7			7	3	22
MAE		5		5			5	4	19
MaE		5		6			7	3	21
MAF	5	10	3	10			10	6	44
MaF		6		5			6	3	20
MAL		6		6			5	4	21
MAM		6		6			5	5	22
MAN		5		5			5	4	19

TABLE A1.3a DISTRIBUTION OF STRESS RUPTURE DATA POINTS FOR 11CrMoVnB AS A FUNCTION OF TEMPERATURE AND TIME

TEMP °C	TOTAL		TEST DURATION, h																		COUNTRY		TOTAL	% B OF TOTAL
	DATA		<10kh		10-20kh		20-30kh		30-50kh		50-70kh		70-100kh		>100kh		$t_{r(max)}$		(i)	(ii)				
	B	UB	B	UB	B	UB	B	UB	B	UB	B	UB	B	UB	B	UB	B	UB						
425	1	1	1	1															2		2	0		
450	12	12	6	3	4	1	2	6	2										16		8	4		
475	14	1	3		4		1														15	4		
500	69	22	34	4	11	1	7	2	6	7	5	3	4	4	2	1	1	1	59		32	22		
550	146	3	72	1	22		10	18	18	1	14	1	8	2	2	1	1	1	67		82	46		
600	73	6	41		17	1	8	4	4		2		1	4	1	1	1	1	51		25	23		
TOTALS	315	45																	195		165	360		

33 casts

% broken test points > 10%

TABLE A1.3b BEST-TESTED CAST ANALYSIS FOR 11CrMoVNb WORKING DATA SET

CAST	TEMPERATURE, °C					TOTALS
	450	475	500	550	600	
320B	3		5	5	7	20
320C	3		5	4	4	16
GC		4		6	7	17
LD		4		6	6	16
LN		4		7	8	17

TABLE A1.4a DISTRIBUTION OF STRESS RUPTURE DATA POINTS FOR TYPE 304H AS A FUNCTION OF TEMPERATURE AND TIME

TEMP °C	TOTAL DATA		TEST DURATION, h												COUNTRY		TOTAL	% B OF TOTAL				
	B	UB	<10kh		10-20kh		20-30kh		30-50kh		50-70kh		70-100kh		>100kh				t _{r(max)}	(i)	(ii)	
			B	UB	B	UB	B	UB	B	UB	B	UB	B	UB	B	UB						
400	8	1	1	1	5													8		8	0	
482	6	6																		6	6	1
500	18	2	3	3	1	1	4												20	20	2	2
538	5	5																	5	5	1	1
550	57	8	2	6	2	1	2	1	3	1	2	2	2	2	2	2	2	20	45	65	7	7
565	31	28	2	2			1												31	31	4	4
570	3	3																	3	3	0	0
593	30	30																	30	30	4	4
600	174	12	14	12	4	1	6	2	8	2	6	2	1	3	3	3	27	159	186	22	22	
620	3	3																	3	3	0	0
625	21	9	11	11	1	1													21	21	3	3
650	261	10	213	27	3	10	7	3	3	1	1	1	1	1	1	1	22	249	271	35	35	
670	3	3																	3	3	0	0
677	1	1																	1	1	0	0
700	118	4	93	13	2	8	2	2	1	1	2	2	2	2	2	1	110.8	12	110	122	15	15
704	7	7																	7	7	1	1
720	3	3																	3	3	0	0
732	19	16	1	1	1	1													19	19	2	2
750	13	9	4	4															13	13	2	2
788	2	2																	2	2	0	0
800	14	3	10	3	1	1													9	17	2	2
816	5	5																	5	5	1	1
871	1	1																	1	1	0	0
899	1	1																	1	1	0	0
	796	47																118	725	843		

96 casts

% broken test points > 10%

% broken test points > 5%

TABLE A1.4b BEST-TESTED CAST ANALYSIS FOR TYPE 304H WORKING DATA SET

CASTS	TEMPERATURE, °C							TOTALS
	500	550	600	650	700	750	800	
121A	6	4	6	7	6		4	33
121B	7	3	4	6	4		3	27
24		5	6	5				16
3504			4	4	6	3		17
3516			5	5	6	3		19
3517			5	5	6	3		19
3518			6	6	5	3		20
3527			5	8	6			19

TABLE A1.5a DISTRIBUTION OF STRESS RUPTURE DATA POINTS FOR INCOLOY 800 AS A FUNCTION OF TEMPERATURE AND TIME

TEMP °C	TOTAL DATA		TEST DURATION, h														COUNTRY			TOTAL % B OF TOTAL		
	B	UB	<10kh		10-20kh		20-30kh		30-50kh		50-70kh		70-100kh		>100kh		t _{r(max)}	(i)	(ii)		(iii)	
			B	UB	B	UB	B	UB	B	UB	B	UB	B	UB	B	UB						
500	42	12	31	1	5	1	5	6	1	4							34.5	2	52		54	8
550	49	3	30		7	1	5		3		4	1					58.8		52		52	10
600	65	9	43	1	11		2	2	6	2	2		1			4	73.2	6	56	12	74	13
650	50	8	28		11		7		2	1	1	3	1			1	79.4	2	56		58	10
700	79	14	58	1	10	2	5	2	4	1	2	3	5				64.0	25	54	14	93	16
750	12	1	10		1						1					1	58.2	2	11		13	2
800	68	2	53		8	1	2	1	4								43.8	22	24	24	70	14
850	8		8														8.3	3	5		8	2
900	56	5	43	2	9		1	2	3	1							48.2	24	11	28	61	11
950	11		10		1												10.2		11		11	2
1000	46	3	39	2	1	1	3		3								43.1	17	10	22	49	9
1050	9		8		1												14.8			9	9	2
TOTALS	495	57																103	342	107	552	

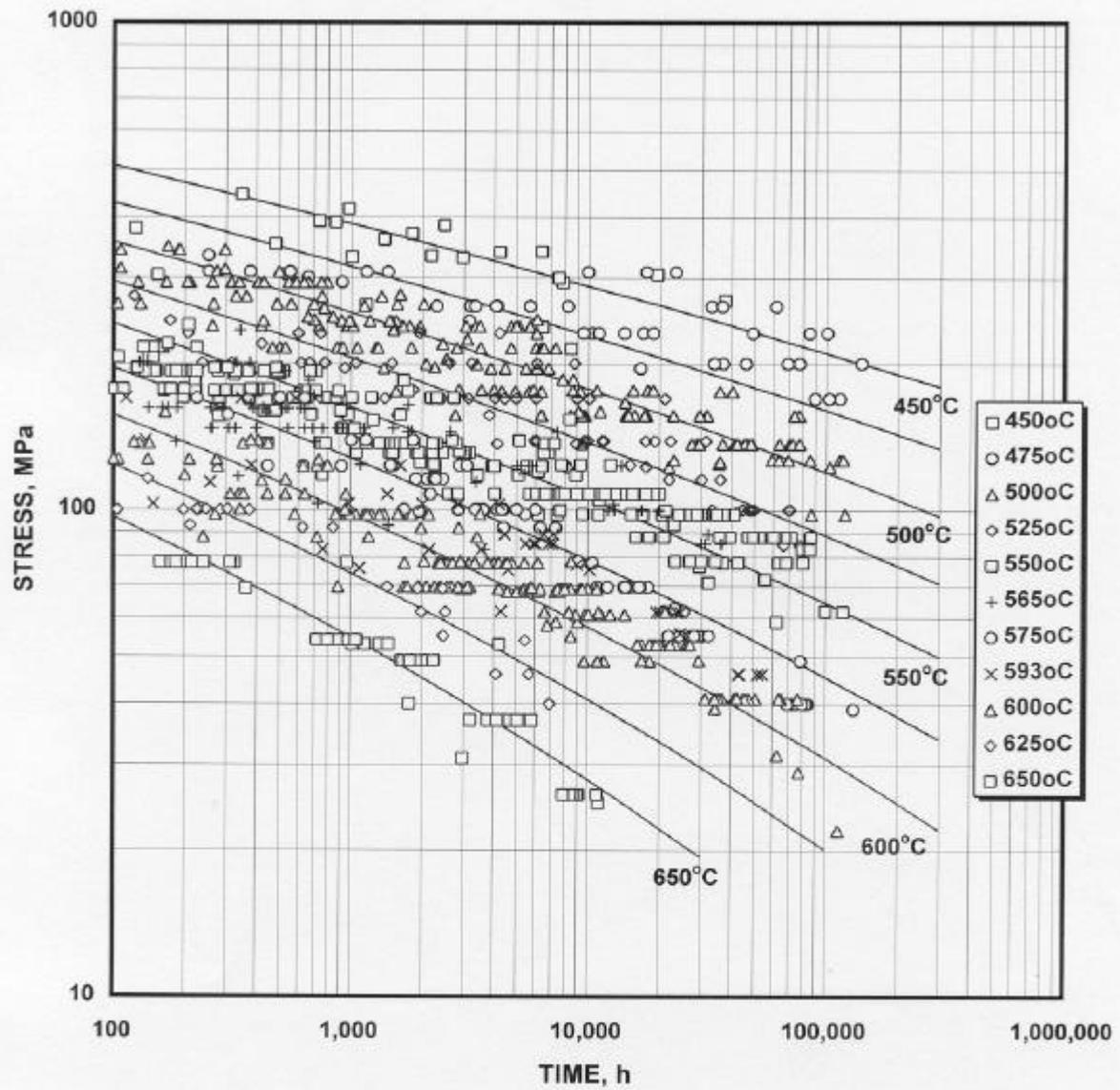
33 casts

% broken test points > 10%

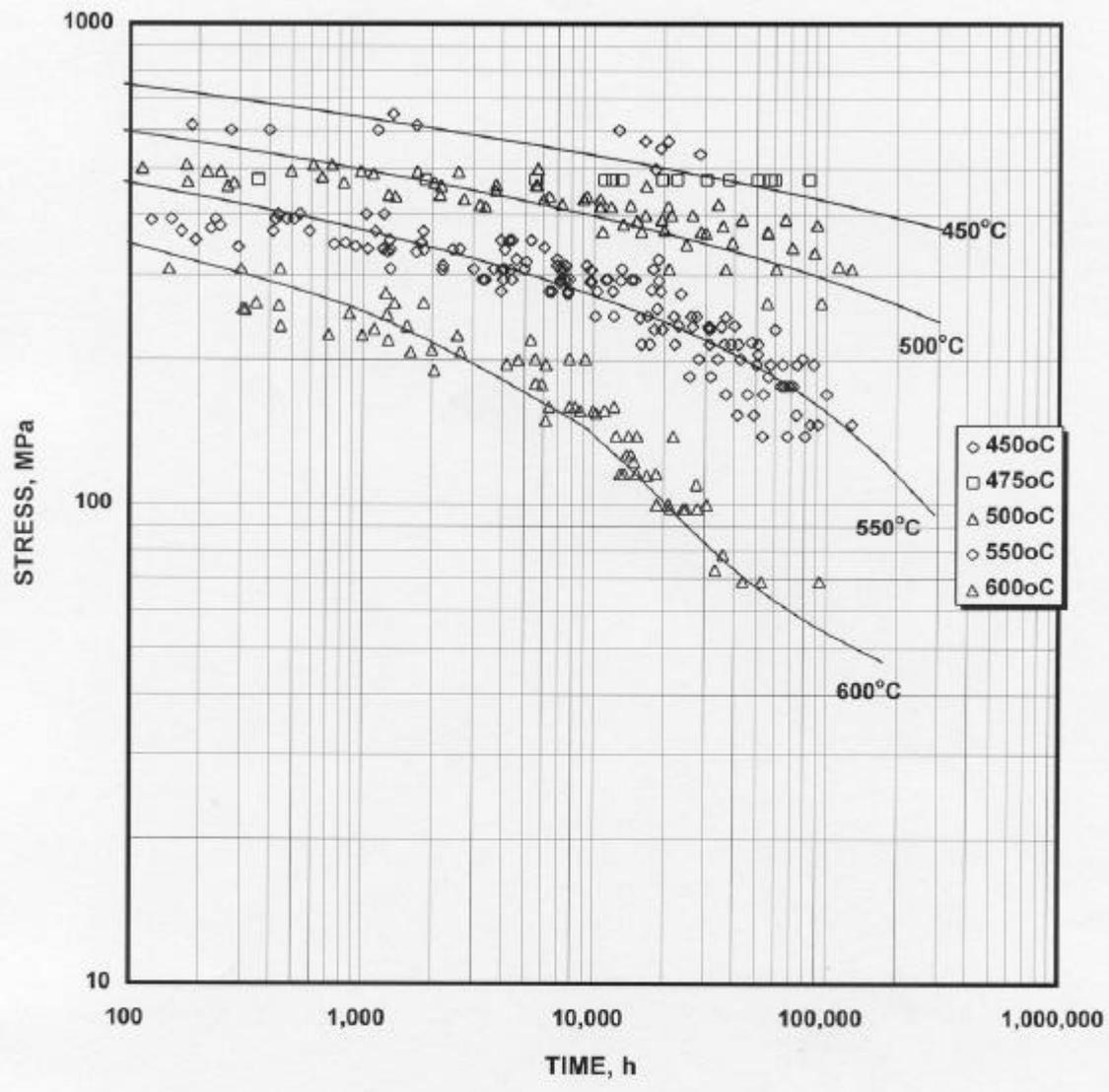
% broken test points > 5%

TABLE A1.5b BEST-TESTED CAST ANALYSIS FOR INCOLOY 800 WORKING DATA SET

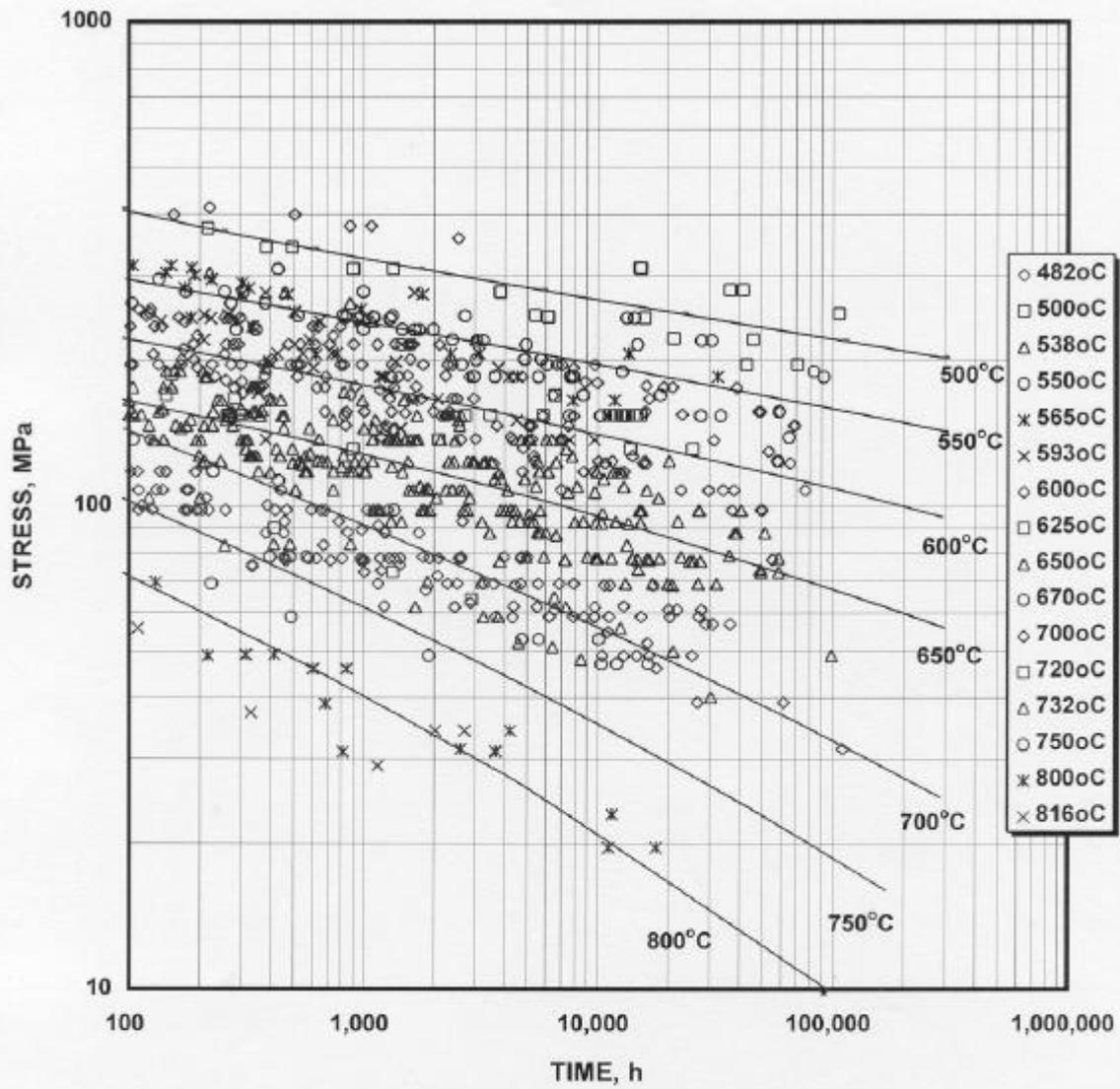
CASTS	TEMPERATURE, °C								TOTALS
	500	550	600	650	700	800	900	1000	
57m					5	5	4	5	19
AAP	3	4	4	3	3				17
ABC	3	4	4	3	3	3	3	3	26
ACE	3	5	4	4	3				19
ACG	3	5	4	3	3				18
AED	2	4	2	2	2	3	3	3	21
AEE	2	4	2	3	3	3	3	3	23
SE	4	3	4	5	3	3			22
VV	3	2	6	4	2	3			20
VY	5	4	5	4	2	3			23
WB	4	3	4	3	2	3			19
fCA			2		2	4	4	4	16
fCB			2		2	4	5	4	17
fCD			2		3	5	5	4	19
fCF			2		2	5	4	4	17



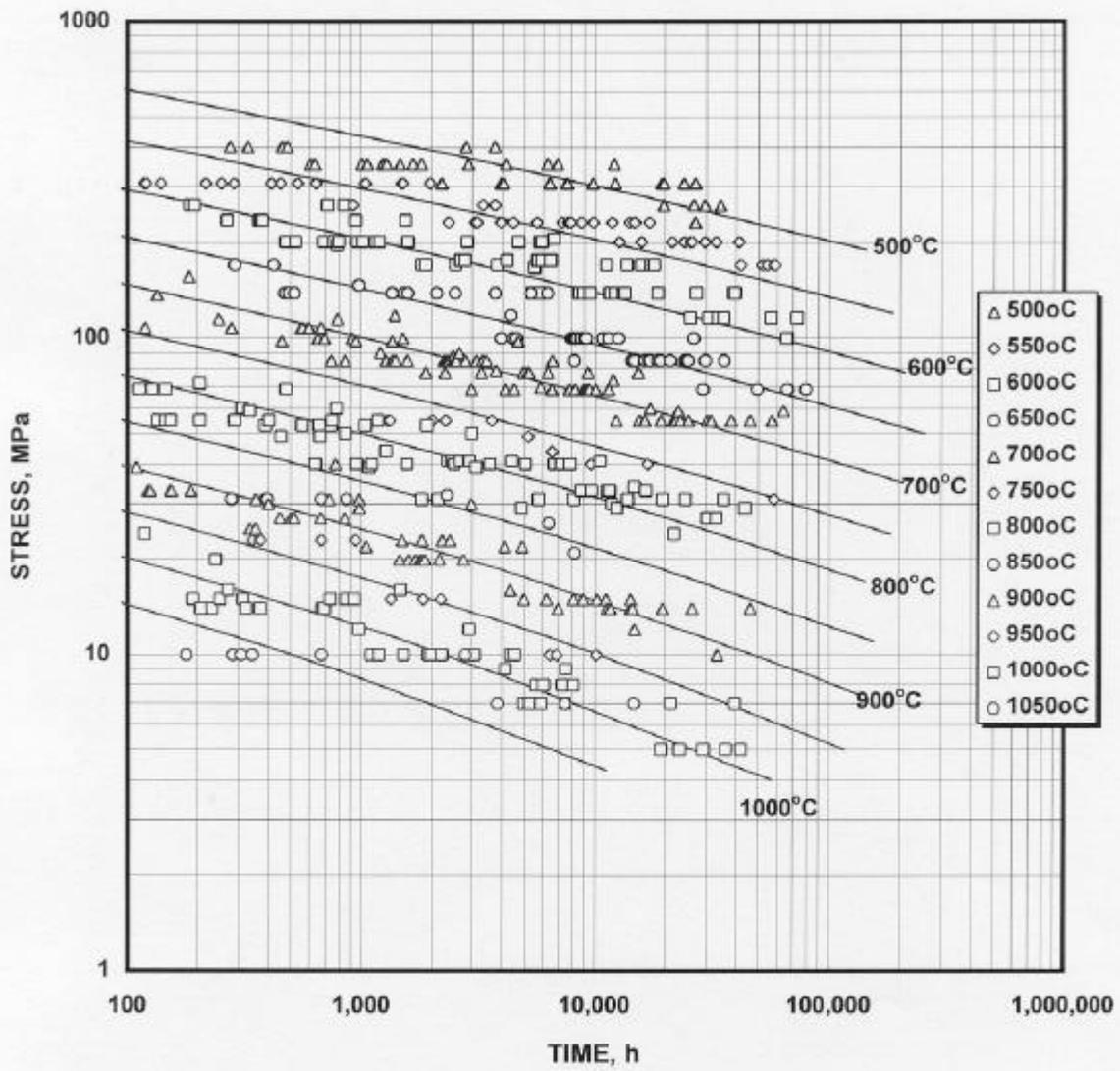
2CrMo working dataset



11CrMoVNb working dataset



Type 304 18Cr11Ni working dataset



Incoloy 800 working dataset

APPENDIX B1
REVIEW OF CREEP RUPTURE DATA ASSESSMENT METHODS

C K Bullough [ALSTOM Power]

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APPENDIX B1

REVIEW OF CREEP RUPTURE ASSESSMENT METHODS

CK Bullough (European Gas Turbines¹)

B1.1 INTRODUCTION

A number of creep rupture data assessment (CRDA) methods were evaluated during the preparation of the ECCC-WG1 Volume 5 Recommendations contained in an earlier section of this Volume. Appendix C contains a review of the *results* of those evaluations. In this Appendix, the methods are characterised and contrasted as to their nature and application. The main features of each method are also summarised in tabular form towards the end of this Appendix. This information has been provided to aid those performing assessments to choose the most appropriate method for their needs, and to understand each method's advantages and limitations.

The Recommendations state the need for at least two CRDAs in order to adequately define the design rupture strength values for standards. They also state that each CRDA should be performed independently, and at least one should be performed using a method for which there is an ECCC procedure document. The underlying reasons for these recommendations are:

- i) the difficulty in different analysts obtaining the same strength values using the same, but poorly defined procedure; and
- ii) the acknowledgement that it is for the time being impractical to recommend a single CRDA methodology for use by ECCC.

At present, there are only two ECCC CRDA procedure documents, for the ISO 6303 method and for the DESA Version 2.2 method (Appendix D). The remaining methodologies described in tables towards the latter part of this Appendix are consequently not ECCC CRDA methodologies, but are included in order to indicate the current state-of-the-art of creep rupture data assessment within ECCC, particularly with regard to the results published in Appendix C².

During an early stage of the work of ECCC WG1 to evaluate CRDA methodologies, it was realised that the details of how the method is applied can markedly affect the resulting strength values (see also Ref. B1.1). By way of illustration, the phrase 'the results were obtained by the Larson-Miller method' may refer to one of several variants. In one variant the value of the Larson-Miller constant 'C' may be set at the value of 20, in another it may be fitted by regression analysis. In addition, the stress function in some variants is

¹ This review was partly prepared whilst the author was employed at ERA Technology Ltd.

² Any methodology can become an "ECCC CRDA Methodology" providing a procedure document is approved by WG1 for inclusion in Appendix D.

represented by a constant and log stress term (that is, a straight line on log stress vs. log time axes), but more commonly by a polynomial in log stress of order 2 through to 5. Sometimes other stress functions are evaluated, and in at least one variant a data reduction stage is applied to the data prior to the fitting of model.

There is therefore no single 'Larson-Miller method', even though it is probably the most widely known technique to fit creep rupture data. Instead, the Larson-Miller model form is encapsulated in several, distinct CRDA methodologies. This justifies the extensive evaluation performed by ECCC WG1 of different methodologies, and the provision of detailed procedures to minimise subjectivity. In this last respect, however, it is noted that metallurgical judgement is subjective, but a highly important component of some methods, and is a valuable input into others. By its very nature, though, metallurgical judgement is difficult to unambiguously record in a written procedure.

B1.2 IMPLEMENTATION

It is assumed that the analyst has access to general computing facilities, including the ability to import and manipulate data, to plot data and the results, and to perform multiple linear regression. In that circumstance many of the CRDA methodologies reported in this Appendix may be applied without the need to purchase any specialised software. For example, some CRDA methodologies (eg the SIMR and SPERA methods) may be readily performed in PC-versions of well-known spreadsheet programmes such as Lotus-123 and Microsoft Excel. Others, however, require more elaborate statistical packages (eg. Nuclear Electric Method), or are most often applied using specially-written or proprietary software (eg ISO 6303 and DESA 2.2), although this may not be strictly necessary.

At least three methodologies are probably best applied using specially-written or proprietary software, owing to their particular requirements. Both the ISO 6303 and DESA 2.2 method use a scanning technique and multi-linear regression to fit some non-linear models³, and such techniques are not widely available (or may be difficult to apply reproducibly). The Minimum Commitment Method employs a double heat-centring technique which would be very difficult to reproduce without the proprietary software programmes. At the other extreme, a third methodology, the Graphical Averaging and Cross-Plotting Method, in theory requires no software at all. In practice, its application is greatly eased by the use of a spreadsheet programme.

B1.2 MODEL FORMS, ERROR DISTRIBUTIONS AND OPTIMISATION METHOD

All methods except the Graphical Averaging and Cross-Plotting Method are based on the concept of a model relating logarithm of rupture life to a function of temperature and stress (Eq.1), an error distribution describing the deviation of the experimental behaviour to the observed behaviour, and an optimisation method for determining the model coefficients (sometimes also the parameters of the error distribution). Many of the methodologies are based on models termed "time-temperature-parameters" (Eq.2). For such models, the systematic variation due to temperature is grouped with the rupture life, and related to a

³ Non-linear models are those in which one or more of the coefficients of the explanatory variables (ie. stress and temperature) are not linear with respect to the response variable (even after transformation).

temperature-independent function in stress. One attraction of time-temperature-parameters is that a master curve is obtained that readily permits interpolation.

The most important class of time-temperature-parameters are those based on the Mendelson-Roberts-Manson (MRM) generalised equation (Eq.3, Ref. B1.2), most commonly fitted as Eq.4, where $P(\sigma_o)$ is a polynomial function of stress (usually the logarithm of stress). By appropriate choice of values of the coefficients, many of the common model forms may be derived. For example, with $q = 0$, $T_a = 0$, $R = -1$ equation 4 reduces to the Larson Miller model (the "constant" $C = -\log t_a$), as shown by equation 5.

$$\log t_r^* = f(T, \sigma_o) \quad \dots \quad (1)$$

$$g(T, \log t_r^*) = h(\sigma_o) \quad \dots \quad (2)$$

where T is the absolute temperature, and σ is the applied stress.

$$P(\sigma_o) = \frac{\sigma_o^q (\log t_r^* - \log t_a)}{(T - T_a)^R} \quad \dots \quad (3)$$

$$\log t_r^* = \frac{P(\sigma_o)}{\sigma_o^q} (T - T_a)^R + \log t_a \quad \dots \quad (4)$$

$$\log t_r^* = \frac{P(\sigma_o)}{T} + \log t_a \quad \dots \quad (5)$$

A number of other time-temperature-parameters exist, and rupture data may also be fitted using algebraic models which do not necessarily result in a master curve.

The majority of assessment methodologies use $\log t_r^*$ as the dependent variable, with a normal error distribution fitted by linear regression. (Effectively, this results in a log-normal distribution about time). The predicted life is most often the mean of the normal distribution of $\log t_r^*$. As noted previously, DESA 2.2 and ISO 6303 use a scanning technique to estimate the value of the non-linear coefficient T_a . The ISO 6303 method uniquely stipulates a preliminary data reduction stage. Isothermal strength values are determined which are then fitted by time-temperature-parameters.

Only the Nuclear Electric Method examines different error distributions. Uniquely, it employs maximum likelihood methods to fit the model and error distribution (several may be evaluated). A further advantage in that approach is that unfailed test points may be included in the estimation process; other methodologies take into account unfailed test data, but do not include them directly.

The Graphical Averaging and Cross-Plotting Method uses a robust but labour-intensive strength-averaging approach that requires no time-temperature-parameter model or optimisation of coefficients. On the other hand, there is no predictive equation with which to

calculate life, which instead is usually calculated graphically. The SIMR method also has no predictive equation, since the tabulated strength values are obtained from the averaged results of three or four time-temperature-parameter models.

B1.3 RESULTS, OUTPUT AND POST ASSESSMENT TESTS

Generally, those programmes that are based on predictive models will report the coefficients of those models, and appropriate statistical measures such as the coefficient of determination, R^2 . In some cases, strength values at specified temperatures and durations will also be reported that have been computed from the model equation and reported coefficients. Where they are not reported (eg the intermediate assessments in the SIMR Method), the analyst will need to compute them. Since polynomials in log stress are common, this will require the use of iterative techniques.⁴ The majority of computerised methods will also produce plots of predicted and observed rupture life. Some, such as the specially-written computer software employed to apply the ISO 6303 procedure, will also show unbroken test points for information.

Whilst no CRDA methodology currently applies all of the ECCC recommended post assessment tests (PATs), it is known that an appropriate module is being developed for DESA 2.2. In addition, some of the methods refer to other aspects of the ECCC recommendations, or have been revised to include the recommendations directly. It is particularly simple to apply the first category of PATs "Physical Realism of Predicted Isothermal Lines" and second category of PATs "Effectiveness of Model Prediction within Range of Input Data" (see Recommendations Section) to those methodologies that are based on the MRM equation (Eq.3) other time-temperature parameters, or algebraic model forms. This is because predicted life, and the differential with respect to stress are readily computed. Those methodologies that have no final predictive model are more difficult to evaluate. In this circumstance, isothermal models must first be fitted to the averaged strength values in order to estimate predicted life.

The third category of PATs, "Repeatability and Accuracy of Extrapolations" will be very labour intensive to perform for those methodologies such as the Graphical Averaging and Cross-Plotting Method that require the re-preparation of new isothermal curves for each material within the culled data sets. On the other hand, this group of PATs are relatively straightforward to perform for highly automated methodologies. Further details on the background to the development of the PATs may be found in Appendix C, an example of their application is to be found in Appendix E.

B1.4 CONCLUDING REMARKS

Of the several methodologies summarised in the following pages only the ISO 6303 and Graphical Averaging and Cross-Plotting Methods have been recently used for the derivation of strength values for European standards. The SIMR Method has been used for some Swedish standards (but it is poorly documented), and the DESA 2.2 method is likely to receive considerable use in future. The Minimum Commitment Method has, in

⁴ That is, a value of strength is used to calculate an estimate of rupture life, and is increased or decreased in an iterative fashion until the estimated rupture life and the the required duration converge.

conjunction with a Larson Miller variant, been used to calculate strength values for US standards, but it has not been widely used in Europe. A new UK method is being prepared within British Standards, that will include many of the state-of-the-art statistical procedures, and will be used for future standardisation purposes.

One of the perceived benefits of the ECCC WG1 post-assessment acceptability criteria is that they objectively test the results of assessments, thereby promoting the target requirements for a European a state-of-the-art CRDA procedure outlined in the Recommendations section. This approach has also stimulated the production of high-quality ECCC Procedure Documents (Appendix D), whilst permitting the new and improved procedures to come into general use as they are developed.

Potential users of each CRDA method should ensure that the results and output meet their requirements, otherwise there may be an unanticipated extra effort for them to prepare appropriate tabulated values, and figures for reporting and application of the post assessment tests.

The summaries of CRDA methodologies have been prepared in association with members of ECCC WG1, whose kind assistance is noted by the author. The overall document controller of Volume 5, welcomes details of any other methodologies used for standardisation purposes or of possible interest to ECCC Members. Potential contributors are invited to provide details under the headings shown.

B1.5 REFERENCES

- B1.1 Y. Monma, K. Kanazawa, S. Nishijima, "Computational Models for Creep and Fatigue Analysis", VAMAS Technical Report 7, Technical Working Area 10 (Materials Databanks), October 1990.
- B1.2 A. Mendelson, E. Roberts, S.S. Manson, "Optimisation of Time Temperature Parameters for Creep and Stress Rupture, with Application to Data from German Long Term Creep Programme" NASA Technical Note NASA TN D-2975, August 1965.

B2 REVIEW OF CREEP STRAIN ASSESSMENT METHODS

Section to be added in Issue 3.

B3 REVIEW OF STRESS RELAXATION ASSESSMENT METHODS

Section to be added in Issue 3.

Abstract**DESA 2.2**

The programme DESA 2.2. is a highly flexible tool for applying time-temperature parametric equations to the assessment of rupture data and creep strength data. A full range of parametric equations may be assessed, comprising a selectable time-temperature parameter in combination with a polynomial of a monotonic function of stress σ_0 in the form σ_0^m , $m = 0.1$ to 1 or $\log \sigma_0$. The order of polynomial can range from 2 to 5 and DESA 2.2 has been prepared for all of these functions to be selectable from a menu. The programme has not yet been used to generate strength values for standards, but has been used for homogeneously as well as inhomogeneously distributed, single heat and multi-heat data sets.

All data are fitted simultaneously, with log time as the dependent variable, and by applying log-normal statistics. Although statistical measures are available to the analyst following the fitting process, these are provided as a guide only. The analyst is expected to use their metallurgical judgement to decide which function best represents the data. Special methods are applied to overcome non-physical behaviour of 2nd and 3rd order polynomials and certain linear and non-linear coefficients can be adjusted manually. These methods can also be used to fit correlated curve families comprising stress rupture curves as well as stress to specific strain curves. Moreover, a temperature dependent time correction is possible to influence the position and slope of the isothermal curves in the lower temperature range.

Note: a full procedure document is available in Appendix D of this volume.

(Source: JG/MM)

Basis

Name / Version:	DESA 2.2
Original Literature References	Granacher J, Monsees, M, und Pfenning, A: Anwenderhandbuch für des Programme DESA 2.2, IfW Th Darmstadt, 1995
Procedure Reference:	DESA assessment procedure document for DESA 2.2, doc ref 5524/WG1/146, Issue 1 (included in Appendix D)
Procedure Owner/ Software Supplier:	Institut für Werkstoffkunde, TH Darmstadt
Computer Platform/OS/ Other	IBM Compatible Personal Computer / DOS 5.0
Data Reduction:	None
General Model Form:	Time temperature parameter $P(t, T)$ with dependence of up to 5th order polynomial of the stress function $f(\sigma_0) = \sigma_0^m$, $m=0.1$ to 1 , or $\log \sigma_0$.
Common Model Forms:	Manson-Haferd, Larson Miller 2nd degree polynomial of $f(\sigma_0)$ see above
Error Distribution:	Normal about $\log t$
Optimisation (Fitting) Method:	Minimises in $(\log t - \log t^*)$, t - measured time, t^* - predicted time by linear or non-linear regression.
Performs ECCC WG1 PAT's?	No. Related programme PASAC under development, see 5524/WG1/146.
Treatment of unfailed points?	No
Cast-by-cast analysis?	Possible
Used for creep strain/ stress relaxation/ other?	Has been used for times to specific strains
Examples of recent use for standardisation	-

Results

tr* to table	No	tr* & data to graph	Yes
model coefficients to table	Yes	master curve to graph	Yes
Variance/std deviation/ deviance or similar	Yes	confidence intervals	Yes
Strength table	Related programme ZDESA available, see 5524/WG1/147.		

Abstract

Graphical Averaging and Cross-Plotting Method

The procedure known as the "Graphical Averaging and Cross-Plotting Method" has been used for many years, principally in Germany but also in Austria and other countries, for the assessment of stress rupture data, stress to specific total plastic strain data and stress relaxation data, to produce the strength values reported in DIN and EN standards.

There has been considerable experience in Germany in applying the procedure for the assessment of large data sets, and it is thought to produce optimised values with consistent accuracy.

The procedure consists of the following steps.

- data selection according to a chosen material specification in national or international standards or one chosen by another authorised body.
- fitting of isothermal curves for each cast graphically or by computerised polynomial least squares fit.
- derivation of stress values for each cast at selected durations, e.g. 100, 300, 1000, 3000, 10,000, 30,000, 100,000 and 200,000h

When preparing the isothermal curves, the extrapolations do not exceed the longest test duration of a broken specimen by more than a factor of 3. Unbroken points are taken into account by manual adjustment of the isothermal curves. The isothermal data fitting generates a several sets of data comprising stress, duration and temperature, one for each cast, which form the data input for the determination of isochronal (constant duration) curves plotted on stress-temperature axes. Strength values for the multi-cast data set are determined at each duration and temperature combination by taking the arithmetic or logarithmic average of the stresses of the individual casts.

The isochronal mean curves for the multi-cast data set are then examined by consideration of the family of curves in isochronal (σ vs. T) and isothermal ($\log \sigma$ vs. $\log t$) plots. During this "cross-plotting" step, the values of the isothermal and isochronal mean curves may be repeatedly manually adjusted by the analyst to give the best fit to the data.

The isothermal mean curves are compared with the test data at each temperature. This stage is used as a final check of the accuracy of the isochronal mean curves with respect to the mean and the overall trend of each isothermal data set.

- All test points are examined to determine if they lie within a $\pm 20\%$ scatterband in stress on the master curve. The material pedigree information, and test data are evaluated for each outlying data point, to determine the reasons for its behaviour. Where outliers result from a material variable, it is usually recommended that the data selection process should be repeated based on a revised input specification, and the analysis re-run.

All of the isothermal mean curves for stress to rupture and stress to specific strains are judged as a family to avoid them crossing over, or converging in an unrealistic manner.

(Source: HK edited by CKB)

Basis

Name / Version:	Graphical Averaging and Cross-Plotting Method
Original Literature References	Bendick, W., Haarmann, K., Wellnitz, G., "Evaluation of design values for Steel 91" Proc. of ECSC Information Day on the Manufacture and Properties of Steel 91 for the Power Plant and Process Industries, 5 November 1992, Dusseldorf, Germany.
Procedure Reference:	ECCC WG1 doc ref 5524/WG1/52, June 1993. An ECCC procedure document is being prepared for inclusion as Appendix D3 in Issue 3 of Volume 5.
Procedure Owner/ Software Supplier:	-
Computer Platform/OS/ Other	A computer is unnecessary, but may help.
Data Reduction:	Yes, data are rejected if they lie outside of the $\pm 20\%$ scatterband on stress applied to the master curve.
General Model Form:	Not applicable.
Common Model Forms:	Not applicable.
Error Distribution:	Not applicable.
Optimisation (Fitting) Method:	Fitting of the mean curves relies on the judgment of the analyst.
Performs ECCC WG1 PAT's?	-
Treatment of unfailed points?	Unfailed points may be used to manually modify the stress values from the isothermal fits applied to the data of each cast. More importantly, unfailed tests often provide information for the assessment of stress to specific strain. The mean curves for stress to rupture and stress to specific strains are judged as a family, and in that sense the unfailed tests may affect stress to rupture .
Cast-by-cast analysis?	In a preliminary stage, the data from each cast is fitted seperately.
Used for creep strain/ stress relaxation/ other?	The method has been used for the derivation of stress to specific total plastic strain and for the assessment of stress relaxation data.
Examples of recent use for standardisaton	All DIN and some EN standards contain rupture and creep strength values obtained by this method.

Results

tr* to table	-	tr* & data to graph	-
coefficients to table	-	master curve to graph	Yes
Variance/std deviation/ deviance or similar	-	confidence intervals	Yes ($\pm 20\%$ on stress)
Strength table	Yes		

Abstract**ISO 6303: 1981 Annex**

The procedure known as the ISO method" or "ISO 6303" has been used for many years, principally in the UK, for the assessment of stress rupture data, to produce the stress values included in BSI and ISO standards. The developed procedure formed the basis of the Annex to the standard ISO 6303: 1981 having been derived from existing procedures.

It is a generalised procedure, whose final equation form can become either a simple Larson Miller type, or a more complex form involving several constants, depending on the optimised curve used to fit the data.

Whilst other procedures also employ parametric equations based on the Mendelson-Roberts-Manson generalised form, the ISO 6303 procedure has a unique preliminary data reduction stage. At temperatures for which there are sufficient data (and sources of data), isothermal lines are fitted using $\log \sigma$ as the dependent variable. Strength values at specified durations are then obtained from the isothermal curves, which are then fitted using several rupture equations derived from the Mendelson-Roberts-Manson generalised form, and \log time as the dependent variable. This preliminary data reduction stage is thought to overcome the inhomogeneity of large data sets, that is, if data are inhomogeneously distributed through temperature, or if there is a preponderance of short-term tests.

A full user guide is available in Appendix D of this document.

(Source: JO/CKB)

Basis

Name / Version:	ISO 6303: 1981 Annex
Original Literature References	See refs 2-5 of Appendix D1 of this volume.
Procedure Reference:	Appendix D1 of this volume.
Procedure Owner:	Owner: British Steel, Swinden Labs, Rotherham, UK. Software cannot ordinarily be supplied.
Computer Platform/OS/ Other	At British Steel the Fortran Programs are currently mounted on DEC-VAX, but may be transferred to PC in future.
Data Reduction:	In a preliminary stage, isothermal curve fits provide input strength data at specified durations for preparation of the master curve.
General Model Form:	Mendelson-Roberts-Manson generalised form.
Common Model Forms:	Several models are evaluated, typically: Larson-Miller, Manson-Haferd, and Manson-Brown. Manson-Haferd most often results.
Error Distribution:	Log-normal about stress (preliminary stage - isothermal) Log-normal about time (master curve)
Optimisation (Fitting) Method:	Linear regression
Performs ECCC WG1 PAT's	-
Treatment of unfailed points?	Unfailed points are considered during the preparation of the input strength data from the isothermal curves, up to the longest broken test duration. The strength data may be manually adjusted.
Cast-by-cast analysis?	(The analyst may consider the acceptability of the computer fitted isothermal curves on the basis of the behaviour of individual casts.)
Used for creep strain/ stress relaxation/ other?	Strain-time: individual or grouped strain-time curves may be evaluated to provide times to specific strain. Stress relaxation: individual or grouped curves may be used to provide data to specified durations. In both cases, isothermal lines are then fitted, followed by the derivation of the master curve, as for rupture data.
Examples of recent use for standardisation	BSI PD 6525: 1990 Part 1 (Amendment No 1)

Results

tr* to table		tr* & data to graph	Yes
coefficients to table	Yes	master curve to graph	Yes
Variance/std deviation/ deviance or similar		confidence intervals	Points evaluated if outside of +20% limits on stress
Strength table	Yes		

Abstract

SPERA

The SPERA method utilizes a stress function identical to that found in the Minimum Commitment Method (MCM) and temperature function that is similar, but which omits the linear temperature term. The stress function is of order 2, and is therefore inherently resistant to turn-back or other instability, and this makes the SPERA method particularly suitable for small data sets. Except for the literature references, there is no documented procedure for SPERA. However, the SPERA method may be a suitable option for the analyst to consider during a more general regression approach to the assessment of rupture properties (see, for example, the SIMR method and Nuclear Electric Method).

(Source: CKB)

Basis

Name / Version:	SPERA
Original Literature References	Spera, D.A., "A linear creep damage theory for thermal-fatigue of materials", Thesis, University of Wisconsin, 1968. Spera, D.A., "Calculation of elevated temperature cyclic life considering low-cycle fatigue and creep" NASA TN D-5317, Lewis Research Centre, Cleveland Ohio, 1969. Spera, D.A., "Calculation of thermal fatigue life based on accumulated creep damage." NASA TN D-5489, Lewis Research Centre, Cleveland Ohio, 1969.
Procedure Reference:	-
Software Supplier:	(Available via HTM-DB, JRC Petten, The Netherlands. May also be fitted by other linear regression packages.)
Computer Platform/OS/ Other	-
Data Reduction:	-
General Model Form:	$t_r = t_0 \cdot F_1(T) \cdot F_2(\sigma_0)$
Common Model Forms:	$F_1(T) = \exp\left(\frac{-Q}{RT}\right)$ $F_2(\sigma_0) = \sigma_0^{B_0} \cdot 10^{(B_1 \cdot \sigma_0 + B_2 \cdot \sigma_0^2)}$
Error Distribution:	Log-normal about time.
Optimisation (Fitting) Method:	Linear regression.
Performs ECCC WG1 PAT's	-
Treatment of unfailed points?	-
Cast-by-cast analysis?	-
Used for creep strain/ stress relaxation/ other?	-
Examples of recent use for standardisation	-

Results

tr* to table	-	tr* & data to graph	-
coefficients to table	-	master curve to graph	-
Variance/std deviation/ deviance or similar	-	confidence intervals	-
Strength table	-		

Abstract

Minimum Commitment Method

The Minimum Commitment Method (MCM) in its fullest form was developed in the United States to represent the state-of-the-art of parametric methods. However, it is nowadays used in a reduced form, and usually in conjunction with other model forms, for the preparation of strength values for American Standards. Its advantages are perceived to be: i) a method of treating data on a cast-by-cast basis; ii) a (second order) stress function that is inherently more stable than the high order polynomials used by other parametric methods; and iii) the option of fitting sigmoidal behaviour and points of inflection.

Unfortunately, there is no rigorous procedure document for MCM, and its present implementation is defined in one specific, computer programme, which is not widely available. The similarity of the SPERA model and the MCM model has already been noted. Neither model contains interaction terms between stress and temperature, and therefore the shape of the curve on log stress vs log time axes cannot alter with increasing temperature, as some data sets require.

MCM's unique cast-by-cast analysis permits the determination of one or two coefficients that describe the behaviour of individual casts relative to the mean behaviour of the data set. Each cast must have a minimum number of data points, and the data from a cast with only 3 data points has the same influence on the "mean" coefficient values as one with many more.

The full MCM analysis, which is hardly if ever used at present, permits: i) stress and temperature interaction terms; ii) temperature station functions, rather than continuous temperature functions; and iii) stress functions composed of two third order functions joined by a spline, to fit points of inflection etc.

(Source: CKB)

Basis

Name / Version:	Minimum Commitment Method
Original Literature References	Goldhoff, R.M., Towards the Standardization of Time-Temperature-Parameter Usage in Elevated Temperature Data Analysis, Int Conf on Creep and Fatigue, Philadelphia, Pa 1973, Paper No 1974. Manson, S.S., and Muraldihan U., Analysis of Creep Rupture Data for Five Multiheat Alloys by the Minimum Commitment Method Using Double Heat Term Centring Technique, Research Project 638-1, EPRI CS-3171, July 1983.
Procedure Reference:	None.
Procedure Owner:	Materials Property Council, New York, New York.
Computer Platform/OS/ Other	IBM PC, DOS, (other computer software required to perform the method is not generally available)
Data Reduction:	None
General Model Form:	$\log t_r + A.P.\log t_r + P = G$
Common Model Forms:	$P = R_1(T - T_{mid}) - R_2 (1/T - 1/T_{mid})$ $G = B + C.\log\sigma_o + D.\sigma_o + E.\sigma_o^2 \quad A = 0$
Error Distribution:	Log normal about time
Optimisation (Fitting) Method:	Linear regression (two stage in order to fit cast coefficients)
Performs ECCC WG1 PAT's	-
Treatment of unfailed points?	-
Cast-by-cast analysis?	Yes. Two coefficients are fitted for each cast.
Used for creep strain/ stress relaxation/ other?	-
Examples of recent use for standardisation	Prager, M., Gold, M., Voorhees, H.R., New stresses for 1 and 1¼Cr-Mo-Si alloys, Symp. on New Alloys for Pressure Vessels and Piping, ASME Pressure Vessel and Piping Conf., June 17-21, 1990.

Results

tr* to table	Yes	tr* & data to graph	-
coefficients to table	Yes	master curve to graph	-
Variance/std deviation/ deviance or similar	Yes	confidence intervals	-
Strength table	-		

Abstract**P***

The P* method has been developed recently, and incorporates the Norton law fitting of minimum creep rate data into the Larson Miller equation for rupture. It was originally proposed for small homogeneously distributed data sets, and has only recently been adapted for use with large, inhomogeneously distributed data sets. In the latter circumstance, a pre-assessment is proposed that includes data reduction. To date, the P* method has not been used to derive strength values for standards, and there is not yet a fully-documented procedure. However, it remains an interesting alternative for the evaluation of high temperature properties of materials for which both minimum creep rate and rupture data are available.

(Source: CKB)

Basis

Name / Version:	P*
Original Literature References	Merckling G., Kriech- und Ermüdungsverhalten ausgewählter metallischer Werkstoffe bei höheren Temperaturen, Doctors Thesis, Karlsruhe, 1989.
Procedure Reference:	No full procedure, some application details in ECCC WG1 doc ref 5524/WG1/68, Sept 1993.
Procedure Owner:	Istituto Ricerca Breda, Milan, Italy
Computer Platform/OS/ Other	-
Data Reduction:	Pre-assessment recommended according to ECCC WG1 doc ref 5524/WG1/126.
General Model Form:	Refinement of Larson Miller Parameters including the Norton equation.
Common Model Forms:	-
Error Distribution:	Implicitly log-normal
Optimisation (Fitting) Method:	Linear regression
Performs ECCC WG1 PAT's	-
Treatment of unfailed points?	No
Cast-by-cast analysis?	Consideration of cast-by-cast behaviour recommended as part of the pre-assessment phase.
Used for creep strain/ stress relaxation/ other?	Creep strain - yes. Stress relaxation - no.
Examples of recent use for standardisation	None.

Results

tr* to table	Yes	tr* & data to graph	Yes
coefficients to table	Yes	master curve to graph	Yes
Variance/std deviation/ deviance or similar	Yes	confidence intervals	Yes
Strength table	Yes		

Abstract**Nuclear Electric Method**

The Nuclear Electric Method has been developed in recent years on the basis of a modern regression approach to data analysis. Two specific features are unique to the procedure: i) the evaluation of error distributions other than log-normal; ii) the simultaneous treatment of all test data (including the incorporation of unfailed test points) in a rigorous fashion. The procedure can include any rupture equation that can be linearised, and may therefore be considered primarily as a general "framework" for evaluating rupture data. To use the Nuclear Electric Method the analyst should be familiar with maximum likelihood optimisation methods, failure distributions other than log-normal, and general techniques for the inclusion of right-censored (unfailed) data.

(Source: CKB)

Basis

Name / Version:	Nuclear Electric Method
Original Literature References	Barraclough, D.R., Evaluation of high temperature design data, ECCC WG1 doc ref 5524/WG1/91 March 1994.
Procedure Reference:	Barraclough, D.R., Logsdon J, The statistical analysis of creep data for low alloy steel, CEBG Report NWR/SSD/84/0069, ECCC WG1 doc ref 5524/WG1/60 Barraclough, D.R., Logsdon J, A revised method for the analysis of stress rupture data, Nuclear Electric Report TD/SEB/REP/1664/92, ECCC WG1 doc ref 5524/WG1/58
Procedure Owner:	Nuclear Electric plc, Berkeley Technology Centre, UK
Computer Platform/OS/ Other	(The statistical analysis was performed in GLIM 4, available from NAG Ltd, Oxford UK. It is not known whether the "macros" are generally available.)
Data Reduction:	-
General Model Form:	Regression approach using a variety of linearisable models.
Common Model Forms:	Mendelson-Roberts-Manson models, algebraic models.
Error Distribution:	A variety of error distributions about time are evaluated as part of the procedure.
Optimisation (Fitting) Method:	Maximum likelihood method.
Performs ECCC WG1 PAT's	-
Treatment of unfailed points?	Direct inclusion during optimisation, using an iterative, maximum likelihood method.
Cast-by-cast analysis?	Regression models may be adapted to include metallurgical variables.
Used for creep strain/ stress relaxation/ other?	-
Examples of recent use for standardisation	None

Results

tr* to table	Yes	tr* & data to graph	Yes
coefficients to table	Yes	master curve to graph	-
Variance/std deviation/ deviance or similar	Yes	confidence intervals	Yes
Strength table	-		

Abstract

SIMR Method

The basis of the SIMR Method is to perform three or four rupture data assessments applied by linear regression using a variety of the well known model forms. It proposes that no one single method is superior in long-term prediction than any other. In that circumstance, an average value for the strength at specified durations is obtained from the arithmetic mean values from the individual assessments. Sometimes, however, the individual assessments may be thought by the analyst to be a poor fit at long-times, and may be removed from the averaging procedure.

Unfortunately, the fairly arbitrary choice of model for each assessment method, the subjectivity of removing the strength values of some assessment results at long times, and the lack of other directions in applying the SIMR method, mean that it would be difficult to apply in a reproducible manner by other analysts. A further disadvantage is that the manner by which strength values are averaged means that there is no final equation for interpolation or extrapolation. (Some of the post assessment tests, for example, require the preparation of isothermal fits through the *strength values* in order to calculate predicted time.)

(Source: CKB)

Basis

Name / Version:	SIMR Method		
Original Literature References	Ivarsson, B., Evaluation of different methods for extrapolation of creep rupture data, SIMR Institutet for Metallforskning Report: IM-1794, June 1983.		
Procedure Reference:	(There are some application details in the above, but no procedure reference.)		
Procedure Owner:	SIMR Institutet for Metallforskning, Stockholm, Sweden		
Computer Platform/OS/ Other	-		
Data Reduction	-		
General Model Form:	Various models based on Mendelson-Roberts-Manson equation, together with algebraic models.		
Common Model Forms:	Manson Brown, Orr-Sherby-Dorn, Manson Haferd, Larson Miller, Soviet Algebraic Methods.		
Error Distribution:	Log-normal about time		
Optimisation (Fitting) Method:	Implicitly linear regression		
Performs ECCC WG1 PAT's	-		
Treatment of unfailed points? (If so, how?)	-		
Cast-by-cast analysis? (If so, how?)	-		
Used for creep strain/ stress relaxation/ other?	-		
Examples of recent use for standardisation	Believed to have been used for Swedish standards.		

Results

tr* to table	-	tr* & data to graph	-
coefficients to table	-	master curve to graph	-
Variance/std deviation/ deviance or similar	-	confidence intervals	-
Strength table	Yes		

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APPENDIX C1

**REVIEW OF WG1 EVALUATION OF CREEP RUPTURE DATA ASSESSMENT METHODS
RECOMMENDATION VALIDATION**

Creep Rupture Data Assessment Original Assessments 1995

S R Holdsworth [ALSTOM Power]

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APPENDIX C1

REVIEW OF WG1 EVALUATION OF CREEP RUPTURE DATA ASSESSMENT METHODS RECOMMENDATION VALIDATION

S R Holdsworth [GEC ALSTHOM LST]

C1.1 INTRODUCTION

In order to formulate ECCC guidelines for the assessment of creep rupture data, members of ECCC-WG1 performed a number of creep rupture data assessments (CRDAs) on four large multi-cast creep rupture data sets for 2¼CrMo, 12CrMoVNb, 18Cr11Ni and 31Ni20CrAlTi (Incoloy 800) (Table C1.1). The materials were selected to represent the spectrum of alloys covered by the four ECCC-WG3.x working groups and specified to enable freely available data to be gathered from several sources. The material specification details and dataset summaries are given in App.A.

The evaluation exercise was also used to refine and validate a series of post assessment acceptability criteria ([C1.1] & Sect.2.4, main text). These were to be a key feature of the ECCC guidelines, but they were a new concept and significant development was necessary to optimise and validate their effectiveness.

Seven CRDA approaches were evaluated by various group members (Table C1.1)¹. The ISO and DESA methodologies offered a selection of model parametric equation options with procedures which were relatively well documented [C1.2,3]. Nevertheless, the results of the comparison exercise indicated that even these were open to interpretation, and more rigorous procedures have been produced for ECCC (Apps.D1,D2). The graphical averaging and cross plotting method [C1.4] is a development of the CRDA procedure recommended in DIN 50 118 [C1.5] and is highly regarded by some specialists. However, this approach is time consuming by comparison to other methods.

The other methods evaluated were less well documented. The SIMR method predicts strength levels on the basis of mean values determined from four independent CRDAs employing different parametric equations [C1.6]. P* is a refinement of Larson-Miller [C1.7], while the TUG approach employs the Spera equation as its first option for parametric curve fitting [C1.8]. The NE predictions employ state-of-the-art modelling techniques and survival statistics to make use of the results from unfailed tests, but the methodology is at an early stage of development [C1.9].

The results of the assessments and their use to develop and validate the post assessment tests (PATs) are reported in the following appendix.

C1.2 CREEP RUPTURE DATA ASSESSMENT

The respective sizes of the four WG1 working data sets for the 2¼CrMo, 12CrMoVNb, 18Cr11Ni and 31Ni20CrAlTi alloys are evident from Tables A2 to A5 and Figs.A1 to A4 (App.A). These are large multi-source, multi-cast, multi-temperature creep rupture data collations typical of those to be evaluated by the ECCC-WG3.x working groups. In each case, rupture lives extend out to around 100,000h. The objective of the WG1 CRDA analyses was to isothermally model the data within the range of the data and to predict 300,000h rupture strength levels (ie. $\sim R_{r/3.tr[max]}^2$).

¹ The reader is referred to App.B1 for a review of CRDA procedures.

² For information on ECCC terms and terminology, the reader is referred to [C1.10].

The results of the WG1 assessments of the four alloys at their $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$ temperatures³ are shown in Figs.C1.1a-4c respectively. These represent a total of 48 assessments by 10 organisations. With the exception of the 18Cr11Ni data, the expectation of achieving a within 10% variability in the prediction of $R_{r/100,000h}$ values when $t_{r/3.tr[\max]}$ is ~100,000h is not unrealistic, although never met (Table C1.2, penultimate row). The reproducibility of $R_{r/300,000h}$ predictions (ie. $R_{r/3.tr[\max]}$) is significantly greater (typically >50%). The evidence of uncertainties of this magnitude should give great cause for concern, particularly since the majority of assessments were performed by nationally recognised high temperature specialists in CRDA analysis. This experience forms the basis for the WG1 recommendation for a repeat check assessment (Rec.1, Sect.2.1 & Fig.1; main text). The evidence also provides a strong justification for the implementation of effective post assessment acceptability criteria (Rec.4, Sect.2.1, main text).

C1.3 VALIDATION OF POST ASSESSMENT ACCEPTABILITY CRITERIA

The PATs and post assessment acceptability criteria defined in Sect.2.4 of the main text assess three main aspects of the results from the CRDA, ie. (i) the physical realism of the predicted isothermal lines, (ii) the effectiveness of the model prediction within the range of the input data, and (iii) the repeatability and stability of extrapolated strength values.

The PATs evolved over the working life of ECCC-WG1. As a consequence, although PATs were applied by most participants in the CRDA evaluation exercise, they were not always the final recommended versions. The PAT-2 tests, in particular, were refined shortly before the first issue of Volume 5 due to feedback from the field trials. As a consequence, their effectiveness was validated by a single analyst using the results from most of the 48 assessments performed. The output from this re-analysis is contained in this appendix. The results from the current PATs are summarised in Table C1.3. The background to the development of the post assessment acceptability criteria is reviewed in the following sections.

C1.3.1 Physical Realism of Predicted Isothermal Lines

There are three physical realism checks. PAT-1.1 is a simple visual check of the fit of the isothermal $\log \sigma_o$ versus $\log t_r^*$ lines to the individual $[\log \sigma_o, \log t_r]$ co-ordinates over the range of the data (eg. Fig.C1.2.1)⁴. The subsequent PATs require significant analytical effort and should not be performed if the predicted isothermal behaviour does not reasonably reflect the experimental observations.

PAT-1.2 and PAT-1.3 provide visual and quantitative indications of the physical realism of the predicted isothermal lines both within and beyond (within practical limits) the range of the experimental data. PAT-1.2 checks that isothermal $\log \sigma_o$ versus $\log t_r^*$ plots do not (a) cross-over, (b) come-together, or (c) turn-back for predicted times between 10 and 1,000,000h and stresses greater than $0.8 \cdot \sigma_{o[\min]}$ at 25°C intervals from 25°C below the minimum test temperature, to 25°C above the maximum application temperature⁵ (eg. Fig.C1.2.2a). PAT-1.3 quantifies the limit of acceptability on the tendency to turn-back by checking that values of minus $\partial(\log t_r^*)/\partial(\log \sigma_o)$ are never less than 2 (ie. n_r in $t_r^* \propto \sigma_o^{n_r}$) (eg. Fig.C1.2.2b). Setting the limit at 2, detects those predicted lines which tend to turn-back for times shorter than $t_{r[\max]}$ or $3 \cdot t_{r[\max]}$ at stress levels below $0.8 \cdot \sigma_{o[\min]}$ (eg. Fig.C1.1.2b).

³ $T_{\min[10\%]}$ and $T_{\max[10\%]}$ refer to the minimum and maximum temperatures at which there are greater than 10% data points (determined during pre-assessment). T_{main} is the temperature with the highest number of data points.

⁴ σ_o is stress, t_r is observed time and t_r^* is predicted time [10]

⁵ the maximum temperature for which predicted strength values are required

C1.3.2 Effectiveness of Model Prediction within Range of Input Data

The second category of PAT tests assess the effectiveness of the model prediction within the range of the input data. PAT-2.1 evaluates the ability of the model equation to represent the behaviour of the complete dataset at all temperatures, whereas PAT-2.2 examines its capability to represent the behaviour of individual casts at certain key temperatures. The format of the PAT-2 tests has developed significantly during the course of the WG1 CRDA assessment activity.

PAT-2.1

The original PAT-2 tests were based on plots of standardised residual log time (A-SRLT⁶ or I-SRLT⁷). Examples of these for A-SRLT versus $\log t_r$, $\log t_r^*$, temperature and $\log \sigma_o$ are given for most of the assessments performed on 2¼CrMo (Fig.C1.3.1), 12CrMoVNB (Fig.C1.3.2), Type 304 18Cr11Ni (Fig.C1.3.3) and Incoloy 800 (Fig.C1.3.4). The attraction of using standardised residuals was that statistically based acceptability limit lines could be set, and ± 2.5 was adopted with a limitation of 1% on the number of data points which could fall outside these bounds⁸. The approach initially appeared to be very successful, but difficulties emerged which led to its refinement.

The original PAT-2.1 test undertook to assess the effectiveness of the model to represent the behaviour of the complete data set by assessing A-SLTRs as a function of (i) $\log t_r^*$, (ii) temperature and (iii) $\log \sigma_o$. The model equation was to be re-assessed if (a) the slope of the A-SRLT versus $\log t_r^*$ trend line exceeded $\pm 0.25^9$, and (b) more than 1% of the A-SLTRs exceeded ± 2.5 (eg. Fig.C1.2.3).

The choice of $\log t_r^*$ or $\log t_r$ as the correlating parameter in part (a) of the test was the subject of much debate within WG1. However, with increasing experience, it became apparent that the employment of either $\log t_r^*$ or $\log t_r$ in isolation could be misleading, since the indication of an acceptable slope on the basis of one did not necessarily mean acceptability in terms of the other (eg. Figs.C1.3.1-1,C1.3.3-3). The solution was to utilise both parameters in the form of a $\log t_r^*$ versus $\log t_r$ plot, incorporating $\pm 2.5.s_{[A-RLT]}$ boundary lines to be consistent with the original form of the test (eg. Fig.C1.2.4).

Three constraints are set in the PAT-2.1 test, and their significance for various assessments is demonstrated for 2¼CrMo (Fig.C1.4.1), 12CrMoVNB (Fig.C1.4.2), 18Cr11Ni (Fig.C1.4.3) and Incoloy 800 (Fig.C1.4.4). These are that:

- (a) more than 1.5% of the $[\log t_r^*, \log t_r]$ data points do not fall outside one of the $\pm 2.5.s_{[A-RLT]}$ boundary lines,
- (b) the slope of the mean $\partial(\log t_r^*)/\partial(\log t_r)$ line is between 0.78 and 1.22, and
- (c) the mean line is contained within $\pm \log 2$ boundary lines for $t_r = 100\text{h}$ and $t_r = 100,000\text{h}$.

⁶ A-SRLT is residual log time divided by the standard deviation for the n_A residual log times at all temperatures, ie. $A-SRLT = \{(\log t_r - \log t_r^*)/s_{[A-RLT]}\}$, where $s_{[A-RLT]} = \sqrt{\{\sum_i (\log t_{r_i} - \log t_r^*)^2/(n_A - 1)\}}$, and $i = 1, 2, \dots, n_A$

⁷ I-SRLT is residual log time divided by the standard deviation for the n_I residual log times at the temperature of interest, ie. $I-SRLT = \{(\log t_r - \log t_r^*)/s_{[I-RLT]}\}$, where $s_{[I-RLT]} = \sqrt{\{\sum_j (\log t_{r_j} - \log t_r^*)^2/(n_I - 1)\}}$, $j = 1, 2, \dots, n_I$

⁸ For a normal error distribution there is an almost 99% probability that all data points will fall within $\pm 2.5.s$

⁹ The numbers given in the box inserts of the (b) diagrams of Fig.C1.3 are the respective $\partial(A-SRLT)/\partial(\log t_r^*)$ slopes.

PAT-2.1a is now used to test for imbalance in the high magnitude residuals. In addition, it acknowledges that the $\pm 2.5.s_{[A-RLT]}$ boundary lines typically intersect the $t_r=100h$ grid line at $t_r^* \leq 1,000h$ and $t_r^* \geq 10h$ (Figs.C1.4.1-4), and that a wider vertical spacing indicates either a non representative model equation fit or excessive data variability. The $\pm 2.5.s_{[A-RLT]}$ boundary lines for the Type 304 18Cr11Ni invariably intersect $t_r=100h$ respectively at $t_r^*=1-2,000h$ and $t_r^*=5-10h$ (Fig.C1.4.3). If, in such circumstances, the distribution of data points about the $\log t_r^* = \log t_r$ line is sensibly uniform, consideration should be given to the scope of the material specification (in conjunction with the assessment instigator, eg WG3.x).

In addition to being a reasonable expectation, the $\partial(\log t_r^*)/\partial(\log t_r)$ slope criterion of PAT-2.1b is effectively consistent with the original $\partial(A-SRLT)\partial(\log t_r^*) < \pm 0.25$ criterion which was validated by the results from the independent assessments. The mean $\log t_r^*$ versus $\log t_r$ line should not only have a slope close to unity, but should also be located close to the ideal line in $[\log t_r^*, \log t_r]$ space. This is checked in PAT-2.1c.

PAT-2.1c requires that the mean line between $t_r=100h$ and $t_r=100,000h$ is contained between the $\pm \log 2$ (or $t_r^* = 2.t_r$ and $t_r^* = 0.5.t_r$) boundary lines. The evidence in Figs.C1.4.1-4 confirms that the selected variance-independent boundary criterion is reasonable, despite its original basis being arbitrary. Ideally, the mean $\log t_r^*$ versus $\log t_r$ line should fall within the $\pm \log 2$ boundary lines at $3.t_{r[\max]}$, to give added confidence in the strength values predicted for time extrapolations of this magnitude.

PAT-2.2

In addition to a visual examination of $\log \sigma_0$ versus $\log t_r$ plots (eg. Fig.C1.2.5), the original PAT-2.2 test assesses the effectiveness of the model to represent the behaviour of individual casts with information from I-SLTR versus $\log t_r^*$ plots constructed for all temperatures for which there are greater than 10% data points (with $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$ as a minimum). However, applying the same logic as that adopted for PAT-2.1, the basis for the main PAT-2.2 tests was changed to the $\log t_r^*$ versus $\log t_r$ diagram.

The requirement from the test is to identify individual casts and to highlight the best-tested casts¹⁰ (eg. Fig.C1.2.6). Ideally, individual casts should have slopes close to unity and be contained within the $\pm 2.5.s_{[I-RLT]}$ boundary lines. The limiting conditions for PAT-2.2a are partly quantified with an individual cast slope criterion of $0.5 \leq \partial(\log t_r^*)/\partial(\log t_r) \leq 1.5$

The distribution of $[\log t_r^*, \log t_r]$ data points about the $\log t_r^* = \log t_r$ line reflect the effectiveness of the predictive capability of the model. Non uniform distributions at key temperatures are taken as strong indications that the model does not effectively represent the specified material within the range of the data, in particular at longer times. There are good examples of this in Figs.C1.5.3 and C1.5.4.

The model equation is re-evaluated if at each temperature:

- the slope of the mean line through the isothermal $[\log t_r^*, \log t_r]$ data points is less than 0.78 or greater than 1.22 (Fig.C1.2.6), and
- the mean line is not contained within the $\pm \log 2$ boundary lines between $t_r=100h$ and $t_r=100,000h$.

¹⁰ The best-tested casts are identified as part of pre-assessment, eg. Tables A2b-A5b (see Sect.2.3(iv)).

C1.3.3 Repeatability and Stability of Extrapolations

The third category of PAT is the most important and the most time consuming to implement, since the two tests involve repeat assessments following data reduction. However, the necessity for such checks on extrapolation stability is clear from the evidence presented in Figs.C1.1.1a to C1.1.4c and the summary information in Tables C1.2a to C1.2d. The uncertainty associated with $3.t_{r[\max]}$ extrapolated strength values can exceed 100%, and every effort should be made to minimise this variability. The results from the WG1 CRDA assessment exercise suggest that by adopting the PAT-3.1 and PAT-3.2 tests, this variability can be reduced to around 20%.

PAT-3.1 and PAT-3.2 represent the most practical solution to the problem of evaluating the reliability of assessed strength values predicted by extrapolation. In reality, the only sure way to check extrapolation reliability is to perform long term tests. The culling tests simulate this situation by removing information from the long term data regime and checking extrapolation reliability and stability by re-assessment of the reduced data sets.

PAT-3.1 aims to check extrapolation repeatability out to $3.t_{r[\max]}$ (typically 300,000h in assessments for standards purposes) by performing a repeat CRDA after random culling of 50% of the data between $t_{r[\max]}/10$ and $t_{r[\max]}$. This typically equates to about 10% of the total dataset. The $R_{r/300,000h}$ (or $R_{r/3.t_{r[\max]}}$ if lower) strength values determined in the PAT-3.1 assessment should be within 10% of those determined from the main assessment. In the event of failure to meet the requirements of PAT-3.1, it is permissible to repeat the test to cover the possibility that the criterion was not initially met due to the removal of all the longer term data points of one or more of the best tested casts.

In contrast, PAT-3.2 checks extrapolation stability/sensitivity out to $3.t_{r[\max]}$ by performing a repeat CRDA after a 10% cull of the lowest stress data points from each of the main test temperatures (ie, 10% from each). The $R_{r/300,000h}$ (or $R_{r/3.t_{r[\max]}}$ if lower) strength values determined in the PAT-3.2 assessment should be within 10% of those determined from the main assessment. For relatively stable alloys, this approach can be extremely effective. Indeed, up to 30% culls have been made without invalidating this criterion [C1.9]. Nevertheless, the evidence from the assessment exercise indicates that PAT 3.2 cannot be mandatory for alloys which are clearly metallurgically unstable at temperatures up to 50°C above the maximum application temperature¹¹. For steels such as 12CrMoVNb, removing all the lowest 10% stress data can, for example, eliminate the limited evidence of sigmoidal behaviour (eg. Fig.C1.1.2c).

C1.3.4 PAT Overview

The strength predictions from the CRDA results which meet the requirements of the post assessment acceptability criteria are highlighted as thick lines in Figs.C1.1.1a to 4c. In addition, $R_{r/100,000h}$ and $R_{r/300,000h}$ ¹² predicted strength values from these CRDAs are summarised in the bottom row of Tables C1.2a to d. The variability in $R_{r/100,000h}$ (ie. typically $R_{r/t_{r[\max]}}$) is reduced to around ~10% from >100%. Similarly, the variability in $R_{r/300,000h}$ (ie. typically $R_{r/3.t_{r[\max]}}$) is reduced to around ~20% from >100%.

¹¹ The maximum temperature for which predicted strength values are required.

¹² $R_{r/70,000h}$ and $R_{r/210,000h}$ strength values for Incoloy 800, since $t_{r[\max]}=70,000h$

C1.4 CONCLUDING REMARKS

The results of an extensive and comprehensive CRDA evaluation exercise form the basis of the ECCC-WG1 recommendations for creep rupture data assessment (defined in the main text). The findings highlight the risk of high levels of uncertainty associated with $R_{r/100,000h}$ and $R_{r/300,000h}$ (ie. $R_{r/tr[max]}$ and $R_{r/3.tr[max]}$) strength predictions, and the need in analysis for key applications for:

- repeat assessments according to well defined procedure documents,
- effective post assessment tests, and
- the acknowledgement and quantification of uncertainties associated with extrapolated strength values

The concept of post assessment acceptability criteria is an ECCC-WG1 innovation requiring a period of intensive development. The resulting tests have been validated as far as possible, and now require further exploitation by the WG3.x working groups.

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Table C1.1 ECCC-WG1 Evaluation of CRDA Methodologies

PROCEDURE	2¼CrMo	12CrMoVNb	18Cr11Ni	31Ni20CrAlTi
ISO [2] ¹³ (App.D1)	BS [12] GECA [13] IRB [14a,b]	BS [12] IRB [14a,b]	BS [12] IRB [14a,b]	IRB [14a-c]
DESA [3] (App.D2)	IFW [15,20] ERA [22]	IFW [15,20] MAN [21] ERA [22]	IFW [15,20] ERA [22]	IFW [15,20] ERA [22]
Graphical [4,5]	IFW [20] ERA [23]	MPA [17] MAN [18] ERA [23]	IFW [20] ERA [23]	MPA [17] ERA [23]
SIMR-Mean [6]	SIMR [16]	SIMR [16]	SIMR [16]	SIMR [16]
P*[7]	IRB [14a,b]	IRB [14a,b]	IRB [14a,b]	IRB [14a-c]
TUG [8]	TUG [8]	TUG [8]	TUG [8]	TUG [8]
NE [9]	NE [9]	NE [9]	NE [9]	
MCM [11]			ERA [19]	

¹³ [C1. reference numbers]

Table C1.2a Summary of Predicted Creep Rupture Strength Values for 2.25CrMo

CODE	PREDICTED CREEP RUPTURE STRENGTH VALUES, MPa					
	500°C		550°C		600°C	
	100kh	300kh	100kh	300kh	100kh	300kh
ISO/BS	126	98	61	41	30	-
ISO/GEC	130	104	66	46	29	22
ISO/IRB	133	106	70	52	23	-
DESA/IFW1	127	105	68	54	32	24
DESA/IFW2	120	97	65	49	31	22
DESA/ERA	116	94	64	47	28	17
GRAPH/IFW	121	97	65	49	29	21
MH/NE	118	95	66	49	27	-
SOV/NE	122	99	65	51	33	25
PT/NE	121	98	65	50	31	21
MEAN/SIMR	113	90	63	46	22	-
SPERA/TUG	117	94	63	47	29	19
P*/IRB	127	109	78	66	31	22
<i>Variability (all CRDAs), %</i>	<i>18</i>	<i>21</i>	<i>27</i>	<i>60</i>	<i>48</i>	<i>42</i>
<i>Variability (PATs passed), %</i>	<i>6</i>	<i>9</i>	<i>6</i>	<i>11</i>	<i>12</i>	<i>18</i>

Table C1.2b Summary of Predicted Creep Rupture Strength Values for 12CrMoVNb

	PREDICTED CREEP RUPTURE STRENGTH VALUES, MPa					
	500°C		550°C		600°C	
	100kh	300kh	100kh	300kh	100kh	300kh
ISO/BS	326	277	163	91	-	-
ISO/IRB	247	172	122	77	61	36
DESA/IFW1	294	241	157	94	54	42
DESA/IFW2	304	250	161	105	52	34
DESA/MAN	310	261	167	90	62	34
DESA/ERA	302	239	156	90	32	-
GRAPH/MAN	296	250	140	100	58	47
GRAPH/MPA	295	207	149	133	54	23
GRAPH/ERA	283	-	149	-	57	-
MH/NE	314	252	146	90	64	41
SOV/NE	315	270	168	117	24	-
MEAN/SIMR	299	244	154	102	-	-
SPERA/TUG	326	275	166	109	-	-
P*/IRB	327	298	168	131	58	37
<i>Variability (all CRDAs), %</i>	<i>32</i>	<i>73</i>	<i>37</i>	<i>73</i>	<i>165</i>	<i>108</i>
<i>Variability (PATs passed), %</i>	<i>7</i>	<i>8</i>	<i>14</i>	<i>5</i>	<i>18</i>	<i>24</i>

Table C1.2c Summary of Predicted Creep Rupture Strength Values for 18Cr11Ni

	PREDICTED CREEP RUPTURE STRENGTH VALUES, MPa					
	600°C		650°C		700°C	
	100kh	300kh	100kh	300kh	100kh	300kh
ISO/BS	109	95	67	56	39	32
ISO/IRB	90	77	60	49	38	30
DESA/IFW1	85	69	54	43	33	25
DESA/IFW2	84	69	54	42	33	25
DESA/ERA	84	69	54	43	34	26
GRAPH/IFW	94	77	58	47	35	27
MH/NE	84	67	56	45	37	29
SOV/NE	87	71	56	45	35	28
PT/NE	86	70	56	44	35	27
MEAN/SIMR	80	63	49	38	30	23
SPERA/TUG	79	63	51	41	35	28
P*/IRB	101	89	69	60	46	39
MCM/ERA	95	78	60	49	38	30
<i>Variability (all CRDAs), %</i>	39	52	40	58	52	70
<i>Variability (PATs passed), %</i>	0	0	0	0	0	0

Table C1.2d Summary of Predicted Creep Rupture Strength Values for Incoloy 800

	PREDICTED CREEP RUPTURE STRENGTH VALUES, MPa					
	600°C		700°C		800°C	
	70kh	210kh	70kh	210kh	70kh	210kh
ISO/IRB	100	81	48	34.5	19.6	-
DESA/IFW1	107	89	46	35.7	18.8	13.4
DESA/IFW2	97	78	44	34.8	20.3	15.4
DESA/ERA	104	88	46	37.7	20.5	16.0
GRAPH/MPA	115	88	50	39.0	23.0	17.6
MEAN/SIMR	101	83	43	33.8	18.9	14.7
SPERA/TUG	103	84	41	32.3	17.9	13.8
P*/IRB	118	102	50	42.3	24.8	21.1
<i>Variability (all CRDAs), %</i>	22	31	22	31	39	57
<i>Variability (PATs passed), %</i>	3	16	0	8	8	20

TABLE C1.3a SUMMARY OF POST ASSESSMENT TEST RESULTS FOR 2.25CrMo

CODE	METHODOLOGY	POST ASSESSMENT ACCEPTABILITY TESTS														
		1.1	1.2	1.3	2.1a	2.1b	2.1c	2.2a	2.2b	2.2c	3.1	3.2	PASS			
ISO/BS	ISO		TB	<<0.3												X
ISO/GECA	ISO													14%		X
ISO/IRB	ISO			<1										>>10%	>>10%	X
DESA/IFW1	DESA															Y
DESA/IFW2	DESA															Y
DESA/ERA	DESA				1.7%									12%		X
GRAPH/IFW	German Graphical															Y
MH/NE	Extended MH			<1.6												X
SOV/NE	Extended Soviet II				1.7%											Y
PT/NE	Extended PT															Y
MEAN/SIMR	Mean [LM,MH,OSD,SA]															Y
SPER/ATUG	Spera		TB	<1.2										>10%	>10%	X
P*/IRB	Pstar				1.6%											Y?
																X

 PAT passed

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TABLE C1.3b SUMMARY OF POST ASSESSMENT TEST RESULTS FOR 12CrMoVnb STEEL

CODE	METHODOLOGY	POST ASSESSMENT ACCEPTABILITY TESTS														
		1.1	1.2	1.3	2.1a	2.1b	2.1c	2.2a	2.2b	2.2c	3.1	3.2	PASS			
ISO/BS	ISO		TB	<0.1	2.0%	*								-	-	X
ISO/IRB	ISO					*				x				1/3	>>10%	X
DESA/IFW1	DESA					*				*				*		Y
DESA/IFW2	DESA					*				*				*	14%	X
DESA/MAN	DESA					*				*				*	17%	Y
DESA/ERA	DESA					*				*				*	19%	X
GRAPH/MAN	German Graphical			<0.9		-				-				1/3	-	X
GRAPH/MPA	German Graphical			-		-				-				-	-	X
GRAPH/ERA	German Graphical			-		-				-				1/3	-	X
MH/NE	Extended MH					*				*				*	>10%	Y
SOV/NE	Extended Soviet II					*				*				1/3	>10%	X
MEAN/SIMR	Mean [LM,MH,OSD,SA]			<0.4		-				x				*	15%	X
SPERA/TUG	Spera			<2.0		-				-				*	-	X
P*/IRB	Pstar			<1.3	2.2%	*				*				*	-	X
														2/3	-	X

PAT passed

* denotes use of $t_{(max)}/100$ approach

TABLE C.1.3c SUMMARY OF POST ASSESSMENT TEST RESULTS FOR 18Cr11Ni STEEL

CODE	METHODOLOGY	POST ASSESSMENT ACCEPTABILITY TESTS														
		1.1	1.2	1.3	2.1a	2.1b	2.1c	2.2a	2.2b	2.2c	3.1	3.2	PASS			
ISO/BS	ISO															Y?
ISO/IRB	ISO				1.8%	0.77	x	1/3	2/3							X
DESA/IFW1	DESA					0.63	x	3/3	3/3							X
DESA/IFW2	DESA					0.62	x	3/3	3/3							X
DESA/ERA	DESA					0.63	x	3/3	3/3							X
GRAPH/IFW	German Graphical				-	-	-	-	-	14%						X
MH/NE	Extended M-H				-	-	-	3/3	3/3							X
SOV/NE	Extended Soviet II					0.65	x	3/3	3/3							X
PT/NE	Extended PT					0.65	x	3/3	3/3							X
MEAN/SIMR	Mean [LM,MH,OSD,SA]				-	-	-	3/3	3/3							X
SPERA/TUG	Spera					0.59	x	3/3	3/3							X
P*/IRB	Pstar				3.4%		x									X
MCM/ERA	Minimum Commitment					0.76	x	1/3	2/3							X

 PAT passed

TABLE C1.3d SUMMARY OF POST ASSESSMENT TEST RESULTS FOR INCOLOY 800

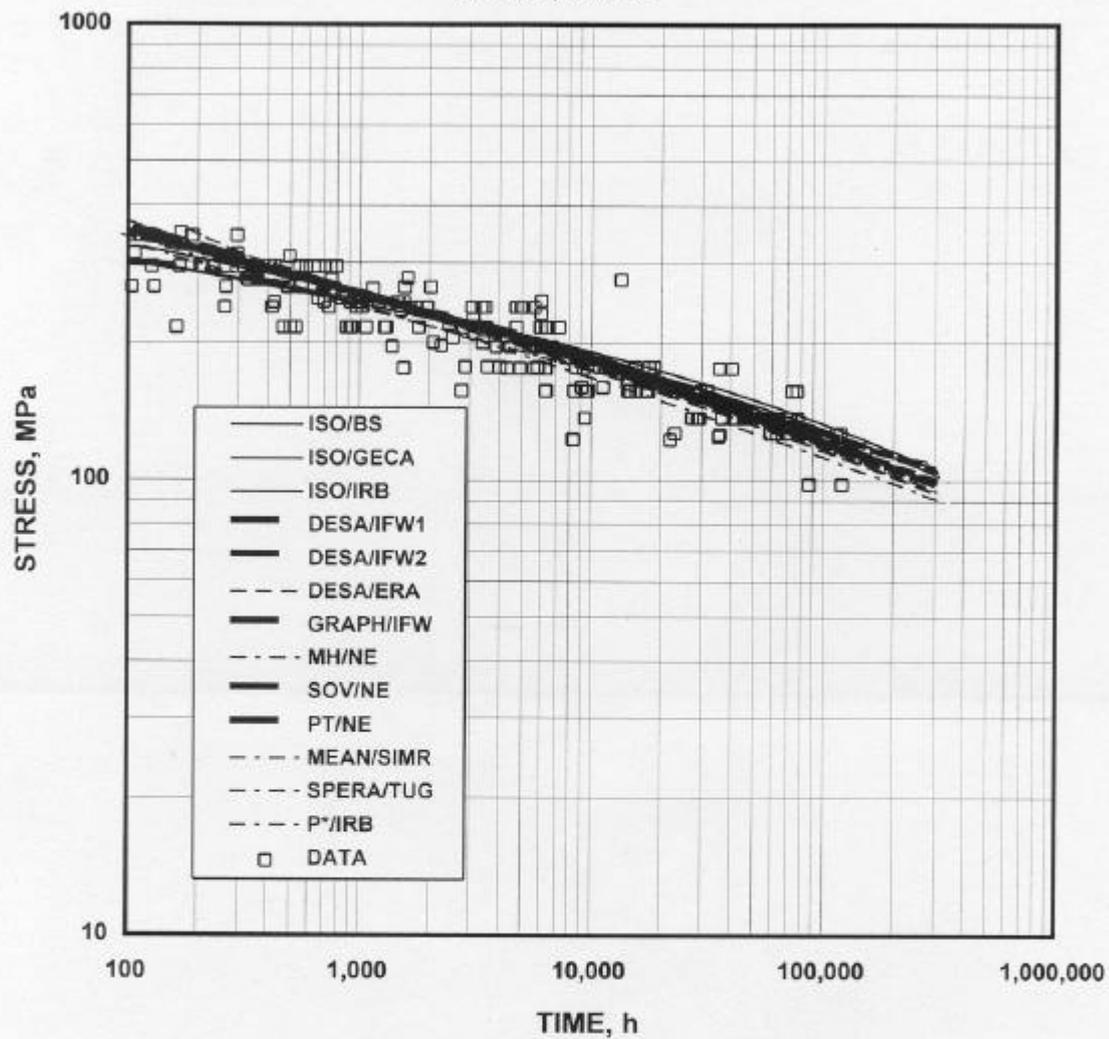
CODE	METHODOLOGY	POST ASSESSMENT ACCEPTABILITY TESTS											PASS			
		1.1	1.2	1.3	2.1a	2.1b	2.1c	2.2a	2.2b	2.2c	3.1	3.2				
ISO/IRB	ISO			<1.7		*	*					1/3	2/3	-	-	X
DESA/IFW1	DESA											1/3	1/3	-	-	X
DESA/IFW2	DESA						x					1/3	2/3			X
DESA/ERA	DESA											1/3	2/3			X
GRAPH/MPA	German Graphical															Y
MEAN/SIMR	Mean [LM,MH,OSD,SA]				-	-	-	-	-	-	-	1/3	1/3			X
SPERA/TUG	Spera											1/3	2/3	-	-	X
P*/IRB	Pstar															Y



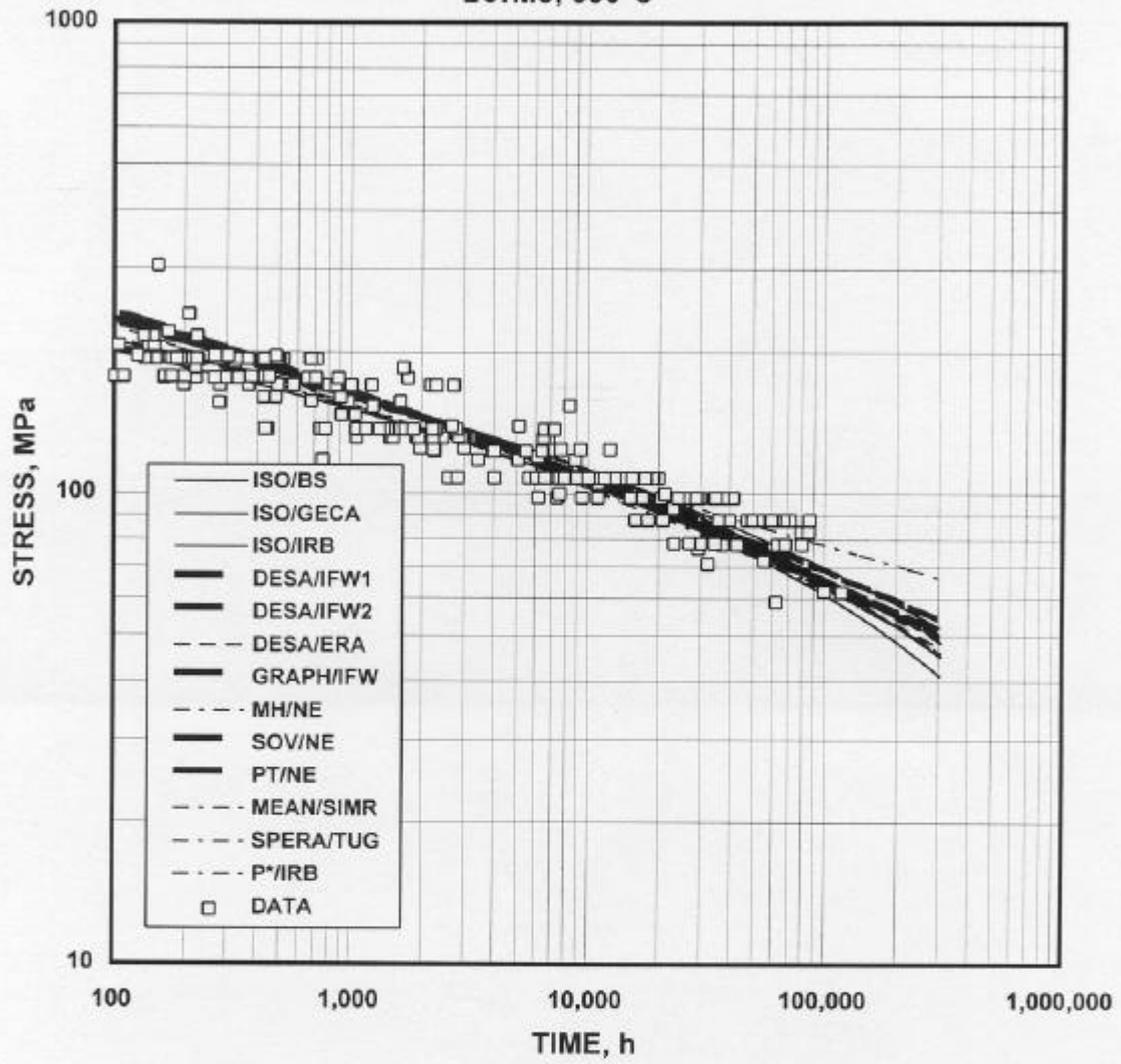
PAT passed

* denotes use of $t_{r(max)}/100$ approach

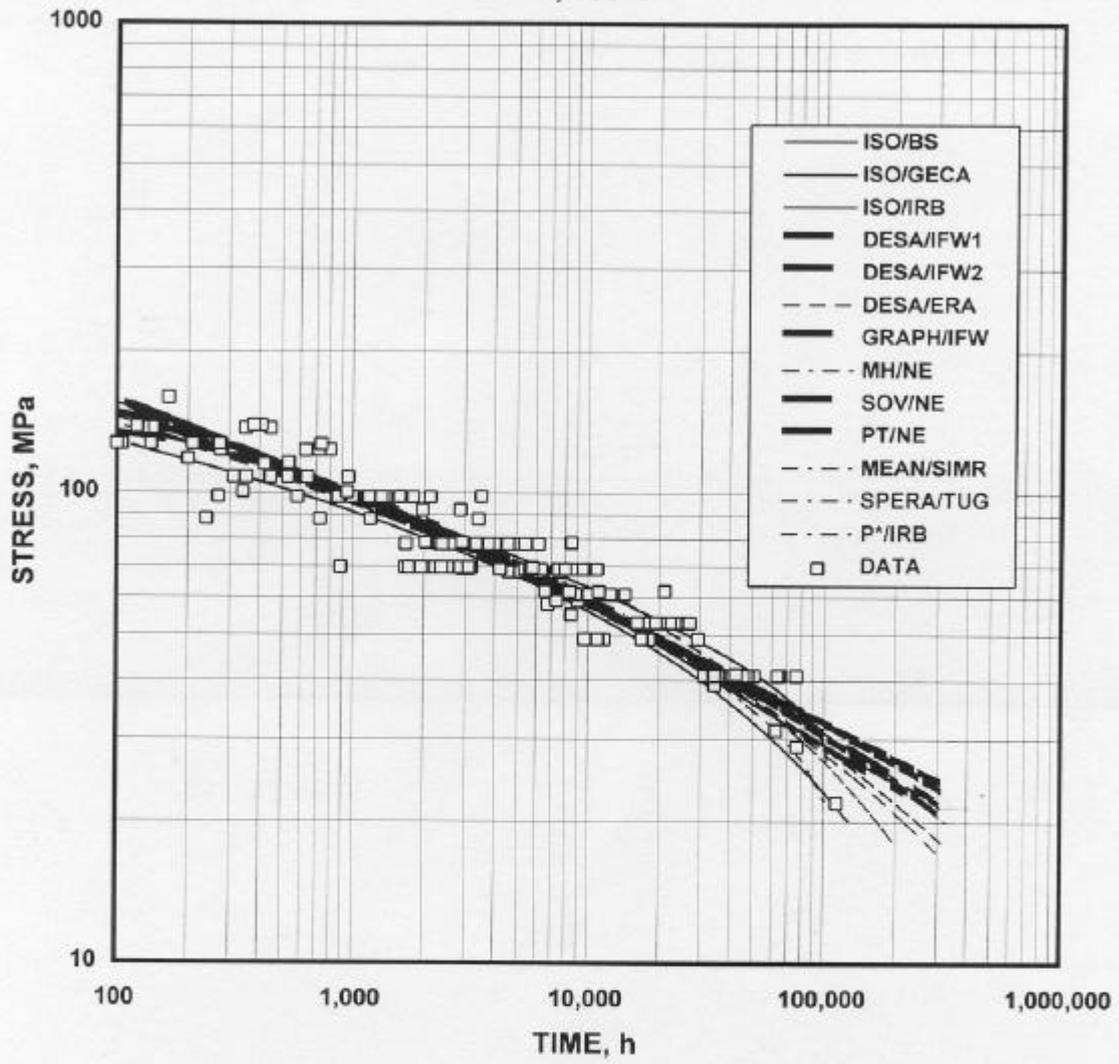
2CrMo, 500°C



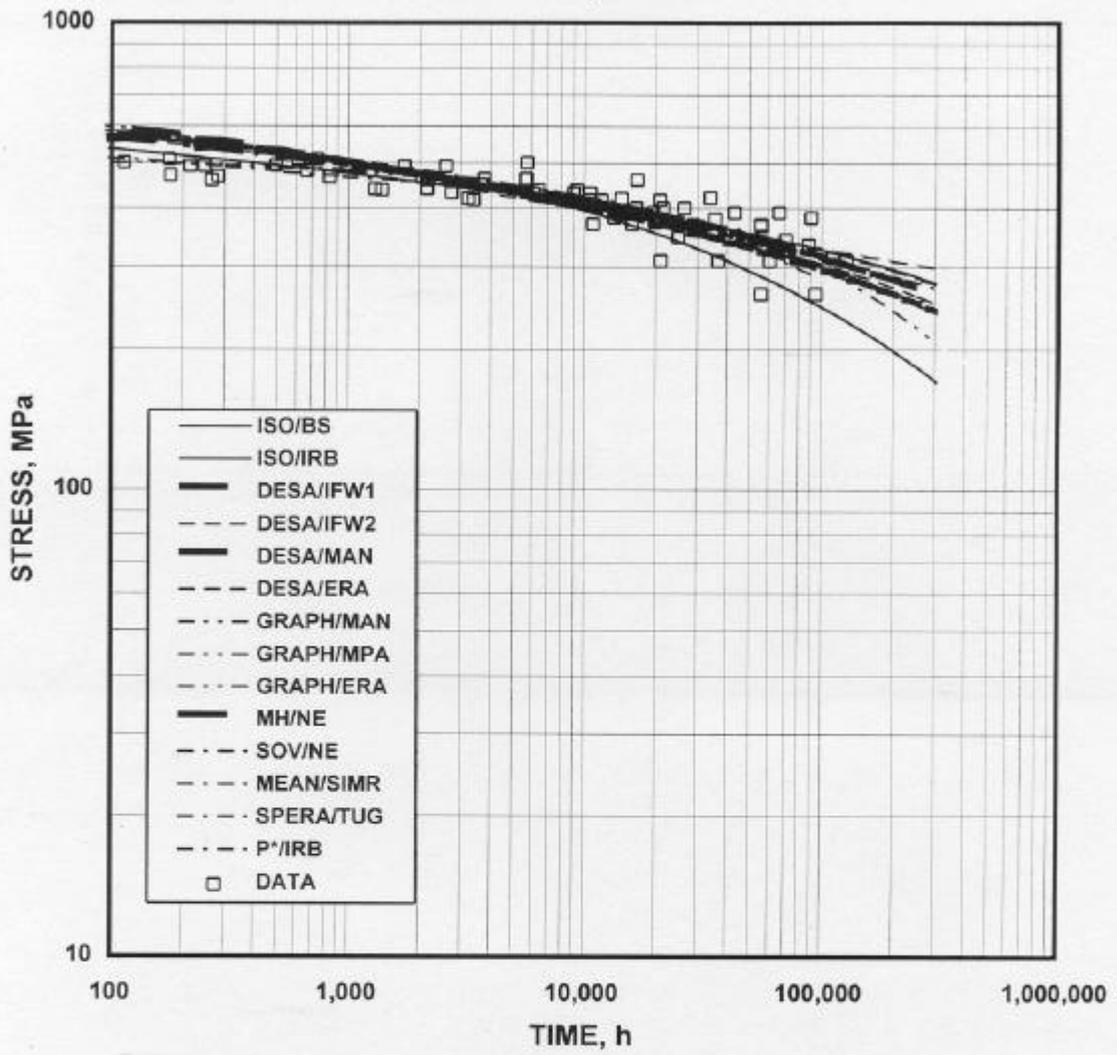
2CrMo, 550°C



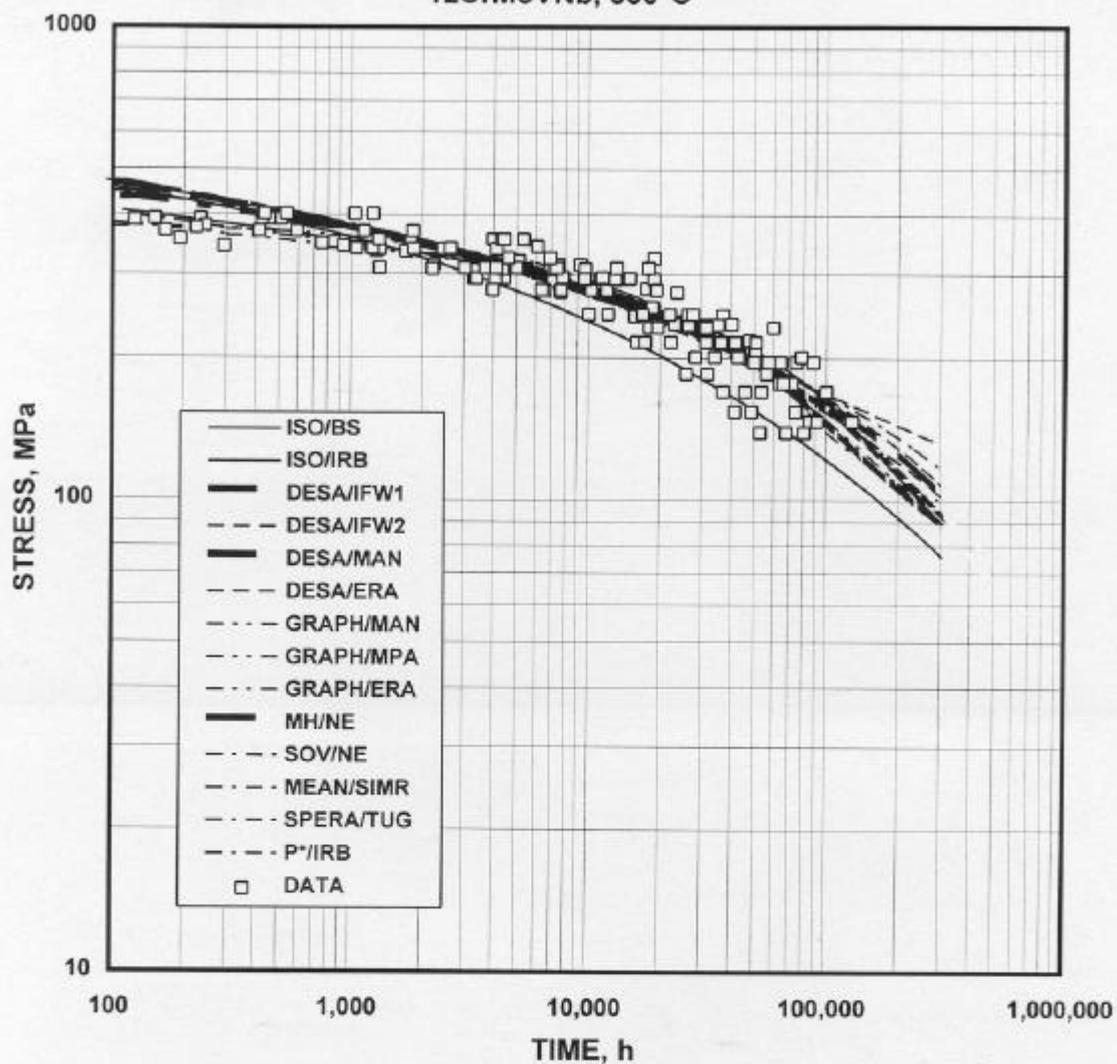
2CrMo, 600°C

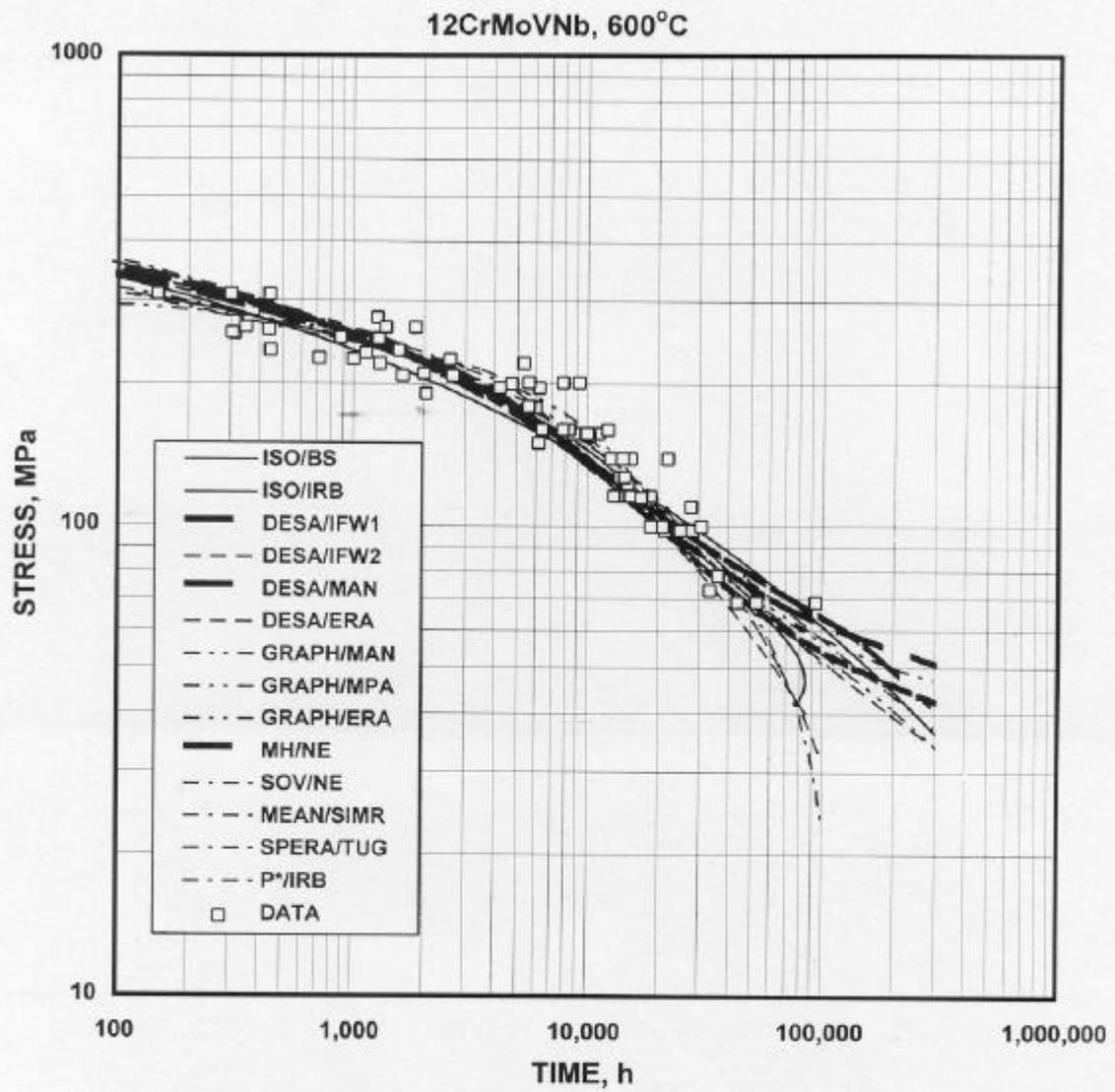


12CrMoVNb, 500°C

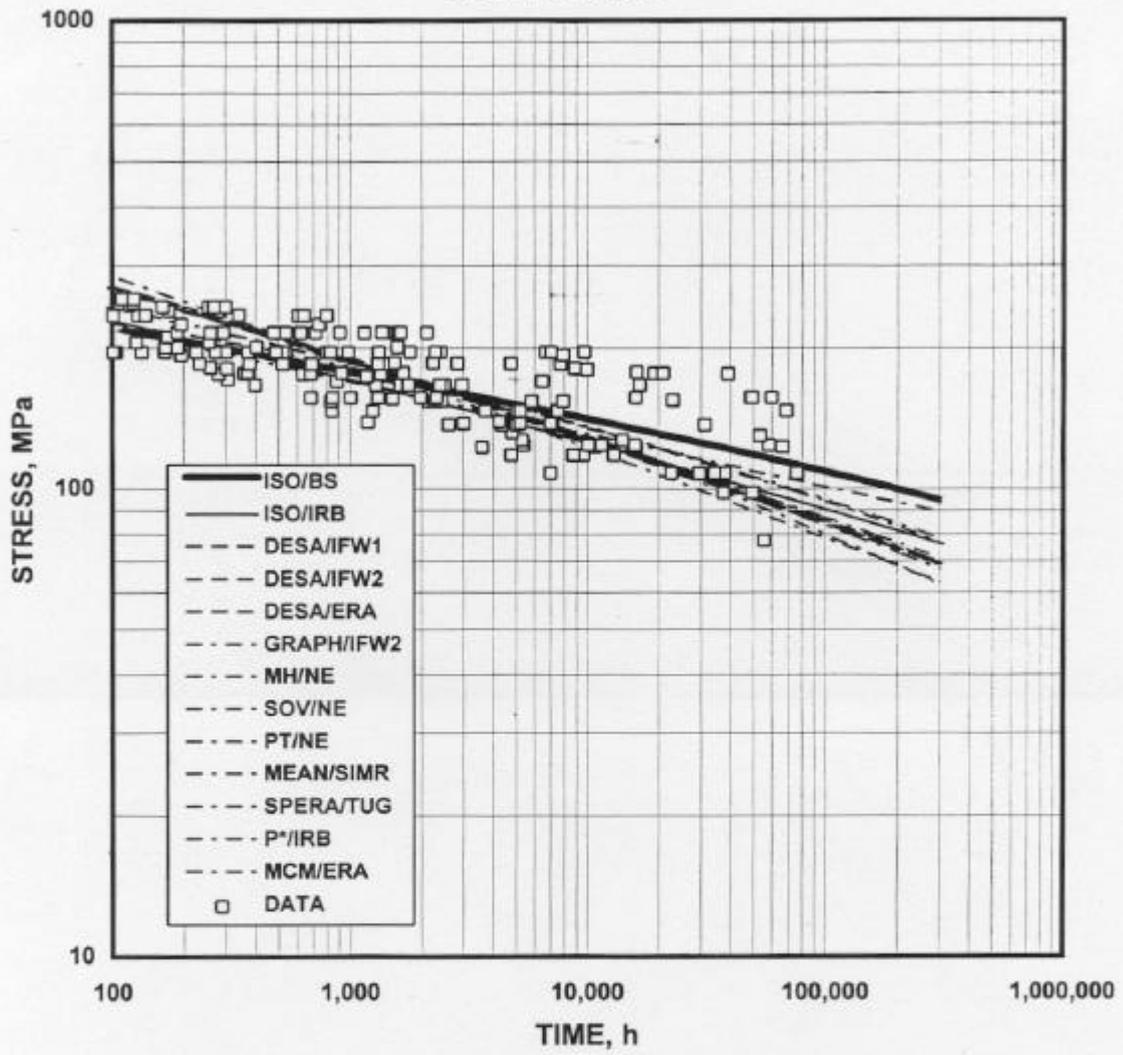


12CrMoVNb, 550°C

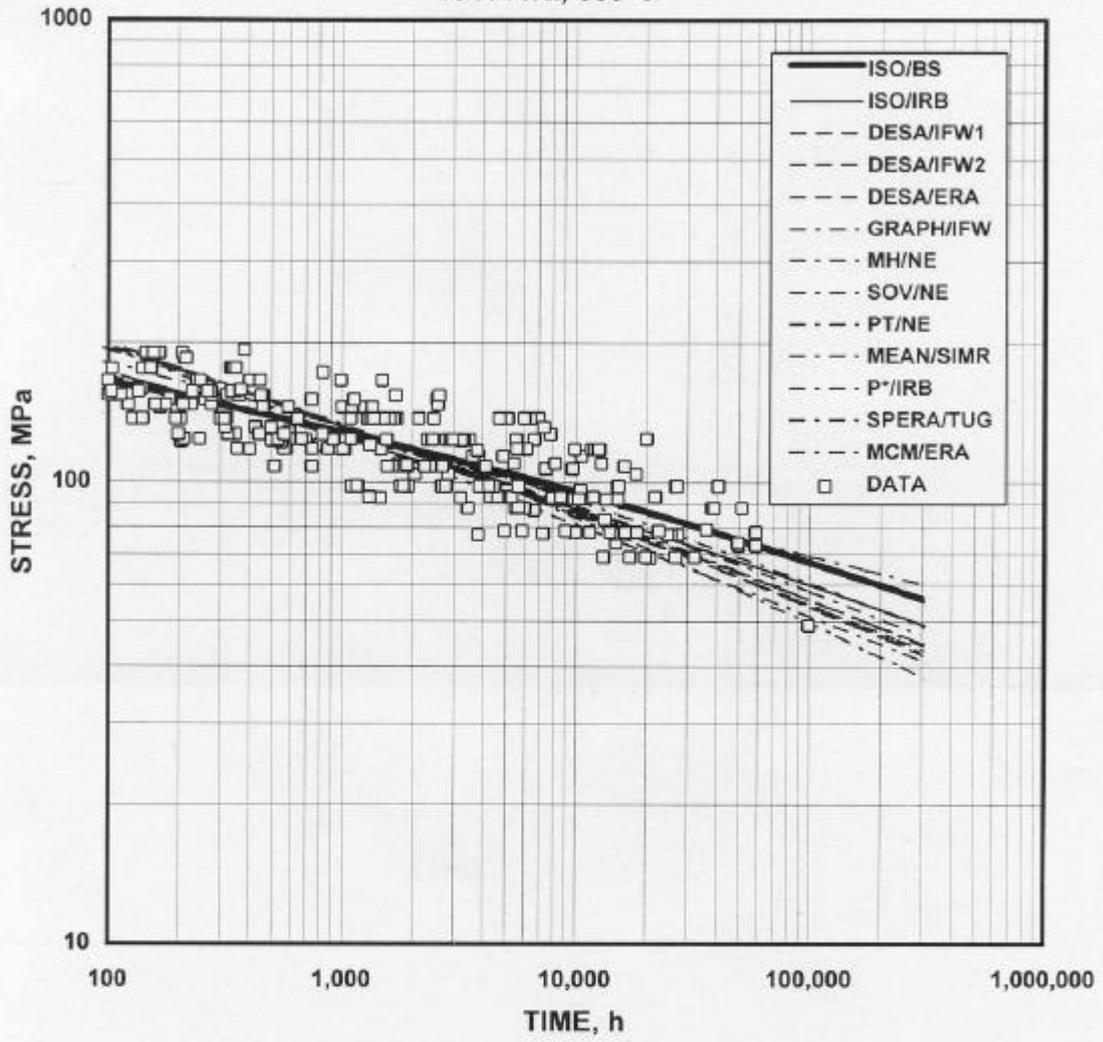




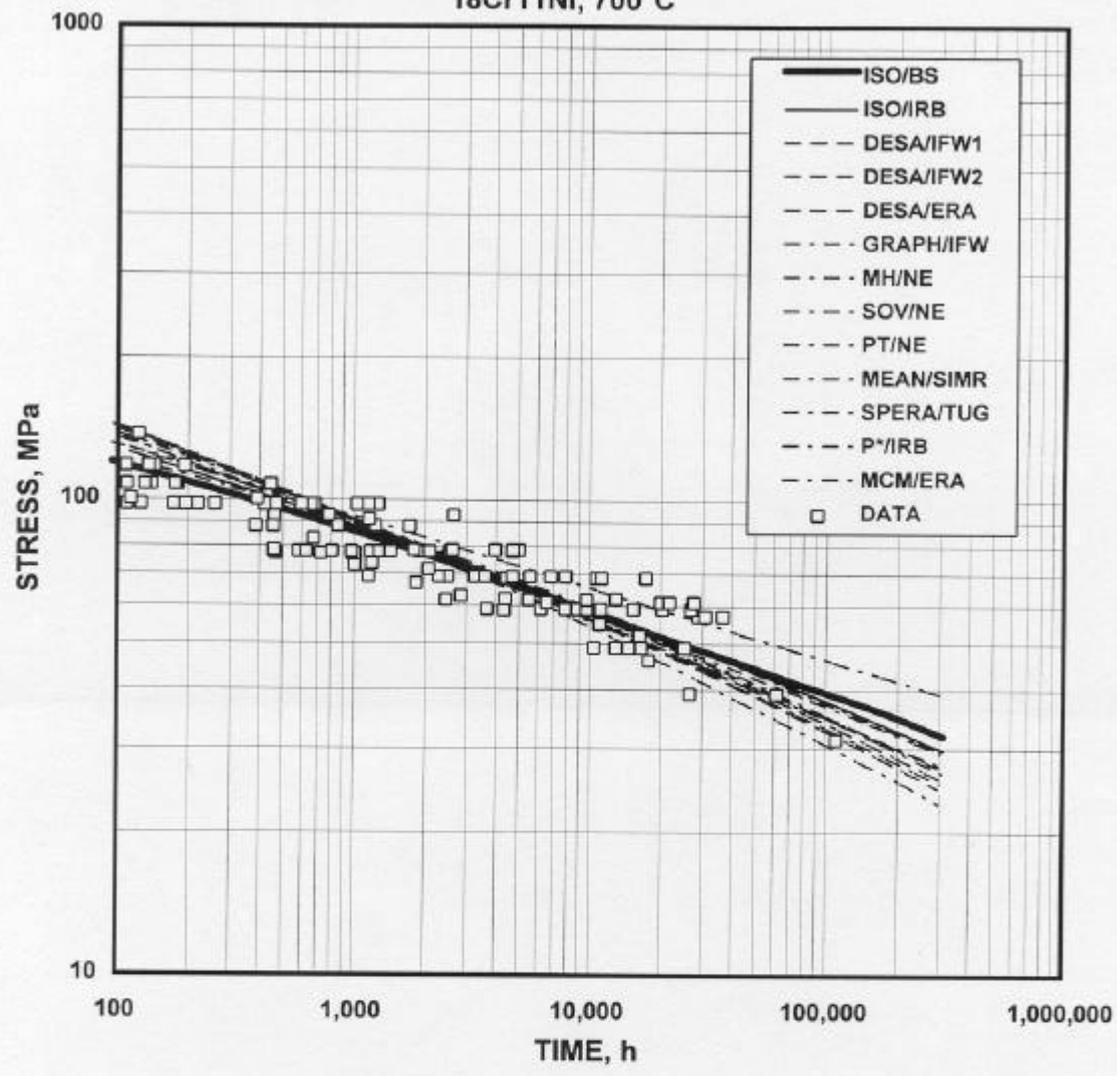
18Cr11Ni, 600°C



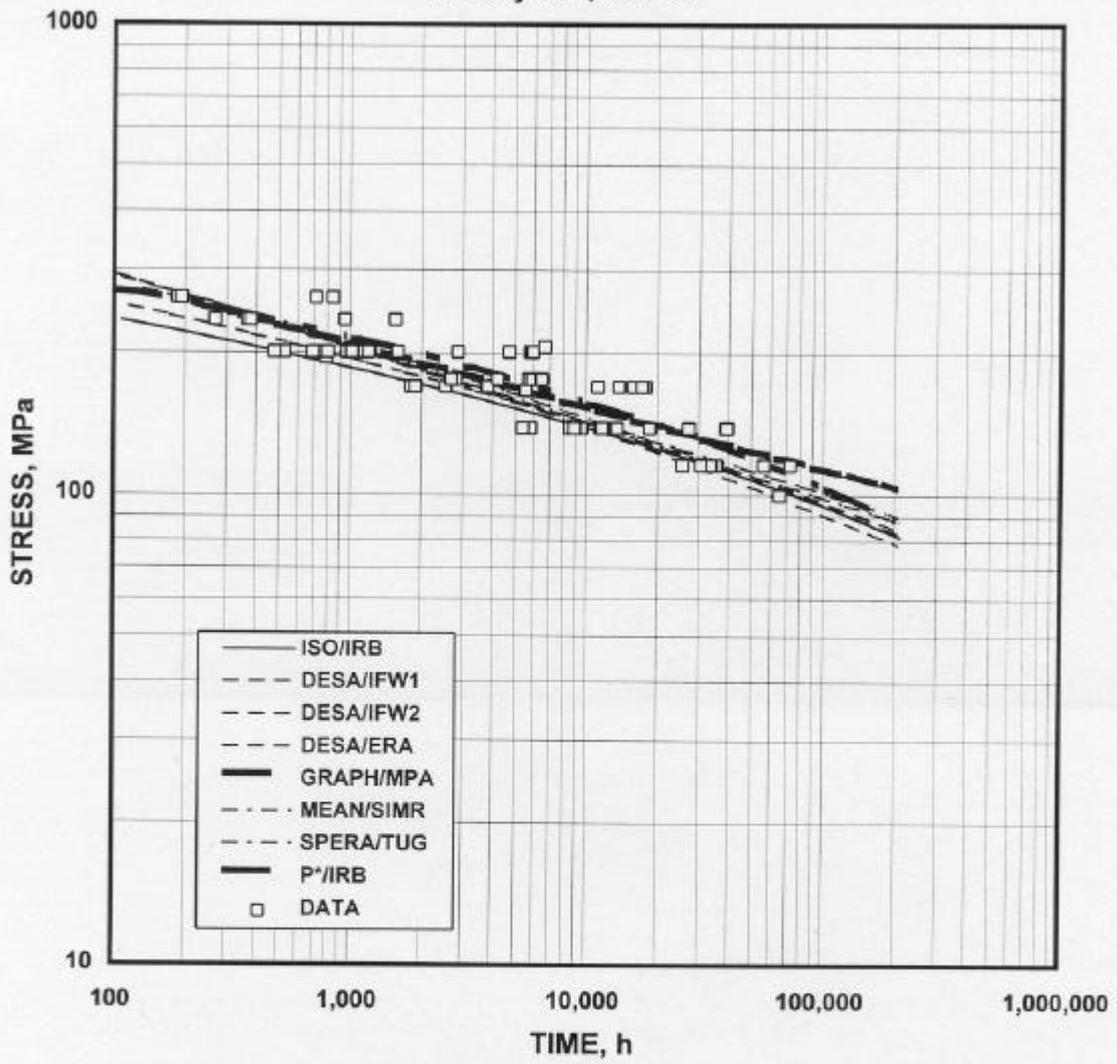
18Cr11Ni, 650°C



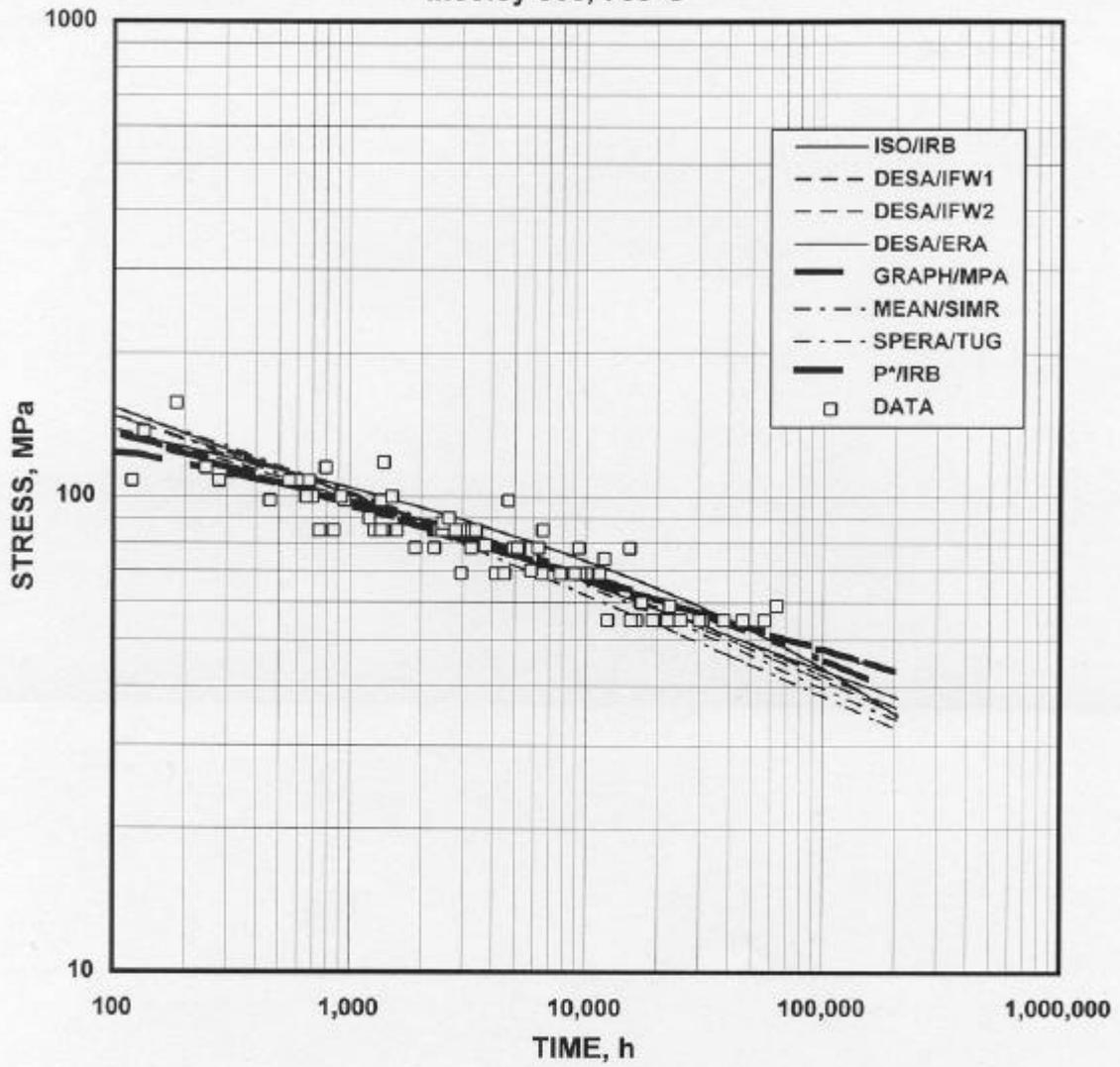
18Cr11Ni, 700°C



Incoloy 800, 600°C



Incoloy 800, 700°C



Incoloy 800, 800°C

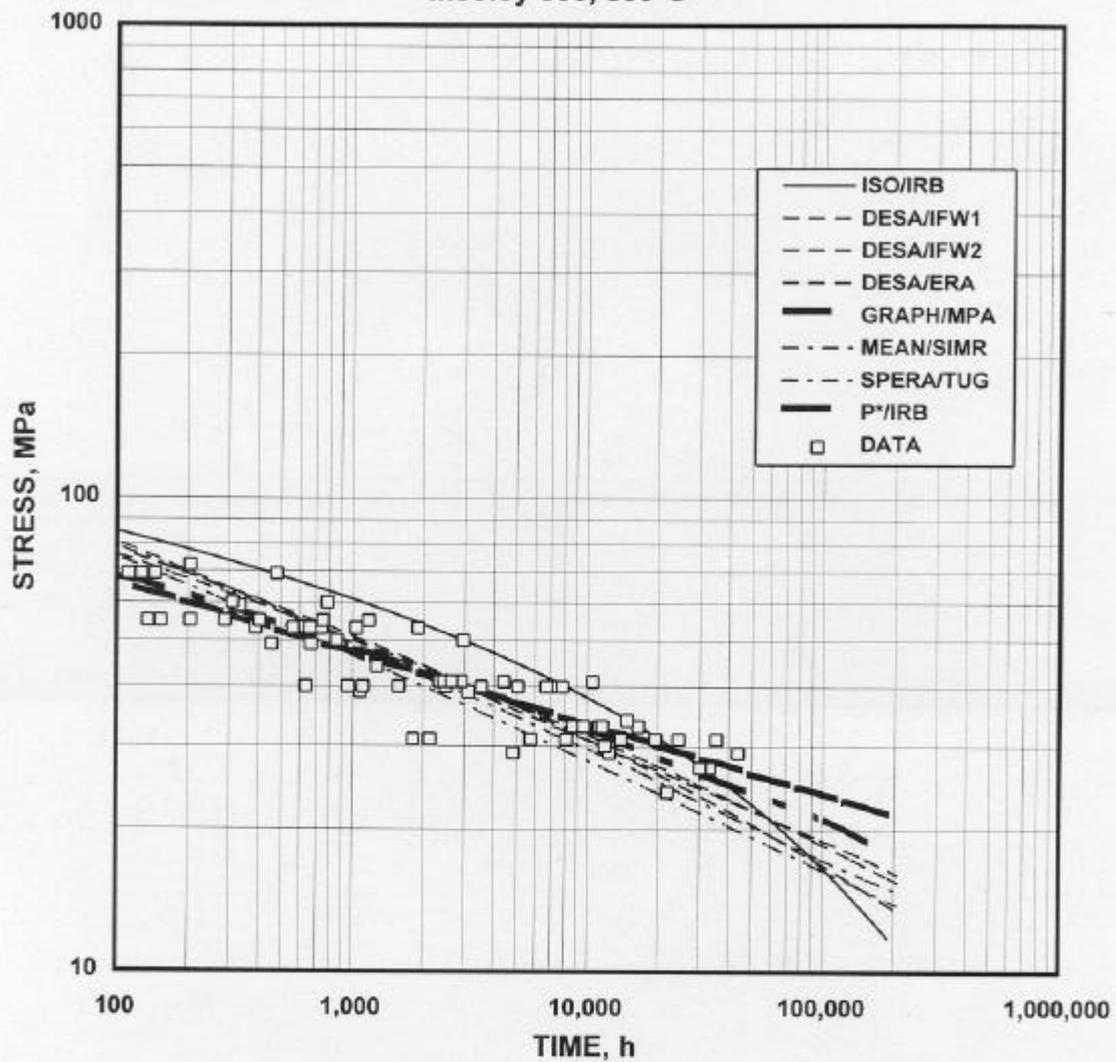
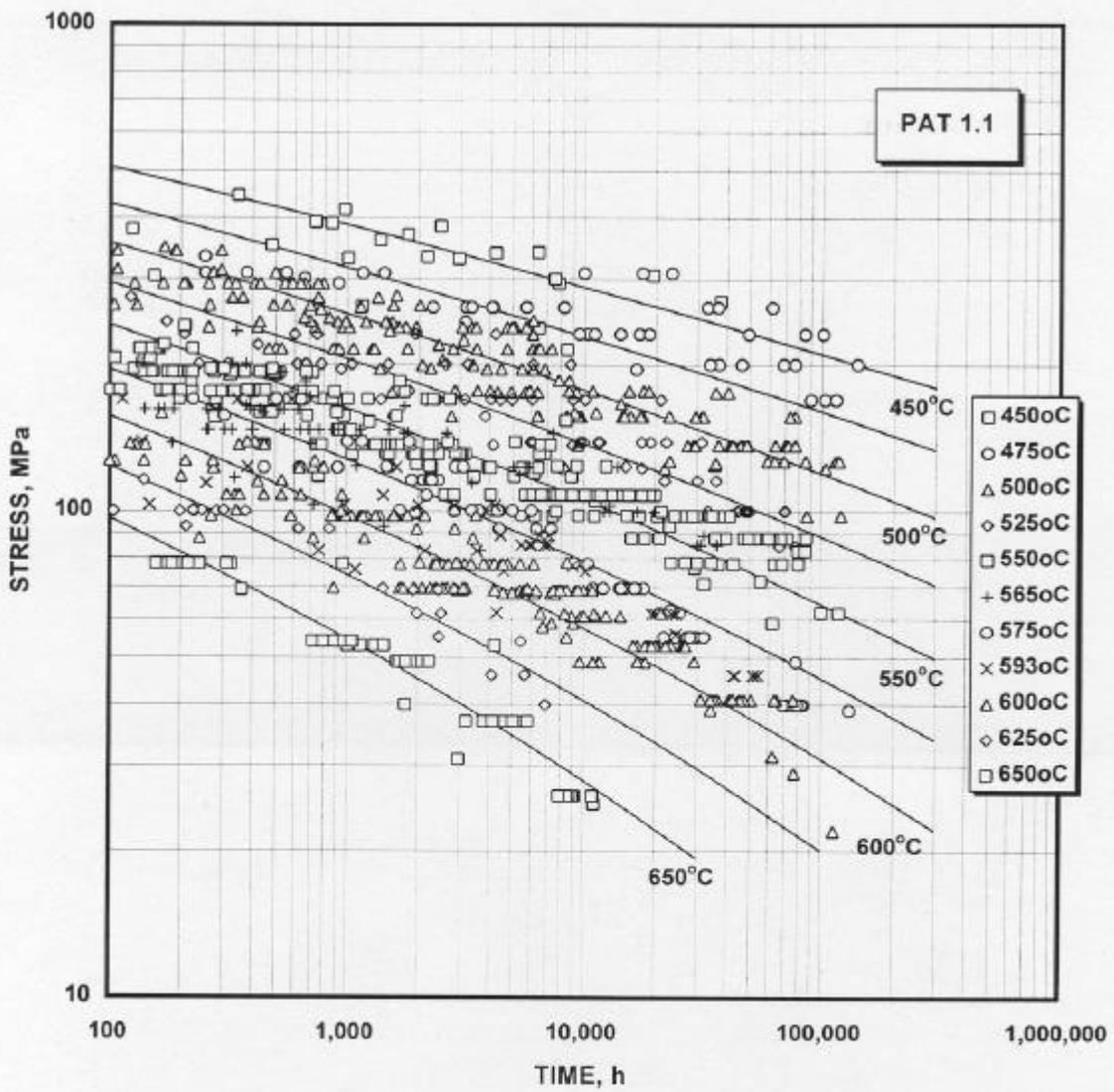
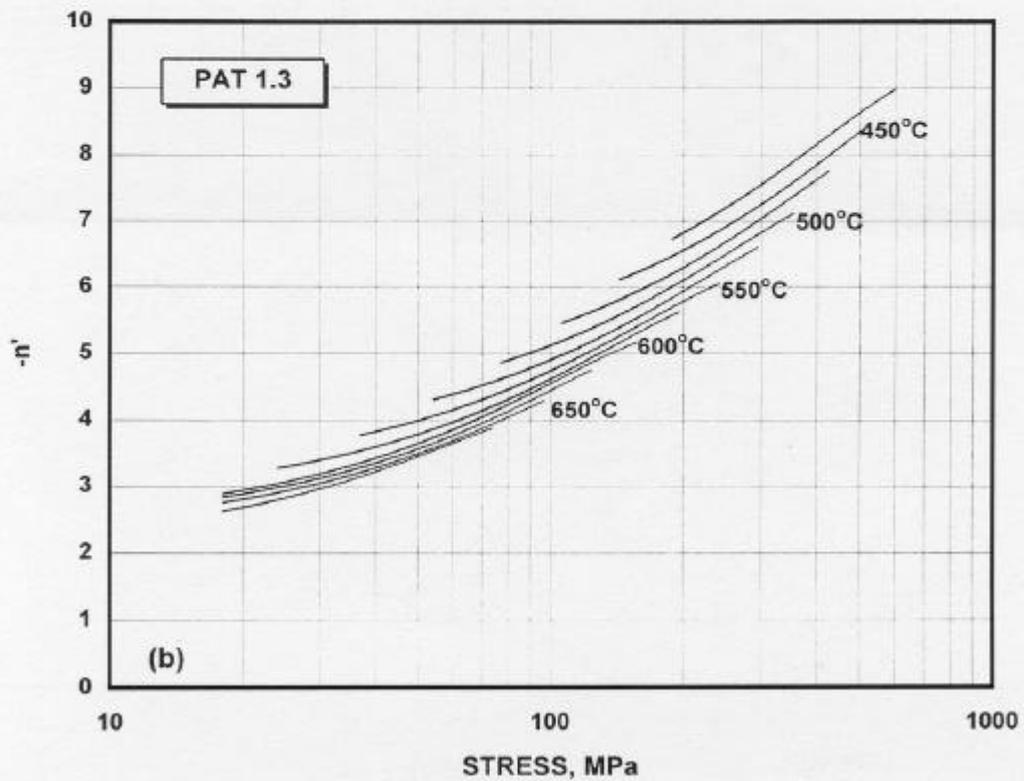
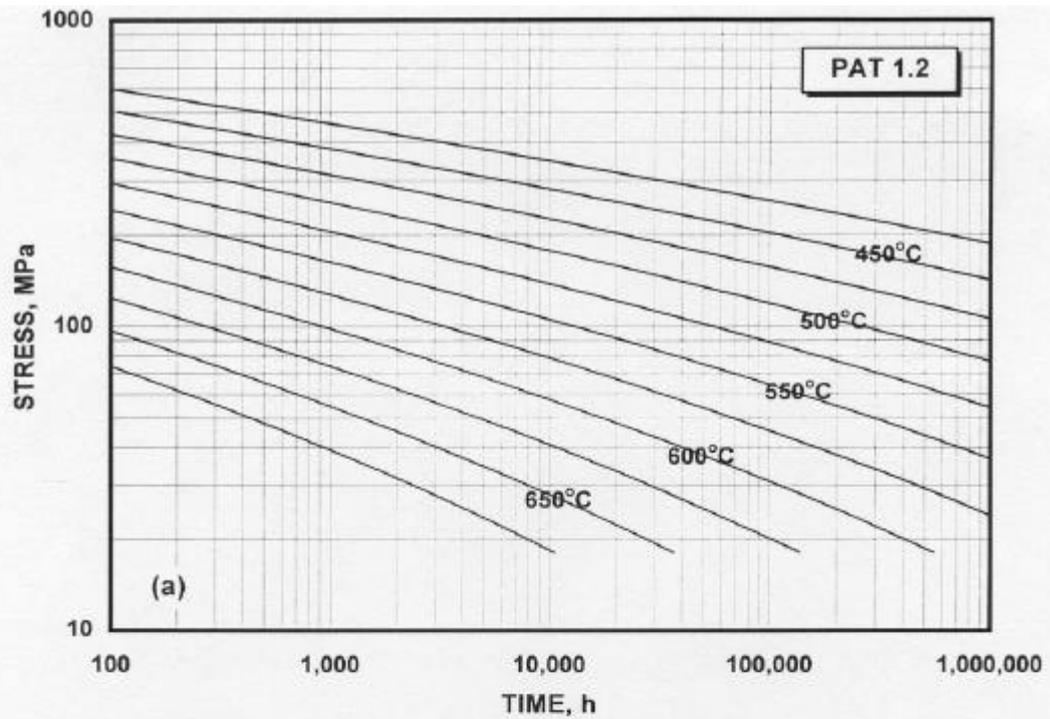


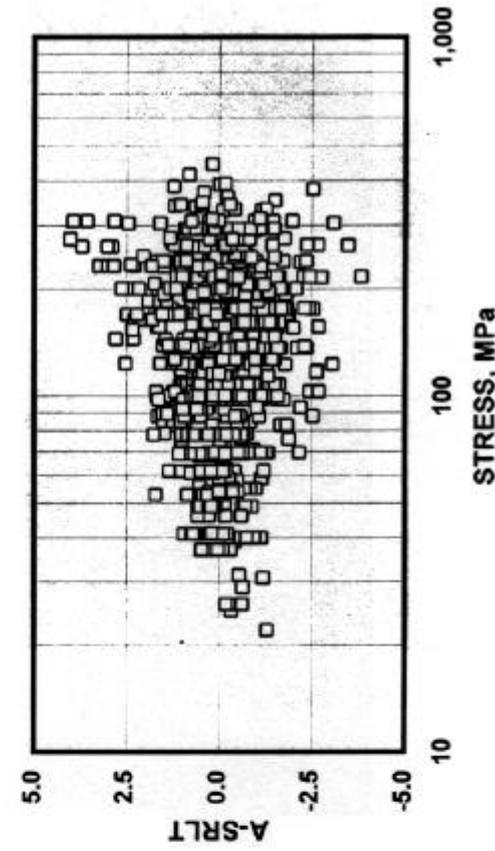
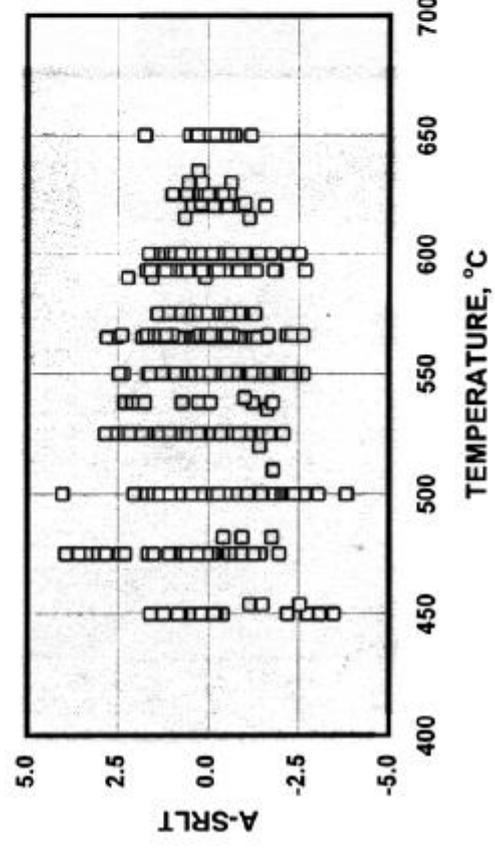
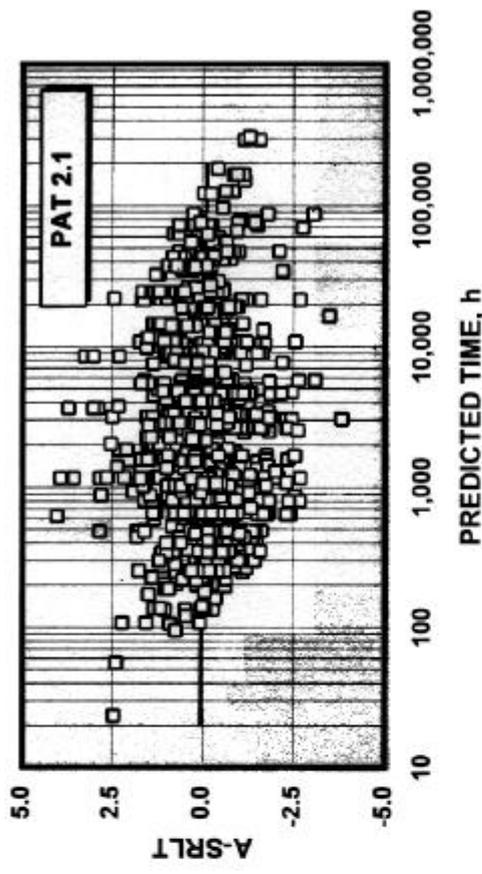
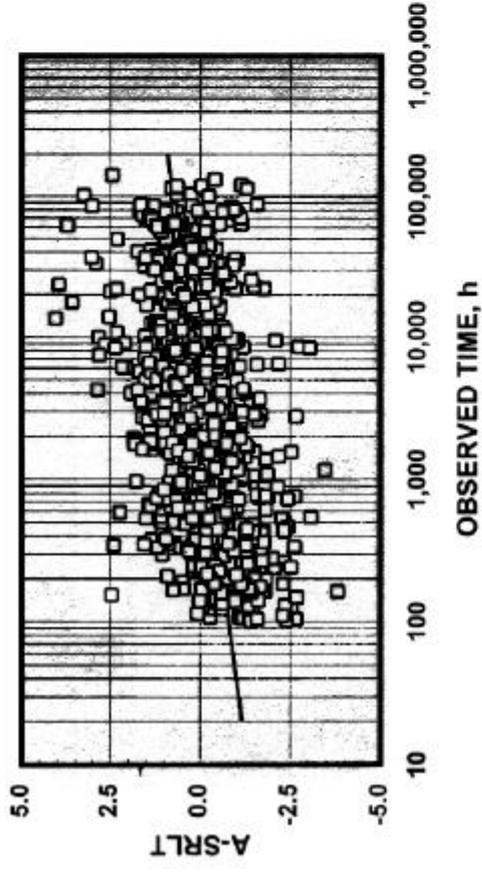
Fig.C1.1.4c



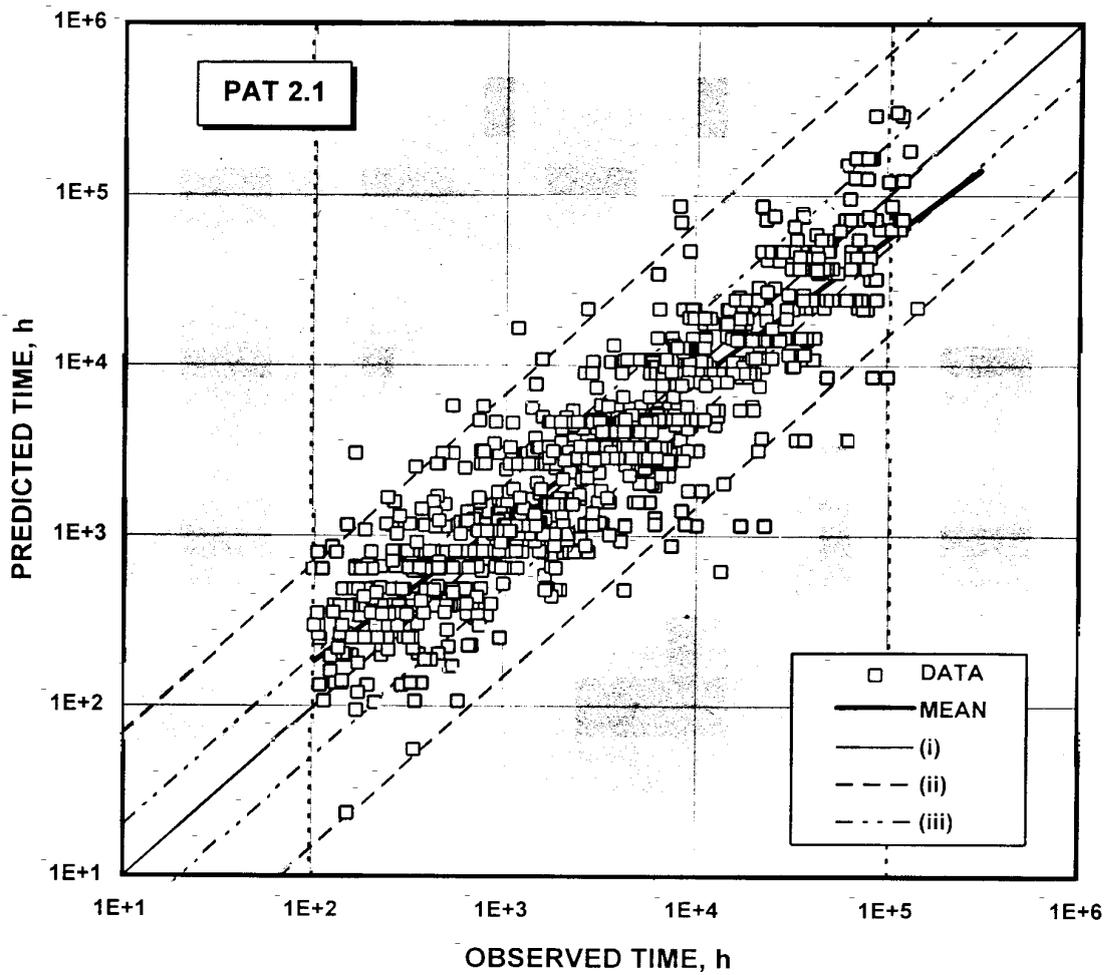
PAT 1.1 - Visual check of credibility of predicted model equation fit to data [2.25CrMo]



PAT 1.2 and PAT 1.3 tests performed on the results from a CRDA assessment of the 2CrMo working dataset



Examination of standardised residual log time variations with (a) observed time, (b) predicted time, (c) temperature and (d) stress resulting from the CRDA assessment of the 2CrMo working dataset (PAT 2.1)



KEY TO REFERENCE/BOUNDARY LINES

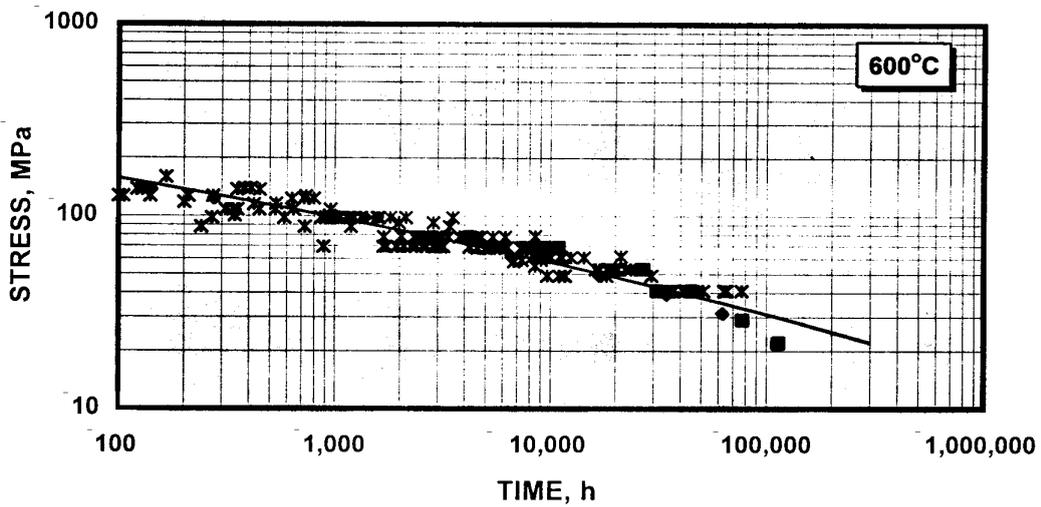
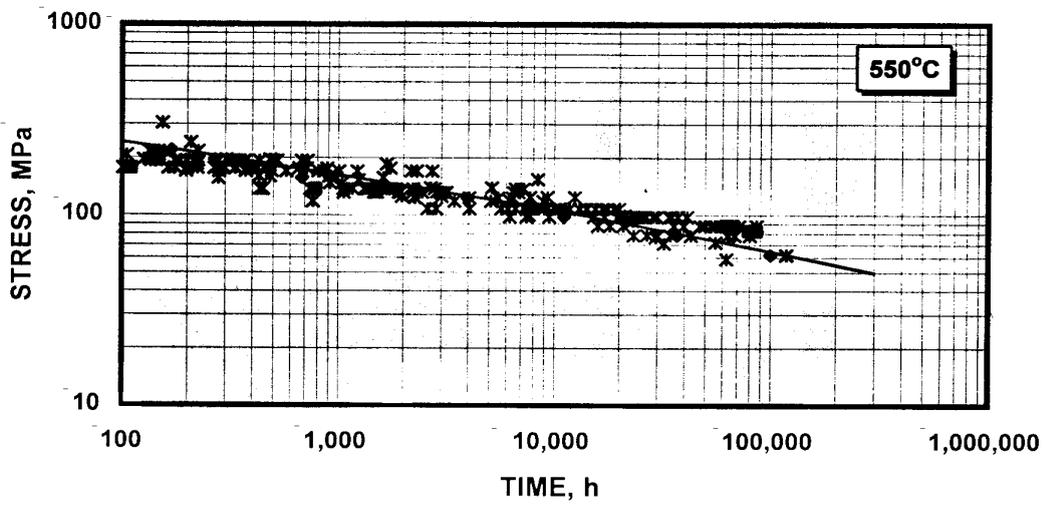
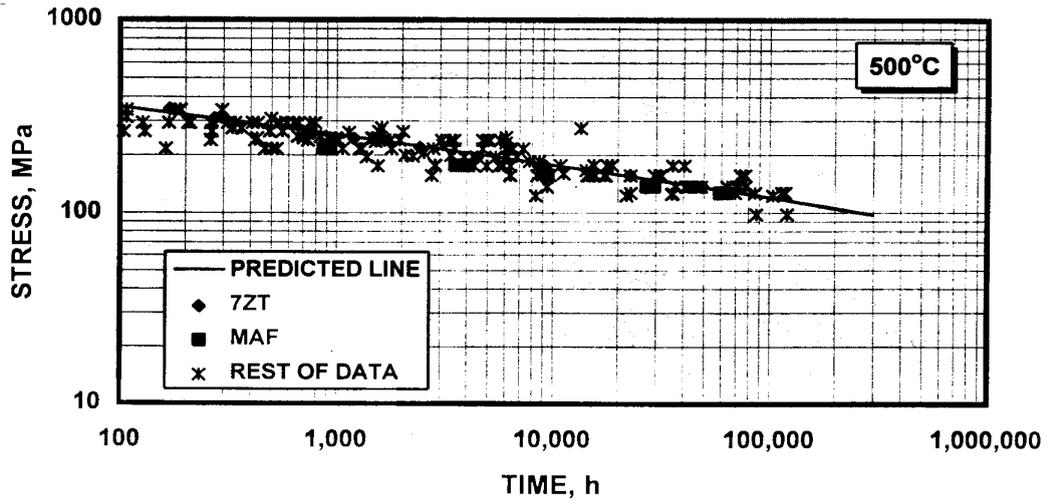
(i) $\log t_r^* = \log t_r$ reference line

(ii) $\log t_r^* = \log t_r \pm 2.5 s_{[A-RLT]}$ boundary lines

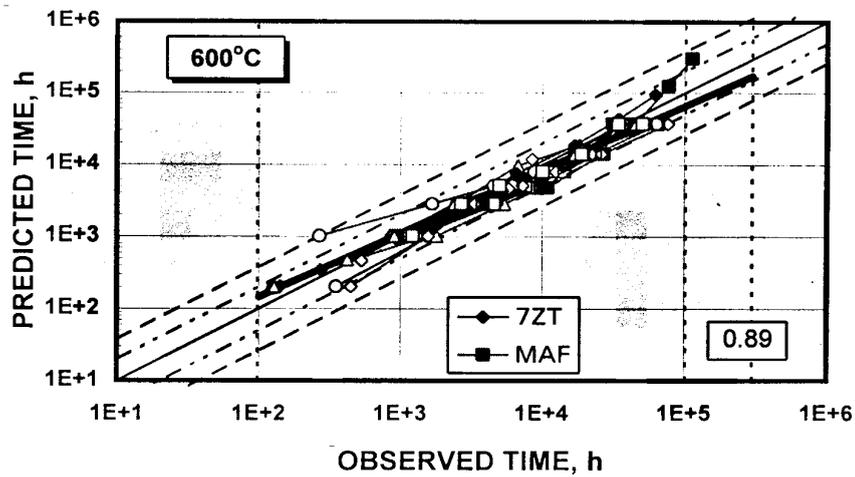
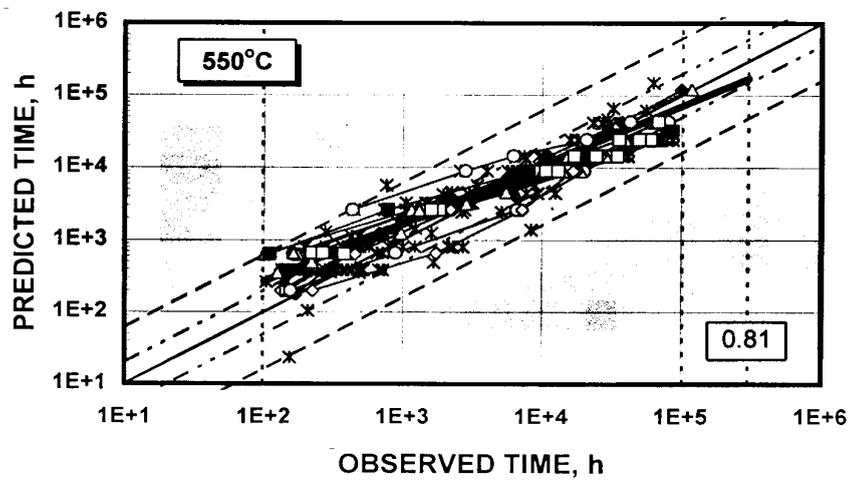
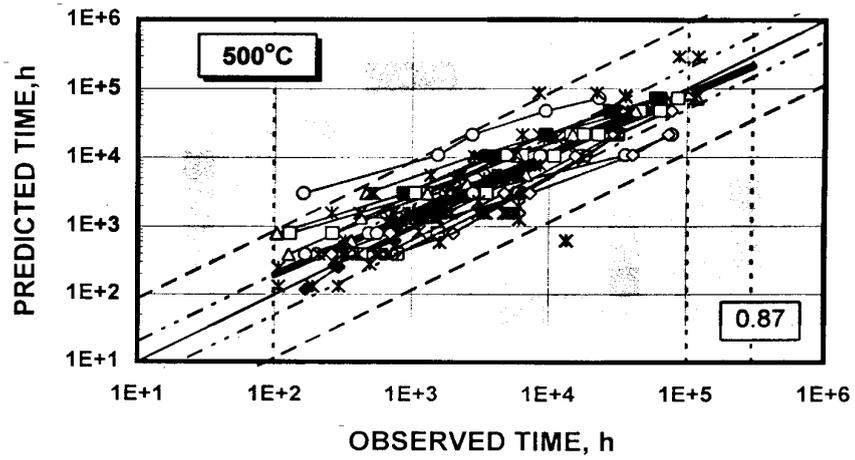
(iii) $\log t_r^* = \log t_r \pm \log 2$ boundary lines

$s_{[A-RLT]}$ is the standard deviation of the residual log times for all the data at all temperatures(see text)

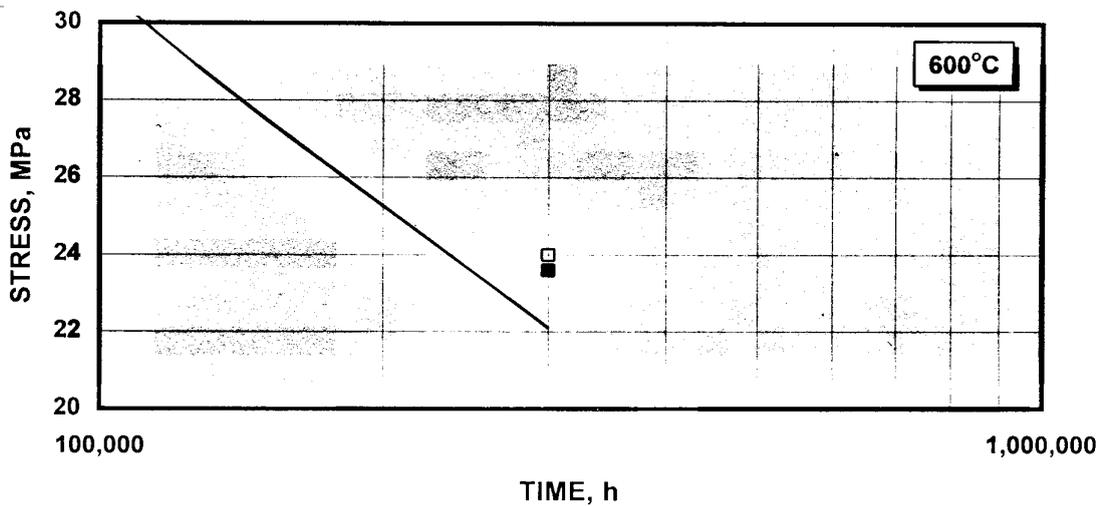
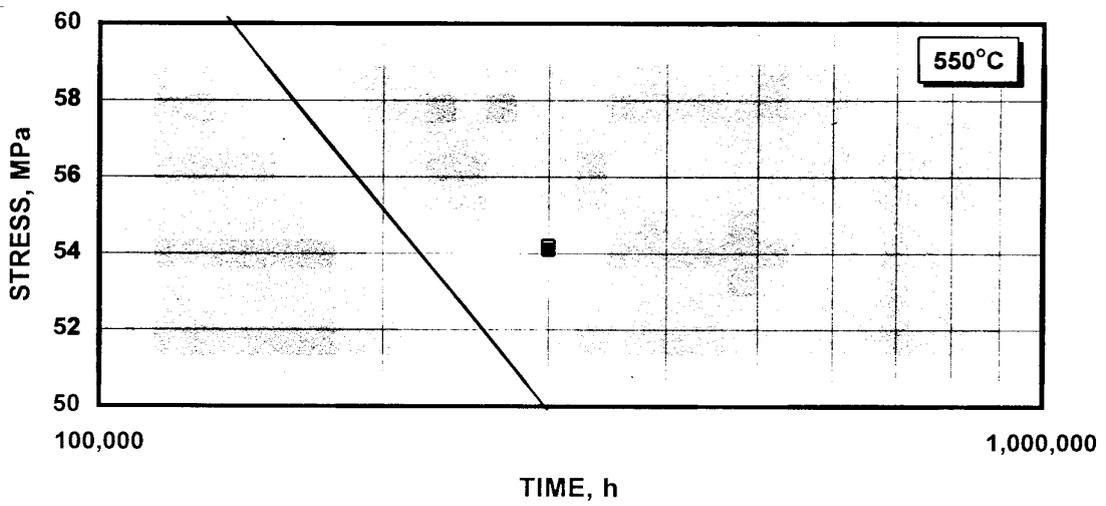
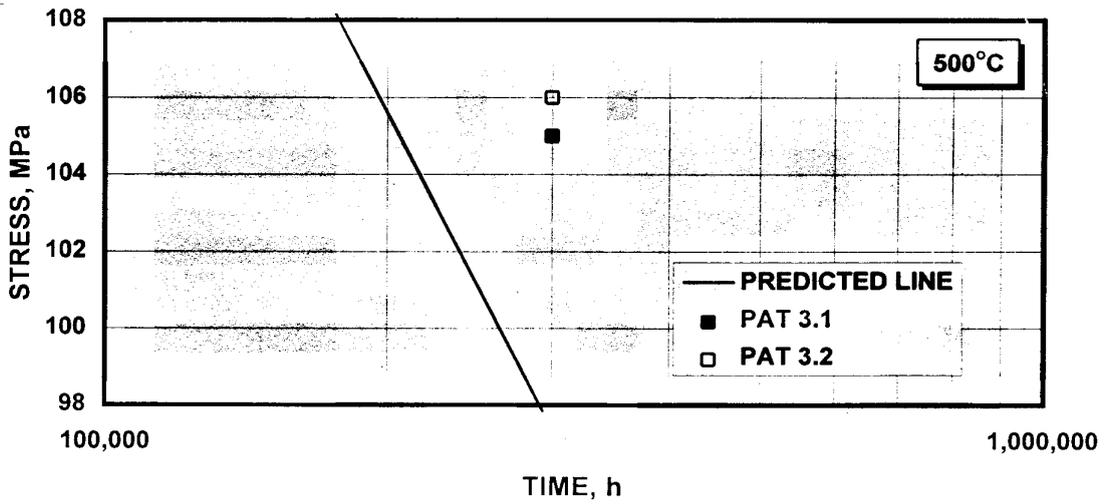
PAT 2.1 - Comparison of predicted versus observed times for the whole dataset



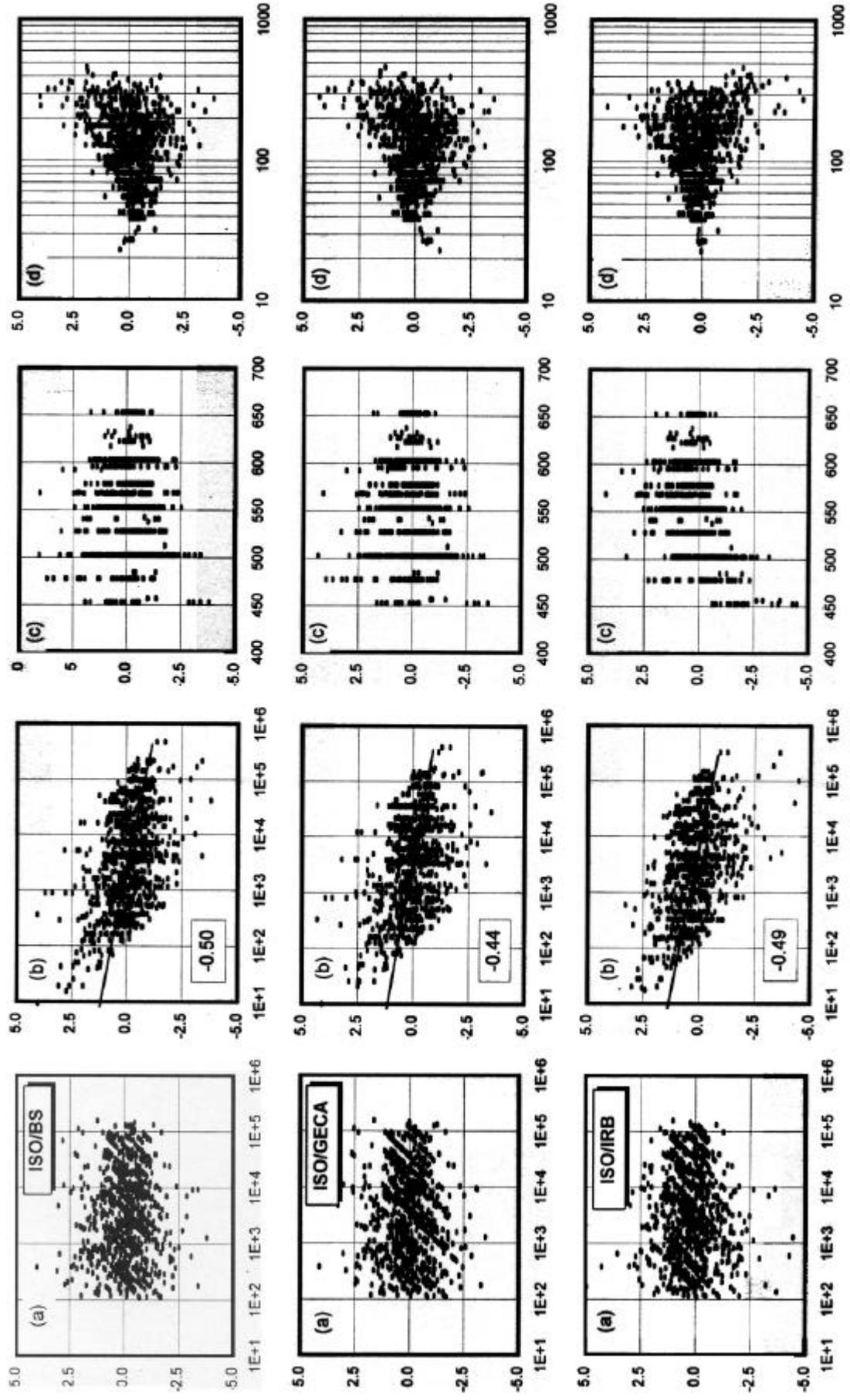
Visual examination of the effectiveness of the CRDA model to represent the 2CrMo working data at 500°C, 550°C and 600°C (PAT2.2)



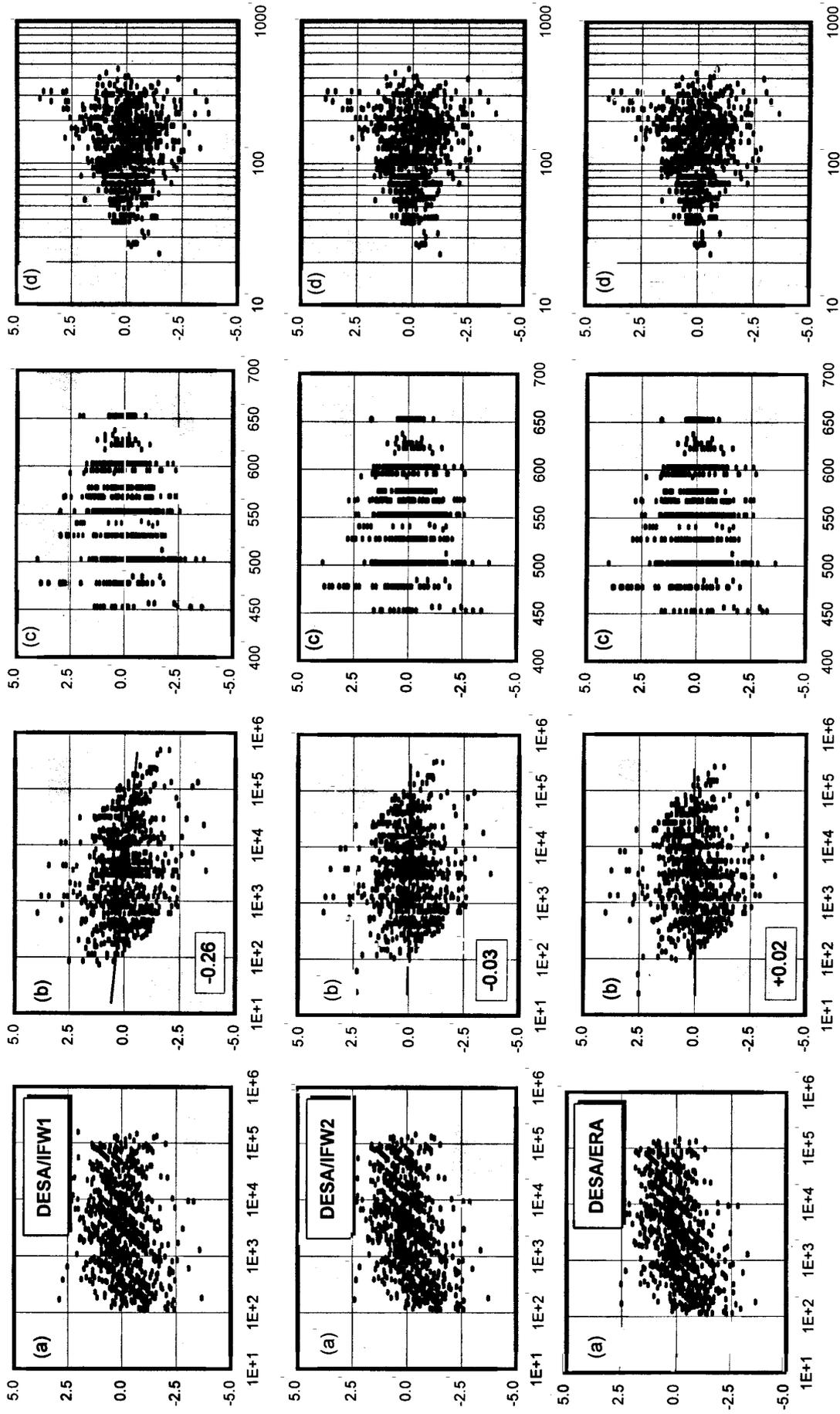
PAT 2.2 - Comparison of predicted versus observed times for individual casts at $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$ (solid line is mean line fit through data points, number inset is slope of mean line)



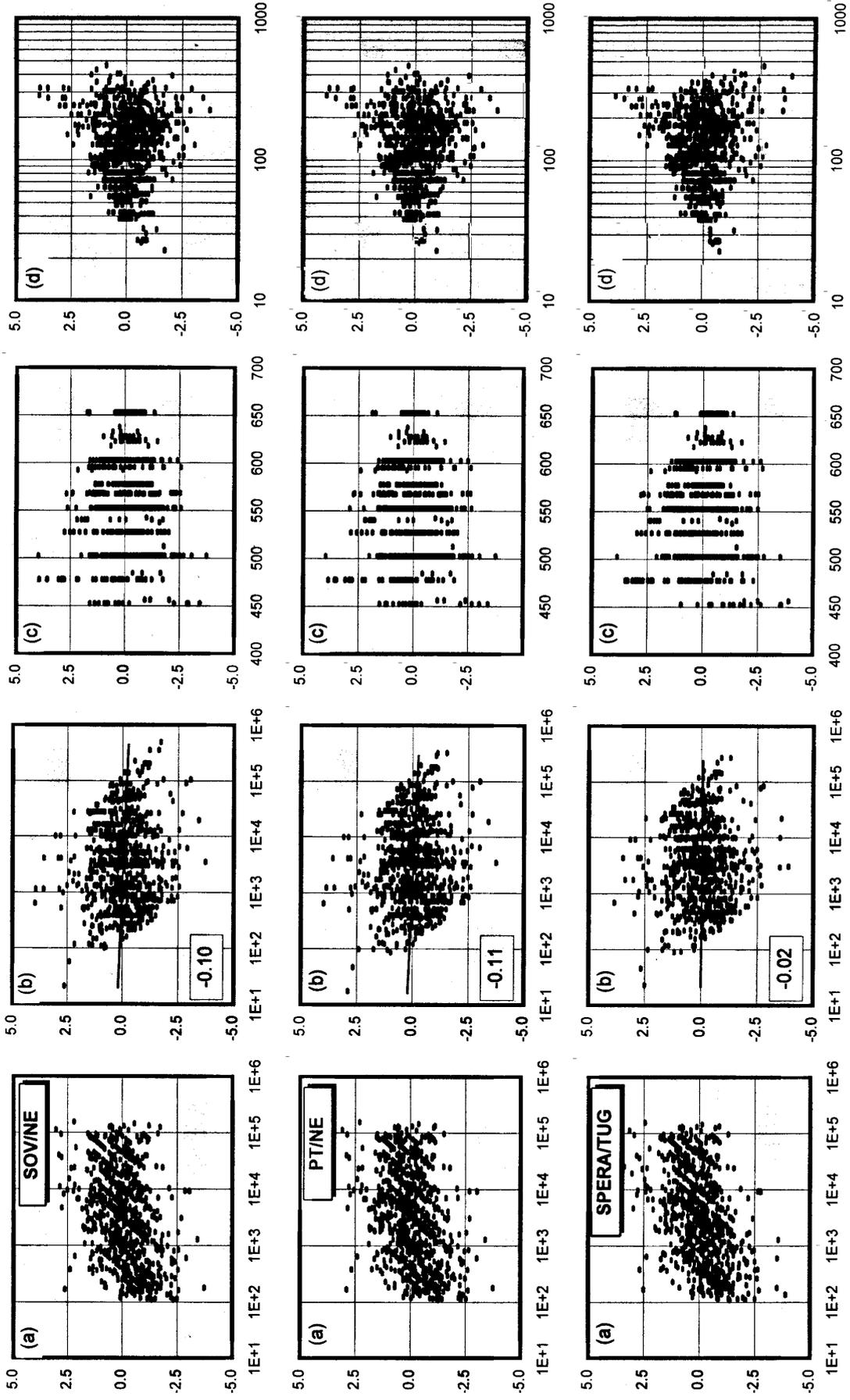
The results of PAT 3.1 and PAT 3.2 tests performed on a CRDA assessment of the 2CrMo working dataset at (a) 500°C, (b) 550°C and (c) 600°C



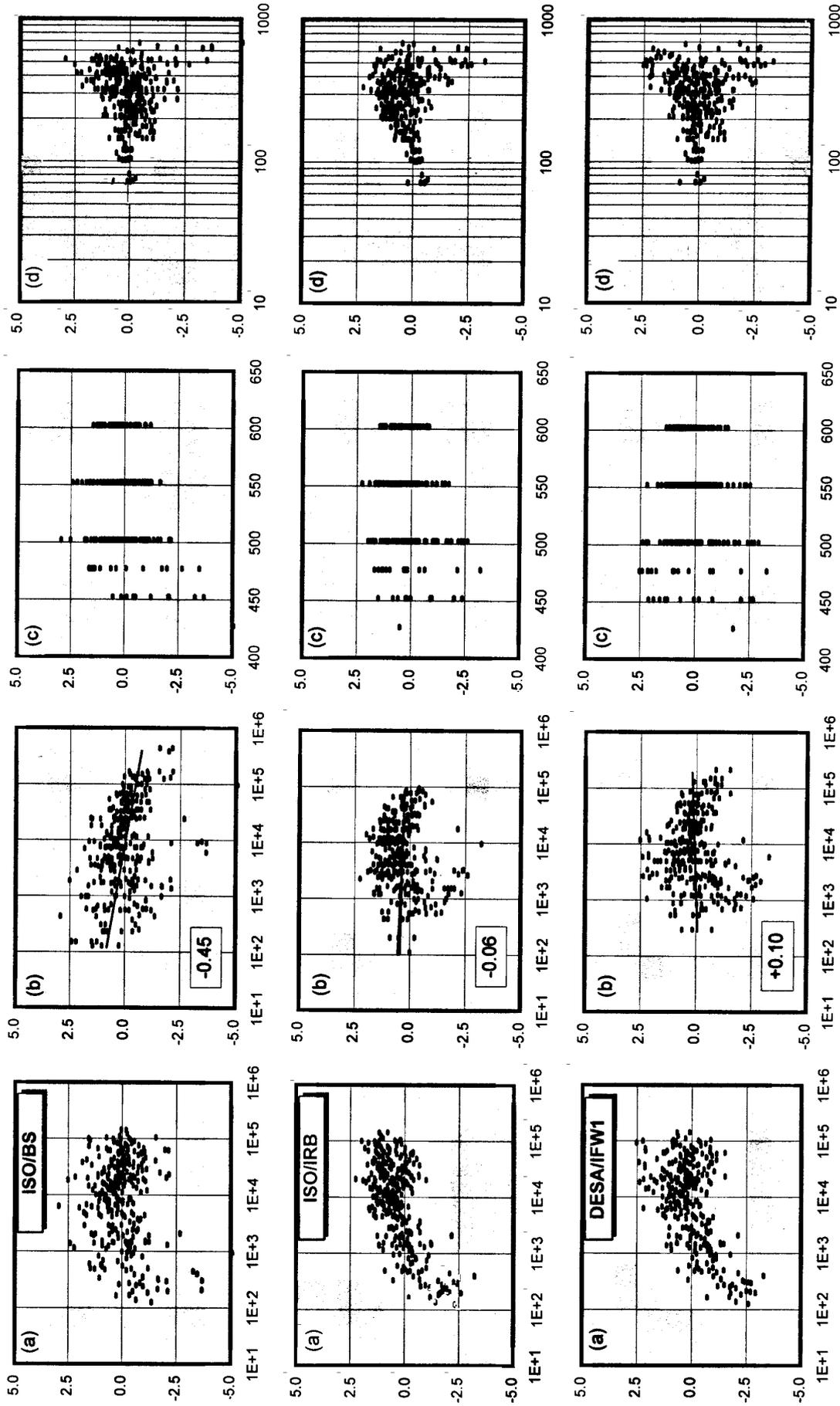
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) for 2CrMo



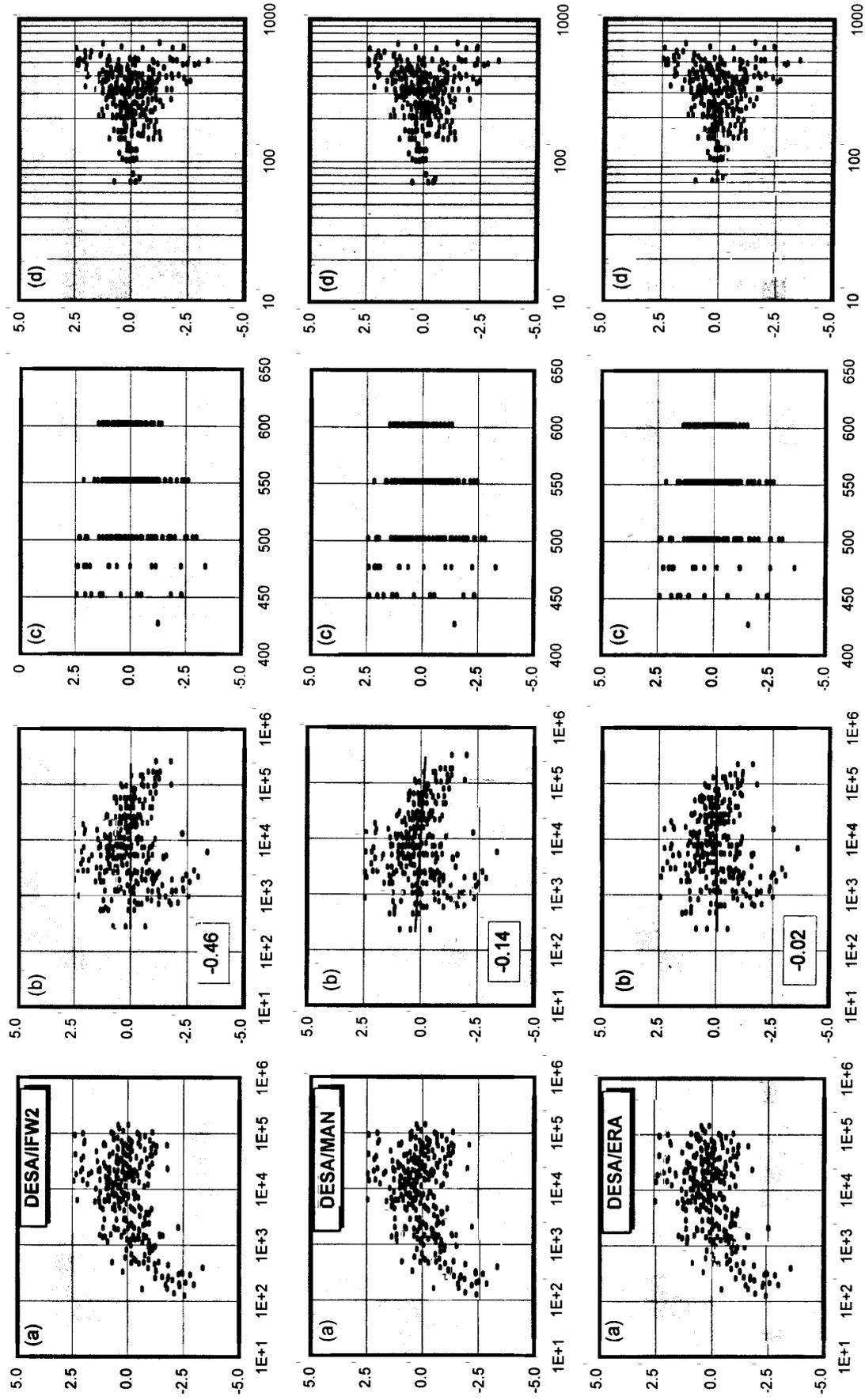
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature ($^{\circ}$ C), and (d) stress (MPa) for 2Cr1Mo



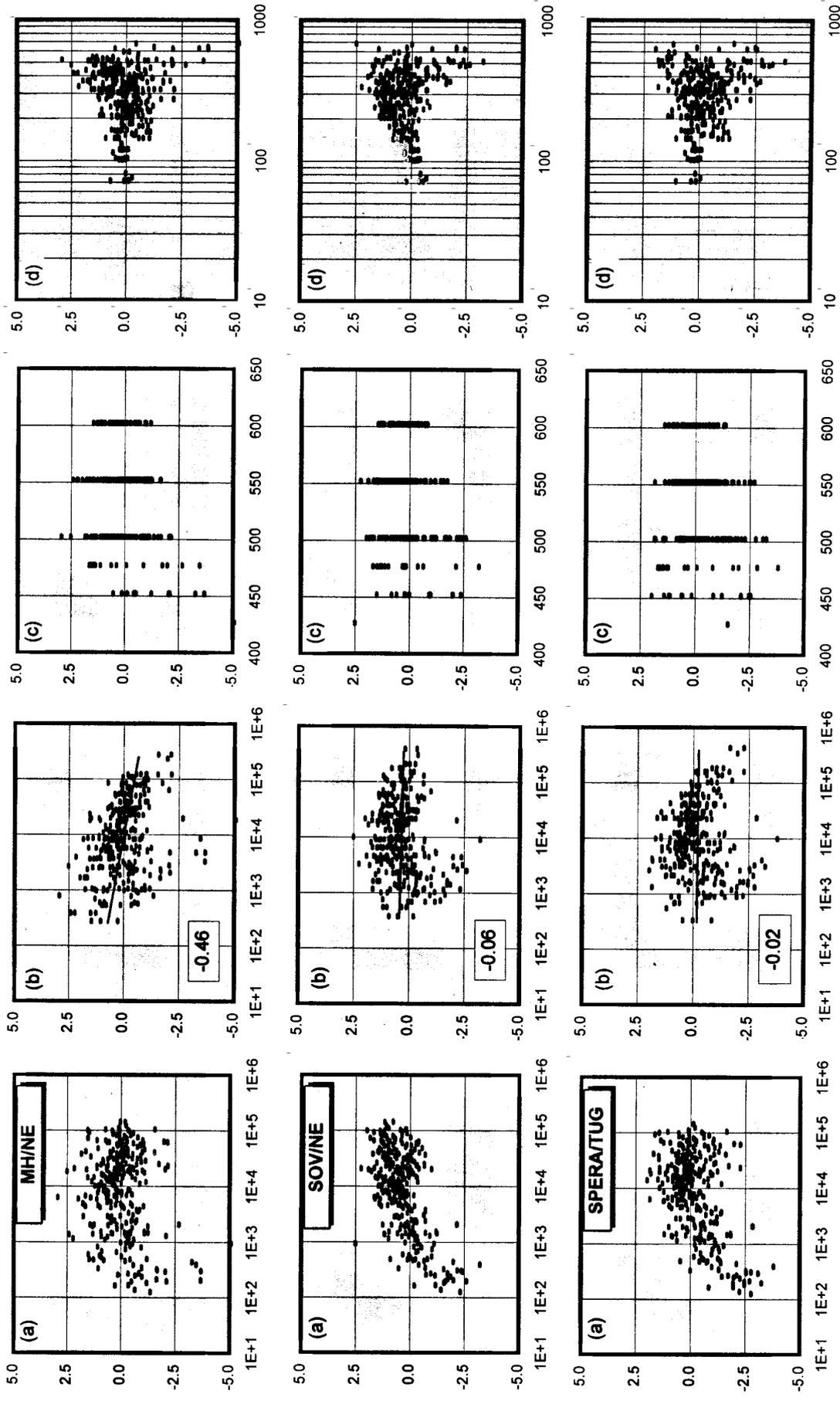
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature ($^{\circ}\text{C}$), and (d) stress (MPa) for 2CrMo



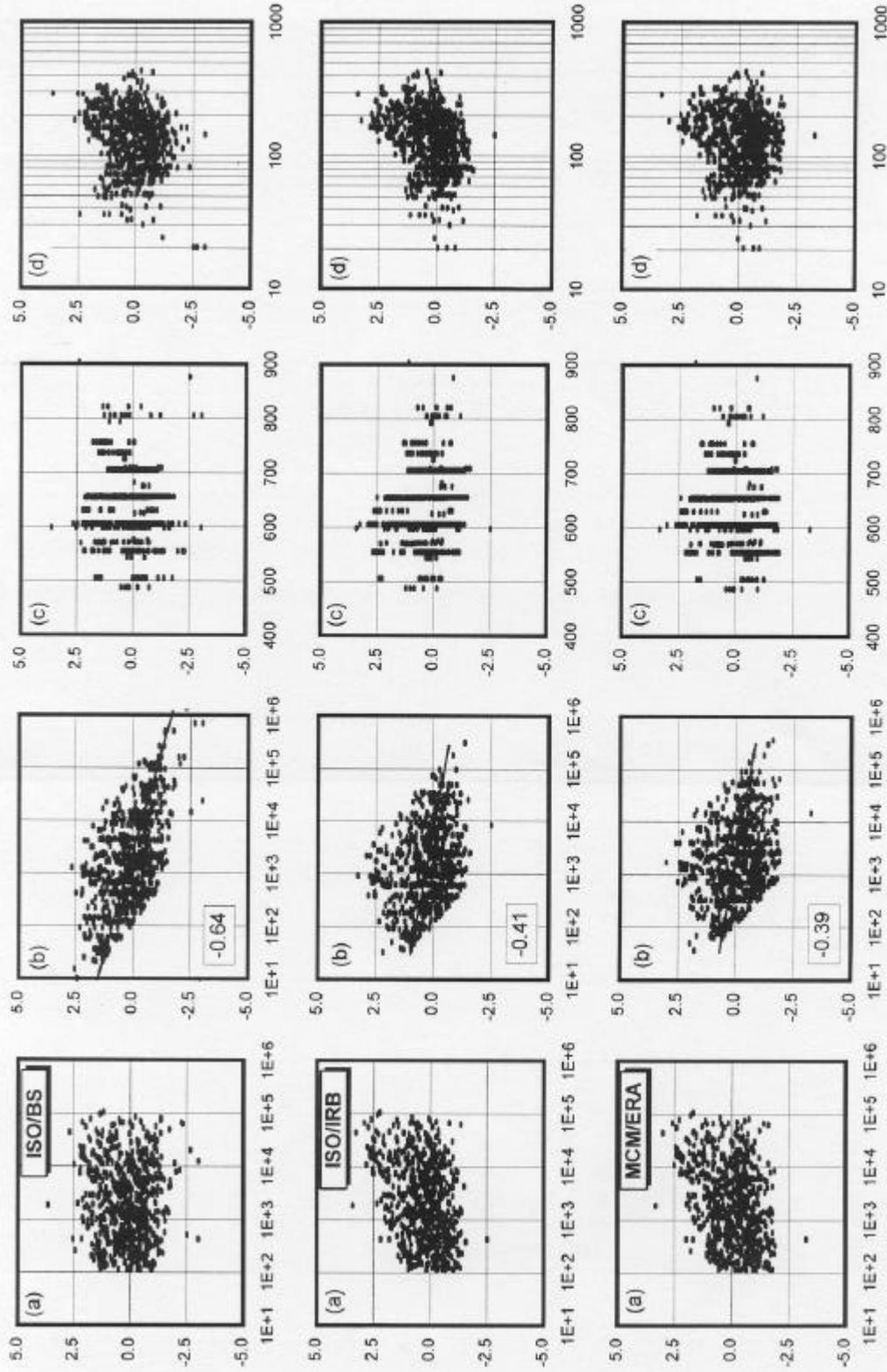
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) for 12CrMoVNb



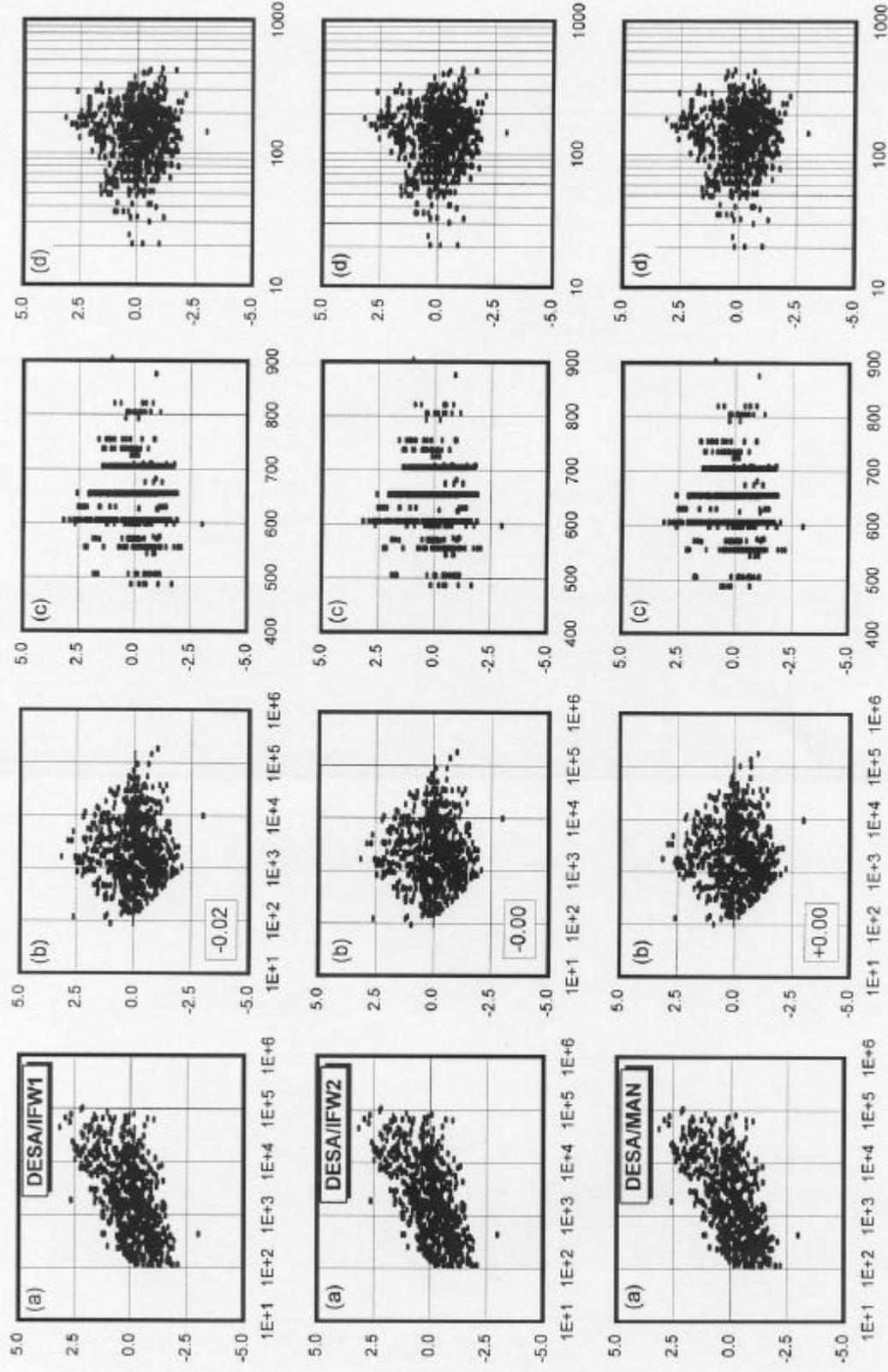
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) for 12CrMoVNb



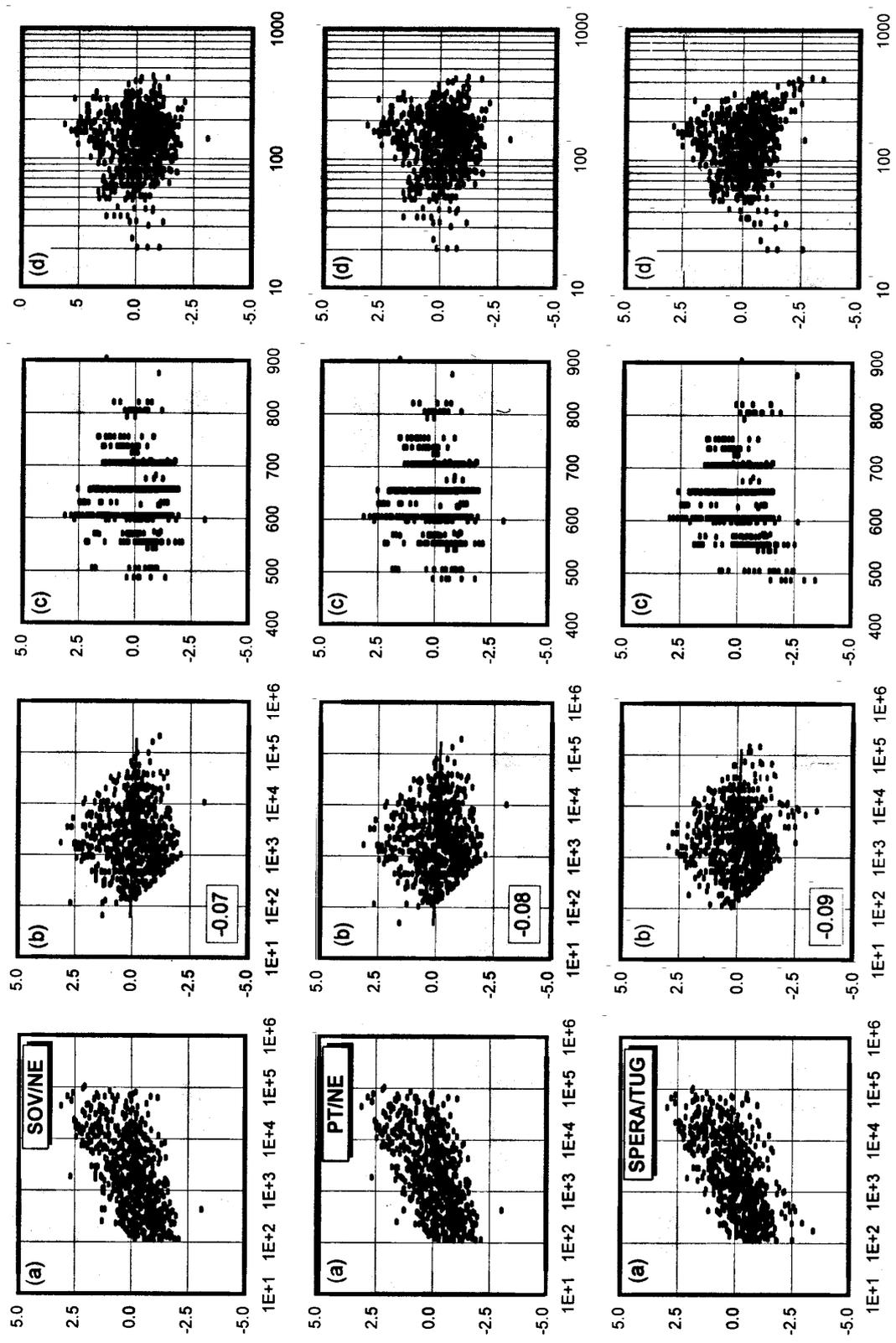
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) for 12CrMoVNb



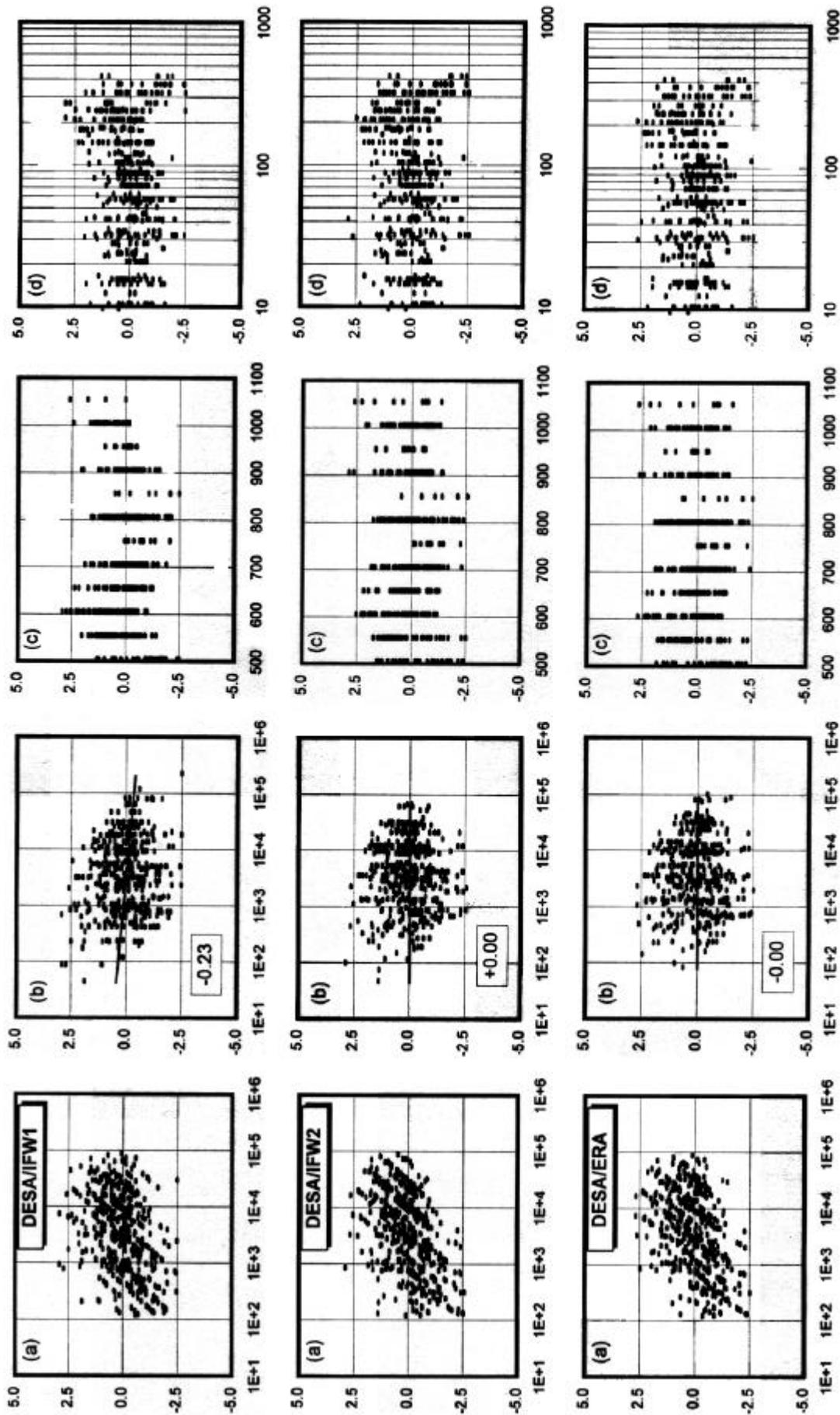
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) Type 304 18Cr11Ni



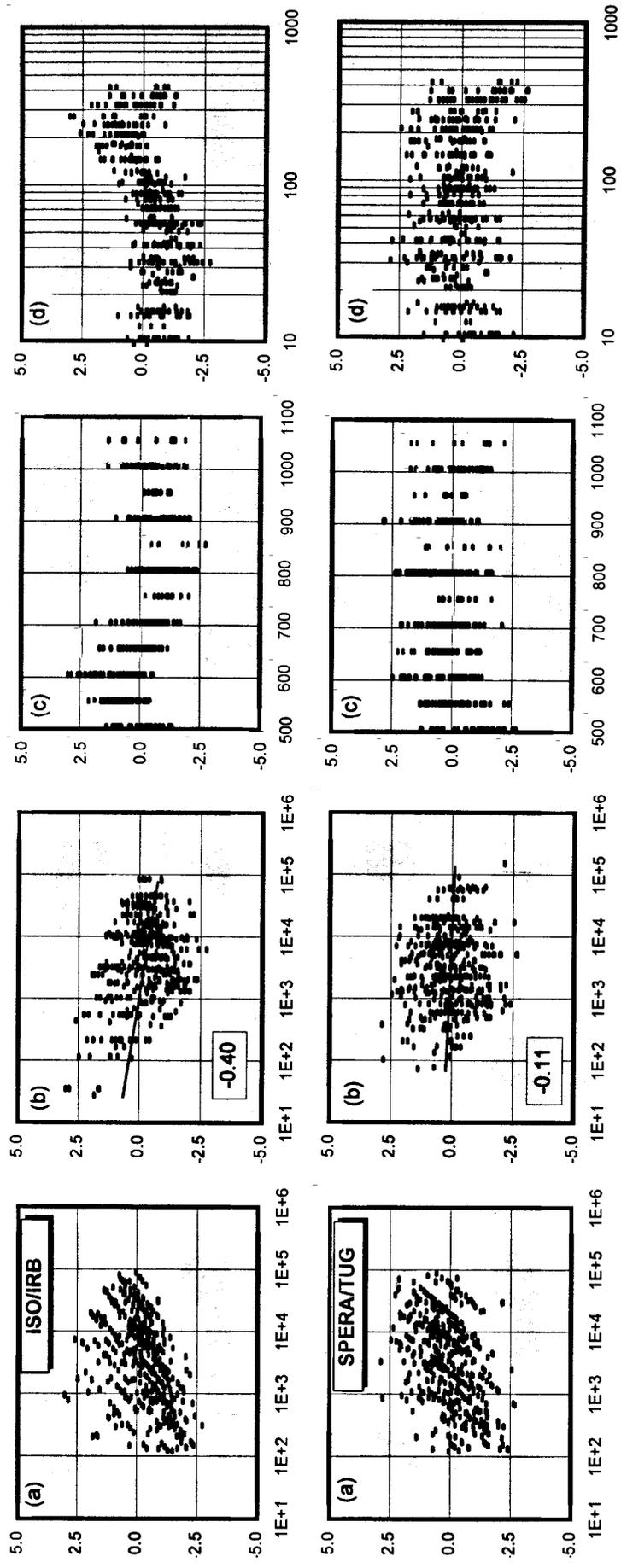
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) Type 304 18Cr11Ni



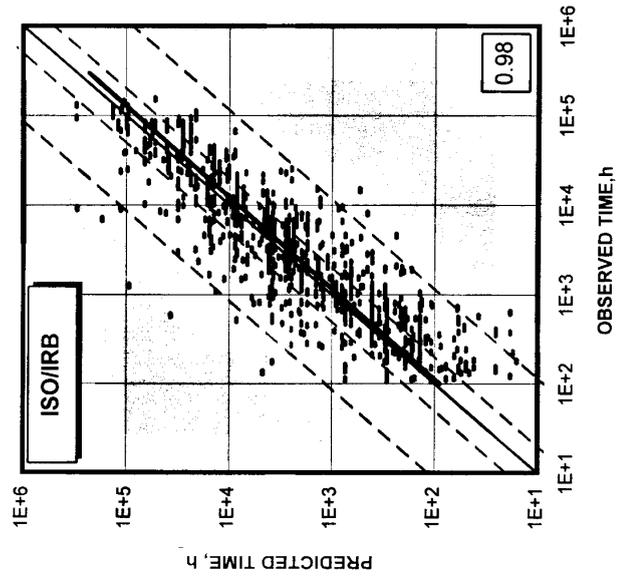
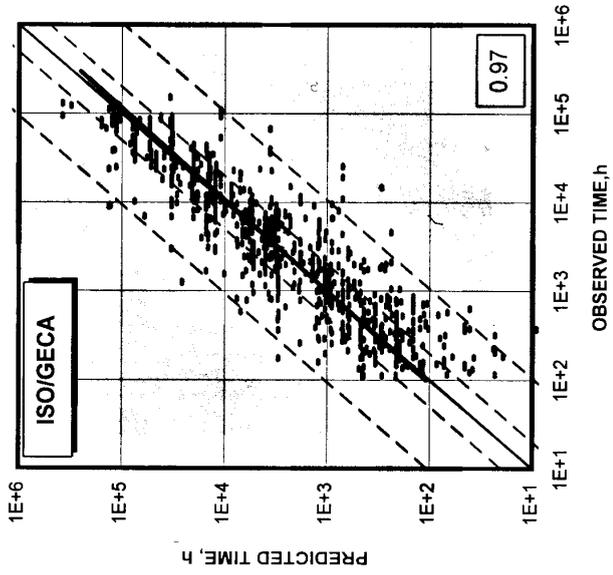
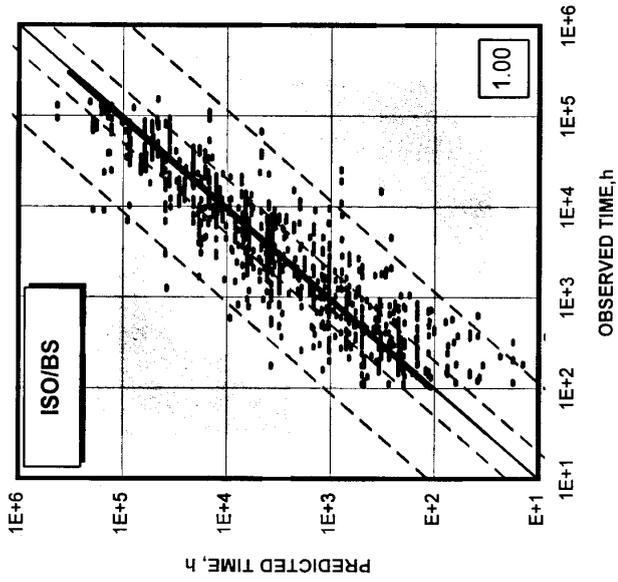
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) Type 304 18Cr11Ni



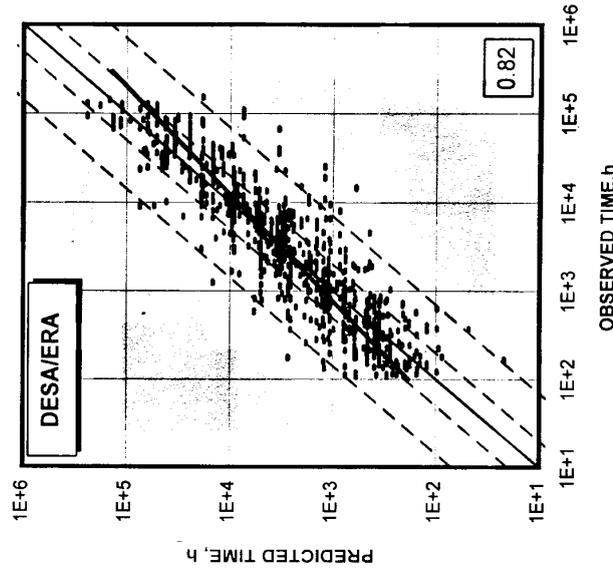
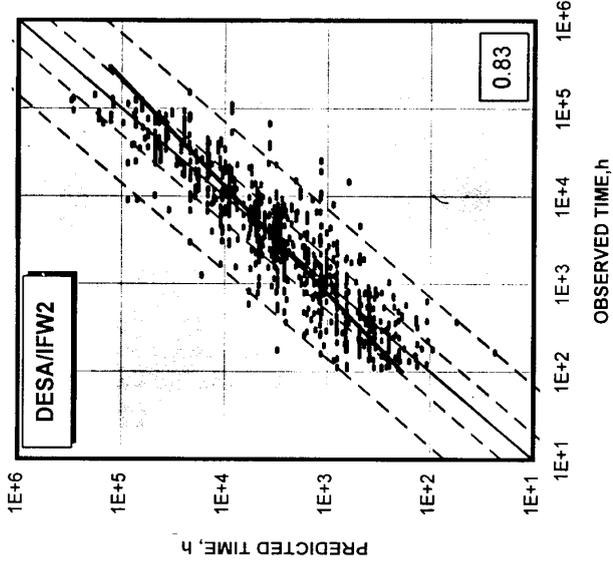
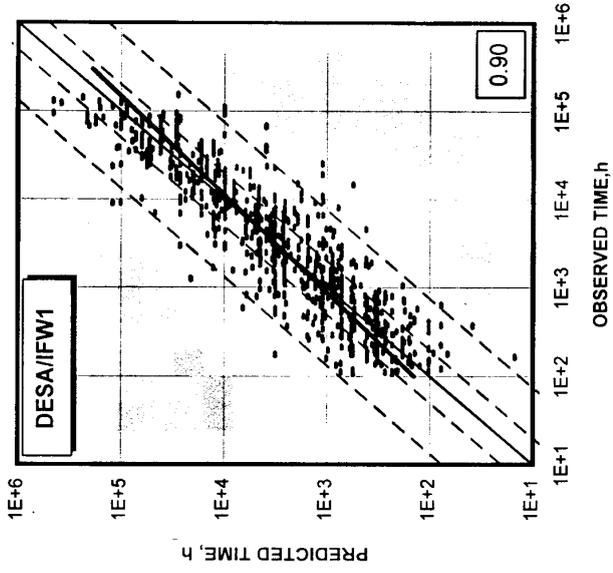
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature ($^{\circ}\text{C}$), and (d) stress (MPa) for Incoloy 800



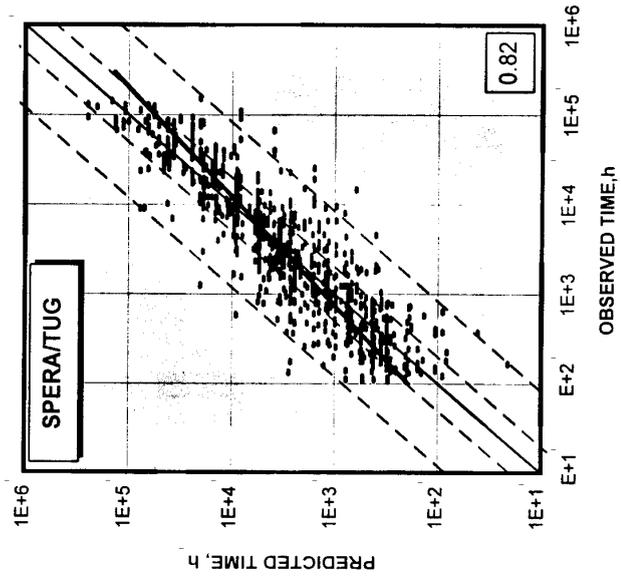
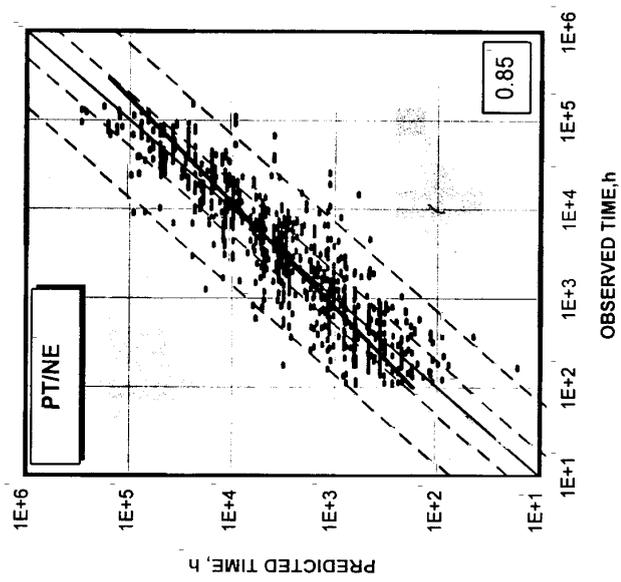
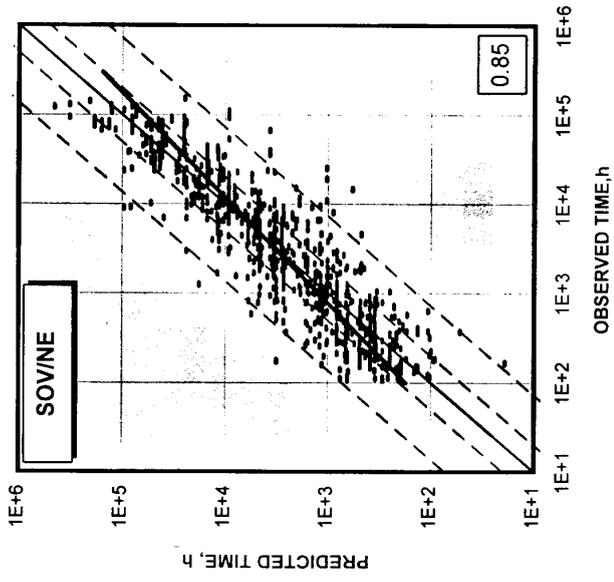
A-SRLT versus (a) observed time (h), (b) predicted time (h), (c) temperature (°C), and (d) stress (MPa) for Incoloy 800



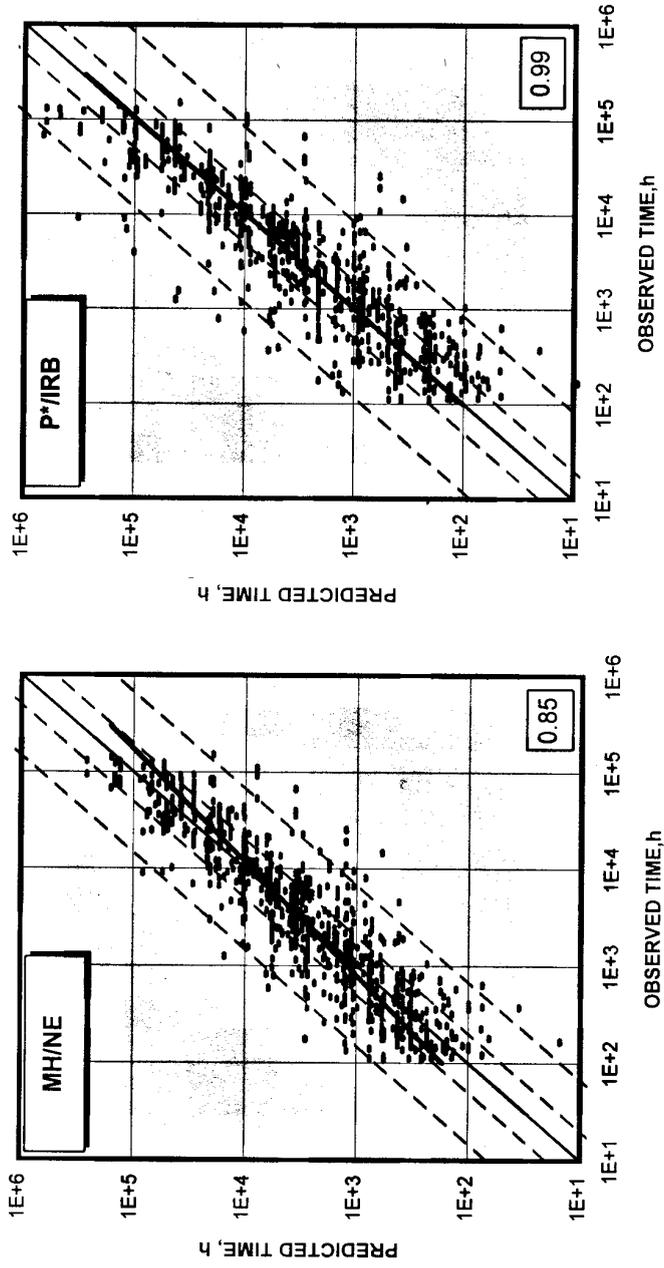
Predicted time versus observed time for 2CrMo
 (the number inset is the slope of the mean line)



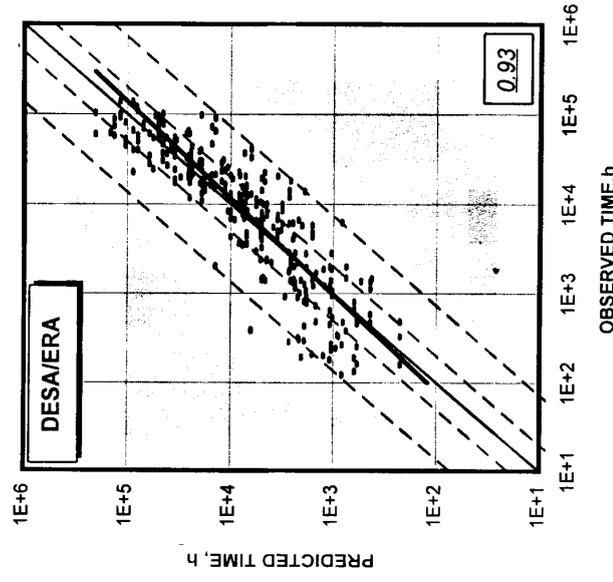
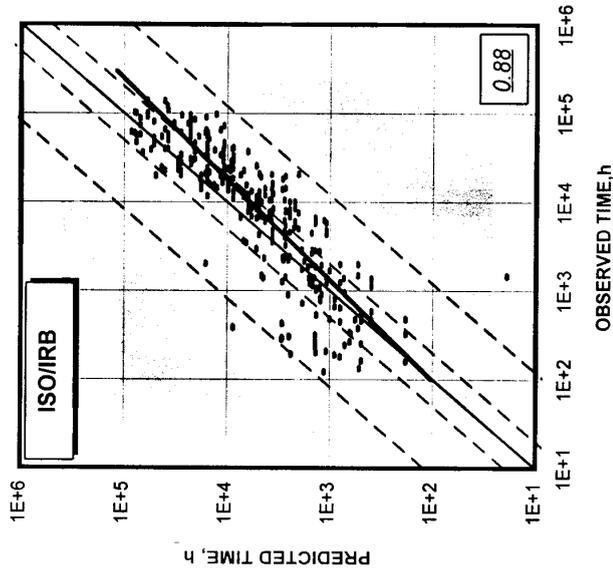
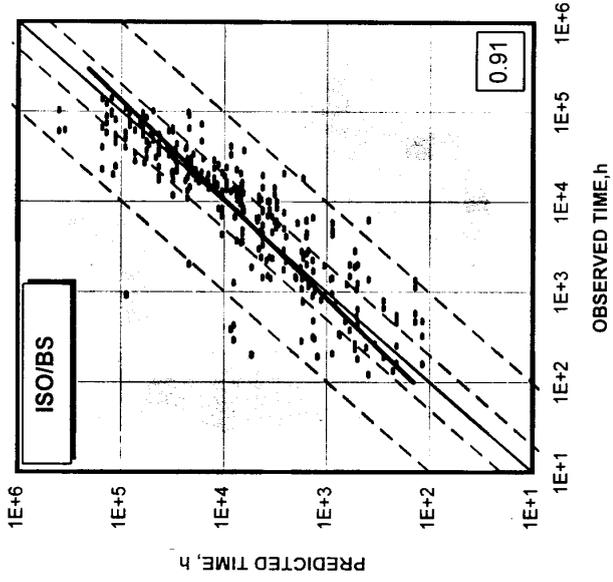
Predicted time versus observed time for 2CrMo
 (the number inset is the slope of the mean line)



Predicted time versus observed time for 2CrMo
 (the number inset is the slope of the mean line)

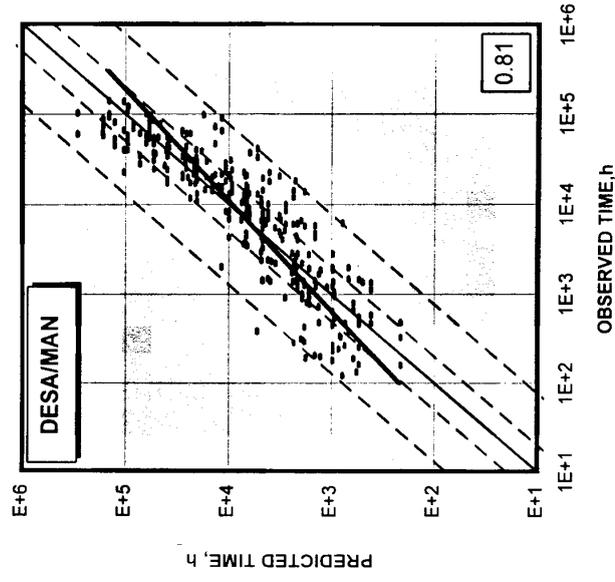
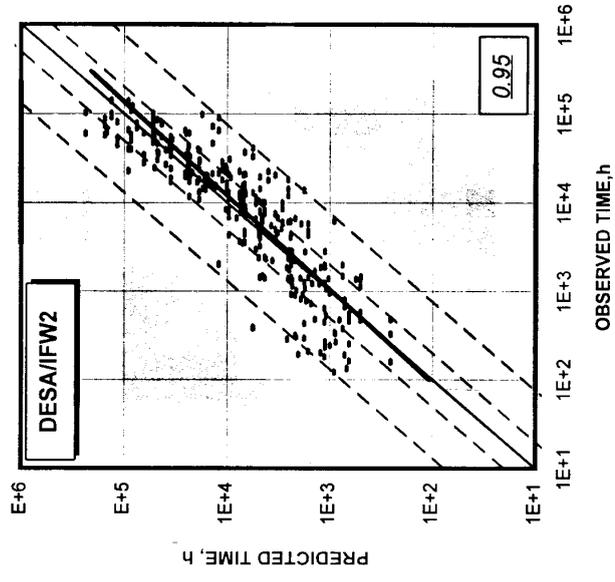
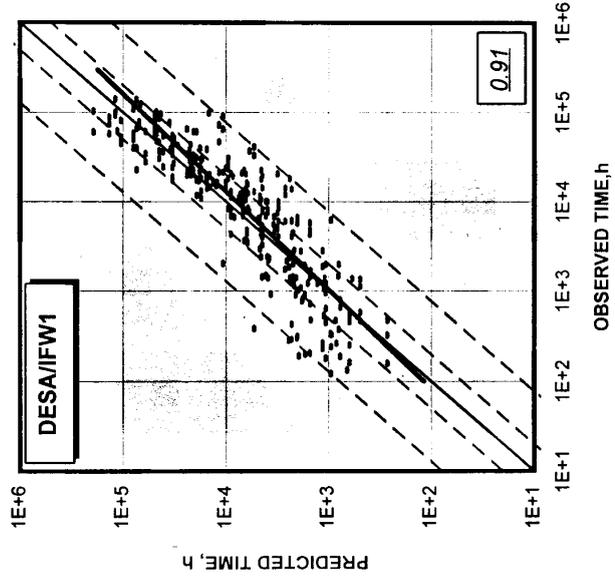


Predicted time versus observed time for 2CrMo
 (the number inset is the slope of the mean line)



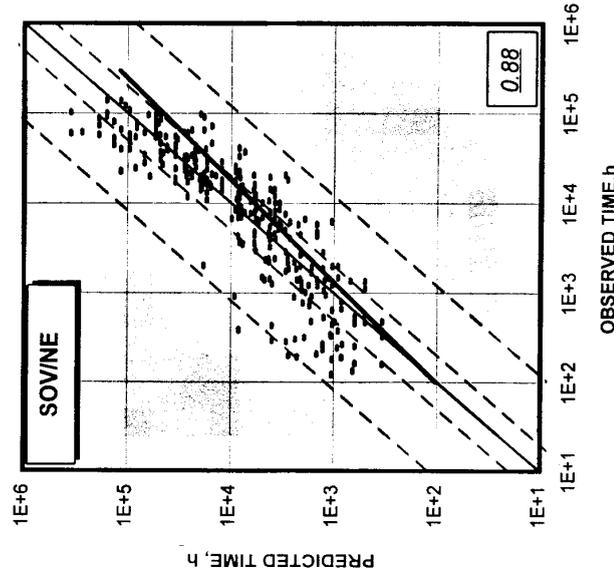
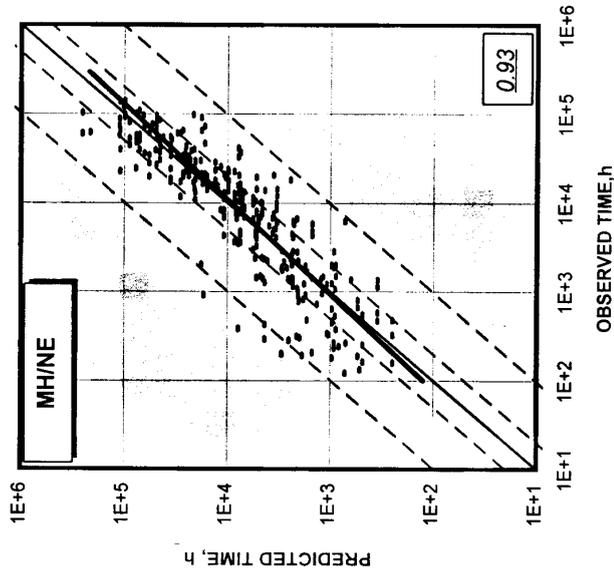
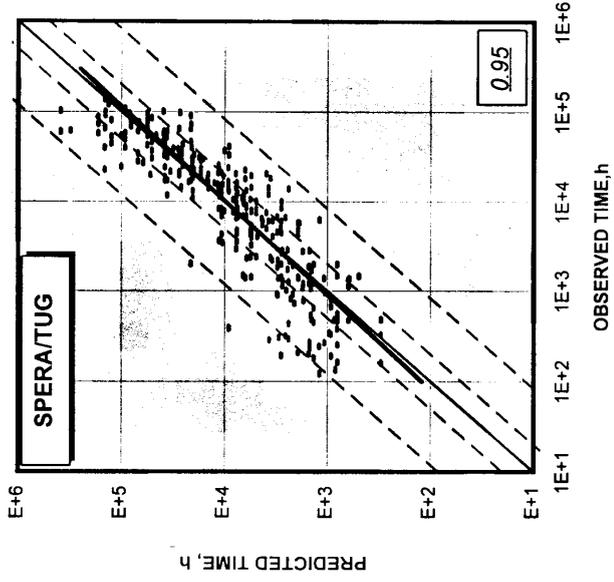
Predicted time versus observed time for ¹²CrMoVNb

(the number inset is the slope of the mean line, underlined when determined between $t_{r(max)}/100$ and $t_{r(max)}$)



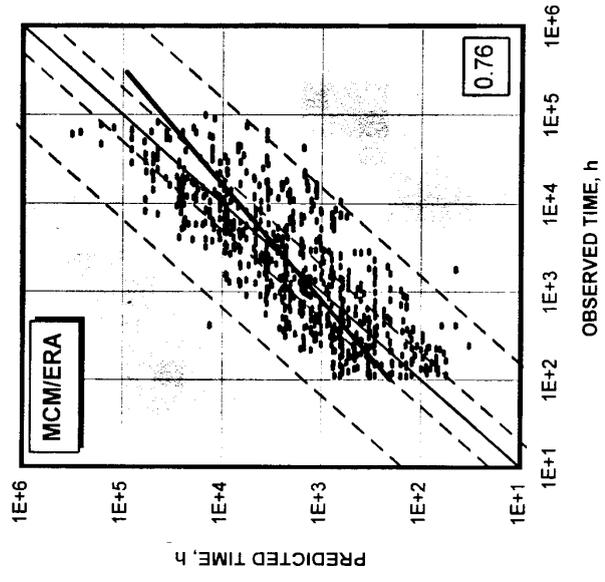
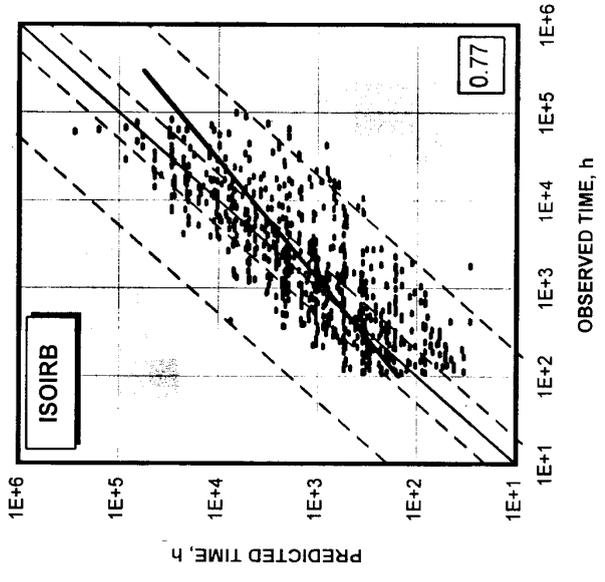
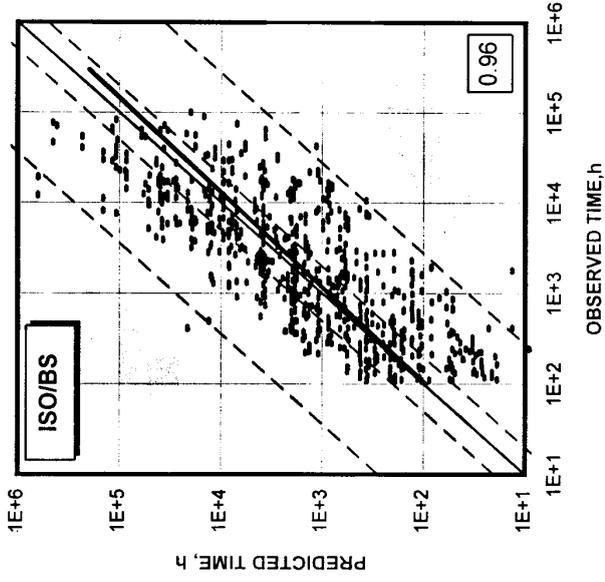
Predicted time versus observed time for $^{12}\text{CrMoVNb}$

(the number inset is the slope of the mean line, underlined when determined between $t_{r(\max)}/100$ and $t_{r(\max)}$)



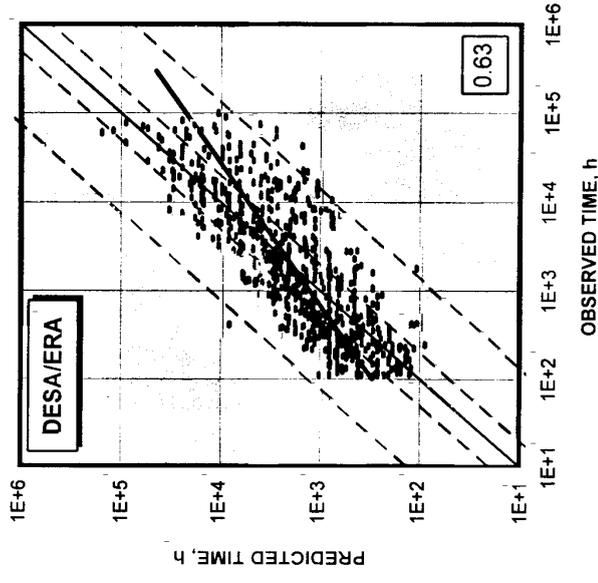
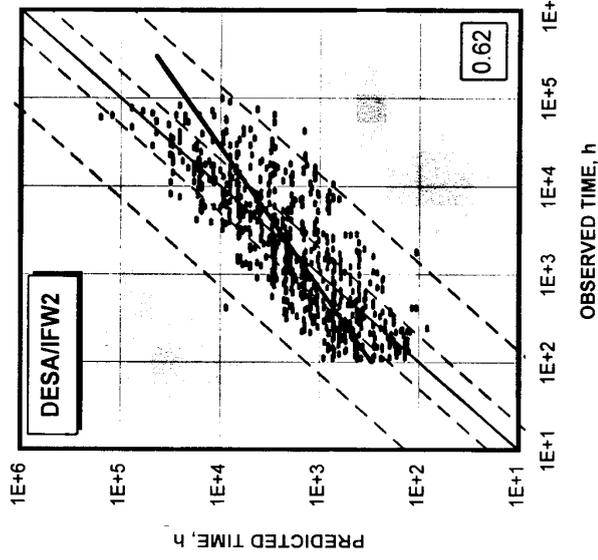
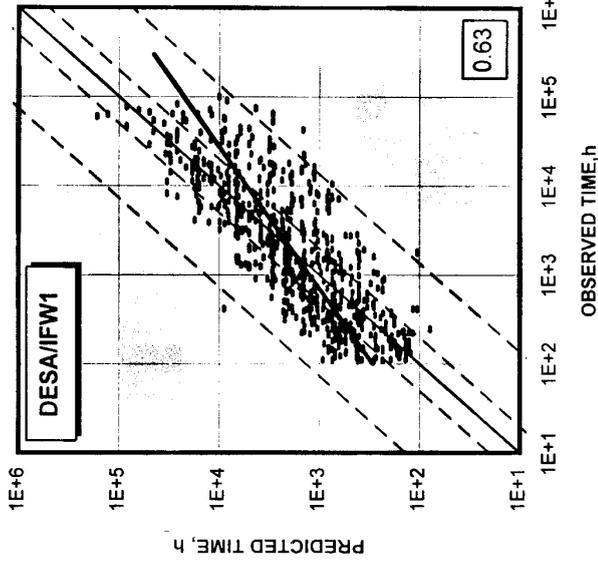
Predicted time versus observed time for ¹²⁵I

(the number inset is the slope of the mean line, underlined when determined between $t_{r(max)}/100$ and $t_{r(max)}$)



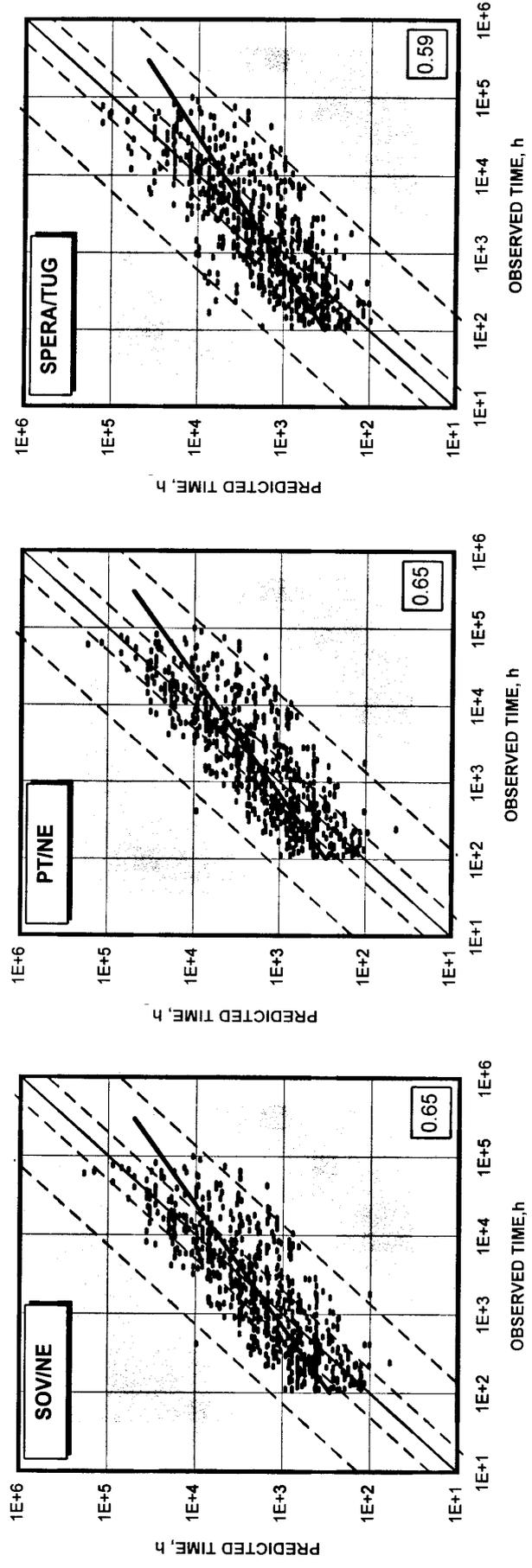
Predicted time versus observed time for Type 304 18Cr11Ni

(the number inset is the slope of the mean line, determination between $t_{t_{[max]}/100}$ and $t_{t_{[max]}}$ does not take slope to within required tolerance)

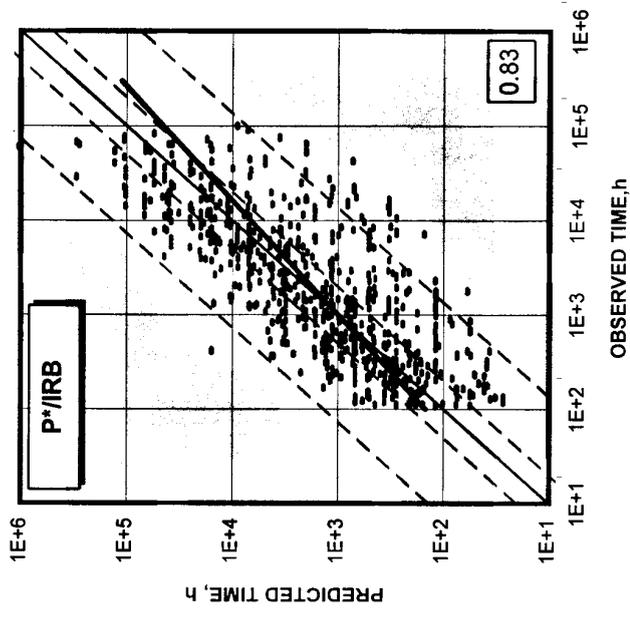


Predicted time versus observed time for Type 304 18Cr11Ni

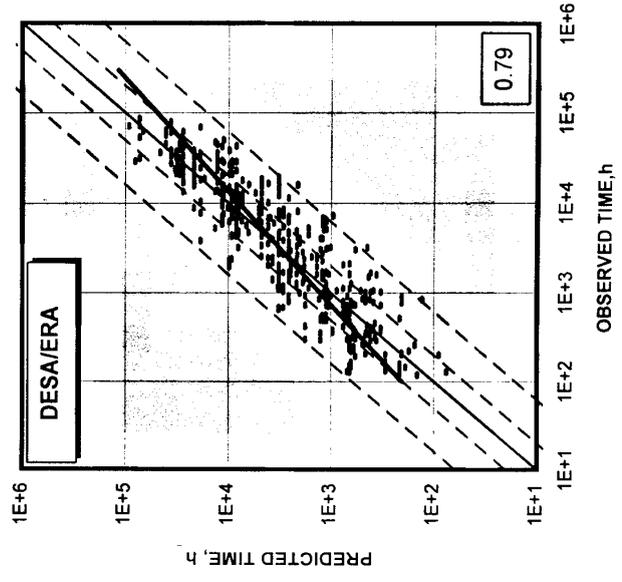
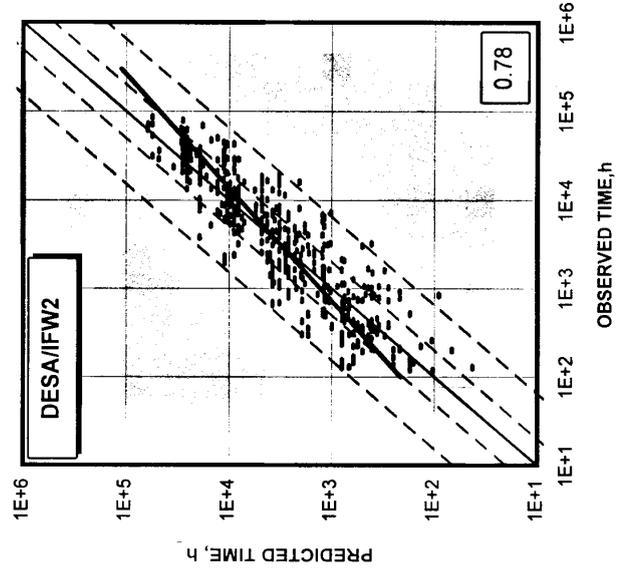
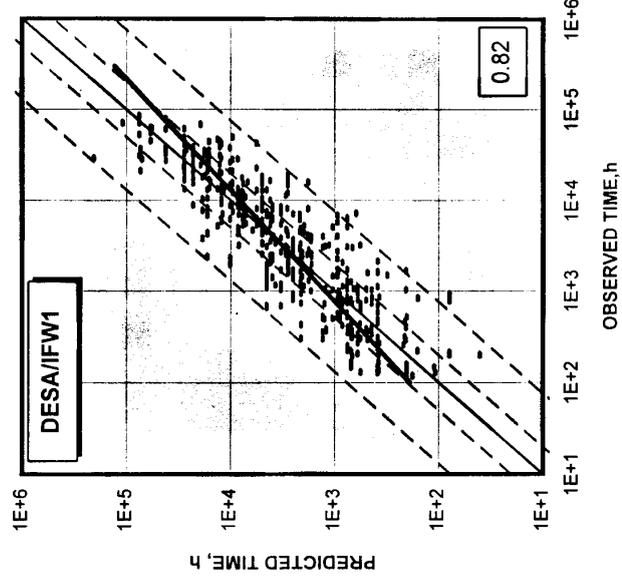
(the number inset is the slope of the mean line, determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope to within required tolerance)



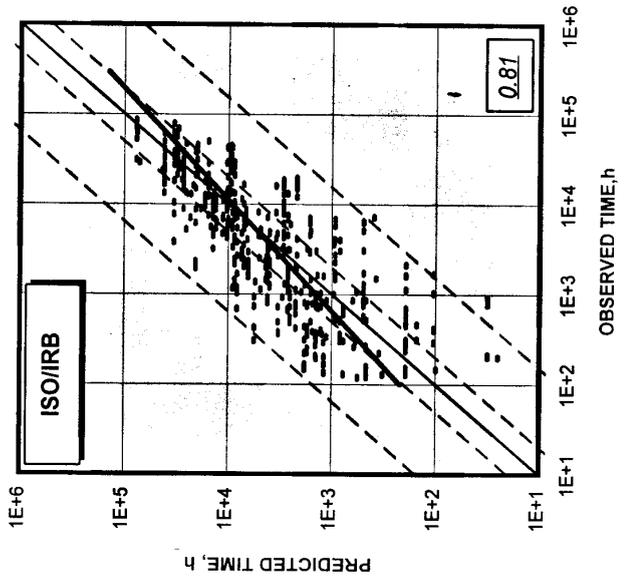
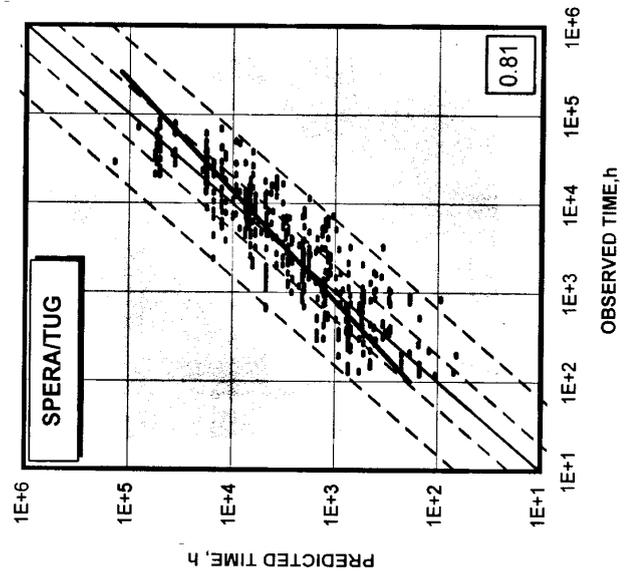
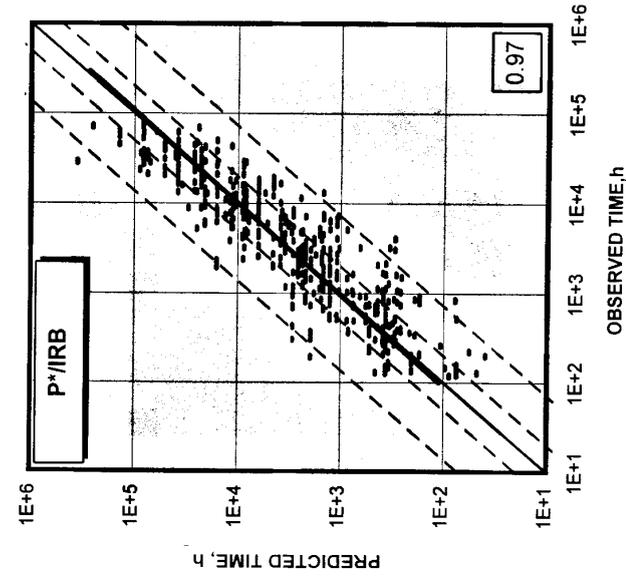
Predicted time versus observed time for Type 304 18Cr11Ni
 (the number inset is the slope of the mean line, determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope to within required tolerance)



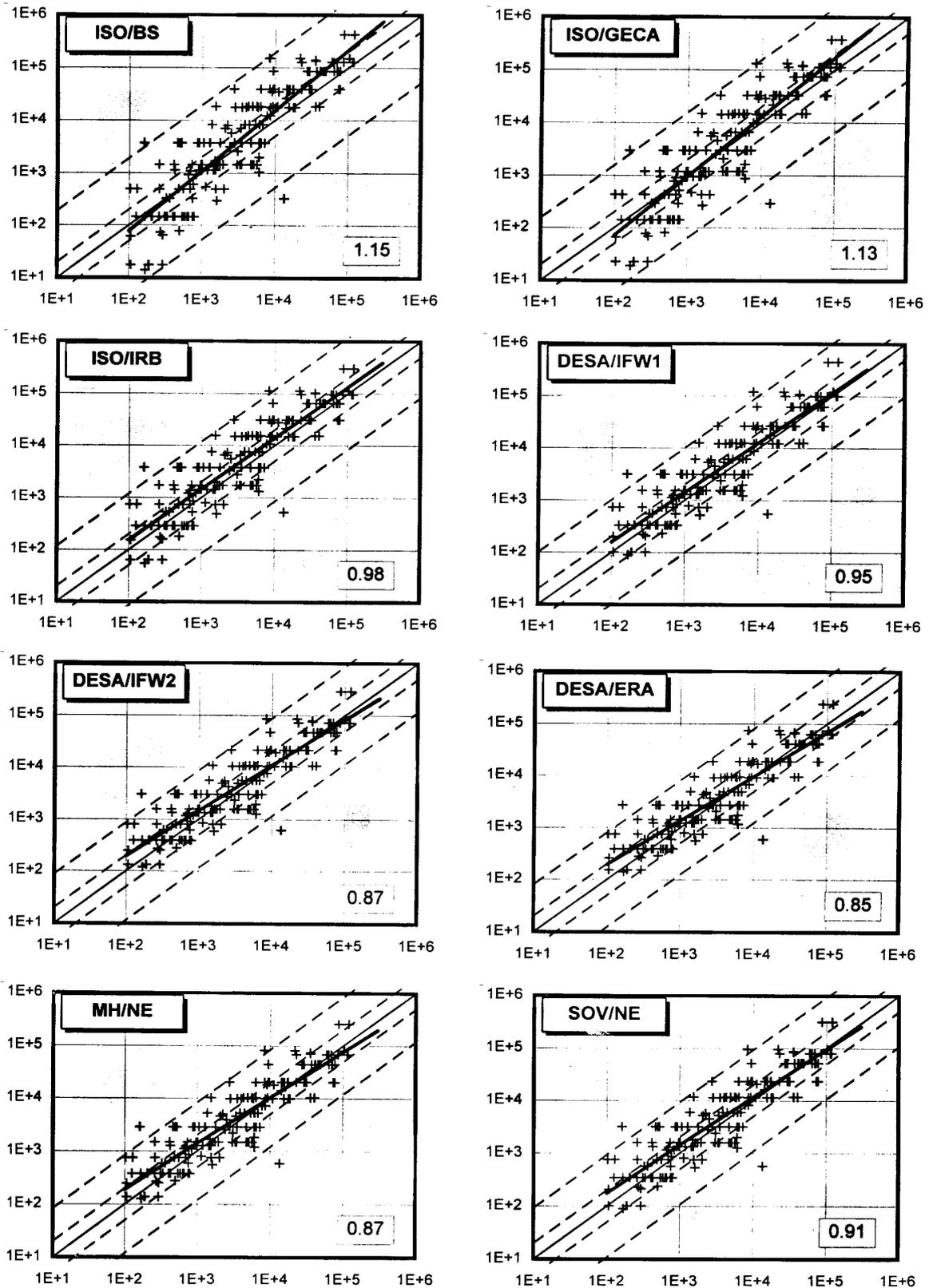
Predicted time versus observed time for Type 304 18Cr11Ni
 (the number inset is the slope of the mean line, determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope to within required tolerance)



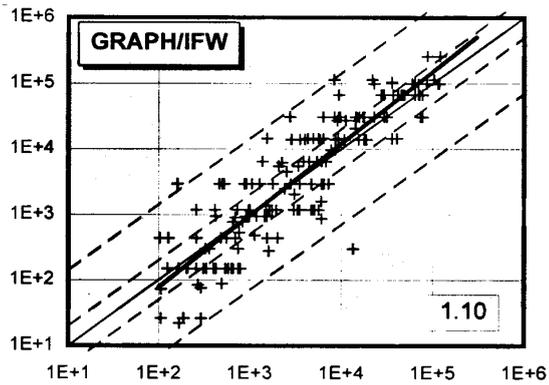
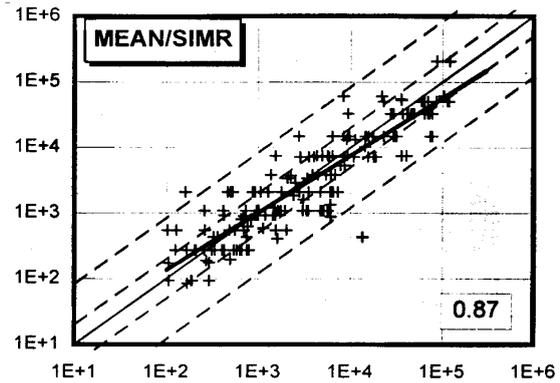
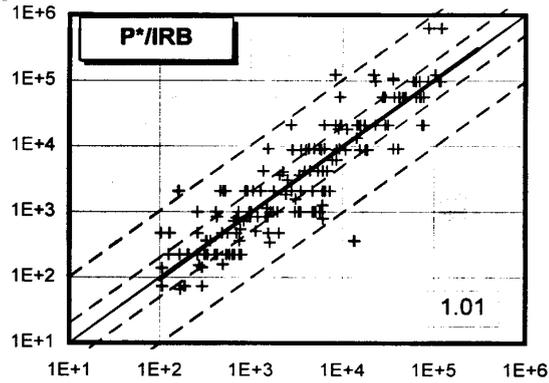
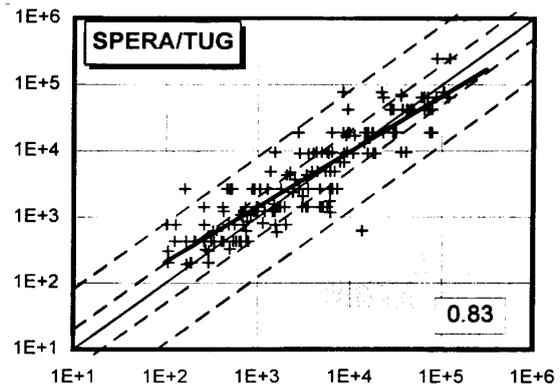
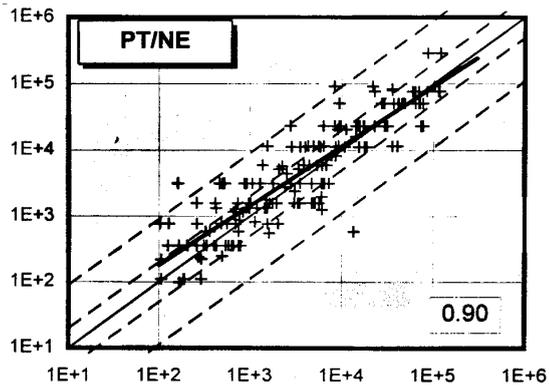
Predicted time versus observed time for Incoloy 800
 (the number inset is the slope of the mean line)



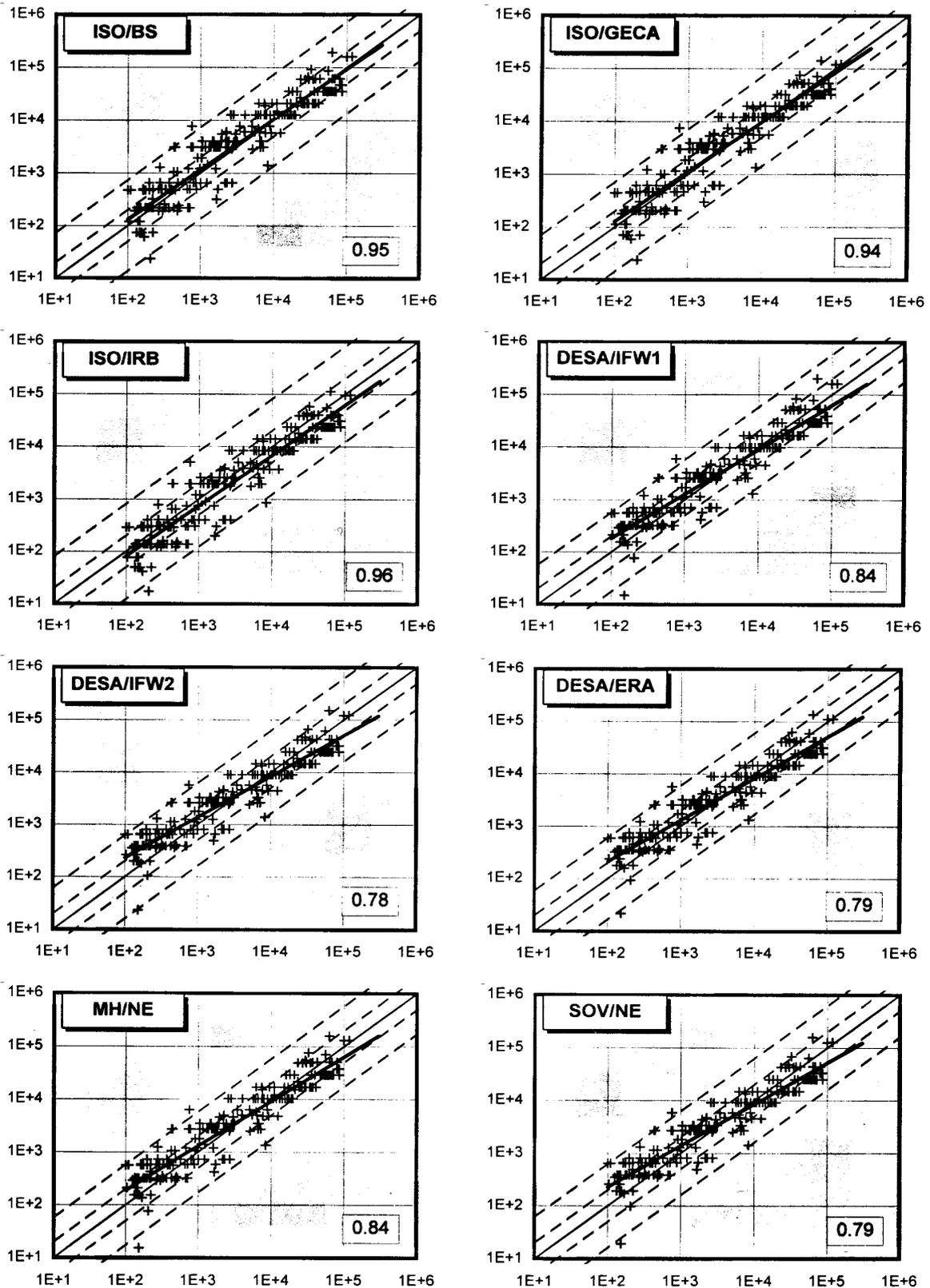
Predicted time versus observed time for Incoloy 800
 (the number inset is the slope of the mean line, underlined when determined between $t_{r(max)}/100$ and $t_{r(max)}$)



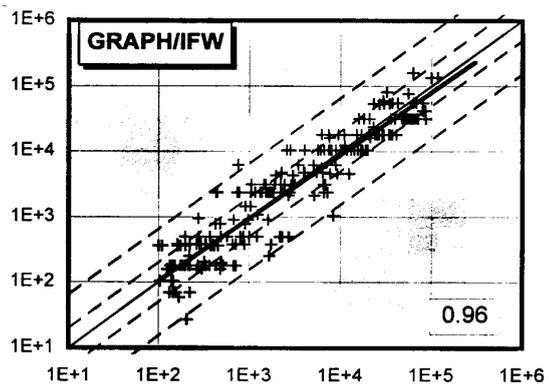
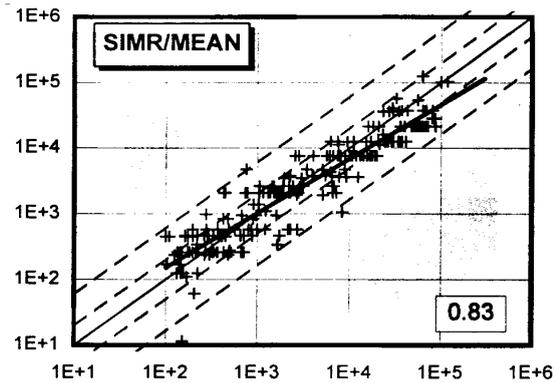
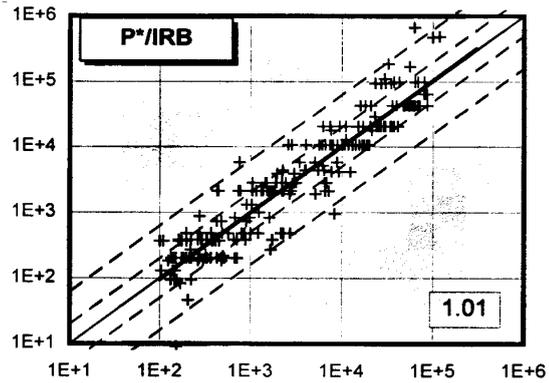
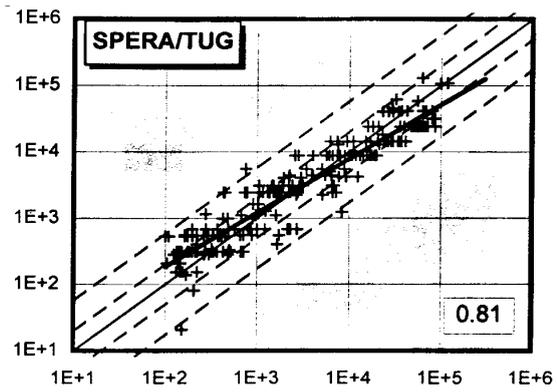
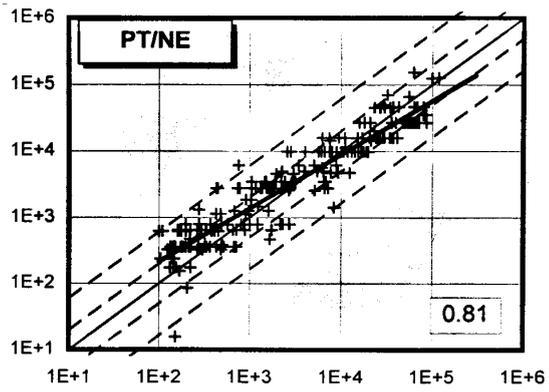
Predicted time versus observed time for 2CrMo at 500°C
(number inset is the slope of the mean line)



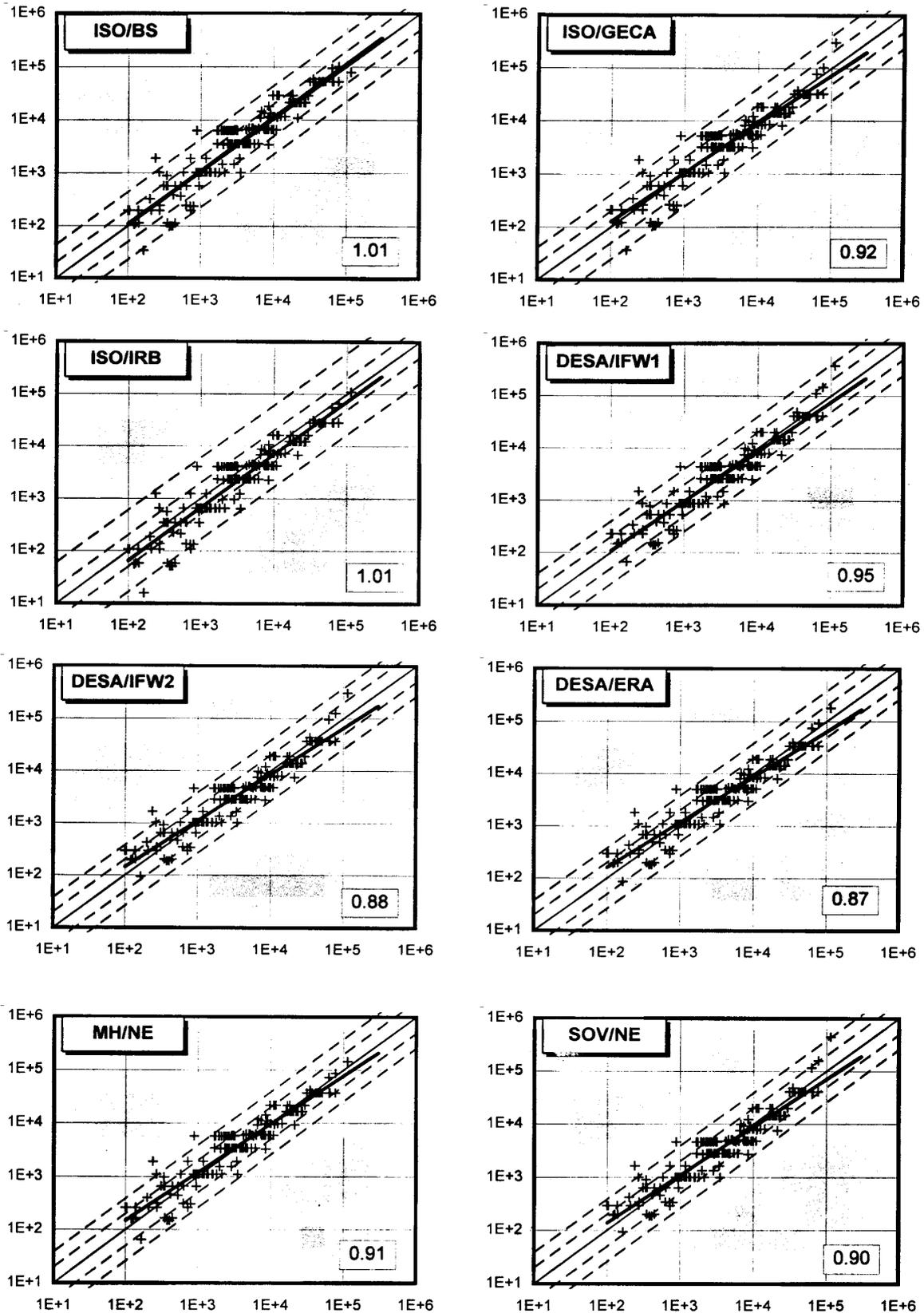
Predicted time versus observed time for 2CrMo at 500°C
 (number inset is the slope of the mean line)



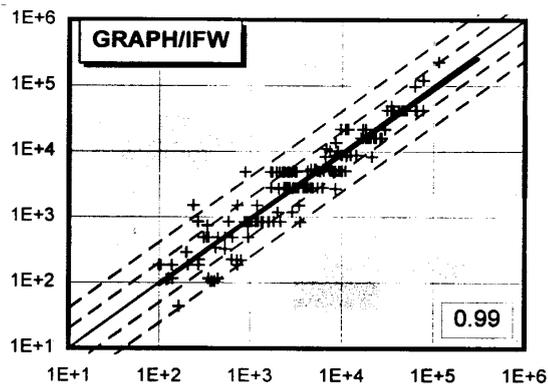
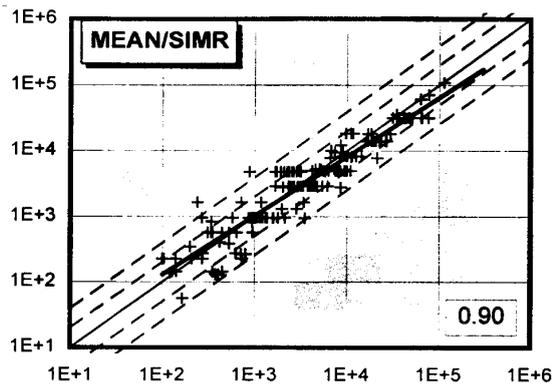
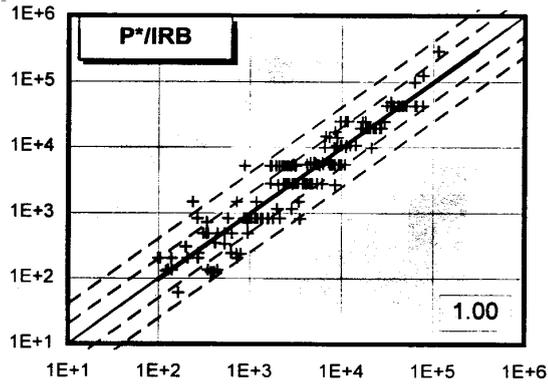
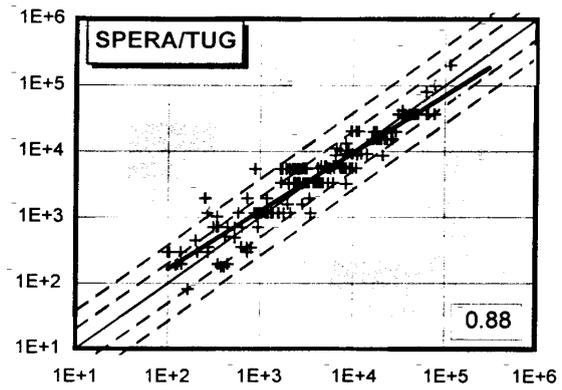
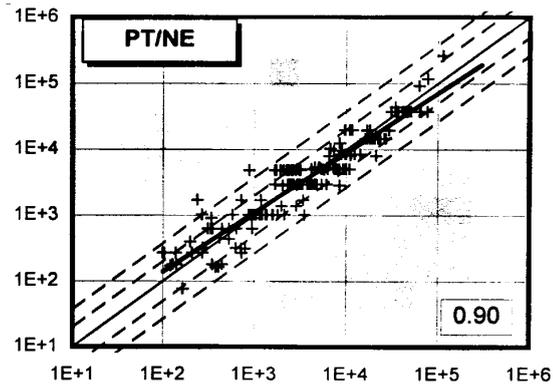
Predicted time versus observed time for 2CrMo at 550°C
(number inset is the slope of the mean line)



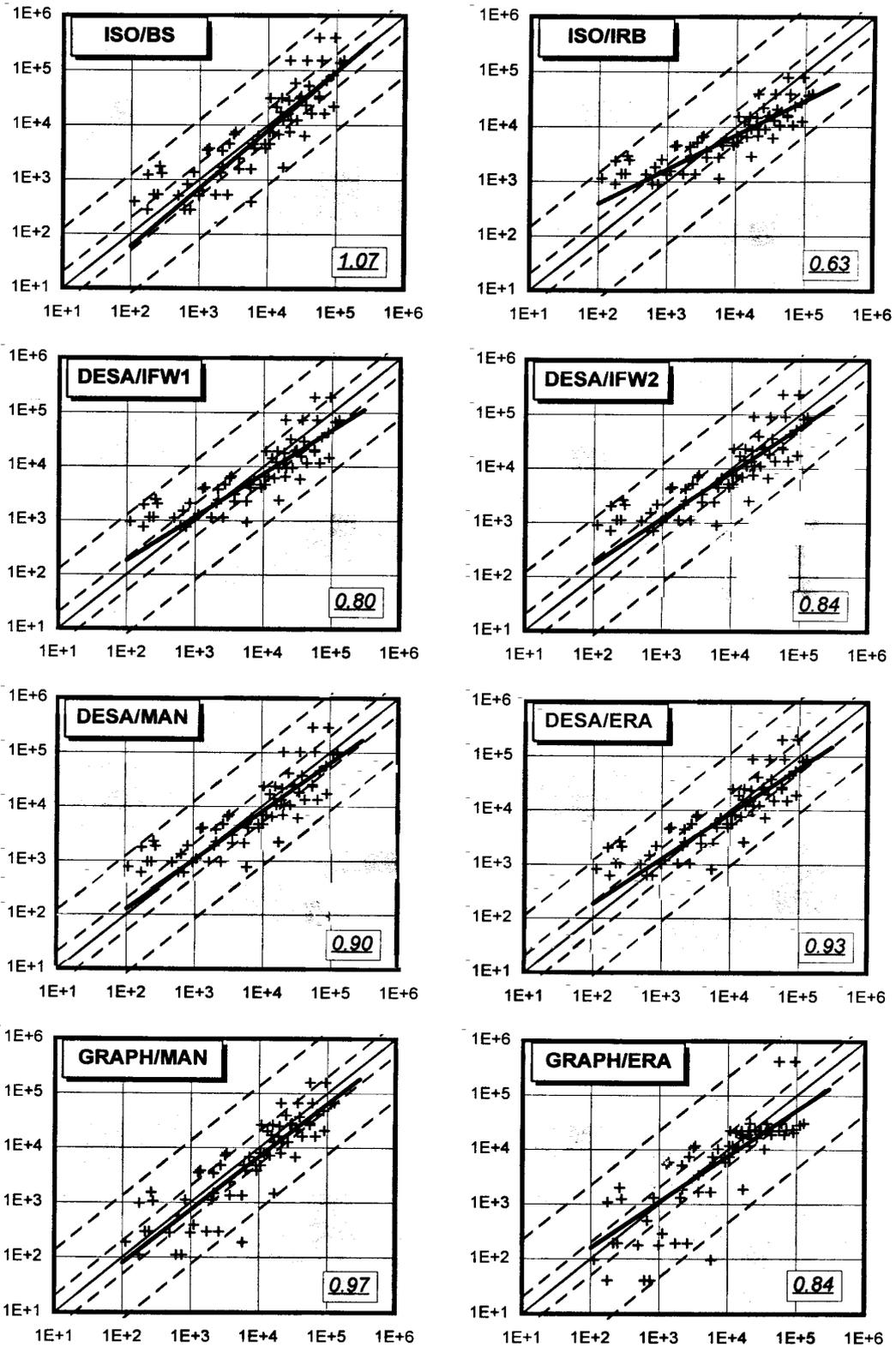
Predicted time versus observed time for 2CrMo at 550°C
 (number inset is the slope of the mean line)



Predicted time versus observed time for 2CrMo at 600°C
(number inset is the slope of the mean line)

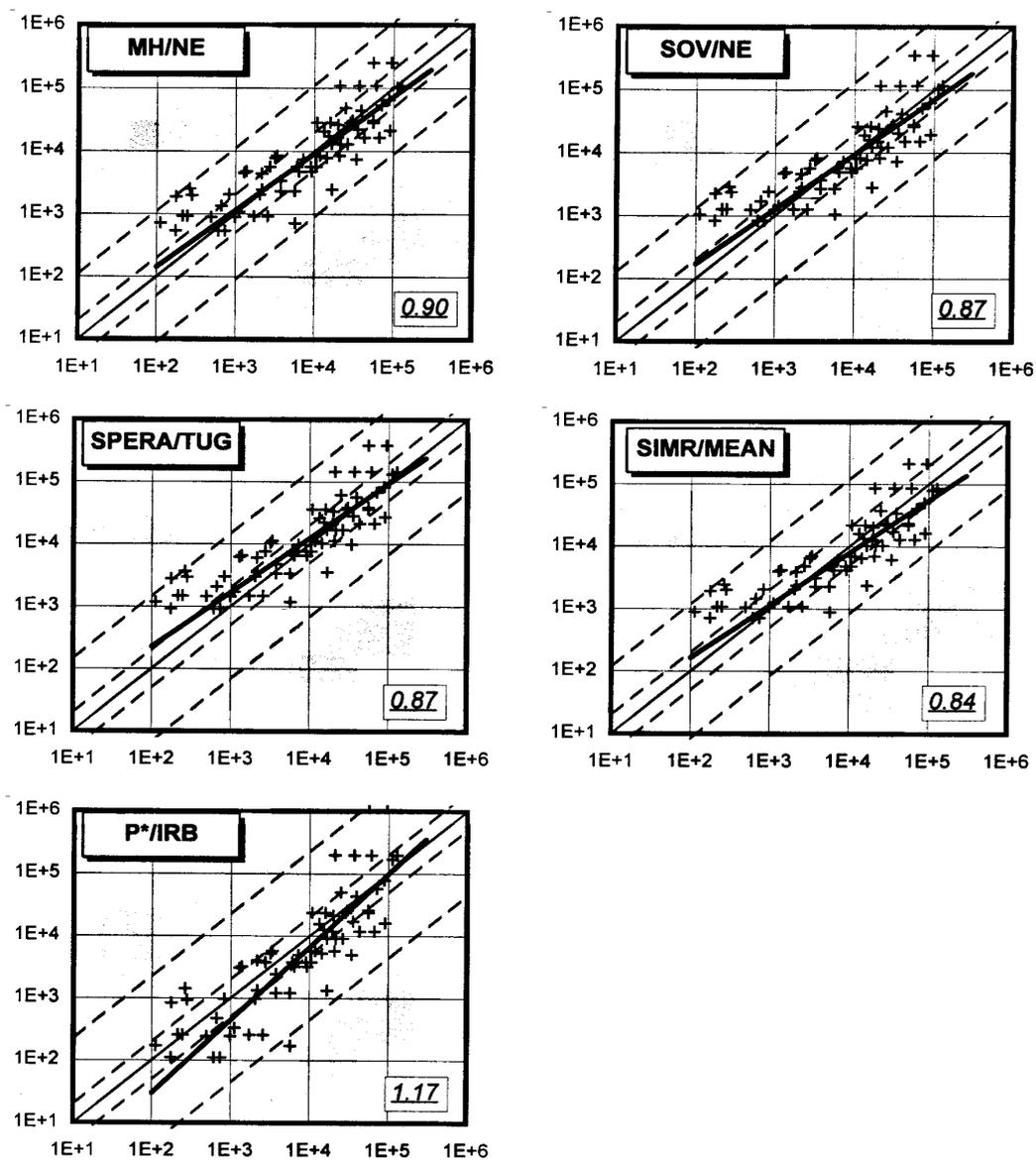


Predicted time versus observed time for 2CrMo at 600°C
(number inset is the slope of the mean line)



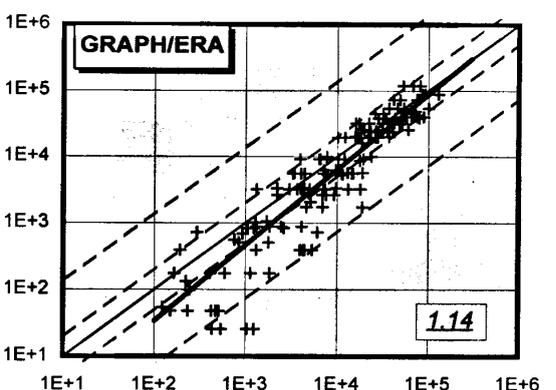
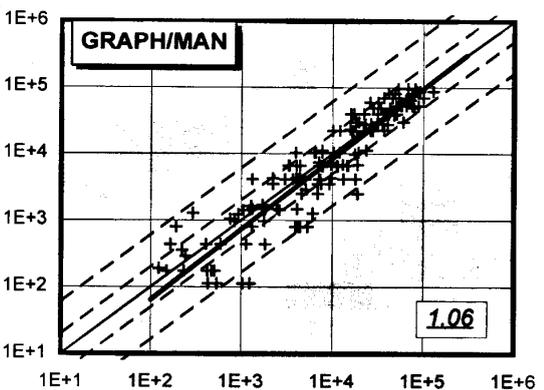
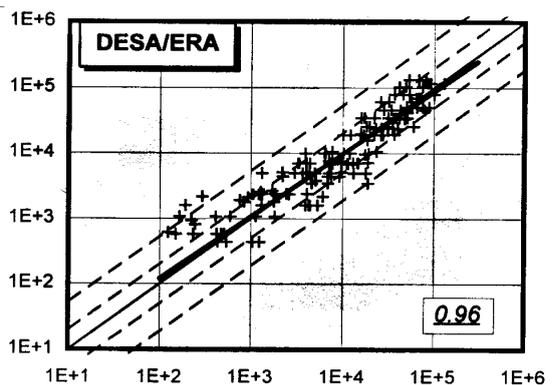
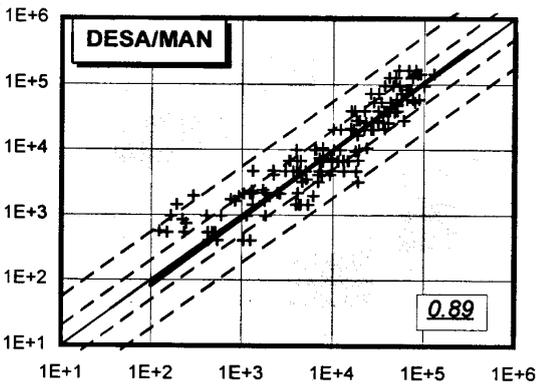
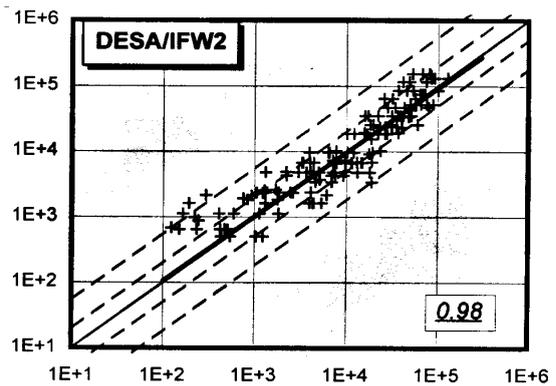
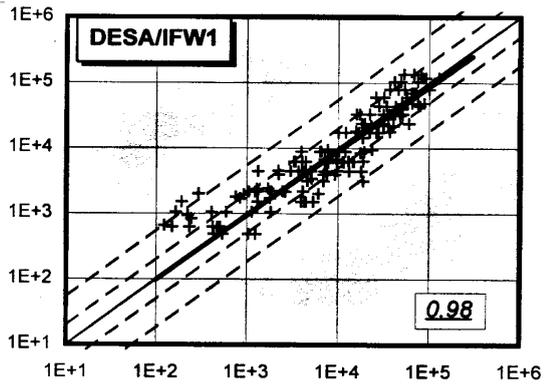
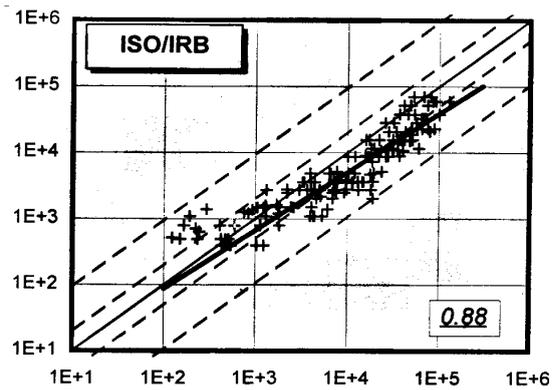
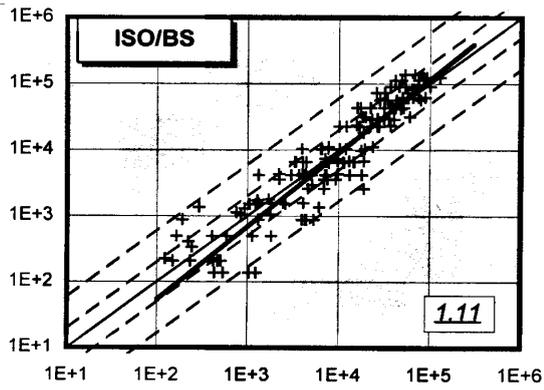
Predicted time versus observed time for 12CrMoVNb at 500°C

(the number inset is the slope of the mean line, underlined when determined between $t_{(max)}/100$ and $t_{(max)}$)



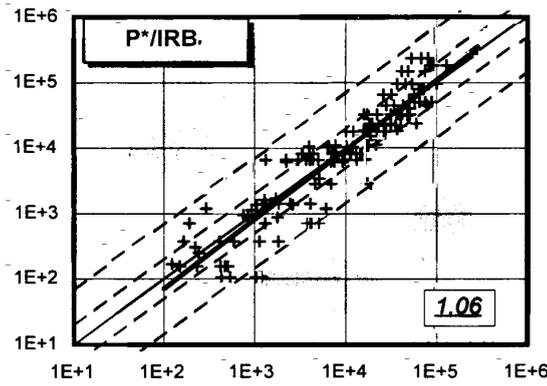
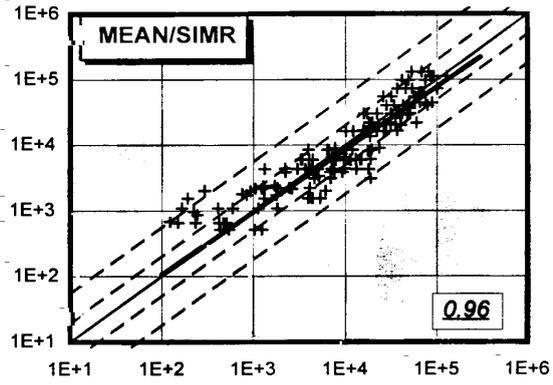
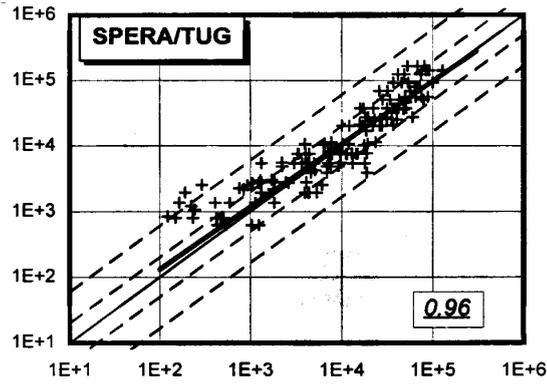
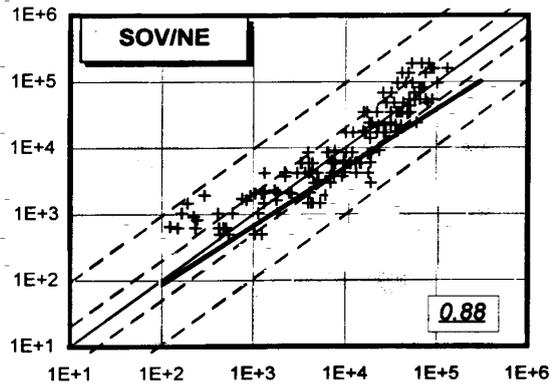
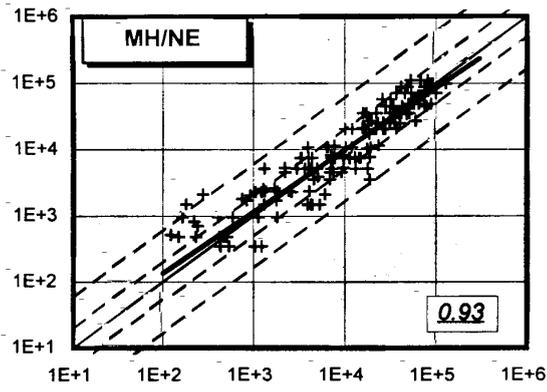
Predicted time versus observed time for 12CrMoVNb at 500°C

(the number inset is the slope of the mean line, underlined when determined between $t_{r(max)}/100$ and $t_{r(max)}$)

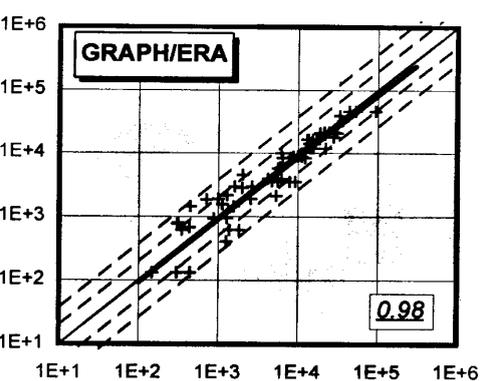
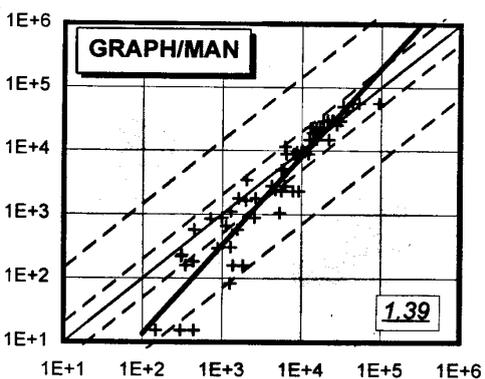
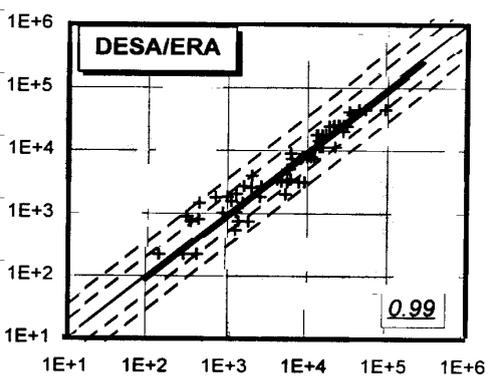
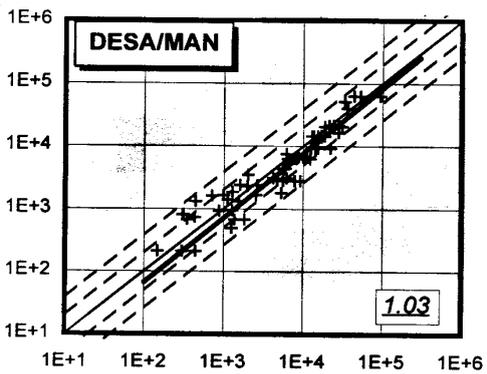
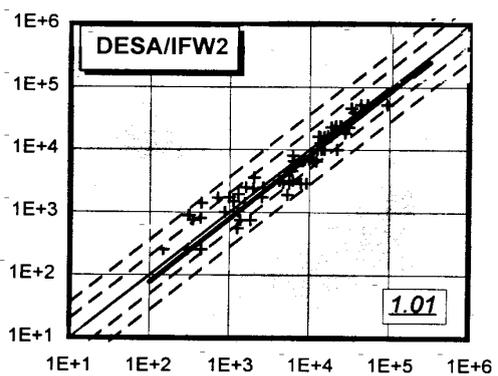
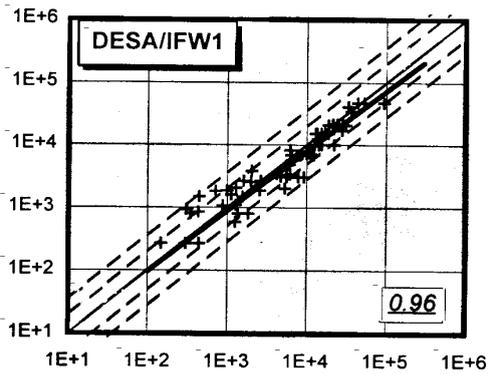
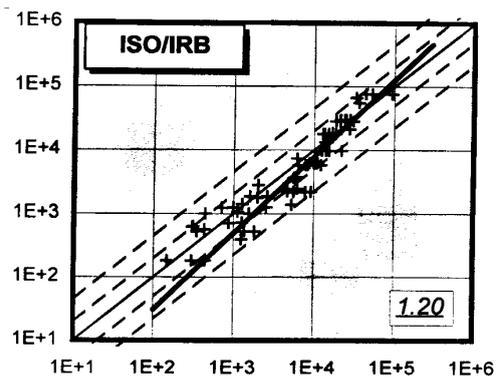
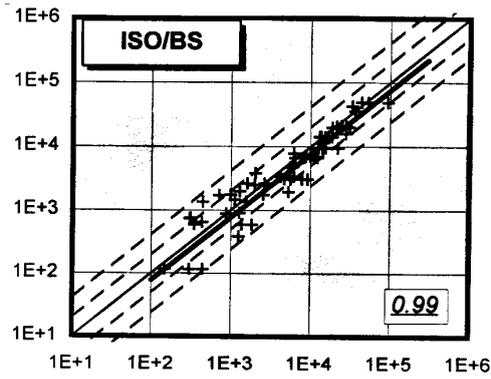


Predicted time versus observed time for 12CrMoVNb at 550°C

(the number inset is the slope of the mean line, underlined when determined between $t_{r(max)}/100$ and $t_{r(max)}$)

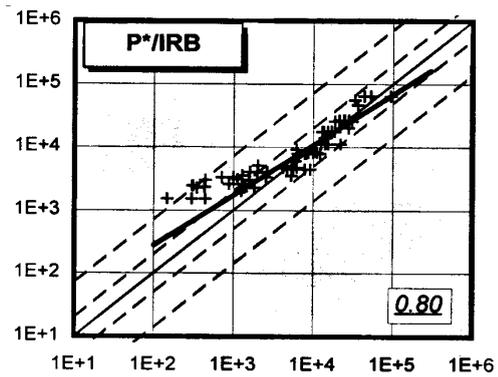
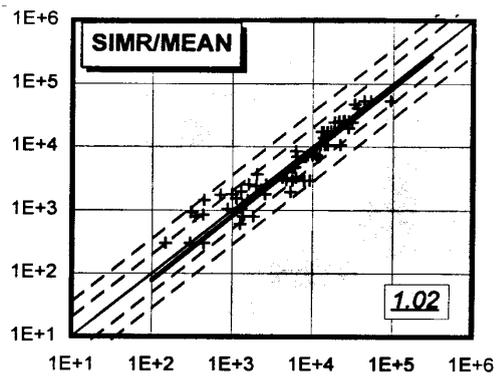
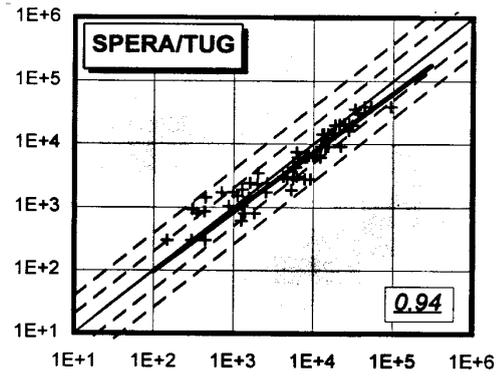
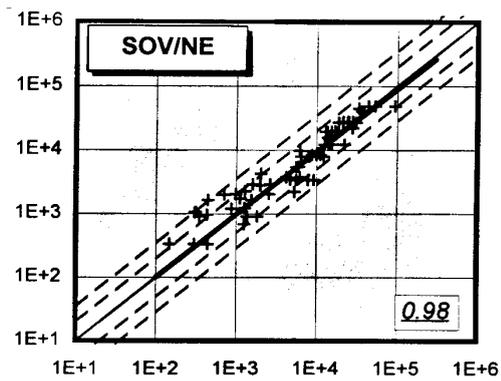
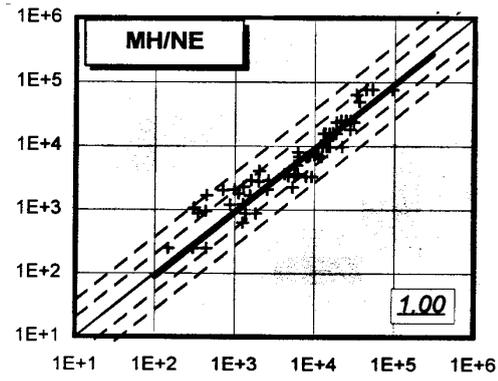


Predicted time versus observed time for 12CrMoVNb at 550°C
 (the number inset is the slope of the mean line, underlined when determined between $t_{f(max)}/100$ and $t_{f(max)}$)



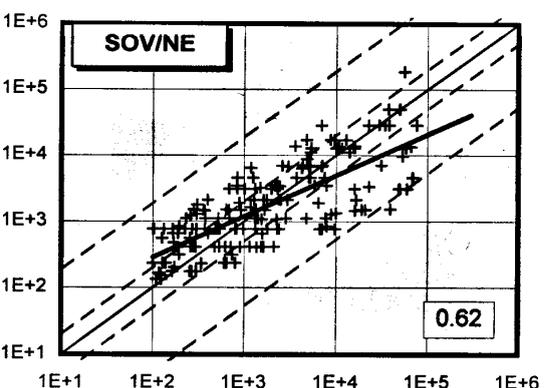
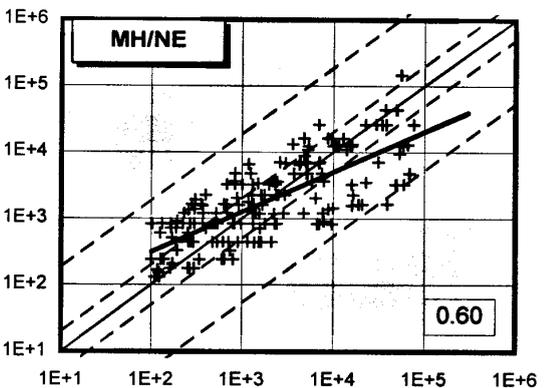
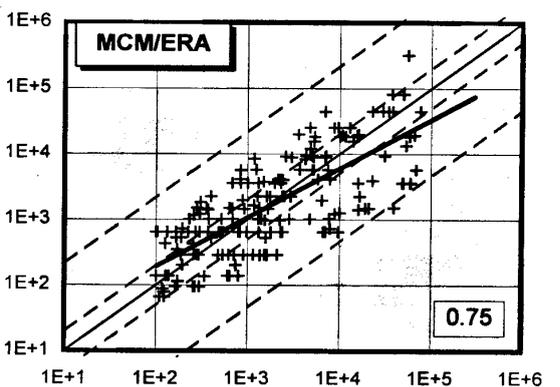
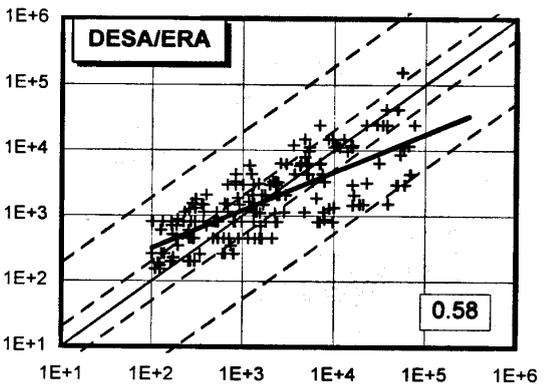
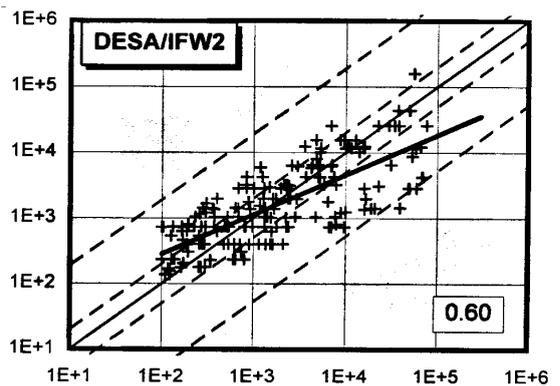
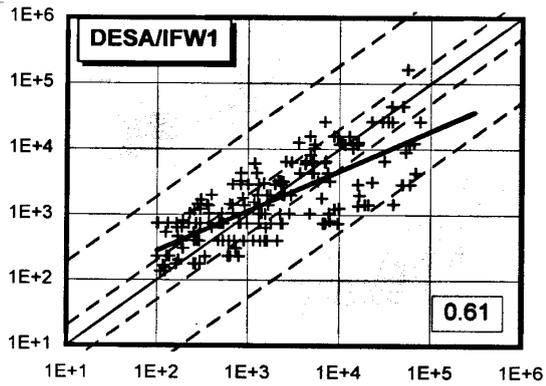
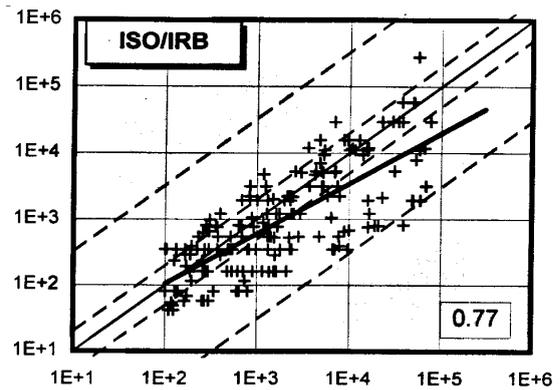
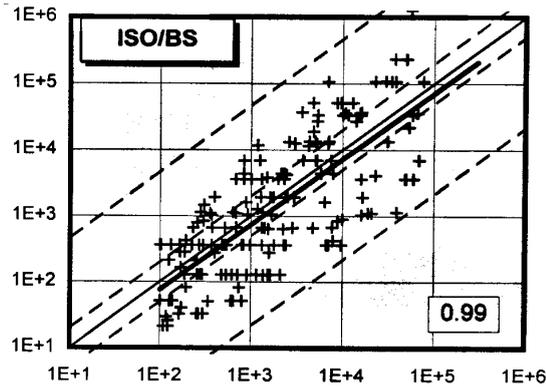
Predicted time versus observed time for 12CrMoVNb at 600°C

(the number inset is the slope of the mean line, underlined when determined between $t_{r(max)}/100$ and $t_{r(max)}$)



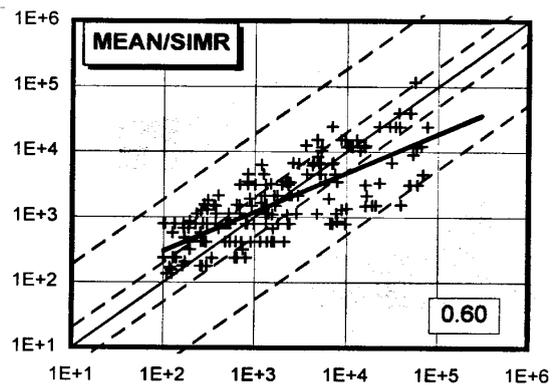
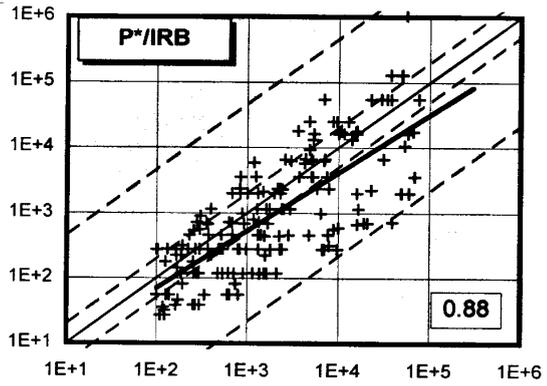
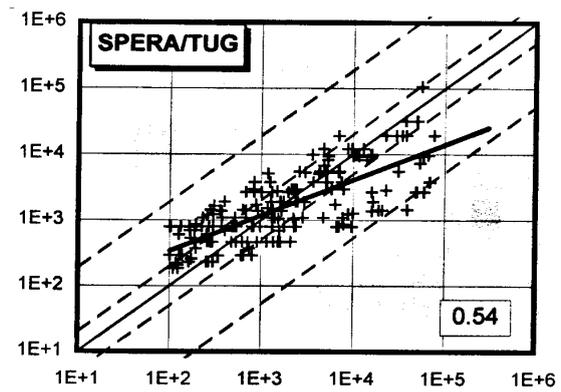
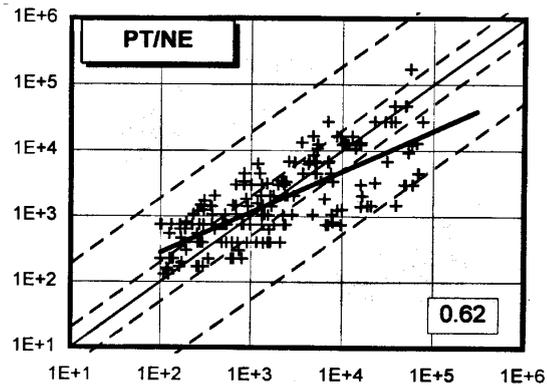
Predicted time versus observed time for 12CrMoVNb at 600°C

(the number inset is the slope of the mean line, underlined when determined between $t_{r(max)}/100$ and $t_{r(max)}$)



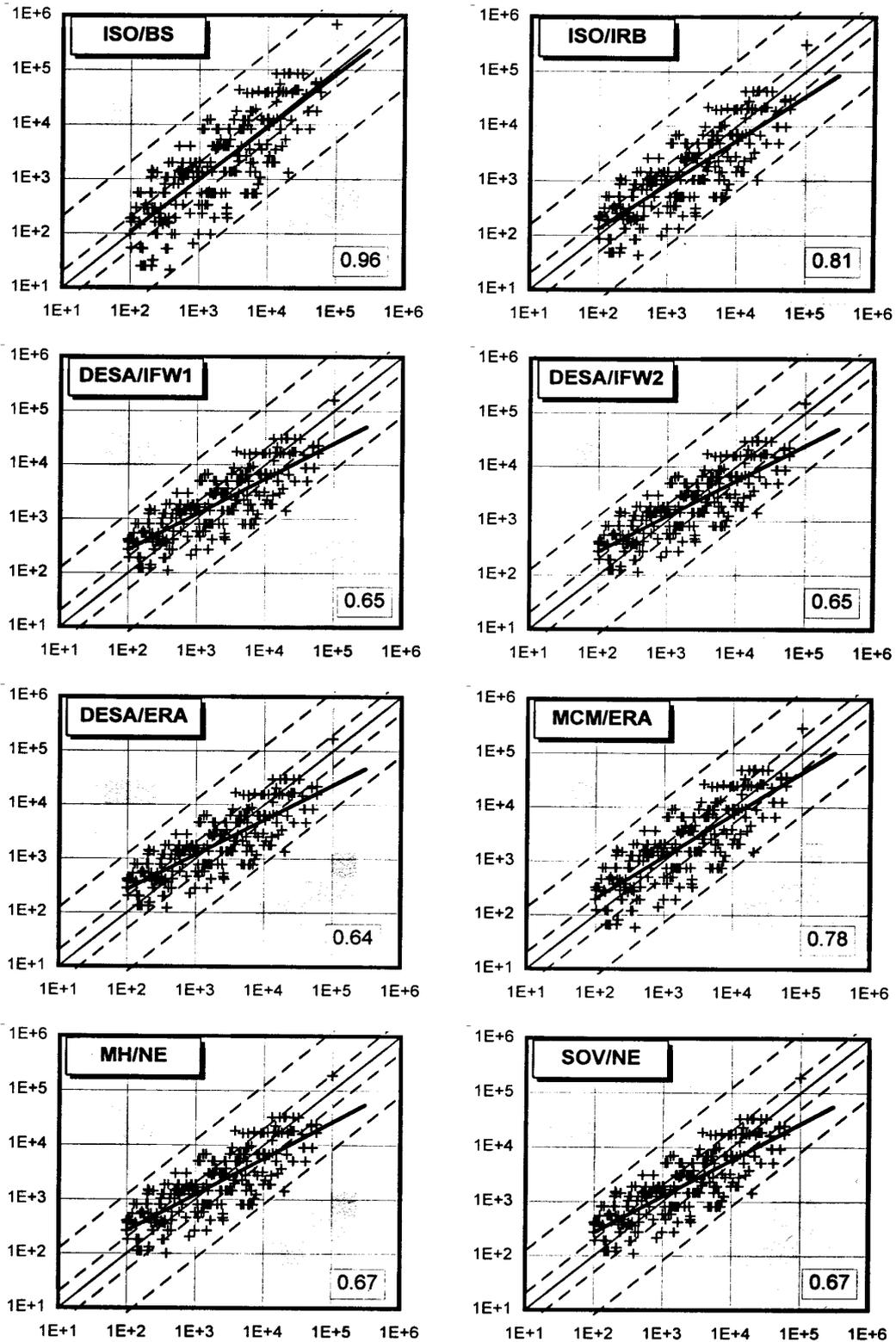
Predicted time versus observed time for Type 304 18Cr11Ni at 600°C

(number inset is the slope of the mean line, determination between $t_{[max]}/100$ and $t_{[max]}$ does not take slope within required tolerance)



Predicted time versus observed time for Type 304 18Cr11Ni at 600°C

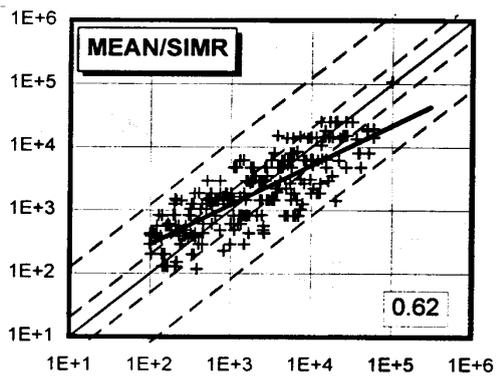
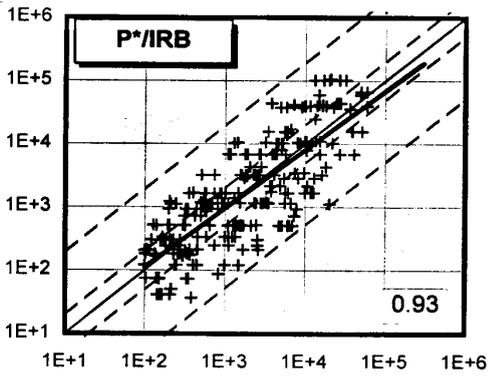
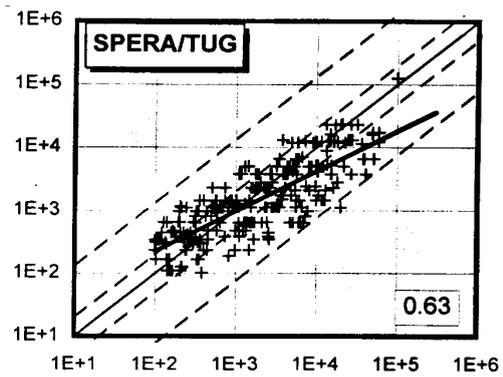
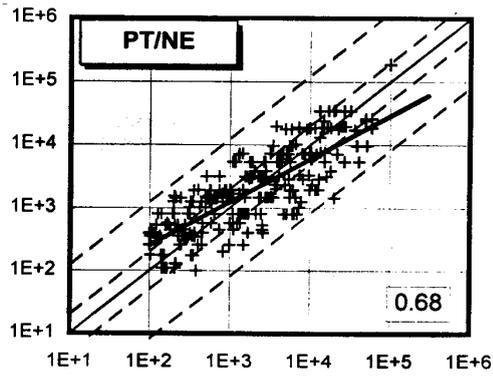
(number inset is the slope of the mean line, determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope within required tolerance)



Predicted time versus observed time for Type 304 18Cr11Ni at 650°C

(number inset is the slope of the mean line,

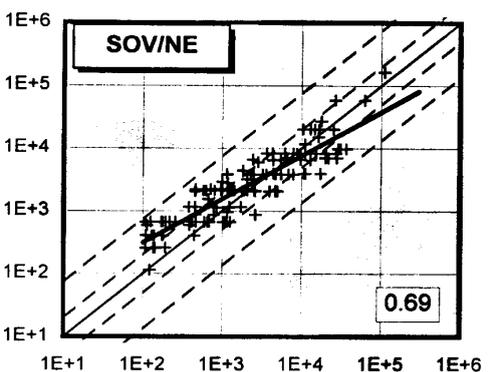
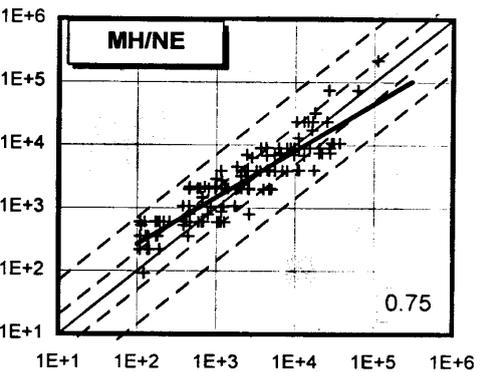
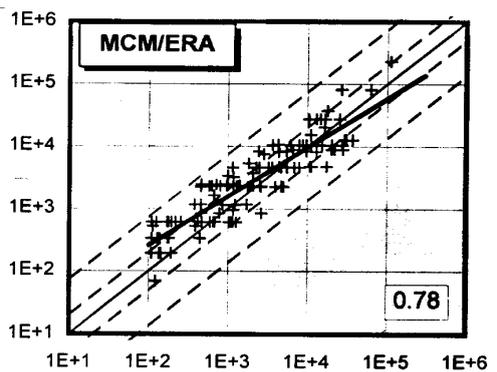
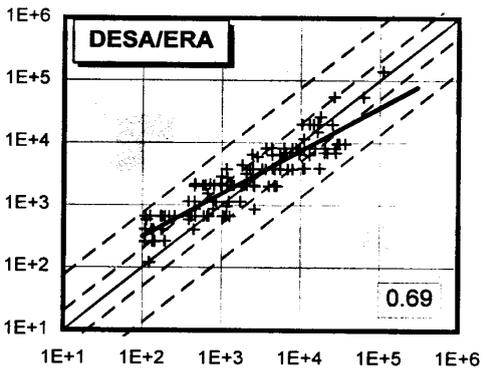
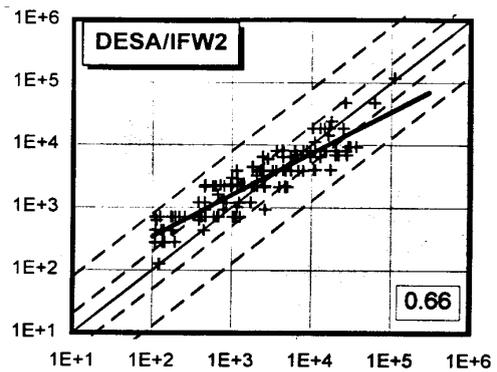
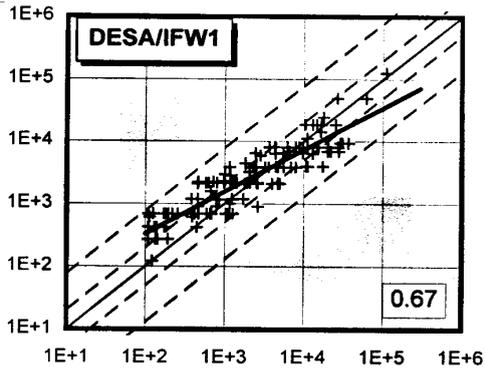
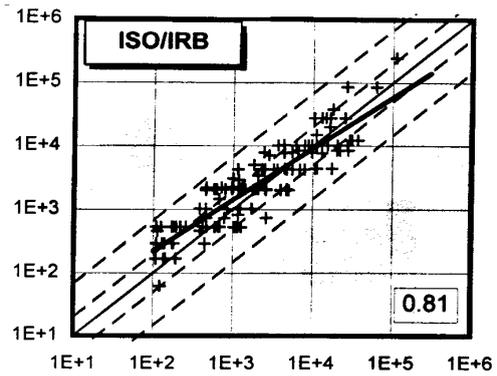
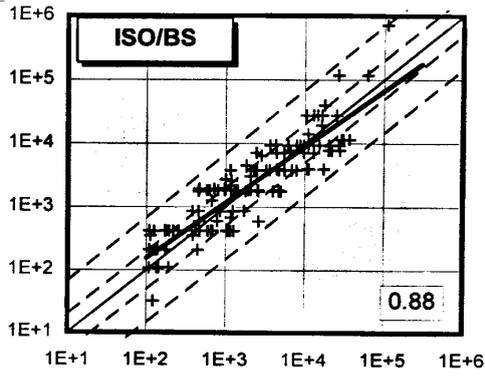
determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope within tolerance)



Predicted time versus observed time for Type 304 18Cr11Ni at 650°C

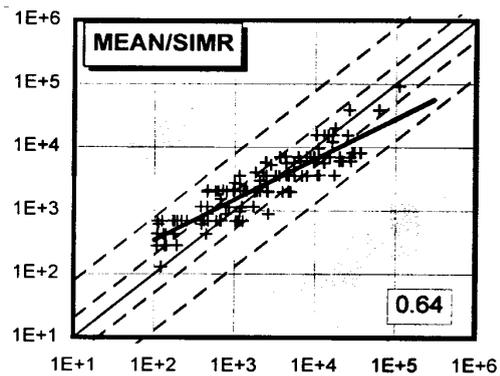
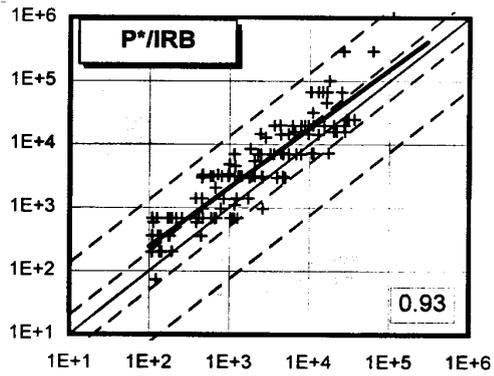
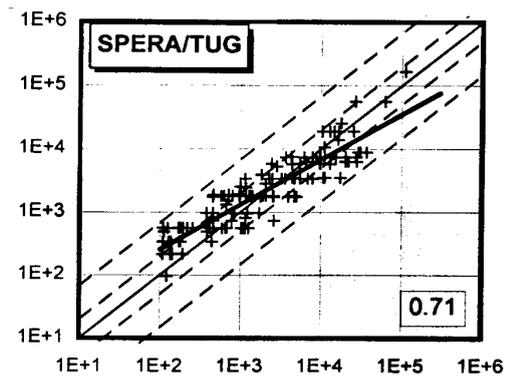
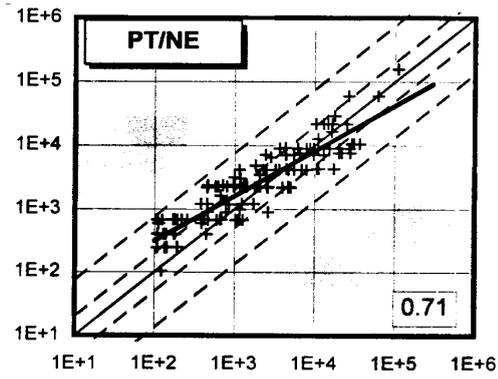
(number inset is the slope of the mean line,

determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope within tolerance)



Predicted time versus observed time for Type 304 18Cr11Ni at 700°C

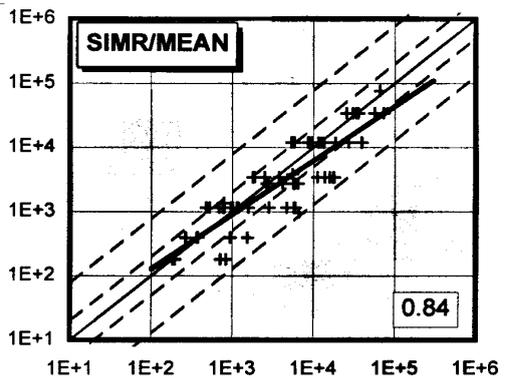
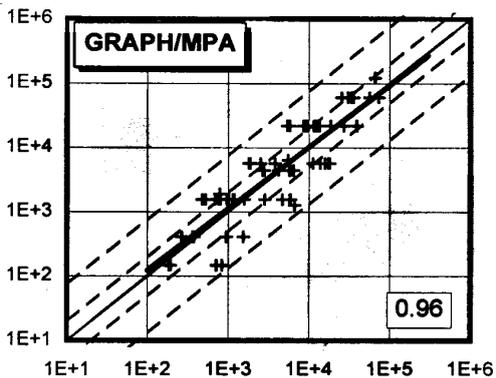
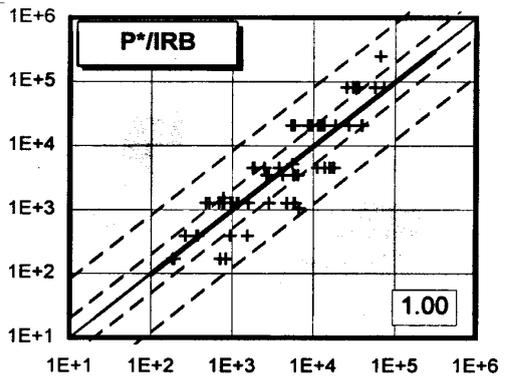
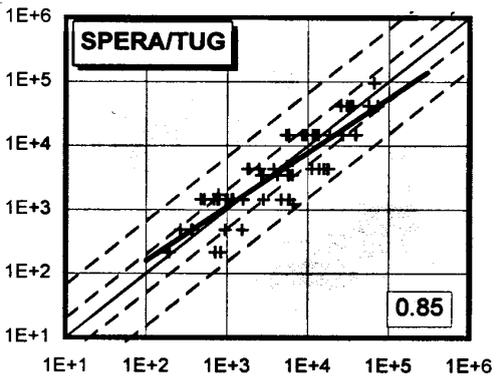
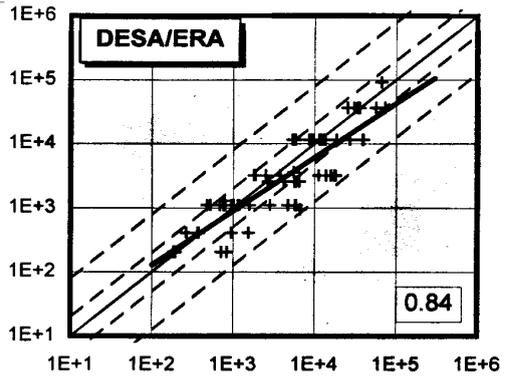
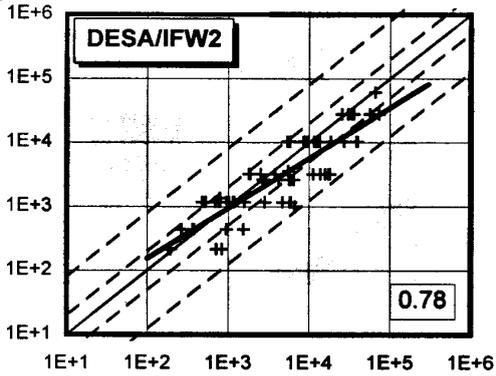
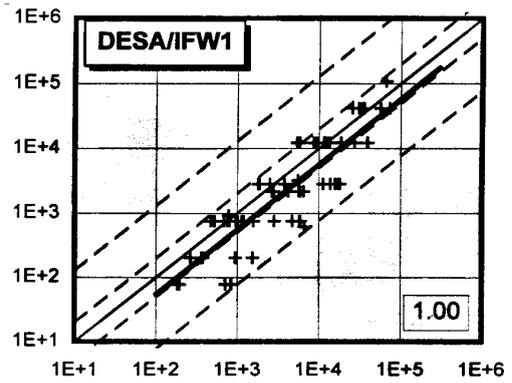
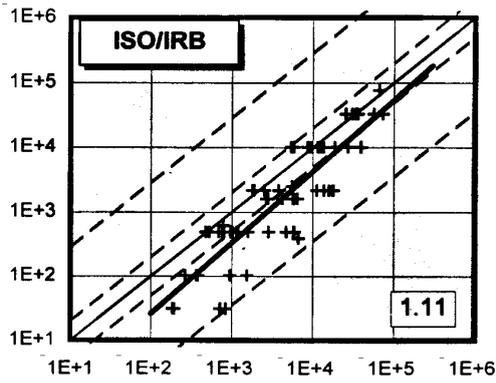
(number inset is the slope of the mean line,
determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope within tolerance)



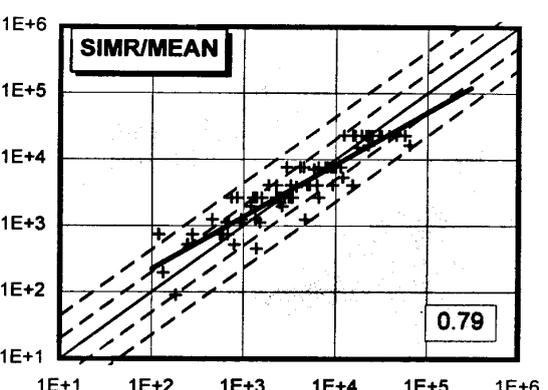
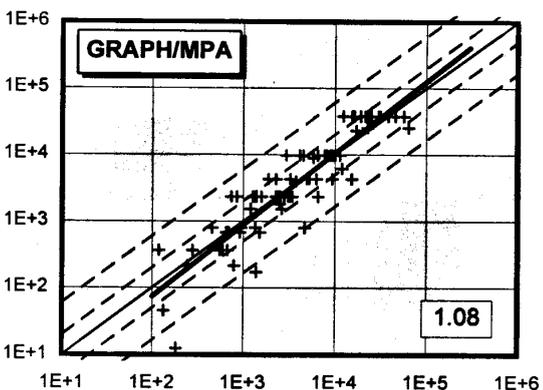
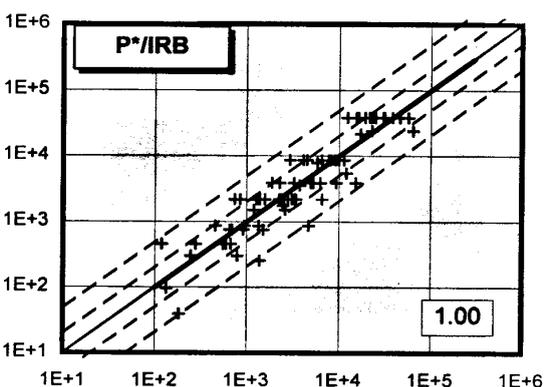
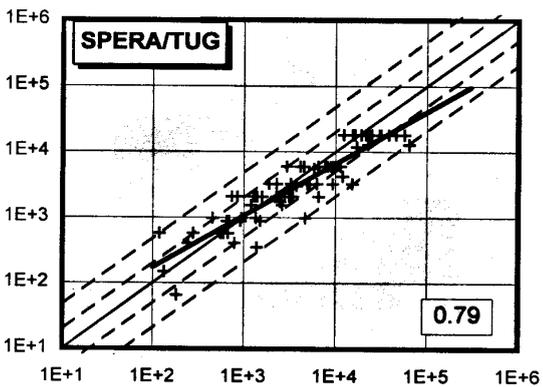
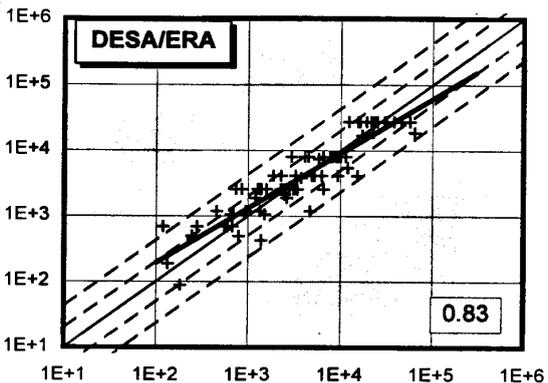
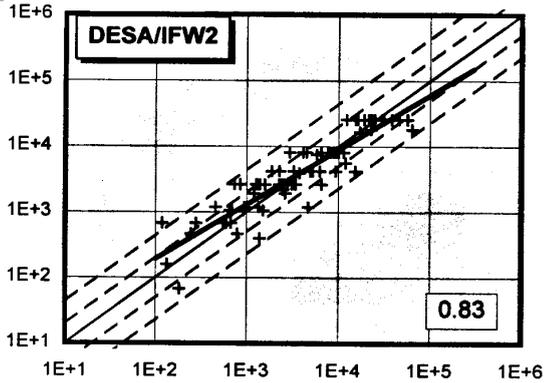
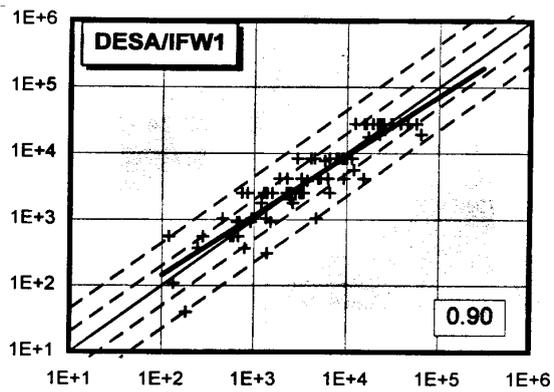
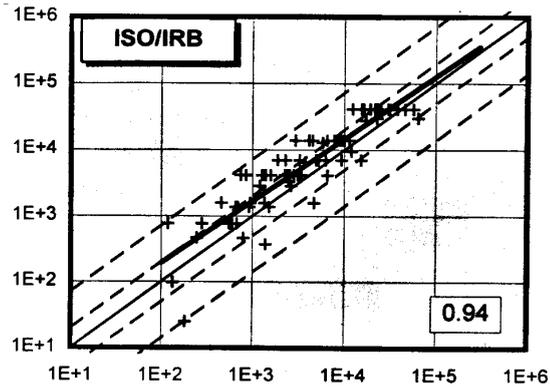
Predicted time versus observed time for Type 304 18Cr11Ni at 700°C

(number inset is the slope of the mean line,

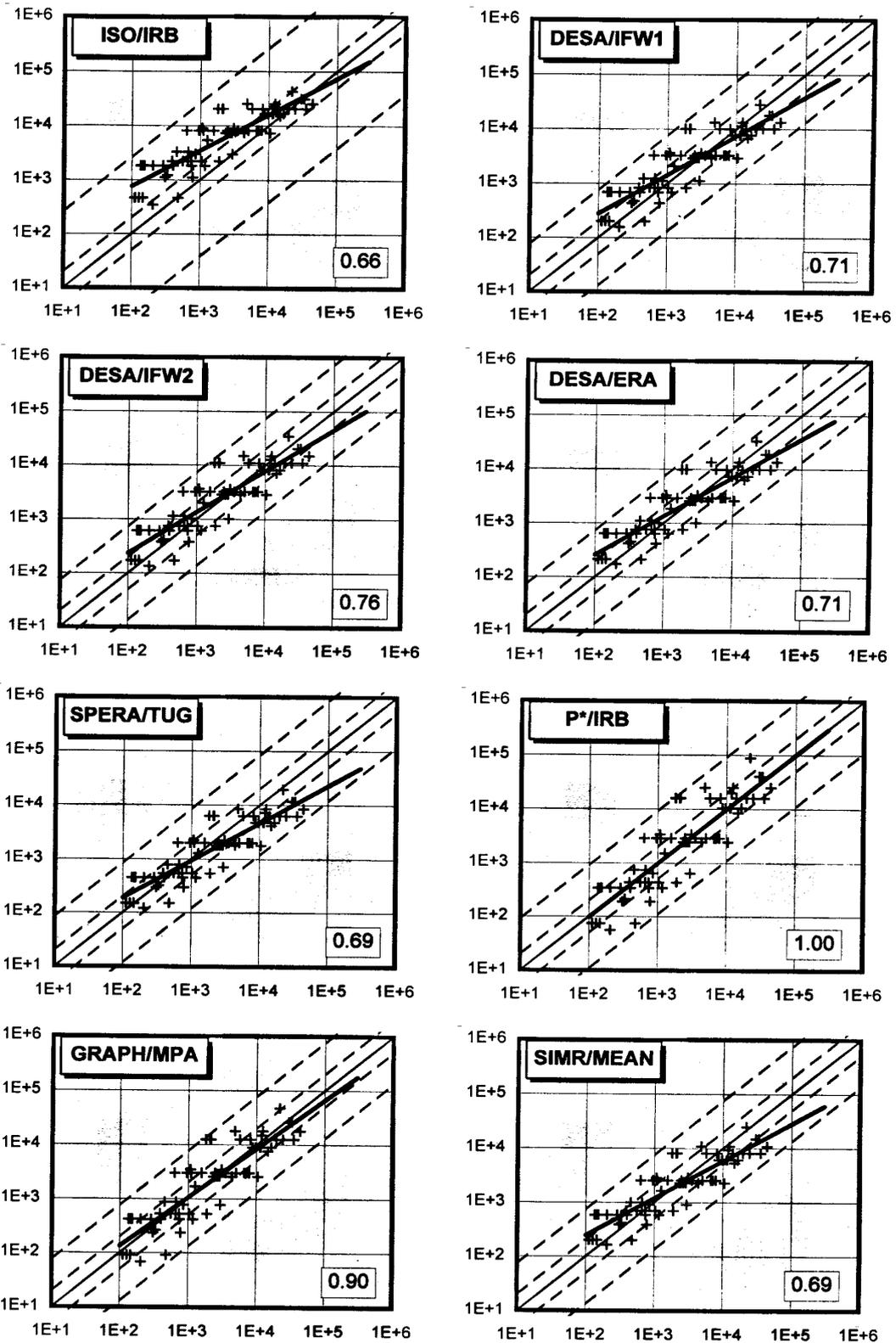
determination between $t_{r(max)}/100$ and $t_{r(max)}$ does not take slope within tolerance)



Predicted time versus observed time for Incoloy 800 at 600°C



Predicted time versus observed time for Incoloy 800 at 700°C



Predicted time versus observed time for Incoloy 800 at 800°C

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APPENDIX C2

**REVIEW OF WG1 EVALUATION OF CREEP RUPTURE DATA ASSESSMENT METHODS
RECOMMENDATION VALIDATION**

Creep Rupture Data Assessment Re-Evaluation 2014

M W SPINDLER [EDF Energy]

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A Re-Evaluation of the ECCC Guidance for The Assessment of Full Size Creep Rupture Datasets

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ABSTRACT

The European Creep Collaborative Committee's "Guidance for the Assessment of Full Size Creep Rupture Datasets" was first published in 1996. Over the last 18 years, a large number of full-sized datasets have been analysed using these procedures and the creep rupture strength values have been used in European Design and Product Standards and within European industry for design and life assessment. Nevertheless, in 18 years there have been many changes to both the software which can be used to fit creep rupture data and to the membership of ECCC Working Group 1 and in addition many observations have been made regarding the effectiveness of the ECCC procedures. It was therefore decided that the effectiveness of the original procedures would be re-evaluated by the current members using the most up-to-date methods for Creep Rupture Data Assessment (CRDA) and then the ECCC Recommendations would be reissued. Four large multi-heat, multi-temperature working datasets on 2¼Cr1Mo, 11CrMoVNB, 18Cr11Ni and 31Ni20CrAlTi steels have been used for this re-evaluation.

INTRODUCTION

The Volume 5 Part Ia of the European Creep Collaborative Committee's Recommendations "Guidance For The Assessment of Full Size Creep Rupture Datasets" [1] was first published in 1996 and represents the work of Working Group 1 (Procedures for Data Generation and Assessment) during the period 1992 to 1996. Since, then there have been a number of minor amendments (up to Issue 5) but no major changes to the original procedures. Nevertheless, a large number of full-sized datasets have been analysed over the last 18 years using the ECCC Recommendations and the assessed strength values have been used in European Design and Product Standards and within the industrial members of ECCC for the purpose of design and life assessment. However, over the last 18 years there have been many changes to both the software which can be used to fit creep rupture data and to the membership of ECCC WG1 and in addition many observations have been made regarding the effectiveness of the procedures in Volume 5 Part Ia. It was therefore decided that the effectiveness of the original procedures would be re-evaluated by the current members using the most up-to-date methods for Creep Rupture Data Assessment (CRDA) and that Volume 5 Part Ia would be reissued.

The original procedures were evaluated using four large multi-heat, multi-temperature working datasets; a low alloy ferritic (2¼Cr1Mo), a high alloy martensitic (11CrMoVNB), and two austenitic

stainless steels (18Cr11Ni and 31Ni20CrAlTi). These same datasets have been used for this re-evaluation.

BRIEF DESCRIPTION OF ECCC PROCEDURES FOR CRDA

There are four main steps to an ECCC Creep Rupture Data Assessment; (1) the pre-assessment of the data, (2) fitting of a model equation to the data, (3) post assessment tests for the effectiveness and credibility of the chosen model and (4) comparison of at least two independent CRDA leading to a final model that will be adopted by ECCC. The following is only a brief summary of the procedures which is intended as an aid to understanding and does not include all of the details; reference should be made to ECCC Recommendations [1] Volume 5 Part Ia for a full description.

Data Pre-Assessment

The careful pre-assessment of the creep rupture data is clearly one of the most important steps in this process. This should ensure that the pedigrees of the materials meet the specification and that the requirements of ECCC Recommendations [1] Volume 3 “Data Acceptability Criteria and Data Generation” are met. It has been found to be very important to ensure that there are no errors in the data which lead to an obvious outlier. This can be done by checking all data at the extremes of the scatter band. In addition, the pre-assessment is expected to evaluate the distribution of broken and unbroken test-piece data points with respect to temperature and time. The distribution of casts at each temperature is used to identify the main cast at each temperature and the best tested casts over a range of temperatures (see Vol. 5 Part Ia Section 2.3 of [1]).

Model Fitting

Working Group 1 has long recognised that it is not practicable to provide a single European procedure for fitting creep rupture data and instead provides guidance on (i) the ISO6303 method [2], (ii) the DESA procedure [3], (iii) BS PD6605 [4] and (iv) Graphical Multi-Heat Averaging and Cross Plotting method (see Vol. 5 Part Ia Appendix D4 of [1]). Other examples of methods to fit creep rupture data are given in Vol. 5 Part Ia Appendix B of [1]. Indeed, the plethora of mathematical and statistical analysis software which are available means that almost any linear or non-linear model equation may be readily fitted to creep rupture data using a wide variety of methods. The procedures therefore call for at least two independent CRDAs, of which one or more would have used either of ISO6303, DESA, PD6605 or the Graphical method. Indeed, up to two further CRDAs may be required if there is a significant difference between the rupture strengths (see later).

Post Assessment Testing

The post assessment tests, PATs, are a key feature of the ECCC recommendations and must be applied to each of the CRDAs. The PATs fall into three main categories; (i) tests for the physical realism of the predicted isothermal lines, (ii) tests for the effectiveness of the model prediction within the range of the input data and (iii) the repeatability and stability of the model equation on extrapolation.

The tests for physical realism start with PAT 1.1 which is a visual comparison at each temperature of the model fit and the data, which is done by plotting the logarithm of the stress versus the logarithm of the rupture time (Figure C2.1). It is a qualitative test and features to look for are: Does the model have the same overall shape as the data at each temperature? For example if the data are sigmoidal then it is acceptable for the model to be sigmoidal. However, a significantly sigmoidal model should be rejected if the data have the same direction of curvature at all temperatures. In addition, it should be remembered that the stress is an explanatory variable whereas the rupture time is a response variable and therefore the model fit would be expected to go through the centre of the scatter band of the data with respect to the logarithm of the rupture time. Post assessment test 1.2 is more quantitative and checks the physical realism of the model fit at 25°C intervals between 10 and 1,000,000 hours (Figure C2.2). The model must not; cross-over, come together or turn back at

stresses greater than 0.8 times the lowest stress to rupture in the assessed dataset. This ensures the physical realism of the model on extrapolation. Post assessment test 1.3 uses a plot of the derivative of the logarithm of the rupture time with respect to the logarithm of the stress to ensure that the predicted isothermal lines do not fall away too quickly at low stress (Figure C2.3). Another way to think of this is as a check that the instantaneous stress exponent for rupture does not fall to unreasonably low values. The quantitative test is that the derivative does not fall below 1.5 at stresses greater than 0.8 times the lowest stress to rupture in the assessed dataset. Nevertheless, if the metallurgical expert can demonstrate that either the rupture behaviour is sigmoidal or the creep mechanism enters the diffusional flow region then a derivative of between 1.0 and 1.5 may be permissible.

The post assessment tests for the effectiveness of the model prediction within the range of the input data (PAT 2.1 and 2.2) have received particular attention in this re-evaluation exercise and will therefore be discussed further later. Nevertheless, in brief the first test PAT 2.1 compares all of the data as predicted logarithm of the rupture time versus the observed logarithm of the rupture time and uses a number of quantitative measures to ensure that the model gives a good fit to the data (Figure C2.4). The recommendations are that the model should be re-assessed if: (a) More than 1.5% of the data fall outside of ± 2.5 standard deviations based on the logarithm of the rupture time, experience has shown that it is useful to check the pre-assessment for numerical errors and whether particular casts show anomalous behaviour before refitting the model to the re-assessed dataset. (b) The slope of a mean linear fit through the predicted logarithm of the rupture time versus the observed logarithm of the rupture time is less than 0.78 or greater than 1.22. This quantitative test has received particular attention in this re-evaluation and will be discussed later. (c) The mean linear fit must also be contained within $\pm \log 2$ boundaries between observed rupture times of 100 and 100,000 hours. A similar set of quantitative tests are also applied in PAT 2.2 to specific isothermal data at the three temperatures; the minimum and maximum temperatures that have more than 10% of the data (T_{\min} and T_{\max}) and the main temperature with the most data (see Figure C2.5). PAT 2.2 is particularly useful at identifying models which might appear to be good fits to all of the data, but which actually do not describe particular temperatures very well. This is shown in Figure C2.5(a), which has been conducted at 475°C, which is not $T_{\min[10\%]}$ but which nevertheless, contains significant long term data and this test appears to show that the model is poor at this temperature. However, please note that more will be said about this observation later. Furthermore, PAT 2.2 is also used to identify the influence of the best-tested casts (casts with a good range of data at a range of temperatures and including durations greater than 10,000 hours). This is done by further investigation of casts which have a significant number of data outside of ± 2.5 standard deviations based on the logarithm of the rupture time or if the slope of a mean linear fit through the predicted logarithm of the rupture time versus the observed logarithm of the rupture time of a single cast is less than 0.5 or greater than 1.5. Note for the example shown in Figure C2.5 all of the best tested casts are in acceptable agreement with the model.

There are two further quantitative tests which specifically examine the repeatability and stability of the model on extrapolation. These tests are arguably the most important to creep rupture data assessment as inevitably creep rupture models are extrapolated in order to provide elevated temperature time dependent design strengths or to calculate the creep life of components in service. These two tests both use culling of the most significant data and re-fitting of the chosen model equation, followed by a comparison of the predicted 300,000 hours rupture strength between the full and culled models (see Table C2.3). If the maximum test duration is less than 100,000h, the predicted strength comparison may be made at 3 times the maximum test duration. The predictions should be within 10% for the model equation to pass these tests. The difference between PAT 3.1 and 3.2 is that PAT 3.1 culls the data on rupture time (removing a random 50% of the data with durations greater than $1/10^{\text{th}}$ of the maximum rupture time) whereas PAT 3.2 removes 10% of the data by taking out the lowest stress data at each temperature. Nevertheless, these tests are doing two subtly different things; PAT 3.1 examines what the outcome would be of having an inhomogeneous test matrix, of the same size in stress and temperature, albeit with lots of short time data but less of the valuable long time test

data. Therefore, PAT 3.1 can be considered to be a practically based approach with regards to potentially lower cost test matrices. An example of the models fitted to a full and PAT 3.1 culled dataset is shown in Figure C2.6. In this case the PAT 3.1 is passed as given in Table C2.3. It can be seen from Figure C2.6 that after culling 50% of the long time data, there still remains enough long time data that the fits to the culled and full datasets are similar. Whereas, PAT 3.2 is a more statistically based approach and examines how well your chosen model would extrapolate if the test matrix was smaller in the important explanatory variable of stress, which by taking out the low stress data also takes out the long time data too. An example of the models fitted to a full and PAT 3.2 culled dataset is shown in Figure C2.7. In this case the PAT 3.2 is failed, at 600°C ($T_{\max[10\%]}$) as given in Table C2.3. It can be seen from Figure C2.7 that culling 10% of the lowest stress data at each temperature is a much more severe cull than PAT 3.1 and removes all of the long term data at $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$. Nevertheless, the fits to the full and culled datasets are similar at $T_{\min[10\%]}$ and T_{main} but the PAT 3.2 is failed at $T_{\max[10\%]}$ because the fits are significantly different. The investigator should now try alternative models and try to find one that does indeed pass all of the ECCC PATs.

Finally, all creep rupture data assessments have to be reported giving details of the above three steps; (1) the pre-assessment of the data, (2) fitting of a model equation to the data, (3) post assessment tests for the effectiveness and credibility of the chosen model. ECCC has conveniently created a summary table which minimises the amount of text that needs to be written (see Vol. 5 Part Ia Appendix E of [1]). In addition, most of the PATs can be simply summarised in figures (PAT 1 & 2, see Figure C2.1 to Figure C2.5) or tables (PAT 3, see Table C2.3), and of course the rupture strengths are presented as a table. The ECCC convenor responsible for that material can then compare the results of the two or more independent CRDAs. Volume 5 Part Ia of the ECCCs Recommendations [1] gives twelve items of advice for this comparison and for the final decision on the recommended CRDA. Nevertheless, the most significant are; that the CRDAs should pass the PATs and that the 100,000 hour rupture strengths at T_{\min} , T_{\max} and main temperatures of the two CRDAs are within 10% of each other and the 300,000 hour rupture strengths are within 20%. With the guidance being that the most conservative of the CRDAs at the main temperature would normally be adopted by ECCC.

A RE-EVALUATION OF ECCC PROCEDURES FOR CRDA

The basis of this re-evaluation is to take the same four original datasets that were used by ECCC during the period 1992 to 1996 ($2\frac{1}{4}\text{Cr1Mo}$, 11CrMoVNb, 18Cr11Ni and 31Ni20CrAlTi steels) and to repeat multiple CRDAs on each dataset in order to test the effectiveness of the original ECCC procedures. Eleven independent experts (identified as #1 to #11) have provided CRDAs for either some or all of the four materials or alternative models for the given material, giving a total of 46 CRDAs. Nevertheless, some investigators fitted the data with a number of models and then chose their preferred option and therefore this work represents the results of a great many fits to the data. The finding of these re-evaluations will now be described and discussed, which the reader will understand will be drastically summarised.

Each of the four datasets had previously been pre-assessed in the early 1990's (see Vol. 5 Part Ia Appendix A of [1]). However, prior to this re-evaluation a second check was done which identified some duplicate data and some outliers in both individual data points and even some casts. These data were corrected if the true values were known or deleted if this was not the case. Nevertheless, this pre-assessment was not exhaustive as it was assumed that the pre-assessment had been done previously. However, subsequent to the re-evaluation it was realised that in particular the $2\frac{1}{4}\text{Cr1Mo}$ dataset contained significant errors the effect of which will be seen later. This highlights the importance of a very thorough pre-assessment. Experience suggests that good practice is to first minimise the number of errors and outliers in the dataset and then to perform a preliminary CRDA following the ECCC recommendations of model fitting followed by post assessment testing and that particularly, PAT 1.1 and 2.1, which compare the data and the model predictions, can help to identify any errors and outliers in the dataset which should be corrected or deleted. For example, PAT 2.1 can

be used to identify which data lie outside of the ± 2.5 standard deviation band (see Figure C2.11). This test is particularly useful at this as it is the only one in which all data are presented. After which the final model fitting and post assessment testing process can be attempted.

The model fitting involved at least 20 different creep rupture equations, not counting different orders of polynomial (typically 2 to 5). Including parametric models, and traditional models with time temperature parameters were used with polynomials in the logarithm of stress as well as stress raised to a power less than one. Different methods were used for the model fitting, linear and non-linear regression (in which either the sum of squares or the chi-square statistic has been minimised) and maximum likelihood fitting have all been used, furthermore different failure distributions were used such as log-normal, log-logistic and Weibull.

So throwing caution and a lot of details to the wind, how do all the different models compare? It was found that the difference between the highest and lowest predicted rupture strengths for 100,000 and 300,000 hours, at the main temperatures were consistently much greater than the 10% and 20% that is required by the ECCC recommendations, see Table C2.2. Indeed the worst case was Type 304H stainless steel at 650°C which gave a difference of 45% between the lowest 100,000 hour rupture strength of 49.5MPa and the highest of 71.7MPa. These models and the data for Type 304H are shown graphically in Figure C2.15. There are similar, though not as great differences between the predicted rupture strength for the other materials (see Table C2.2 and Figure C2.13 to Figure C2.16). Of course the big question is can the ECCC PATs be used to discriminate between the reliable and unreliable CRDAs? The results of the ECCC PATs are presented for each material in Table C2.4 to Table C2.7, which highlight the models that failed the PATs and those which passed the PATs. Also included in the Tables is the Z-factor which ECCC WG1 have used to define the scatter in the logarithm of the rupture time to give ± 2.5 standard deviations assuming a log-normal distribution and is given by

$$Z = 10^{2.5 \sqrt{\frac{\sum (\log(t_u^*) - \log(t_u))^2}{n_A - 1}}}$$

where t_u^* is the predicted rupture time, t_u is the observed rupture time and n_A is the total number of data. It can be seen from Table C2.4, Table C2.6 and Table C2.7 that for materials 2¼Cr1Mo, 18Cr11Ni and 31Ni20CrAlTi that only a small number of the models actually pass all of the ECCC PATs. Whereas, for 11CrMoVNb none of the models pass all of the PATs (Table C2.5). It should be noted that models that do not pass all of the PATs have in the past been accepted by ECCC, although there has usually been a sound reasoned argument as to why the model is reliable. However, when presented with such a large range of different strengths it is difficult to choose the model that is most reliable. So the next questions is; has the ECCC PATs selected the most reliable models?

Looking at the reasons why various models failed the PATs, relatively few models failed PAT 1.1 and 1.2, which probably reflects the subjective nature of such qualitative tests. Nevertheless, these tests are the basic fundamental output of a creep rupture model and are therefore vital. However, the sigmoidal shape of the 11CrMoVNb data did present a problem for any model that does not follow a sigmoidal shape and these can be rejected such as the second order polynomials in the logarithm of stress (which includes the Manson Haferd second order MH2 #5 Table C2.5). PAT 1.3 is quantitative and the derivative falling below 1.5 rejects more models, such as models which turn-back and are therefore useless on extrapolation (MH2 #5 Table C2.5, Figure C2.8), models with a very extreme sigmoidal inflection (MH3 #1 Table C2.5, Figure C2.9) which is physically unrealistic. Such model rejections are reasonable, however, PAT 1.3 also rejects some models with the derivative falling below 1.5 at some very long times (greater than 10^6 hours) and it could be argued that these models are not necessarily unreliable and should be considered further (these are shown as Fail¹). For example, the fit to the 31Ni20CrAlTi Model MH4Svt #8 is shown in Figure C2.10, which shows that although the model fails PAT 1.3 it does so only for times greater than 1,000,000 hours.

The quantitative tests for effectiveness of the model prediction within the range of the input data (PAT 2.1 and 2.2) failed a great many of the candidate models (see Table C2.4 to Table C2.7). It is

therefore very enlightening to investigate the reasons for these failures. Quite a few models (16 out of 46) failed with more than 1.5% of the data falling outside of ± 2.5 standard deviations, especially for the ferritic steels; 4 out of 9 of the models for 2¼Cr1Mo and 10 out of 11 of the models for 11CrMoVNB. Since ± 2.5 standard deviations would be expected to encompass all but 1.25% of the data, the 1.5% allowance is fairly small. However, this test assumes that the scatter is homogeneous and does not allow for variance heterogeneity, which is commonly observed in creep rupture data where there is more scatter in high stress data than in the low stress data (for example Figure C2.17). Consequently, the majority of the data that fall outside of ± 2.5 standard deviations commonly have high stresses and this means often at low temperatures. Furthermore, this test tends to fail some of the models with the lowest Z-factors but passes some models with high Z-factors. Since Z-factor is a measure of goodness of fit, this should be treated with caution and models should not necessarily be rejected on the grounds of this test's result. Nevertheless, the main value of this test is in identifying outlying data points, which after further investigation can often be removed due to problems with the whole cast, such as heat treatment or errors in individual data points such as typographical errors in stress, temperature or rupture time. For example, in Figure C2.11, 2.75% of the data fall outside of ± 2.5 standard deviations. A re-evaluation of the pre-assessment has identified a number of errors in these data for example the data at (254,78088) was entered as being at 520°C and a check of the source data showed that the actual temperature was 620°C. In addition, other outliers included Cast 2¼Cr1Mo which was inadvertently included with the wrought data. Therefore, the test is very useful to identify if the pre-assessment should be revisited before the model is re-fitted. However, a paradox that should be born in mind is that models with high Z-factors i.e. poor fits to the data may pass this test, whereas models with low Z-factors i.e. good fits to the data may fail this test (for example Table C2.4). It is therefore clear that the test regarding whether data fall outside of ± 2.5 standard deviations should not be used to reject or accept models, but rather as a guide to whether a greater understanding is required such as whether the pre-assessment should be revisited before the model is re-fitted and a better understanding for the reasons for cast to cast scatter in the alloy being fitted.

The majority of the models that failed PAT 2.1 or 2.2 did so because either the slope of a mean linear fit is outside of the 0.78 to 1.22 acceptable range or the mean fit line fell outside the $\pm \log 2$ boundaries between 100 and 100,000 hours. Both of these criteria rely on the same mean linear fits and therefore it is important to investigate these fits further. For the 18Cr11Ni steel the three models that passed all of the PAT 2.1 and 2.2 tests had high Z-factors (Table C2.6) and are therefore among the worst fits to the data. These models were also among the most optimistic on rupture strength (Table C2.2) and it is therefore suggested that these models may be non-conservative.

It is clear that the linear fits through the predicted logarithm of the rupture time versus the observed logarithm of the rupture time are favouring the most optimistic models, and it is important to understand why. When least squares regression is used it is usual in the majority of the available software for the error in the y-value to be minimised, with the assumption that there is no error in the x-value. However in the PAT 2.1 and 2.2 the linear line is fitted through the predicted logarithm of the rupture time (as the y-value) versus the observed logarithm of the rupture time (as the x-value). Clearly, this is at odds with what the fitting software is actually doing. This is because the predicted logarithm of the rupture time for multiple tests at the same stress and temperature are identical with no variation, whereas the observed logarithm of the rupture time for multiple tests at the same stress and temperature will clearly be different and will exhibit variation. The obvious solution is to make a simple revision to the PAT 2.1 and 2.2 linear fits and change to fitting through the observed logarithm of the rupture time (as the y-value) versus the predicted logarithm of the rupture time (as the x-value). For example a revised PAT 2.1 is shown in Figure C2.11 and a revised PAT 2.2 is shown in Figure C2.12. By doing this simple change the observed logarithm of the rupture time, which are clearly different and exhibit variation are plotted on the y-axis and the predicted logarithm of the rupture time, which for multiple tests at the same stress and temperature are identical with no variation are plotted on the x-axis. This is now consistent with the way that most software for linear regression works. It is interesting to note that at 475°C (see Figure C2.12(a)) the revised PAT 2.2 now passes the quantitative tests and makes the fit at 475°C appear realistic. This is contrary to what was found with the original Pat 2.2 (see Figure C2.5(a)) and it is suggested that this shows how the original PAT

2.2 may have given rise to some poor judgments regarding the goodness of fit of creep rupture models.

The results of the revised ECCC post assessment tests (including revised PAT 2.1 and 2.2) are given in Table C2.8 to Table C2.11.

It should be noted that PAT 1.1, 1.2, 1.3, 2.1(a), 3.1, 3.2 are identical and that the quantitative tests in PAT 2.1 and 2.2 are otherwise unchanged. It can be seen from Table C2.8 to Table C2.11 that the revised PAT 2.1 and 2.2 fail less of the models than the original ECCC PAT. In addition, the revised PAT 2.1 and 2.2 now tends to pass models with lower Z-factors and fails models with high Z-factors. Furthermore, comparing the models with the data at the main temperatures (compare Figure C2.13(c) to Figure C2.16(c) with Figure C2.13(d) to Figure C2.16(d)) shows that the most optimistic and possibly non-conservative models have been rejected and that all of the models that now pass PAT 1 and 2 are similar to one another giving a small range of rupture strength values.

With regards to the most important tests PAT 3.1 and 3.2 for the repeatability and stability of the model equation on extrapolation (for example Table C2.3), not all models have been subjected to these tests nevertheless, where available these are reported in Table C2.4 to Table C2.11. Clearly, there is no correlation between models which pass and fail PAT 2.1 2.2, 3.1 and 3.2. This is because these tests examine different attributes of the models, PAT 2.1 and 2.2 testing effectiveness of the model prediction within the range of the input data and PAT 3.1 and 3.2 the repeatability and stability of the model equation on extrapolation. Surprisingly, for the ferritic steels there is no clear correlation between models which pass and fail PAT 1.3, 3.1 and 3.2 (Table C2.4 & Table C2.5 and Table C2.8 & Table C2.9). Nevertheless, for 18Cr11Ni there does appear to be a correlation between models which pass and fail PAT 1.3, 3.1 and 3.2 (Table C2.6 and Table C2.10). Unfortunately, for 31Ni20CrAlTi too few of the models have yet to be tested using PAT 3.1 and 3.2. Therefore there is insufficient evidence to suggest further improvements to PAT 3.1 and 3.2. Nevertheless, it is strongly advised that only models that pass PAT 3.1 and 3.2 should be used for extrapolation, which effectively means that only these models should be recommended at all. Nevertheless, for metallurgically unstable steels such as 11CrMoVNb ECCC recommendations [1] do allow a model to be recommended which fails PAT 3.2 (such as those models in Table C2.5 & Table C2.9). In addition, ECCC recommendations [1] do allow PAT 3.1, which uses a random cull to be repeated if the first attempt fails. For example see the results of PAT 3.1 for 11CrMoVNb, which are given in Table C2.3. Experience has shown that whether this repeat passes is highly sensitive to whether the small number of low stress very long time data are culled or not. Further work will be conducted by ECCC WG1 to better understand the effectiveness of PAT 3.1 and 3.2. Nevertheless, in the mean time these tests remain the most important in the ECCC recommendations and exceptions can only be granted for metallurgically unstable steels which show strong sigmoidal behaviour.

DISCUSSION

The purpose of the ECCC recommendations [1] is to ensure that the rupture strength models that are produced by the model fitting process are reliable. It can be seen from Figure C2.13 to Figure C2.16(a & b) that this is a challenging task because when multiple models are fit to the same data a wide range of fit lines can be produced. Furthermore, it can be seen from Table C2.2 that these models produce a very wide range of rupture strength values. It is common amongst researchers simply to test rupture models by a visual comparison at each temperature of the model fit with the data, which is done by plotting the logarithm of the stress versus the logarithm of the rupture time (ECCC PAT 1.1). However, this simple qualitative approach does not differentiate between reliable and unreliable rupture models as can be seen from Table C2.4 to Table C2.11, where every model was passed by this test. The ECCC post assessment tests are designed to select the reliable models and reject the unreliable ones. In this paper Working Group 1 has re-evaluated the PATs by fitting four different materials to a total of 46 models. The ECCC PATs have been applied to each of these 46 models and the results will be discussed for each of the materials. In particular, consideration will be

given to advice on the application of the PAT and to differences between the results of the original PAT 2.1 and 2.2 and the revised version, which is proposed above.

Ten models were proposed for 2¼Cr1Mo (see Table C2.4, Table C2.8 and Figure C2.13). However, only two models (see Table C2.4) passed the PAT 1 and 3 and the original PAT 2 (ignoring PAT2.1(a) % of the data outside of ± 2.5 SD, since there are some outliers in this dataset which should really be removed). These two models gave the highest strengths (see Table C2.2 and Figure C2.13(c)) and showed the highest Z-factors (see Table C2.4), i.e. the most scatter. It is judged that these models would therefore be non-conservative. Nevertheless, the revised PAT 2.1 and 2.2 (see Table C2.8) now fail these models and select a different two models. These two models have low Z-factors (less scatter) and give very similar strengths which are neither the lowest nor highest (see Table C2.2 and Figure C2.13(d)). It is judged likely that these two models called MCmod #4 and MB3 #5 are the most reliable for 2¼Cr1Mo.

Eleven models were proposed for 11CrMoVNb (see Table C2.5, Table C2.9 and Figure C2.14). However, none passed all of the ECCC PAT (see Table C2.5). This is a metallurgically unstable steel which shows sigmoidal behaviour, particularly at 600°C. Unfortunately, this is the only temperature clearly showing sigmoidal behaviour which makes it difficult for models to be reliably fitted to this dataset. Furthermore, as 600°C is also the maximum temperature in the dataset it makes the culled datasets for PAT 3.1 and 3.2 too different from the full dataset. Two models were initially shortlisted which were the only ones that passed the original PAT 2.1 (Table C2.5). However, these models both show large Z-factors, furthermore there is a wide discrepancy between these two models (see Table C2.2 and Figure C2.14(c)), greater than the required 10% and is it unclear which one is reliable. With the revised PAT 2.1 and 2.2 (Table C2.9) many more models pass PAT 2.1 although they all failed one of the other PAT (Table C2.9) and it is difficult to choose between the these other models. It is suggested here that 11CrMoVNb is a very difficult material to fit reliably and that efforts should be made to obtain additional data, perhaps at 525, 575 and 625°C to improve the stability of the fitted equations (not 650°C as the material is tempered at 650-720°C). Nevertheless, if the results of PAT 1 and the revised PAT 2.1 and 2.2 are taken into account (ignoring PAT2.1(a) since most of the data outside of ± 2.5 SD have low observed rupture times) then two models can be shortlisted SM-mod #4 and OSD3 #9. Both of these exhibits a gentle sigmoidal behaviour at 600°C and give very similar strengths which are neither the lowest nor highest (see Table C2.2 and Figure C2.14(d)). It is judged likely that these two models give reasonably reliable rupture strength values for 11CrMoVNb, but that further investigation is required.

Ten models were proposed for 18Cr11Ni (see Table C2.6, Table C2.10 and Figure C2.15) of which three passed all of the original PATs. However, these had relatively high Z-factors and include the two most optimistic models on rupture strength (Table C2.2 and Figure C2.15 (c)) and it is judged that these models would therefore be non-conservative. Nevertheless, the revised PAT 2.1 and 2.2 (see Table C2.10) now fail these models. However, it remains difficult to select a clear shortlist of models as every model fails at least one PAT. A shortlist of four models has been selected by considering those that pass PAT 1, 2.1 (ignoring PAT2.1(a)) and 3. In particular, PAT 2.2 at 700°C has been ignored. Nevertheless, these four models have low Z-factors (less scatter) and give very similar strengths which are neither the lowest nor highest (see Table C2.2 and Figure C2.15(d)). It is judged likely that these four models are the most reliable for 18Cr11Ni.

Fifteen models were proposed for 31Ni20CrAlTi (see Table C2.7, Table C2.11 and Figure C2.16) of which three passed the original PAT 2.1 and 2.2 (ignoring PAT2.1(a)). However, these had relatively high Z-factors and include the two most optimistic models on rupture strength (Table C2.2 and Figure C2.16(c)) and it is judged that these models would be non-conservative. Nevertheless, the revised PAT 2.1 and 2.2 (see Table C2.11) allow six models to be selected that pass all PATs. These six models have low Z-factors (less scatter) and give very similar strengths which are neither the lowest nor highest (see Table C2.2 and Figure C2.16(d)). It is judged likely that these six models are the most reliable for 31Ni20CrAlTi.

CONCLUSIONS

It has been found that fitting creep rupture data using a range of different models and methods gives rise to a very wide range of best fit lines and rupture strength values. This is of concern as it questions the reliability of creep rupture data assessments. The ECCC post assessments tests fall into three main categories; (i) tests for the physical realism of the model, (ii) tests for the effectiveness of the model prediction within the range of the data and (iii) the repeatability and stability on extrapolation. Their effectiveness has been re-evaluated by Working Group 1. A simple modification has been made to a Revised PAT 2.1 and 2.2, for effectiveness of the model prediction within the range of the data, which now plots the observed logarithm of the rupture time (as the y-value) versus the predicted logarithm of the rupture time (as the x-value). It has been shown that the application of the full range of ECCC post assessment tests including the Revised PAT 2.1 and 2.2, allows the assessor to discriminate between unreliable and reliable creep rupture data assessments, and models. In particular, the shortlisted models produce similar mean fits and rupture strength values.

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Table C2.1: Summarised Extent of Failed Creep Rupture Data for the ECCC Working Datasets (excluding unbroken data). See Volume 5 Part Ia Appendix A for the full details of these datasets.

Material	Temperatures °C (No. at each)	Data 70-100kh	Data >100kh	Min Stress (MPa)
2¼Cr1Mo	450(19), 454(3), 475(45), 482(3), 500(174), 525(73), 535(12), 550(230), 565(70), 575(71), 593(38), 600(184), 620(15), 625(10), 650(65)	30	12	22
11CrMoVNb	425(1), 450(12), 475(14), 500(71), 550(145), 600(67)	14	4	69
18Cr11Ni	482(6), 500(18), 538(5), 550(57), 565(24), 593(28), 600(170), 625(21), 650(251), 700(120), 732(19), 750(13), 800(14)	6	2	10
31Ni20CrAlTi	500(42), 550(49), 600(65), 650(50), 700(79), 750(12), 800(68), 850(8), 900(56), 950(11), 1000(46), 1050(9)	2	0	5

Table C2.2: Creep Rupture Strengths (MPa) at the Main Temperatures for the Model Equations. *Red* showing the most optimistic and potentially non-conservative strengths. Models which are shortlisted by the Revised ECCC PAT are shown *Bold*.

2¼Cr1Mo at 550°C	AJB #1	SM2M x #2	SM2D #3	SM2P #3	MCmod #4	MB2 #5	MB3 #5	LM5 #9	Seifert #10	MMR 4 #11					
100kh	63.0	67.0	63.0	66.2	62.9	63.6	64.6	63.5	<i>71.8</i>	<i>71.7</i>					
300kh	45.1	51.1	48.9	50.4	48.9	47.6	48.5	49.7	<i>57.4</i>	<i>57.4</i>					
11CrMoV Nb at 550°C	MH3 #1	MH3 #2	MC-D #3	MCP #3	SM-mod #4	MH2 #5	MB3 #5	LMP 2 #6	OSD3 #9	Seifer t #10	MMR 4 #11				
100kh	136	134	166	147	154	<i>168</i>	<i>175</i>	161	153	<i>169</i>	150				
300kh	77.5	77.3	111	97.2	100	<i>122</i>	<i>128</i>	112	98.5	<i>130</i>	103				
18Cr11Ni at 650°C	MR #1	SM2M #2	SM1-D #3	SM1-P #3	MB3 #5	OSD3S 0.5 #6	MH2 S0.4 #6	MH3 #9	Seifert #10	MMR 4 #11					
100kh	54.8	56.3	52.6	54.4	64.2	65.4	49.5	66.4	<i>71.7</i>	<i>68.8</i>					
300kh	43.7	45.0	41.2	42.0	54.1	54.0	36.1	53.0	<i>61.8</i>	<i>58.8</i>					
31Ni20CrAlTi at 700°C	SM1 #1	SM1#2	SM1-D #3	SM1-P #3	MH3 #4	MB3 #5	LM3 #7	MH4t vS #8	MH4S vt #8	MB4S vt #8	OSD3 #8	OSD 4+ #8	MR 4 #9	Seifer t #10	MMR4 #11
100kh	41.6	42.0	40.0	42.8	38.9	40.2	42.9	37.7	44.0	36.2	42.3	39.7	41.2	<i>48.8</i>	<i>48.3</i>
300kh	32.9	33.2	31.2	34.0	28.8	32.0	35.5	28.5	35.8	27.3	33.4	31.7	33.7	<i>41.5</i>	<i>41.0</i>

Table C2.3: Results of PAT 3.1 and 3.2 For ECCC Datasets analysed by Investigator #1.

PAT		Extra Temp.	T _{min} [10%]	T _{main}	T _{max} [10%]	Time	Test Result
2¹/₄Cr1Mo Model AJB #1							
		475°C	500°C	550°C	600°C		
Full Model	R _{u/300kh}	129.6	94.27	45.14	17.79	300kh	
3.1	R _{u/300kh}	123.0	90.19	44.47	19.03	300kh	
	%	5.34	4.51	1.51	6.55		Pass
3.2	R _{u/300kh}	128.4	94.59	47.94	21.80	300kh	
	%	0.94	0.34	6.20	22.55		Fail
11CrMoVNb Model MH3 #1							
		475°C	500°C	550°C	600°C		
Full Model	R _{u/300kh}	313.1	228.7	77.47	55.22	300kh	
3.1 1 st Attempt	R _{u/300kh}	298.8	216.5	70.07	50.58	300kh	
	%	4.80	5.64	10.55	9.18		Fail
3.1 2 nd Attempt	R _{u/300kh}	307.9	227.1	78.38	56.46	300kh	
	%	1.74	0.75	1.29	2.45		Pass
3.2	R _{u/300kh}	323.8	240.2	80.19	54.92	300kh	
	%	3.42	5.01	3.51	0.55		Pass
18Cr11Ni Model MR #1							
		550°C	600°C	650°C	700°C		
Full Model	R _{u/300kh}	108.4	70.04	43.66	25.95	300kh	
3.1	R _{u/300kh}	101.1	65.27	40.81	24.49	300kh	
	%	7.17	7.30	6.99	5.96		Pass
3.2	R _{u/300kh}	107.8	69.92	44.15	26.97	300kh	
	%	0.53	0.17	1.12	3.90		Pass
31Ni20CrAlTi Model SM1 #1 at 300kh							
		550°C	600°C	700°C	900°C		
Full Model	R _{u/300kh}	131.7	83.58	32.85	6.35	300kh	
3.1	R _{u/300kh}	130.1	81.72	31.45	5.99	300kh	
	%	1.23	2.28	4.45	5.95		Pass
3.2	R _{u/300kh}	131.2	82.95	32.43	6.26	300kh	
	%	0.42	0.76	1.30	1.40		Pass
31Ni20CrAlTi Model SM1 #1 at R_{u/3.tu[max]}, 3.tu[max] = 238293h							
Full Model	R _{u/3.tu[max]}	136.7	87.20	34.54	6.70	238.3kh	
3.1	R _{u/3.tu[max]}	135.1	85.35	33.12	6.34	238.3kh	
	%	1.18	2.17	4.27	5.73		Pass
3.2	R _{u/3.tu[max]}	136.1	86.58	34.11	6.61	238.3kh	
	%	0.39	0.71	1.25	1.34		Pass

Table C2.4: Results of Original ECCC Post Assessment Tests for 2¼Cr1Mo. Shortlisted models are shown **Bold**. Shortlist is based on PAT 1 and 2 (ignoring PAT2.1(a) % of data outside ±2.5 SD).

	AJB #1	SM2Mx #2	SM2D #3	SM2P #3	MCmod #4	MB2 #5	MB3 #5	LM5 #9	Seifert #10	MMR4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.3	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
Z Factor	7.475	7.164	7.213	7.779	7.213	7.026	6.980	7.987	9.673	8.407
PAT-2.1 (a)	Fail	Fail	Pass	Pass	Pass	Fail	Pass	Pass	Fail	Pass
All data (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
(c)	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 500°C (c)	Pass	Pass	Fail	Pass	Fail	Pass	Fail	Pass	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Fail	Pass	Fail	Pass	Pass	Fail	Pass	Pass
at 550°C (c)	Pass	Pass	Fail	Fail	Fail	Fail	Fail	Fail	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 600°C (c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-3.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-3.2	Fail	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass

PAT 2 Criteria (a) % of the data outside of ±2.5 SD (b) slope of a mean linear fit (c) contained within ±log 2

Table C2.5: Results of Original ECCC Post Assessment Tests for 11CrMoVNb. Shortlisted models shown **Bold** are based on PAT 2.1 **only** (ignoring PAT2.1(a) % of the data outside of ±2.5 SD).

	MH3 #1	MH3 #2	MC-D #3	MCP #3	SM-mod #4	MH2 #5	MB3 #5	LMP2 #6	OSD3 #9	Seifert #10	MMR 4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass
PAT-1.3	Fail	Fail	Fail	Pass	Pass	Fail	Fail	Fail	Pass	Pass	Pass
Z Factor	10.53	10.12	9.51	9.90	8.96	9.97	10.12	9.31	9.00	9.80	11.74
PAT-2.1 (a)	Fail	Fail	Fail	Fail	Pass	Fail	Fail	Fail	Fail	Fail	Fail
All data (b)	Fail	Fail	Pass	Fail	Fail	Fail	Pass	Fail	Fail	Pass	Pass
(c)	Fail	Fail	Fail	Fail	Fail	Fail	Pass	Fail	Fail	Fail	Pass
PAT-2.2 (b)	Fail	Fail	Pass	Pass	Pass	Fail	Fail	Fail	Fail	Fail	Pass
at 500°C (c)	Fail	Fail	Fail	Fail	Fail	Fail	Fail	Fail	Fail	Fail	Pass
PAT-2.2 (b)	Fail	Fail	Pass	Fail	Pass	Pass	Pass	Fail	Pass	Pass	Pass
at 550°C (c)	Fail	Fail	Pass	Fail	Fail	Fail	Pass	Fail	Fail	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 600°C (c)	Fail	Fail	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-3.1	Pass	Pass	Fail	Pass	Pass	Pass	Fail	Pass	Pass	Fail	Pass
PAT-3.2	Pass	Pass	Pass	Pass	Fail	Pass	Fail	Fail	Pass	Pass	Fail

PAT 2 Criteria (a) % of the data outside of ±2.5 SD (b) slope of a mean linear fit (c) contained within ±log 2

Table C2.6: Results of Original ECCC Post Assessment Tests for 18Cr11Ni. Shortlisted models shown **Bold** are based on all PAT.

	MR #1	SM2M #2	SM1-D #3	SM1-P #3	MB3 #5	OSD3 S0.5 #6	MH2 S0.4 #6	MH3 #9	Seifert #10	MMR 4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.3	Pass	Pass	Pass	Pass	Pass	Pass	Fail ¹	Pass	Pass	Pass
Z Factor	13.95	14.36	13.75	14.48	17.96	22.08	13.96	30.30	26.17	24.21
PAT-2.1 (a)	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
All data (b)	Fail	Fail	Fail	Fail	Pass	Pass	Fail	Pass	Pass	Pass
(c)	Fail	Fail	Fail	Fail	Pass	Pass	Fail	Pass	Pass	Pass
PAT-2.2 (b)	Fail	Fail	Fail	Fail	Fail	Pass	Fail	Pass	Pass	Pass
at 600°C (c)	Fail	Fail	Fail	Fail	Fail	Pass	Fail	Fail	Pass	Pass
PAT-2.2 (b)	Fail	Fail	Fail	Fail	Pass	Pass	Fail	Pass	Pass	Pass
at 650°C (c)	Fail	Fail	Fail	Fail	Fail	Pass	Fail	Pass	Pass	Pass
PAT-2.2 (b)	Fail	Fail	Fail	Fail	Pass	Pass	Fail	Pass	Pass	Pass
at 700°C (c)	Fail	Fail	Fail	Fail	Pass	Pass	Fail	Fail	Pass	Pass
PAT-3.1	Pass	Pass	Pass			Fail	Fail	Fail	Pass	Pass
PAT-3.2	Pass	Pass	Pass			Fail	Fail	Fail	Pass	Pass

PAT 2 Criteria (a) % of the data outside of ± 2.5 SD (b) slope of a mean linear fit (c) contained within $\pm \log 2$
 Fail¹ Derivative less than 1.5 only for times greater than 1,000,000 hours.

Table C2.7: Results of Original ECCC Post Assessment Tests for 31Ni20CrAlTi. Shortlisted models shown **Bold** are based on PAT 2.1 and 2.2 only (ignoring PAT2.1(a) % of data outside ± 2.5 SD).

	SM 1 #1	SM1 #2	SM1-D #3	SM1-P #3	MH3 #4	MB 3 #5	LM3 #7	MH4t vS #8	MH4S vt #8	MB4S vt #8	OSD3 #8	OSD4+ #8	MR4 #9	Seifert #10	MMR4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass							
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass							
PAT-1.3	Pass	Fail ¹	Fail¹	Fail ¹	Pass	Pass	Pass	Pass	Pass						
Z Factor	5.87	6.08	5.82	6.12	6.35	5.73	6.10	5.79	7.63	6.12	6.36	6.19	5.73	7.62	7.28
PAT-2.1 (a)	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass							
All data (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass							
(c)	Pass	Fail	Pass	Fail	Fail	Pass	Fail	Fail	Pass	Fail	Pass	Pass	Pass	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 600°C (c)	Pass	Pass	Pass	Pass	Fail	Fail	Fail	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Fail	Pass	Pass	Fail	Pass	Fail	Pass	Fail	Pass	Pass	Fail	Pass	Pass
at 700°C (c)	Fail	Pass	Fail	Pass	Fail	Fail	Pass	Pass							
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass							
at 900°C (c)	Pass	Pass	Fail	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass
PAT-3.1	Pass	Pass	Pass		Pass	Pass							Pass	Fail	Pass
PAT-3.2	Pass	Pass	Pass		Pass	Pass							Pass	Pass	Pass

PAT 2 Criteria (a) % of the data outside of ± 2.5 SD (b) slope of a mean linear fit (c) contained within $\pm \log 2$
 Fail¹ Derivative less than 1.5 only for times greater than 1,000,000 hours.

Table C2.8: Results of Revised-ECCC Post Assessment Tests for 2¼Cr1Mo. Shortlisted models shown **Bold** are based on all PAT.

	AJB #1	SM2Mx #2	SM2D #3	SM2P #3	MCmod #4	MB2 #5	MB3 #5	LM5 #9	Seifert #10	MMR4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.3	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
Z Factor	7.475	7.164	7.213	7.779	7.213	7.026	6.980	7.987	9.673	8.407
PAT-2.1 (a)	Fail	Fail	Pass	Pass	Pass	Fail	Pass	Pass	Fail	Pass
All data (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
(c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass
at 500°C (c)	Fail	Pass	Pass	Fail	Pass	Pass	Pass	Fail	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 550°C (c)	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 600°C (c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-3.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-3.2	Fail	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass

PAT 2 Criteria (a) % of the data outside of ±2.5 SD (b) slope of a mean linear fit (c) contained within ±log 2

Table C2.9: Results of Revised-ECCC Post Assessment Tests for 11CrMoVNb. Shortlisted models shown **Bold** are based on PAT 1.1, 1.2, 1.3, 2.1 and 2.2 only (ignoring PAT2.1(a) % of the data outside of ±2.5 SD and PAT 3.2).

	MH3 #1	MH3 #2	MC-D #3	MCP #3	SM-mod #4	MH2 #5	MB3 #5	LMP2 #6	OSD3 #9	Seifert #10	MMR4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass
PAT-1.3	Fail	Fail	Fail	Pass	Pass	Fail	Fail	Fail	Pass	Pass	Pass
Z Factor	10.53	10.12	9.51	9.90	8.96	9.97	10.12	9.31	9.00	9.80	11.74
PAT-2.1 (a)	Fail	Fail	Fail	Fail	Pass	Fail	Fail	Fail	Fail	Fail	Fail
All data (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
(c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail
at 500°C (c)	Pass	Pass	Fail	Fail	Pass	Pass	Pass	Pass	Pass	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 550°C (c)	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Fail	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at 600°C (c)	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Fail	Pass
PAT-3.1	Pass	Pass	Fail	Pass	Pass	Fail	Pass	Pass	Pass	Fail	Pass
PAT-3.2	Pass	Pass	Pass	Pass	Fail	Fail	Fail	Fail	Pass	Pass	Fail

PAT 2 Criteria (a) % of the data outside of ±2.5 SD (b) slope of a mean linear fit (c) contained within ±log 2

Table C2.10: Results of Revised-ECCC Post Assessment Tests for 18Cr11Ni. Shortlisted models shown **Bold** are based on PAT 2.1 and 2.2 at 600 and 650°C only (ignoring PAT2.1(a) % of the data outside of ±2.5 SD).

	MR #1	SM2M #2	SM1-D #3	SM1-P #3	MB3 #5	OSD3S 0.5 #6	MH2 S0.4 #6	MH3 #9	Seifert #10	MMR4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.3	Pass	Pass	Pass	Pass	Pass	Pass	Fail ¹	Pass	Pass	Pass
Z Factor	13.95	14.36	13.75	14.48	17.96	22.08	13.96	30.30	26.17	24.21
PAT-2.1 (a)	Fail	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
All data (b)	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	Fail	Fail
(c)	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	Fail	Fail
at 600°C (c)	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	Fail	Fail
at 650°C (c)	Pass	Pass	Pass	Pass	Fail	Fail	Pass	Fail	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Fail	Pass	Pass	Fail	Pass	Pass	Pass
at 700°C (c)	Fail	Fail	Fail	Fail	Pass	Pass	Fail	Fail	Fail	Pass
PAT-3.1	Pass	Pass	Pass	Pass	Fail	Pass	Fail	Fail	Pass	Pass
PAT-3.2	Pass	Pass	Pass	Pass	Fail	Pass	Fail	Fail	Pass	Pass

PAT 2 Criteria (a) % of the data outside of ±2.5 SD (b) slope of a mean linear fit (c) contained within ±log 2

Fail¹ Derivative less than 1.5 only for times greater than 1,000,000 hours.

Table C2.11: Results of Revised-ECCC Post Assessment Tests for 31Ni20CrAlTi. Shortlisted models shown **Bold** are based on all PAT.

	SM 1 #1	SM 1#2	SM1- D #3	SM1- P #3	MH 3 #4	MB 3 #5	LM3 #7	MH4t vS #8	MH4S vt #8	MB4S vt #8	OSD 3 #8	OSD4+ #8	MR4 #9	Seifert #10	MMR 4 #11
PAT-1.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
PAT-1.3	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail ¹	Fail ¹	Fail ¹	Pass	Pass	Pass	Pass	Pass
Z Factor	5.87	6.08	5.82	6.12	6.35	5.73	6.10	5.79	7.63	6.12	6.36	6.19	5.73	7.62	7.28
PAT-2.1 (a)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass
All data (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
(c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Pass	Pass
at															
600°C (c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Fail	Pass	Pass	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass
at															
700°C (c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Fail
PAT-2.2 (b)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Fail	Fail
at															
900°C (c)	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass	Pass	Pass	Pass	Fail	Fail
PAT-3.1	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Fail	Pass
PAT-3.2	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass	Pass

PAT 2 Criteria (a) % of the data outside of ± 2.5 SD (b) slope of a mean linear fit (c) contained within $\pm \log 2$
 Fail¹ Derivative less than 1.5 only for times greater than 1,000,000 hours.

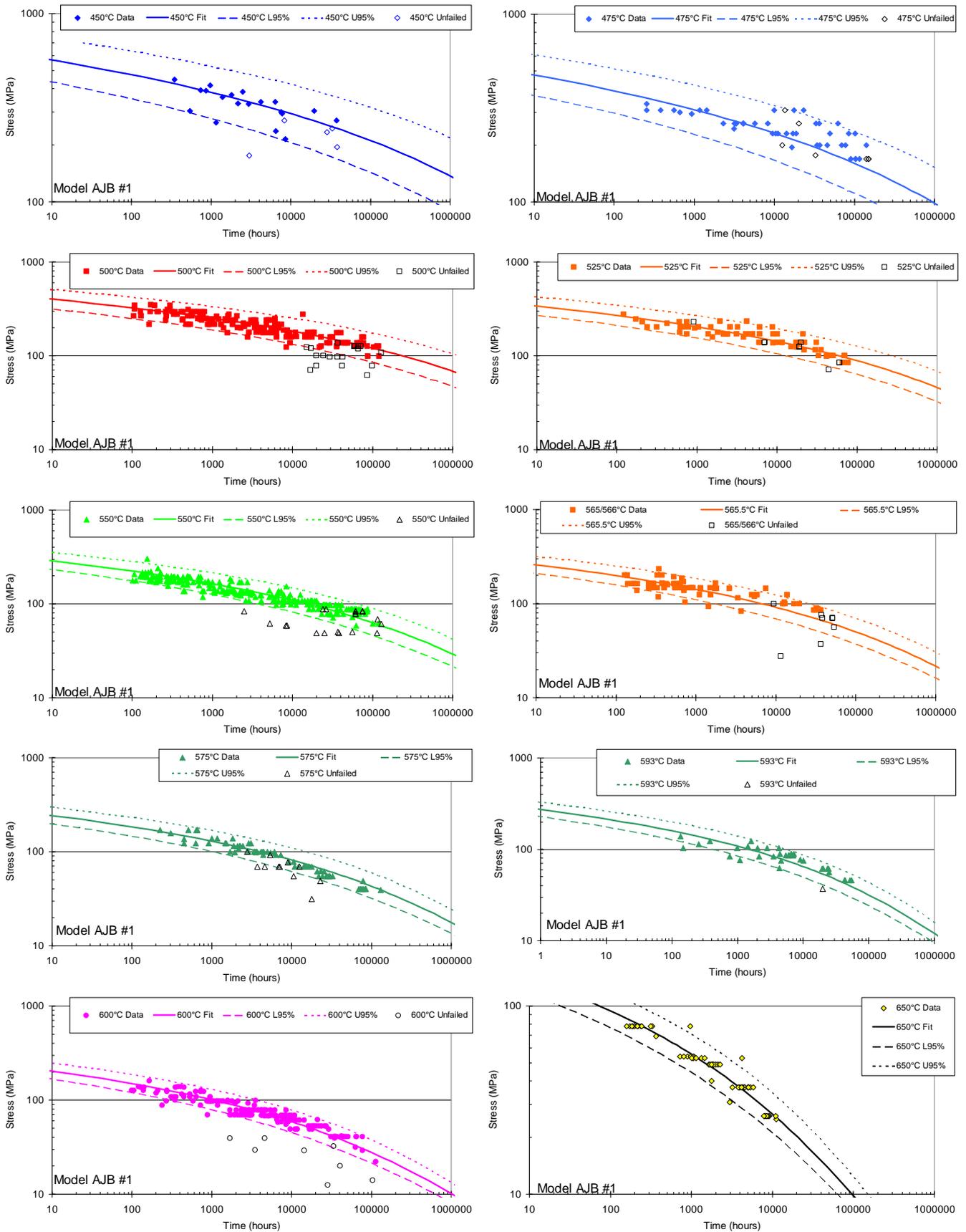


Figure C2.1: PAT 1.1 For Model AJB #1 Fitted to $2\frac{1}{4}$ Cr1Mo using PD6605 [4]. Test Passed, although the apparent bias at 450 and 475°C is noted. An investigation of the data showed that the majority of the data at these temperatures comes from only one country and that the country providing most data is different at the different temperatures.

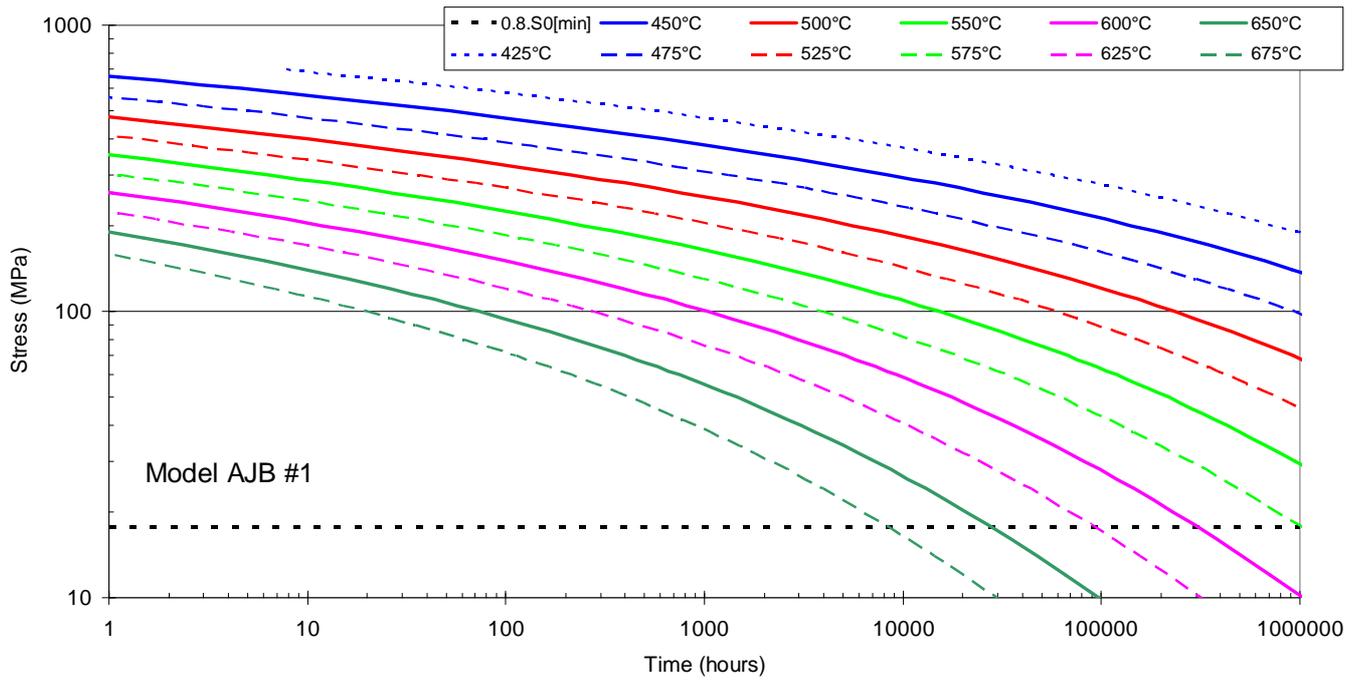


Figure C2.2: PAT 1.2 For Model AJB #1 Fitted to 2¼Cr1Mo using PD6605 [4]. Test Passed.

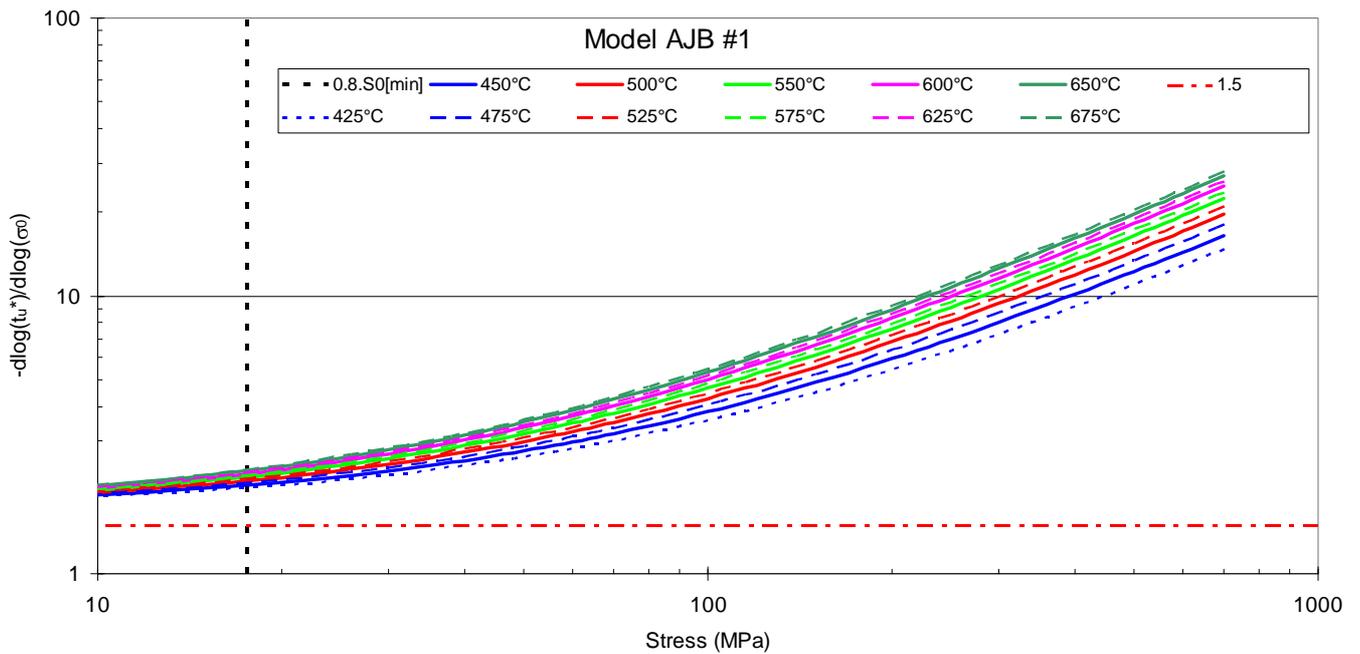


Figure C2.3: PAT 1.3 For Model AJB #1 Fitted to 2¼Cr1Mo using PD6605 [4]. Test Passed.

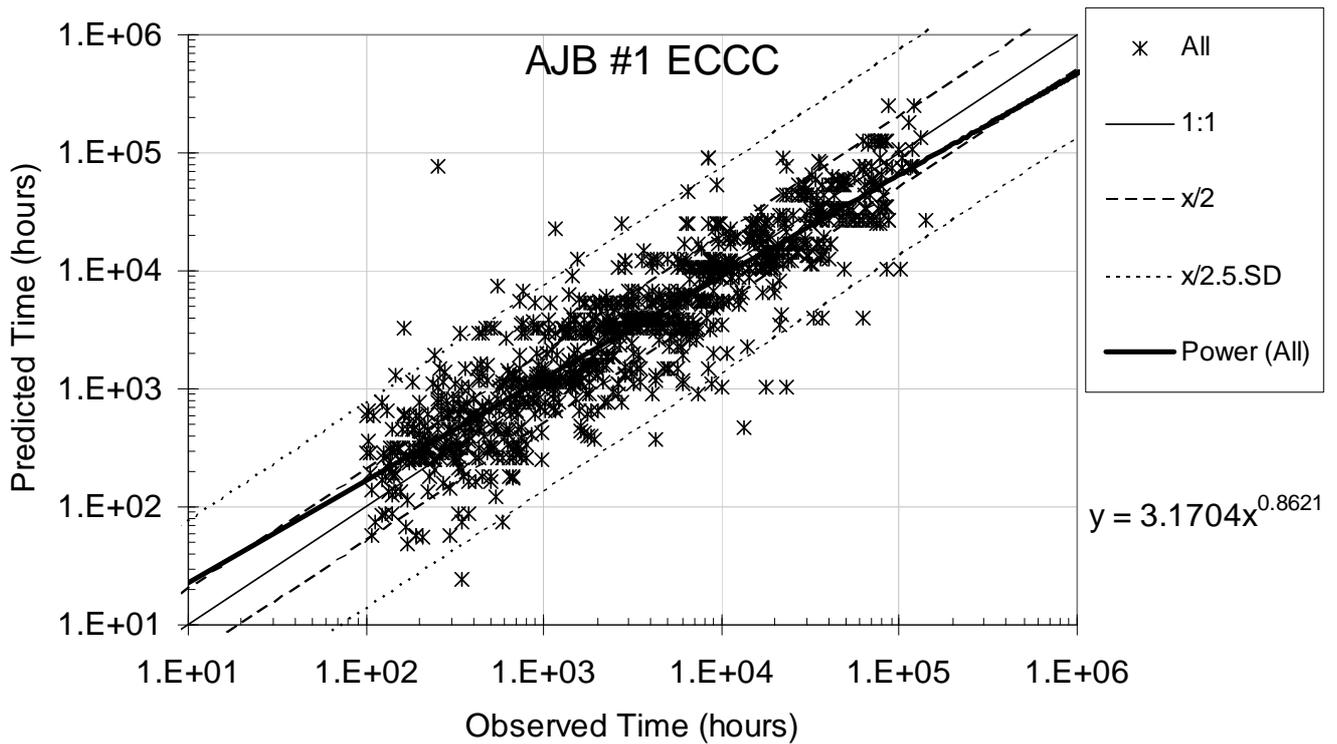
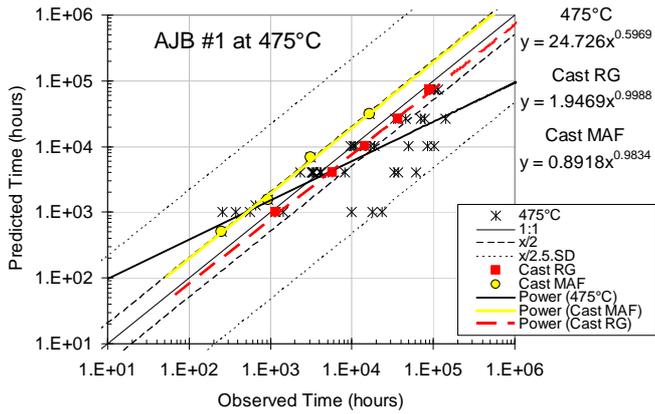


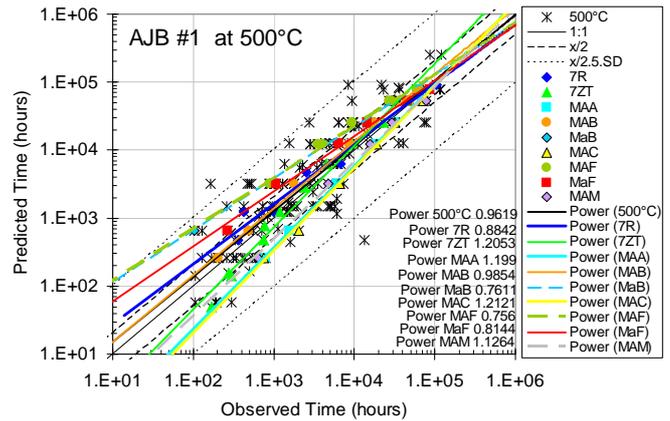
Figure C2.4: Original ECCC PAT 2.1 (predicted logarithm of the rupture time versus the observed logarithm of the rupture time) for Model AJB #1 Fitted to 2¼Cr1Mo using PD6605 [4]. Overall test Failed.

- (a) More than 1.5% (actual value 2.75%) of the data fall outside of ± 2.5 standard deviations. Test Failed
- (b) The slope of a mean linear fit is 0.8621 which is between 0.78 and 1.22. Test Passed.
- (c) The mean linear fit is contained within $\pm \log 2$ boundaries between observed rupture times of 100 and 100,000 hours. Test Passed.

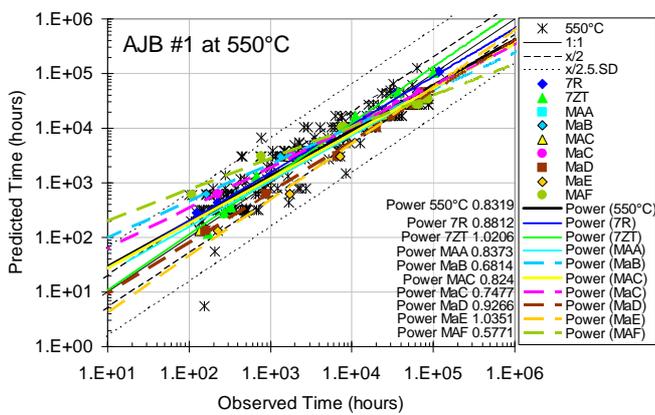
Note: A re-evaluation of the pre-assessment has identified a number of errors in these data for example the data at (254,78088) was entered as being at 520°C and a check of the source data showed that the actual temperature was 620°C. In addition, other outliers included data for Cast 2¼Cr1Mo which was inadvertently included with the wrought data. This shows the value of PAT 2.1 at identifying outliers.



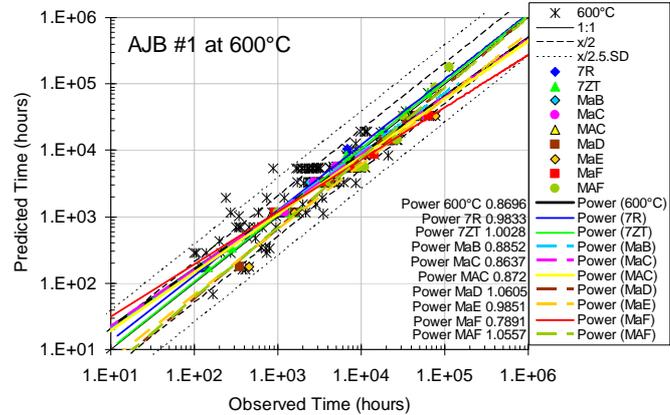
(a) 475°C (note this is not $T_{\min[10\%]}$ but contains long term data.)



(b) 500°C $T_{\min[10\%]}$



(c) 550°C T_{main}



(d) 600°C $T_{\max[10\%]}$

Figure C2.5: Original ECCC PAT 2.2 (predicted logarithm of the rupture time versus the observed logarithm of the rupture time) for Model AJB #1 Fitted to 2¼Cr1Mo using PD6605 [4]. Overall test Passed.

(a) 475°C. Note this is not $T_{\min[10\%]}$ but contains significant long term data tests, which would be failed at this temperature on the slope of a mean linear fit is 0.5969, which is not between 0.78 and 1.22. In addition, the mean linear fit is not contained within $\pm \log 2$ boundaries.

(b) 500°C $T_{\min[10\%]}$. Quantitative tests passed.

(c) 550°C T_{main} . Quantitative tests passed.

(d) 600°C $T_{\max[10\%]}$. Quantitative tests passed.

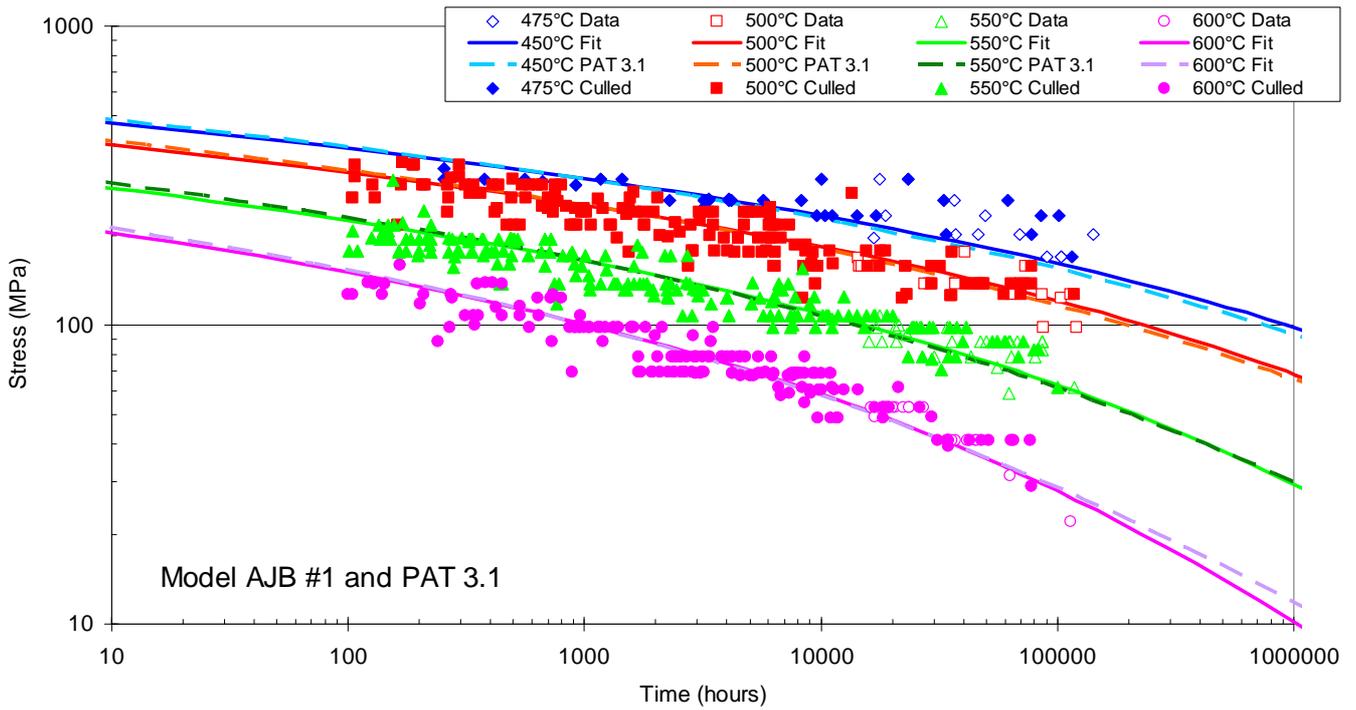


Figure C2.6: An Example of The Data (full dataset and culled dataset) and Fits for PAT 3.1 Applied to Model AJB #1 Fitted to 2¼Cr1Mo using PD6605 [4]. Overall test Passed.

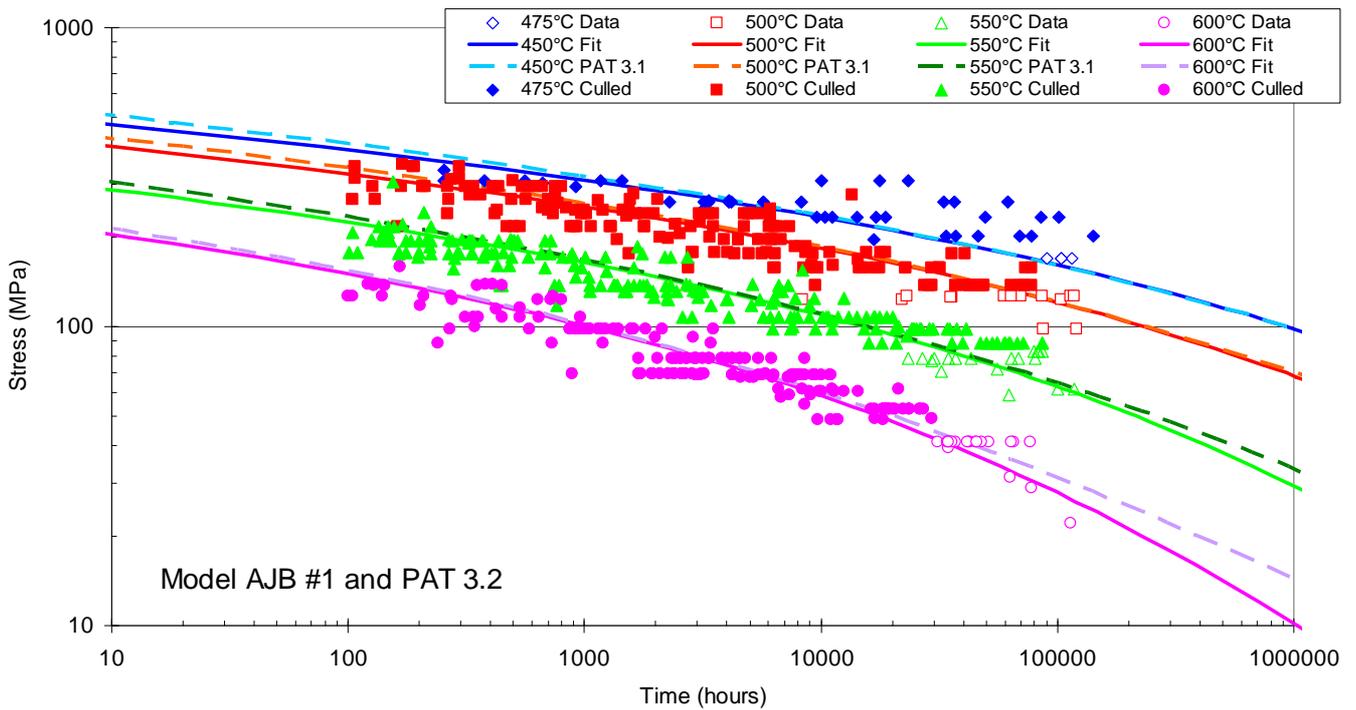
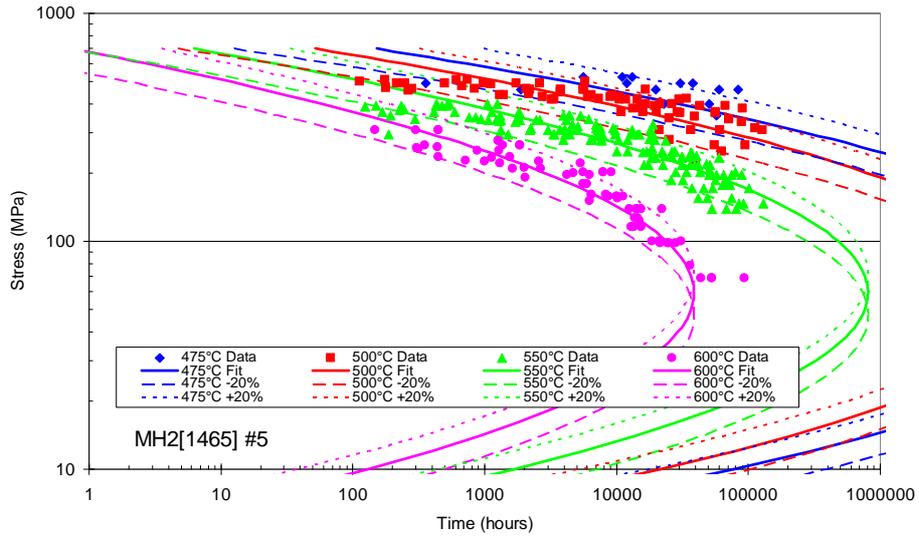
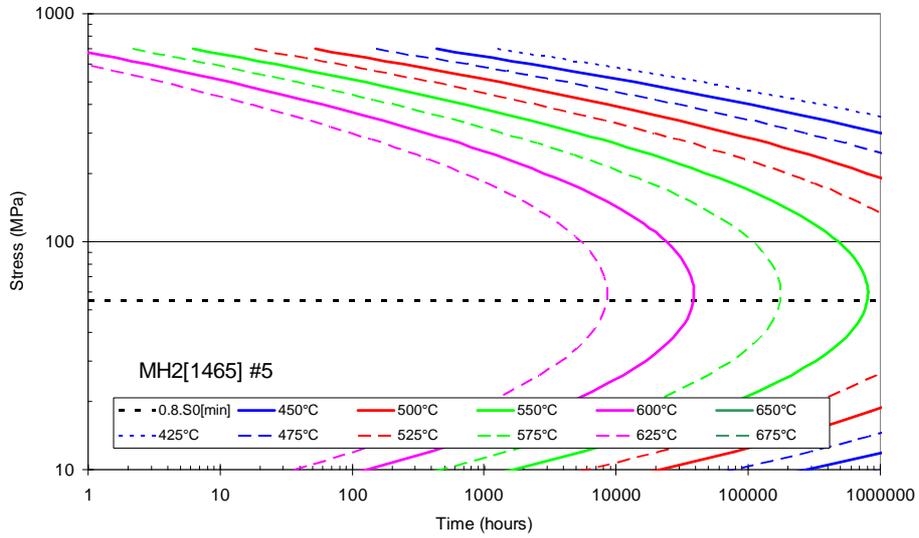


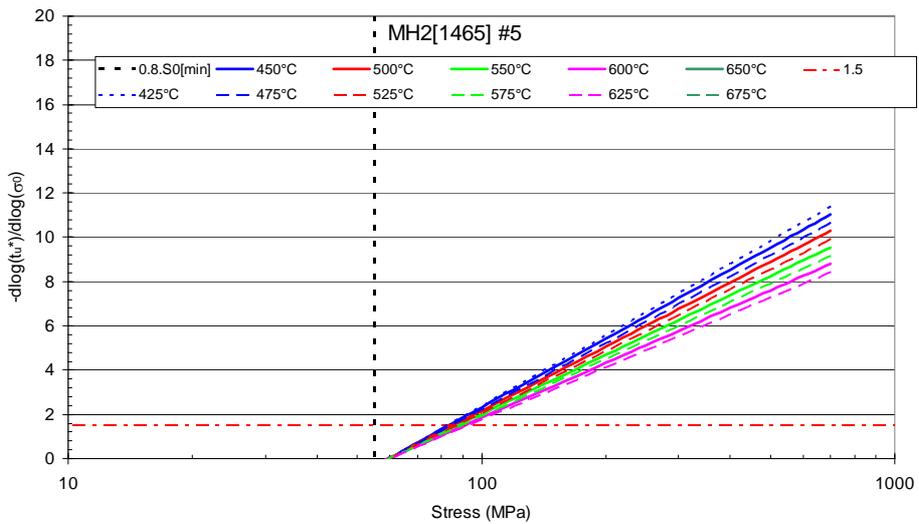
Figure C2.7: An Example of The Data (full dataset and culled dataset) and Fits for PAT 3.2 Applied to Model AJB #1 Fitted to 2¼Cr1Mo using PD6605 [4]. Overall test Failed at 600°C $T_{[max]}$.



(a) PAT 1.1

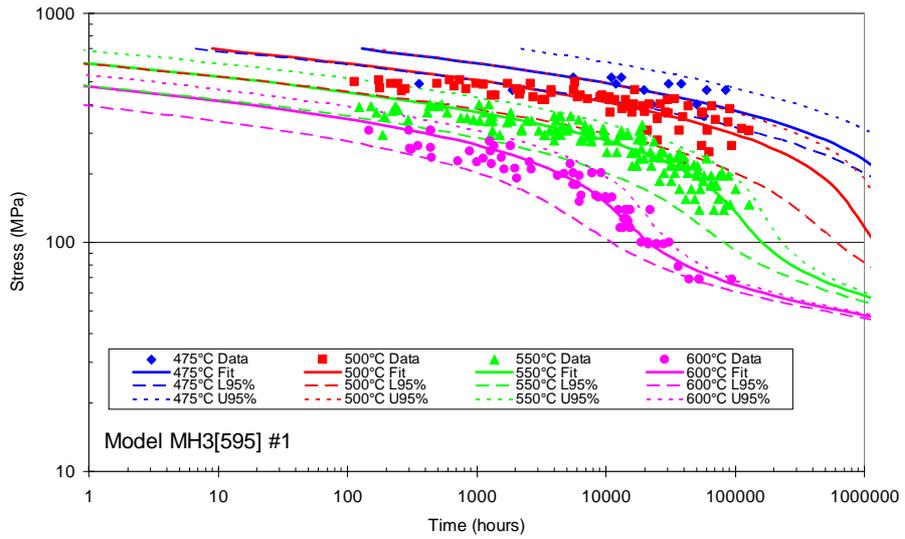


(b) PAT 1.2

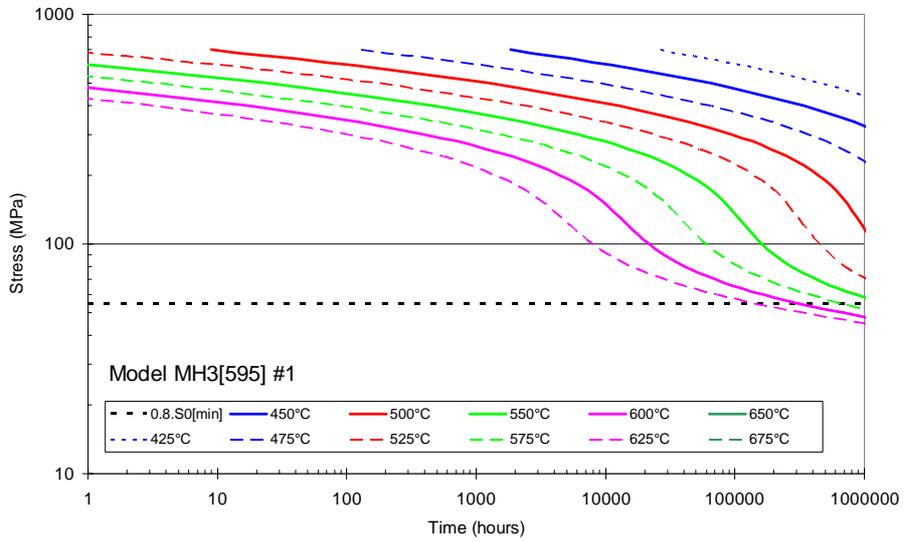


(c) PAT 1.3

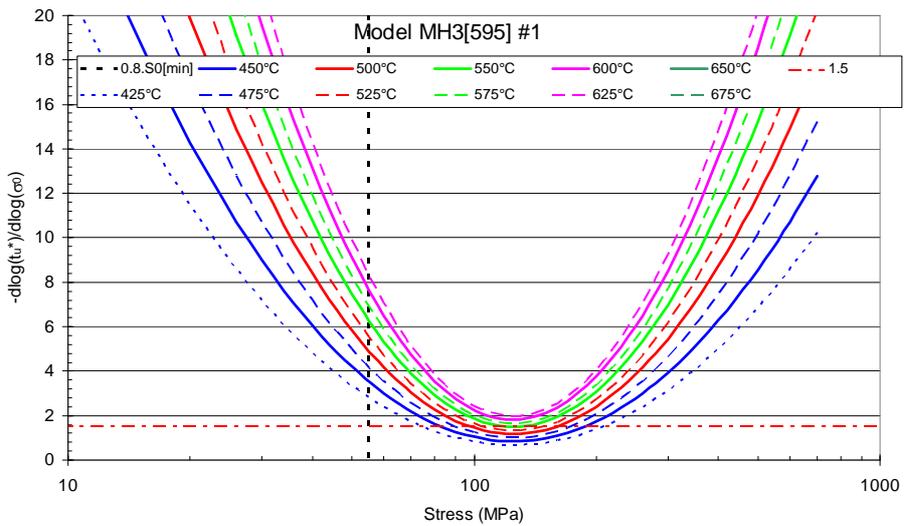
Figure C2.8: Example of a Fit to 11CrMoVNb Model MH2 #5 that Fails PAT 1.1, 1.2 and 1.3.



(a) PAT 1.1

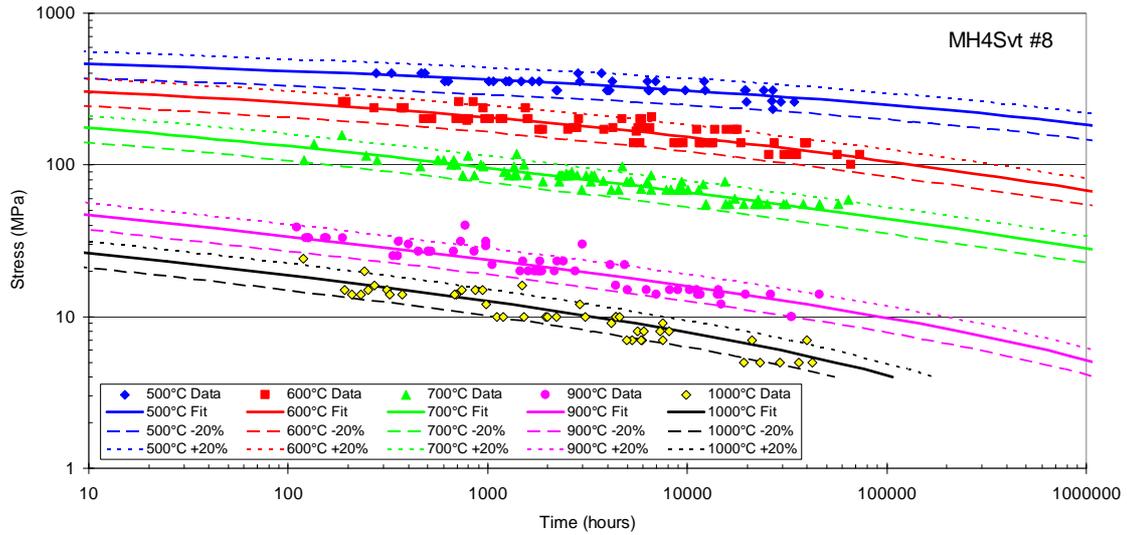


(b) PAT 1.2

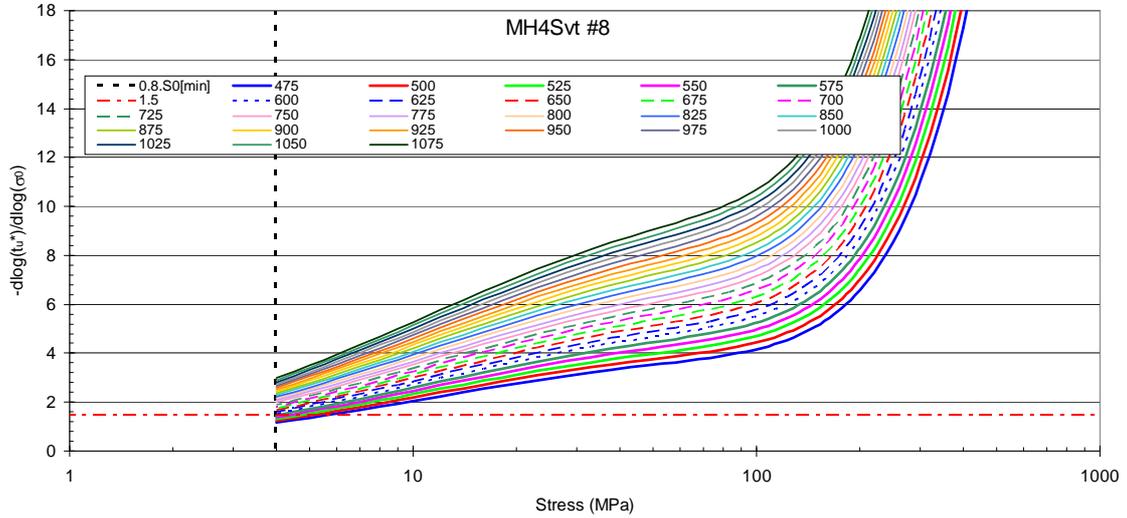


(c) PAT 1.3

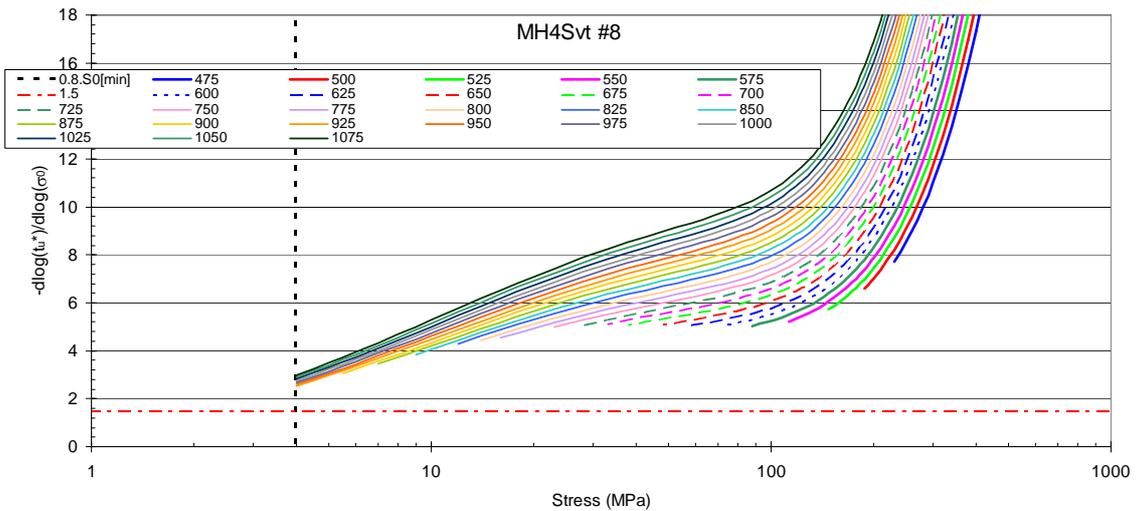
Figure C2.9: Example of a Fit to 11CrMoVNb Model MH3 #1 that Passes PAT 1.1, 1.2 but Fails PAT 1.3. Note derivatives fall below 1, which is not physically realistic even for diffusional creep. In addition, values less than 1.5 are obtained for times less than 1,000,000 hours.



(a) PAT 1.1



(b) PAT 1.3 showing all times



(c) PAT 1.3 showing only times less than 1,000,000 hours.

Figure C2.10: Example of a Fit to 31Ni20CrAlTi Model MH4Svt #8 that Passes PAT 1.1, 1.2 but Fails PAT 1.3, albeit only at times much greater than 1,000,000 hours.

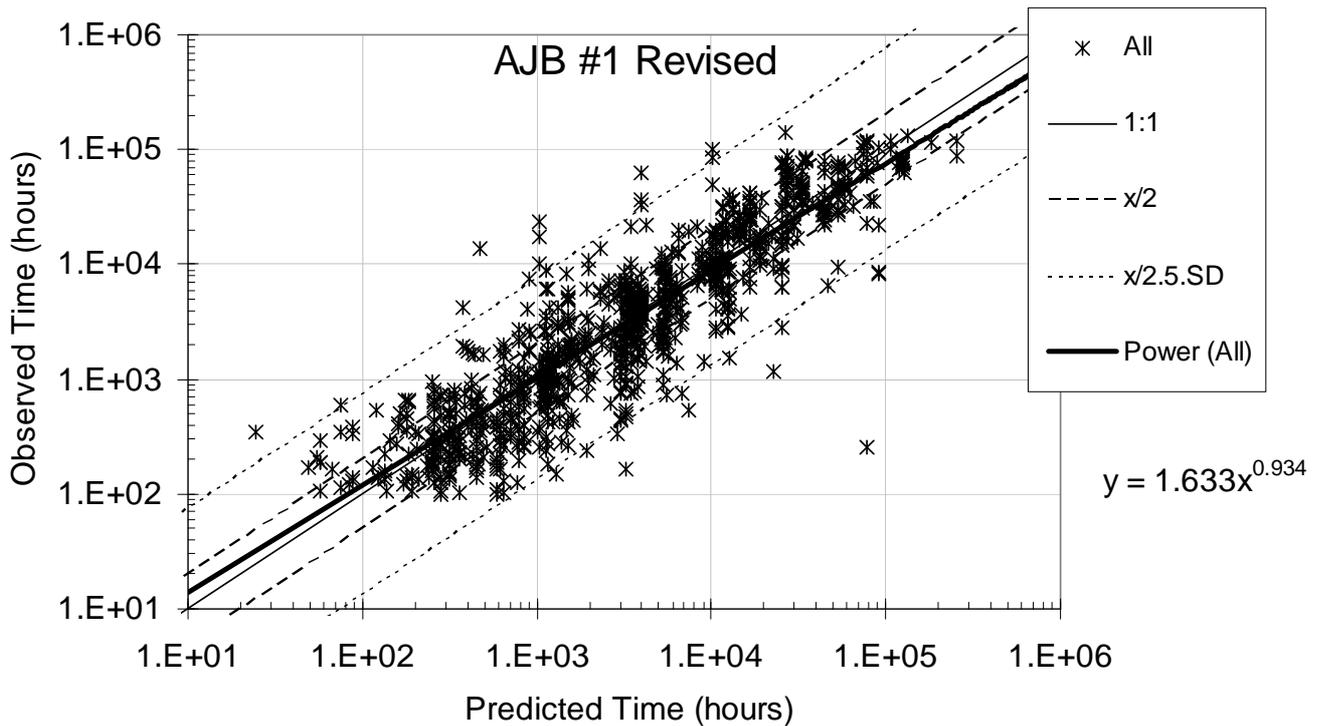
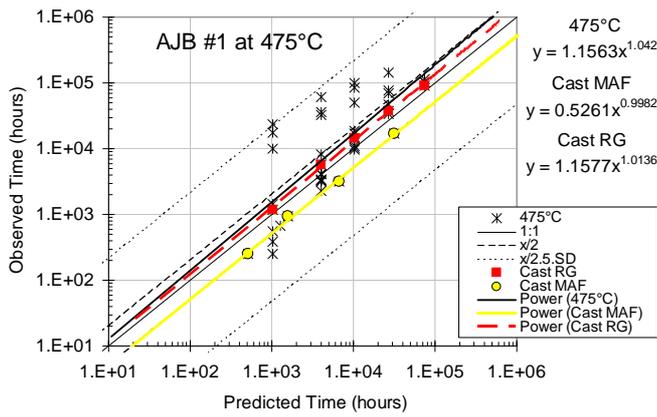


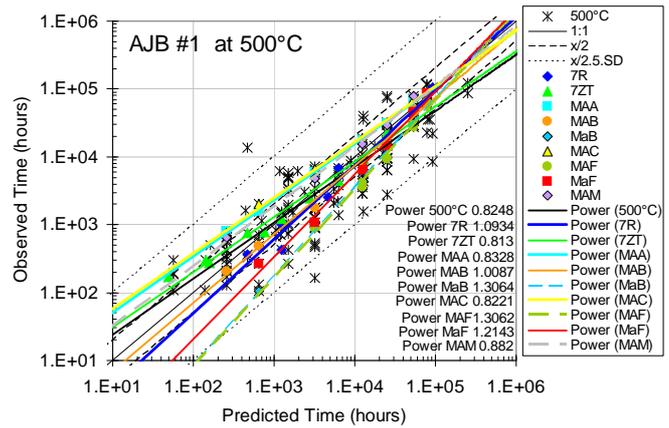
Figure C2.11: Revised ECCC PAT 2.1 (Observed logarithm of the rupture time versus the Predicted logarithm of the rupture time) for Model AJB #1 Fitted to 2¼Cr1Mo using PD6605 [4]. Overall test Failed.

- (a) More than 1.5% (actual value 2.75%) of the data fall outside of ± 2.5 standard deviations. Test Failed
- (b) The slope of a mean linear fit is 0.934 which is between 0.78 and 1.22. Test Passed.
- (c) The mean linear fit is contained within $\pm \log 2$ boundaries between observed rupture times of 100 and 100,000 hours. Test Passed.

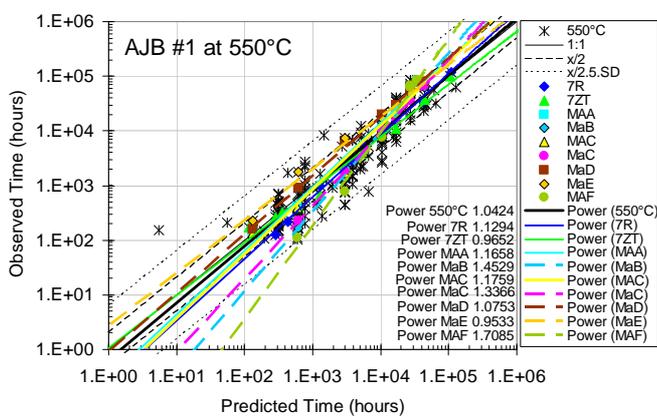
Note: A re-evaluation of the pre-assessment has identified a number of errors in these data for example the data at (254,78088) was entered as being at 520°C and a check of the source data showed that the actual temperature was 620°C. In addition, other outliers included data for Cast 2¼Cr1Mo which was inadvertently included with the wrought data. This shows the value of PAT 2.1 at identifying outliers.



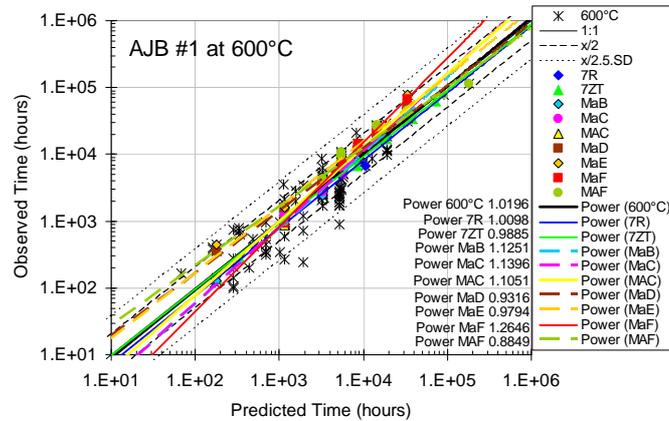
(a) 475°C (note this is not $T_{\min[10\%]}$ but contains long term data.)



(b) 500°C $T_{\min[10\%]}$



(c) 550°C T_{main}



(d) 600°C $T_{\max[10\%]}$

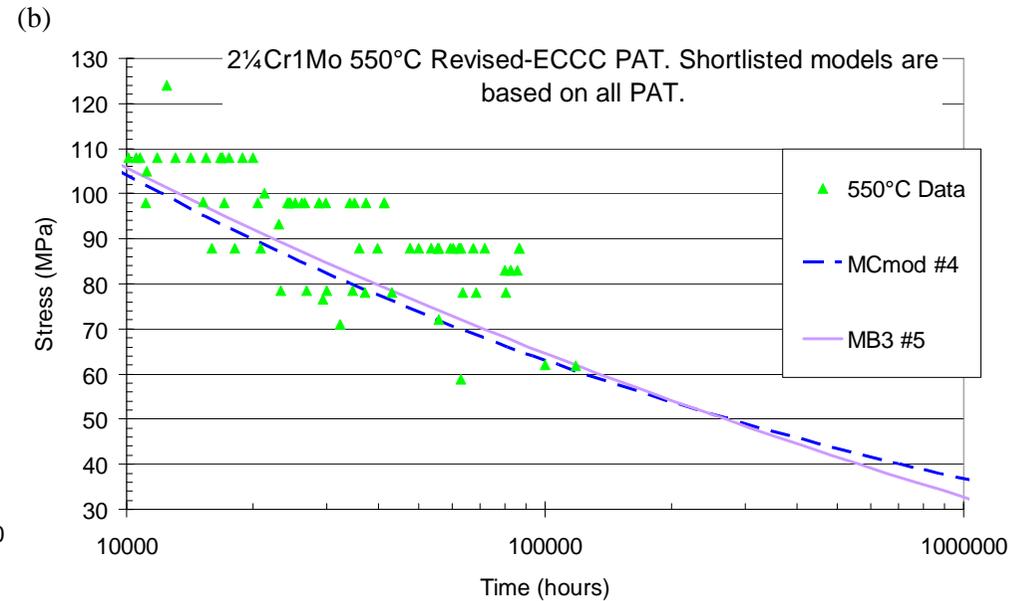
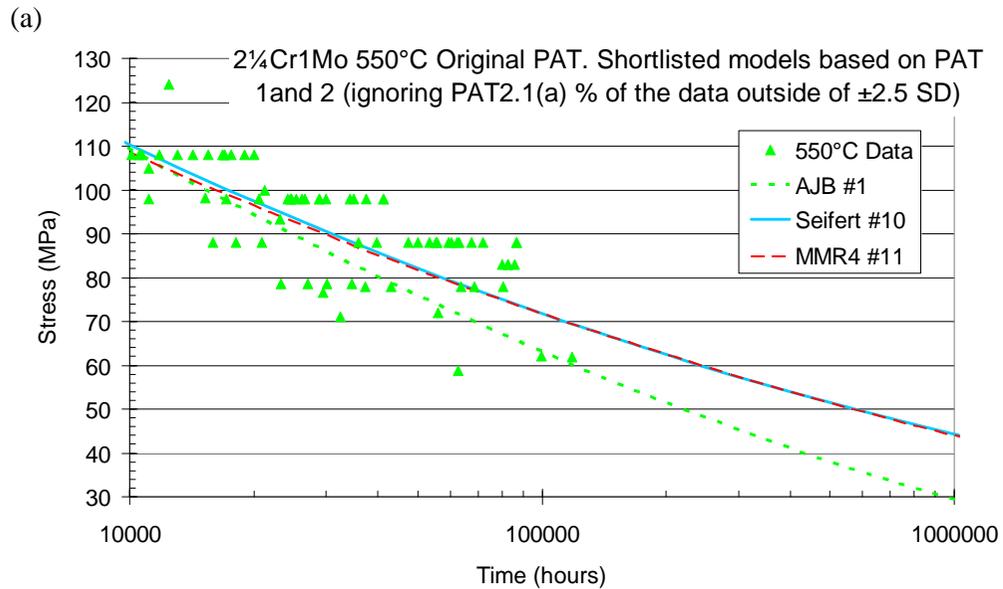
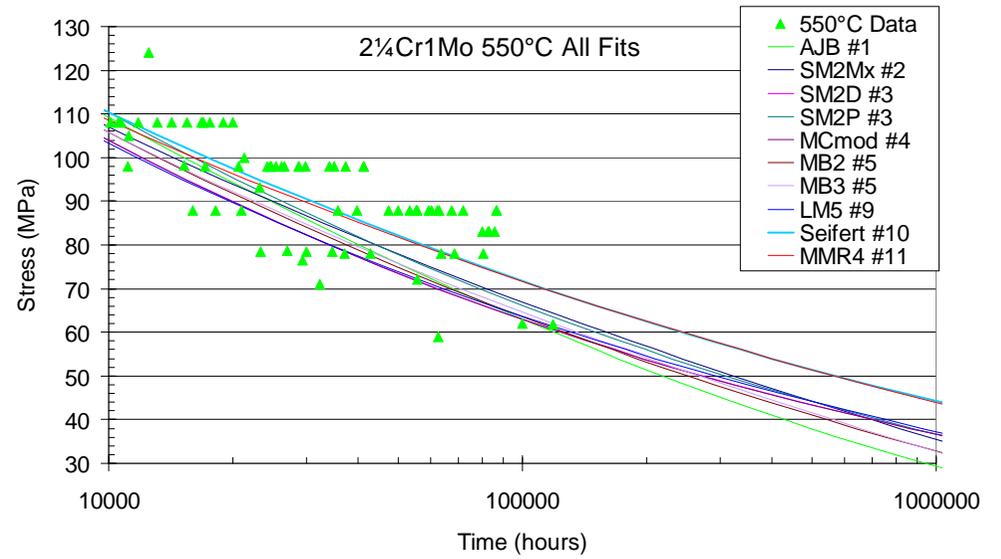
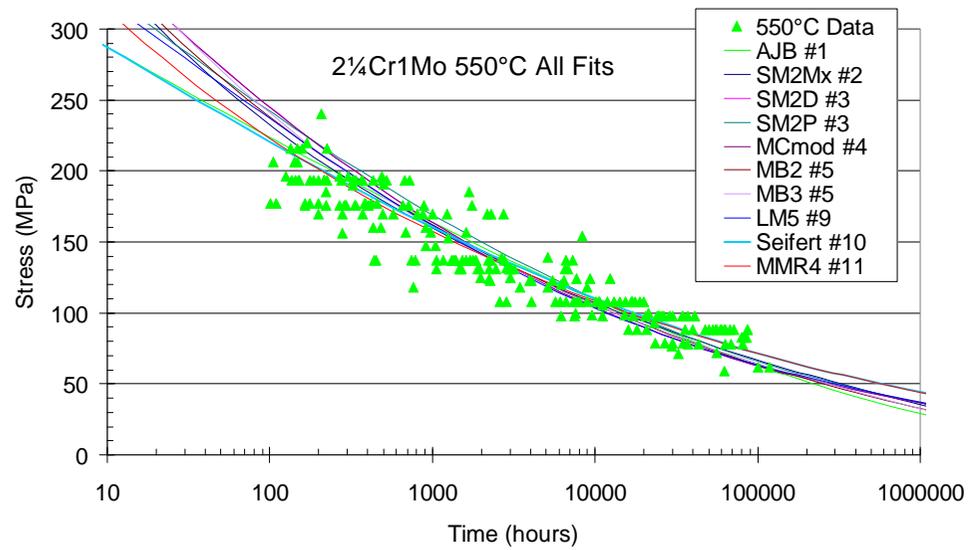
Figure C2.12: Revised ECCC PAT 2.2 (Observed logarithm of the rupture time versus the Predicted logarithm of the rupture time) for Model AJB #1 Fitted to $2\frac{1}{4}\text{Cr1Mo}$ using PD6605 [4]. Overall test Passed.

(a) 475°C. Note this is not $T_{\min[10\%]}$ but contains significant long term data tests. This test was failed in the Original PAT 2.2 see Figure C2.5(a). However, with the Revised PAT 2.2 it is now passed.

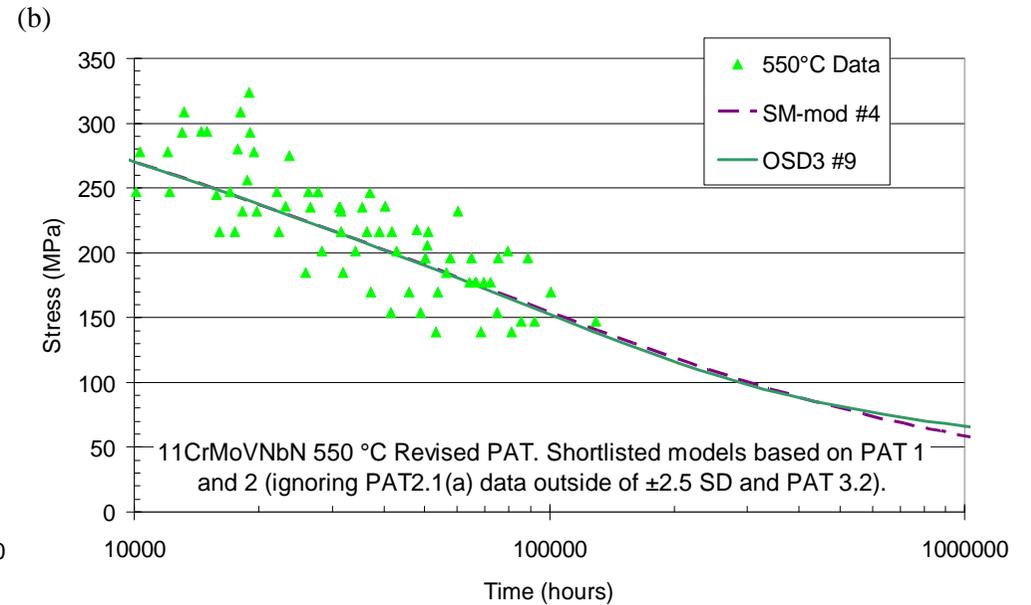
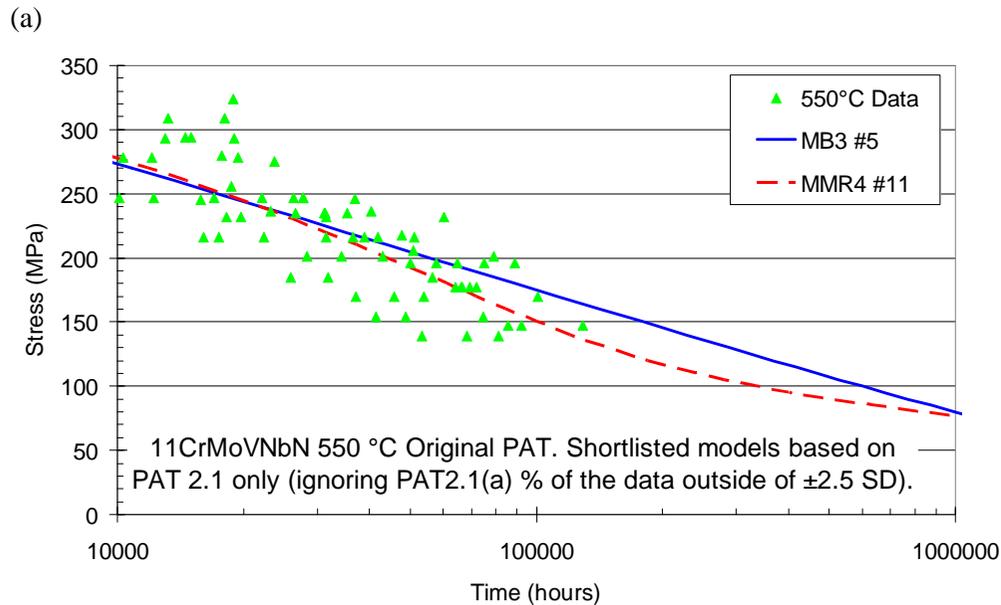
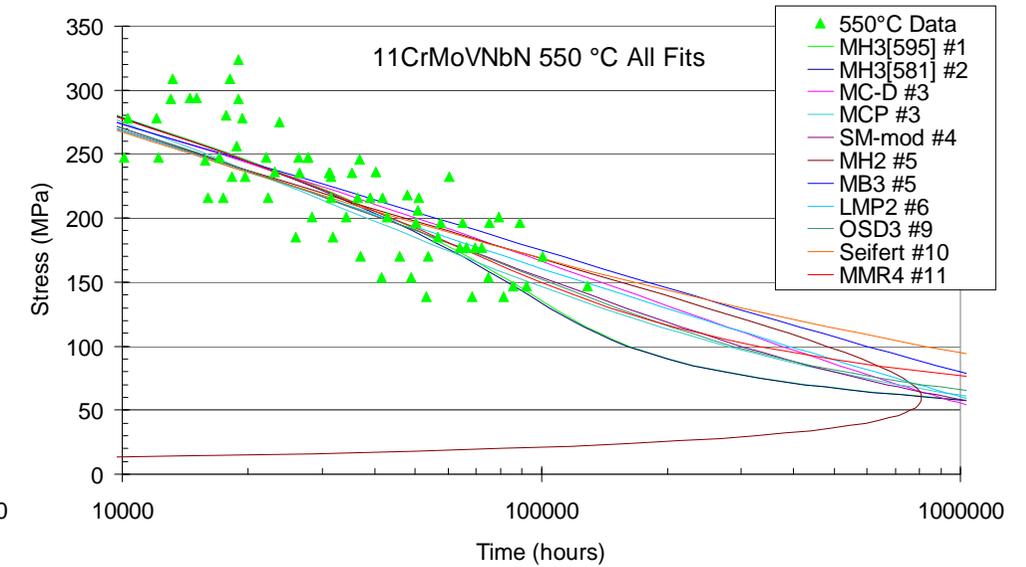
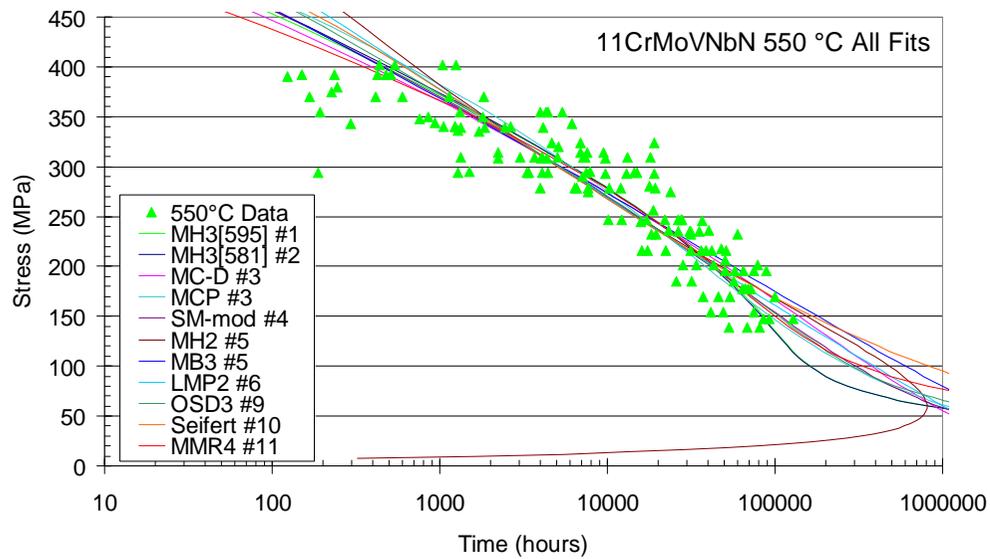
(b) 500°C $T_{\min[10\%]}$. Quantitative tests passed.

(c) 550°C T_{main} . Quantitative tests passed.

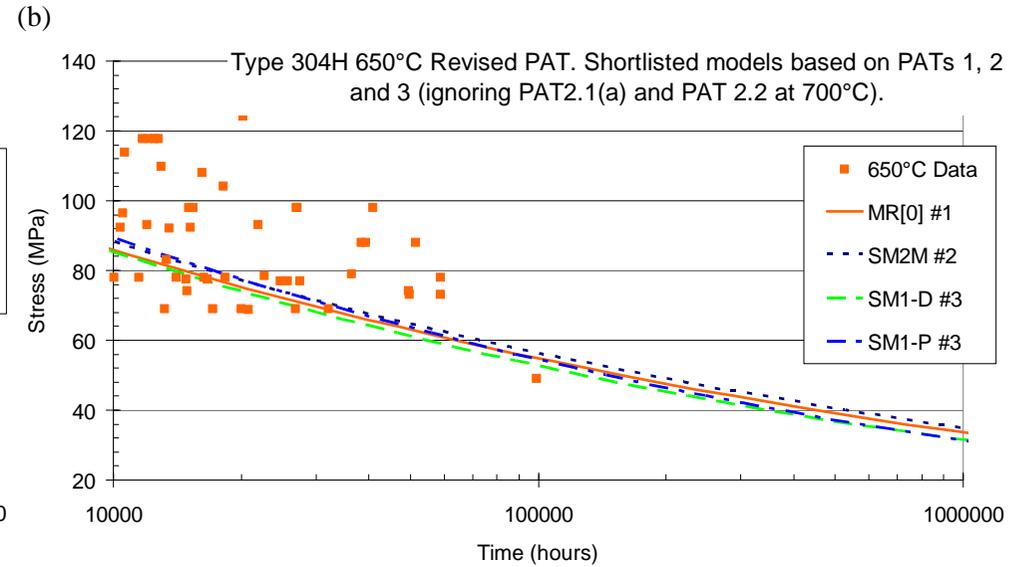
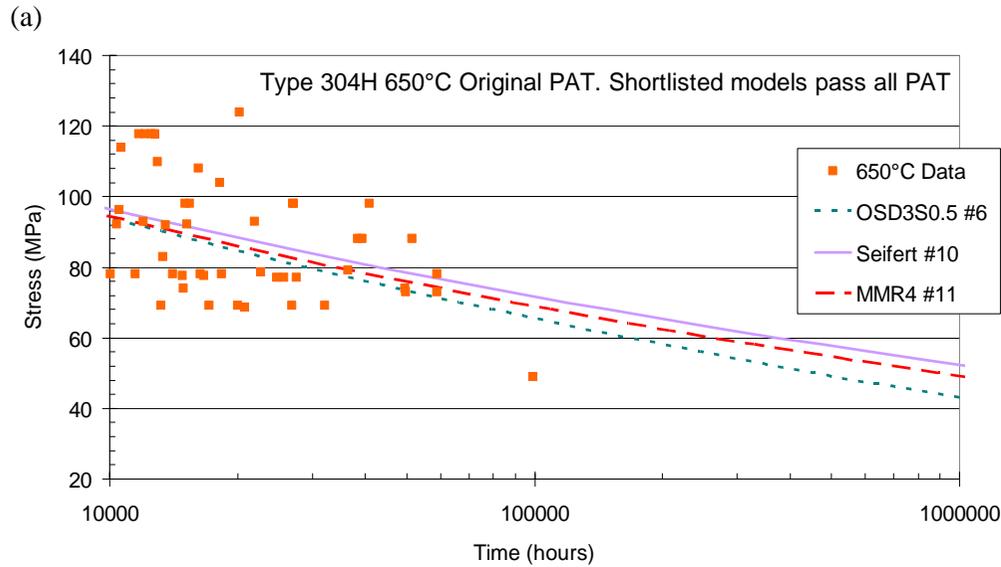
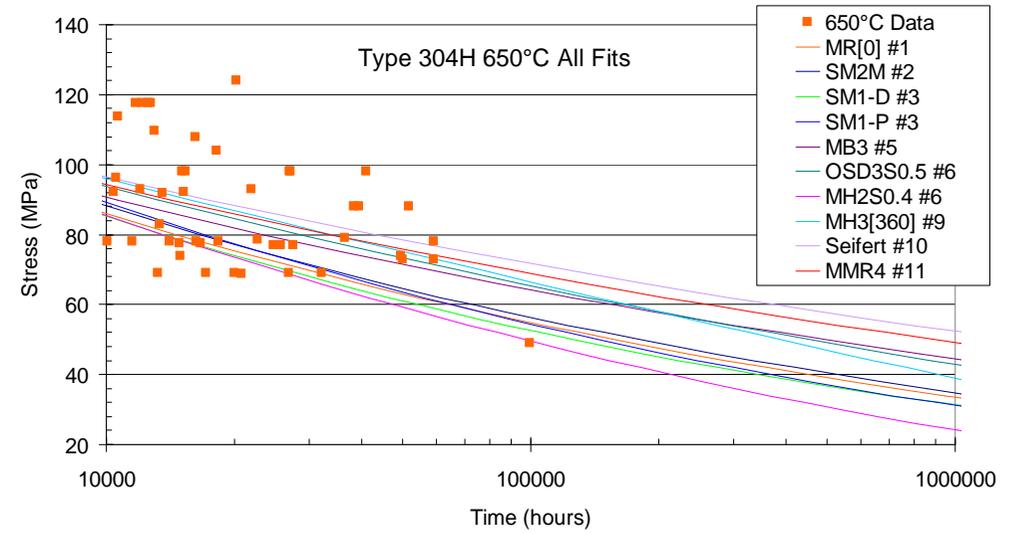
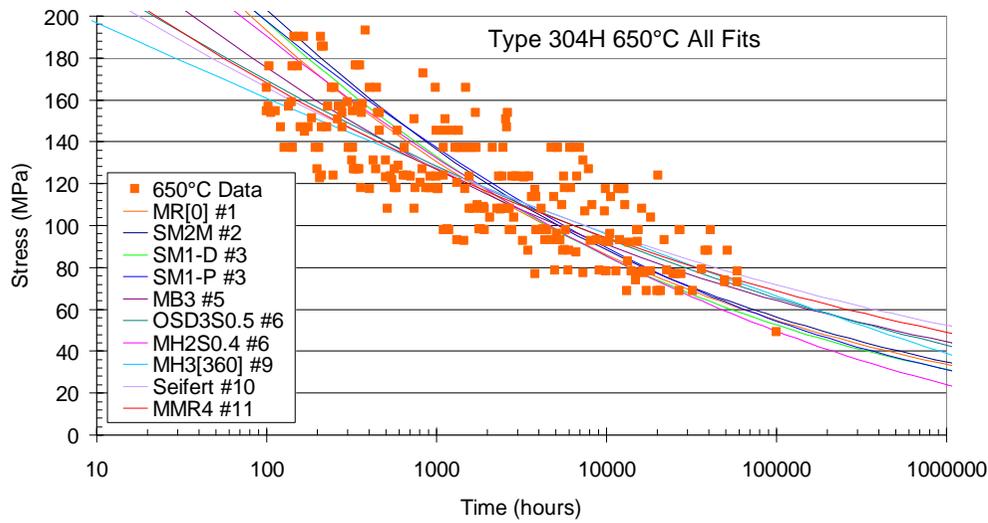
(d) 600°C $T_{\max[10\%]}$. Quantitative tests passed.



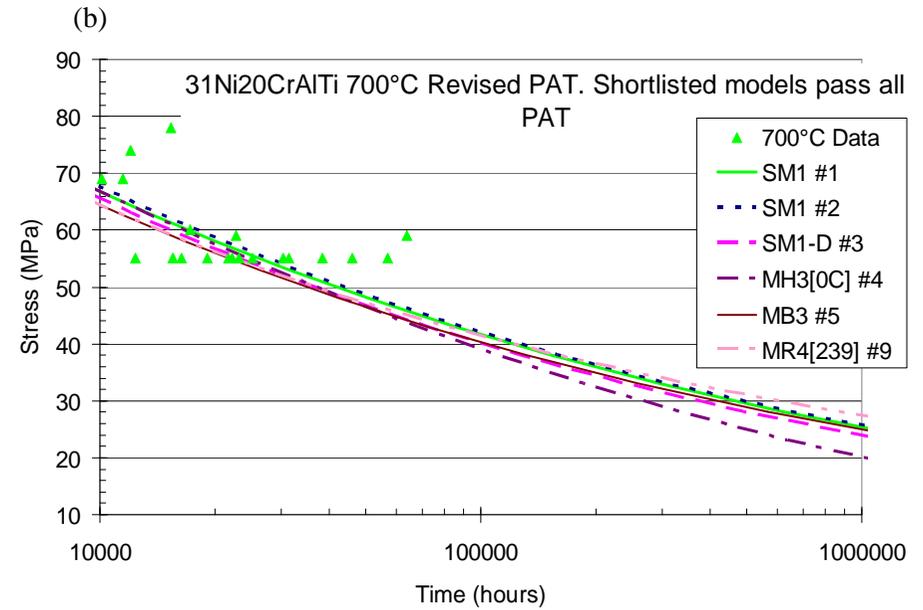
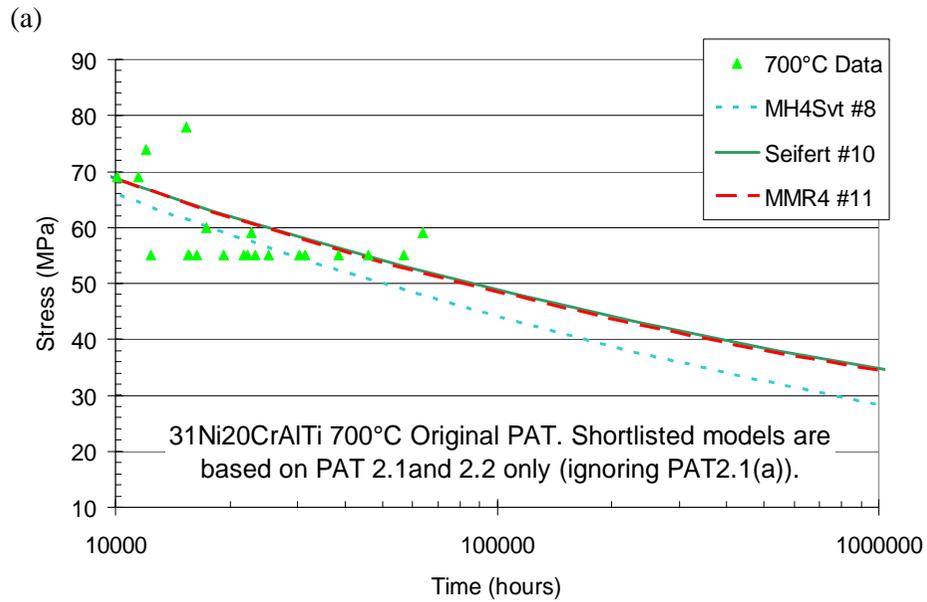
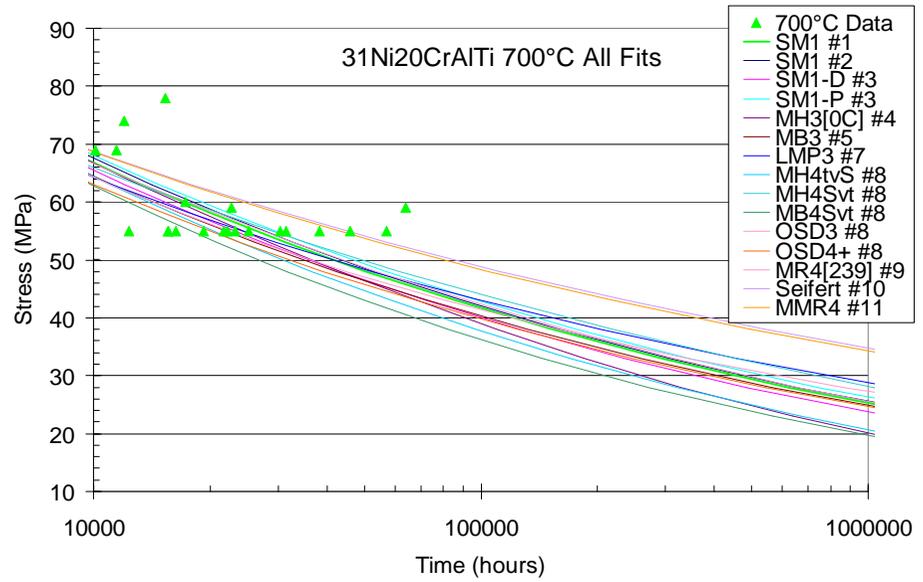
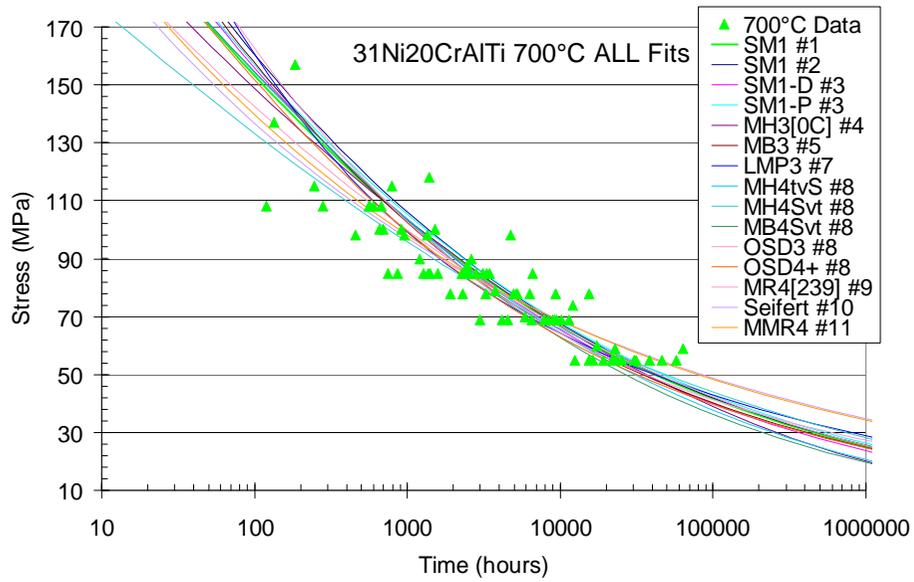
(c) Figure C2.13: Rupture models with data for 2 1/4 Cr1Mo at the main temperature of 550°C; (a) all models, (b) all models 10k to 1000k hours, (c) shortlisted models based on Original ECCC PAT 2, (d) shortlisted models based on Revised ECCC PAT 2.



(c) Figure C2.14: Rupture models with data for 11CrMoVNb at the main temperature of 550°C; (a) all models, (b) all models 10k to 1000khours, (c) shortlisted models based on Original ECCS PAT 2.1, (d) shortlisted models based on Revised ECCS PAT 2.



(a) (b) (c) (d)
 Figure C2.15: Rupture models with data for 18Cr11Ni at the main temperature of 650°C; (a) all models, (b) all models 10k to 1000khours, (c) shortlisted models based on Original ECCC PAT 2.1, (d) shortlisted models based on Revised ECCC PAT 2.



(a) (b) (c) (d)

Figure C2.16: Rupture models with data for 31Ni20CrAlTi at the main temperature of 700°C; (a) all models, (b) all models 10k to 1000khours, (c) shortlisted models based on Original ECCC PAT 2.1, (d) shortlisted models based on Revised ECCC PAT 2.

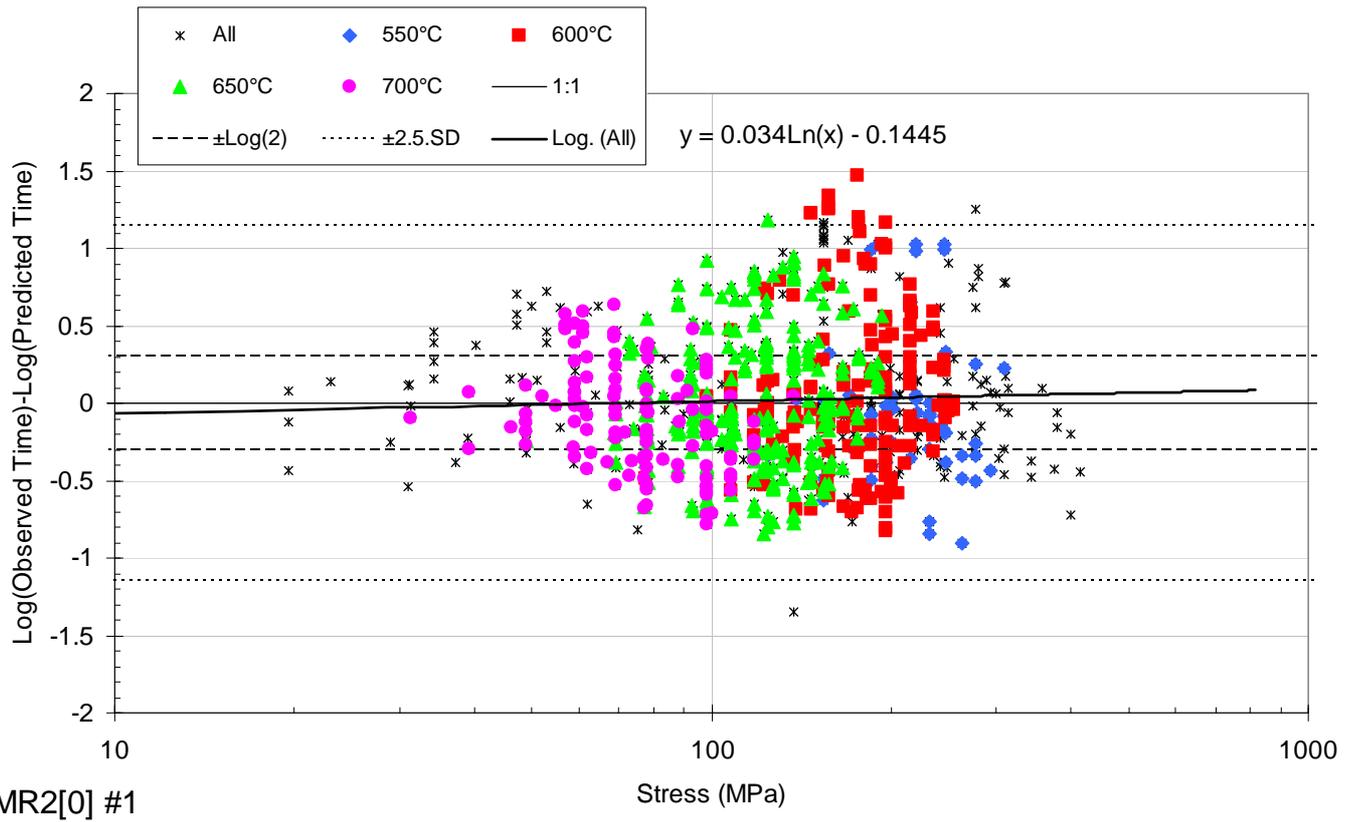


Figure C2.17: Plot of Residual versus Stress for Model MR2 #1 Fitted to 18Cr11Ni using PD6605 [4]. This plot shows how the scatter is different at different stresses, which is called variance heterogeneity.

APPENDIX D1a
ECCC ISO CRDA PROCEDURE DOCUMENT
J Orr [CORUS]

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Appendix D1

A USER'S GUIDE TO THE ISO EXTRAPOLATION PROCEDURE (ISO 6303)

J Orr (British Steel Technical)

1 INTRODUCTION

The procedure known as 'the ISO method' or 'ISO 6303' has been used for many years, principally in the UK, for the assessment of stress rupture data, to produce the stress values included in BSI (Ref. 1) and ISO Standards. The developed procedure formed the basis for the Annex to the Standard ISO 6303-1981 (Ref. 2) having been derived from existing procedures (Refs. 3,4).

It is a generalised procedure, whose final equation form can become either a simple Larson Miller type or have a more complex form involving several constants, depending on the optimised curve fitted to the data used.

The purpose of this document is to describe the steps used in the procedure, the assumptions and the judgements made to determine the flow of information generated during the procedure which is computerised for the majority of the steps used (Ref. 5).

The objectives of the computerised procedure are to give maximum efficiency and relativity in assessments of large amounts of data and produce optimised values with consistent accuracy.

2 DATA USED

For all assessments carried out for BSI and ISO Standards, the data sets used are generally not homogeneous, often called the 'messy' data situation, since the data available do not derive from specifically designed programmes, but are a collection of information available from many sources. Thus several casts/batches in the data pool are represented by different amounts of data.

The homogeneous type of data situation, which can be seen as a special case of the more general situation is for data from a small number of casts/batches which have been tested in specific programmes over a range of temperatures and nominated stresses.

Thus the data available, usually from different sources, gives a typical situation as in Fig. 1. In addition to the descriptions in Fig. 1 it should be noted that test duration is not necessarily related to the number of samples tested and/or the temperatures used. A real case would be that the longest duration test data could occur for a temperature where there were the fewest test data, which in the case of Fig. 1 would be for example at 538 °C. However, it is usually the case that the longest duration tests are carried out at those temperatures which correspond most closely with the normal service temperature for the steel for which data are being assessed - in the case of Fig. 1 this would occur for example at 550/565 °C.

Since one of the usual early steps in the procedure is the fitting of isothermal curves, this means that data at some temperatures may not be used because they are too few in total, represent too few sources, are of insufficient duration span, or maximum test duration; the former usually being the limiting case.

As a general rule, isothermal curves would only be generated for those temperatures where there are data from at least three casts/batches and durations spanning at least two log decades (in hours) and with the longest test durations exceeding 10,000 h.

Apart from these specific points, data are accepted for an assessment, provided the composition and heat treatment(s) correspond with customer specified ranges, e.g. to a national or international specification, and that the data comprised as a minimum, stress, temperature and test duration. All data are treated equally in the initial stages of the procedure.

Data for unbroken/incomplete tests, are included in the data pool and may be used to determine the final form of the isothermal curves.

A typical data pool for a given steel could comprise over 1,000 stress rupture test results, with corresponding materials data (meta data), drawn from several sources, usually different laboratories and/or countries. Such large data pools can be assumed to cover most, if not all, of the associated variables of product form, composition, heat treatment(s), (and therefore 'initial' microstructure) and testing (Ref. 5).

Thus an initial implicit assumption is made that the data available for the assessment are representative and, therefore, contains the trends and distributions associated with the important metallurgical variables. Explicit examinations of the data are made during the assessment to establish that derived information matches closely with the real trends.

These, so called, initial or pre-assessment steps are, therefore, important otherwise these assumptions are not correct and would make invalid the results of the assessment.

3 EXTRAPOLATION METHOD

The ultimate purpose of any extrapolation method and, therefore, also of the ISO method is to extrapolate to durations and stress values beyond the range of those of the test data, to provide the information required for design and/or remanent life assessments. Therefore, the choice of the model selected for carrying out extrapolation is fundamental.

After a study of the various procedures/methods available in the 1960's, the authors of the ISO method selected a generalised equation (Ref. 3)

$$P(\sigma) = \frac{\sigma^{-q} \log t - \log t_a}{(T-T_a)^r} \quad (1)$$

where t = time in hours
 T = temperature °K
 $q, \log t_a, T_a, r$ are constants

However, experience showed that the stress exponent q could be set to zero without affecting significantly the accuracy of fit of the master curve. Thus equation 1 became the standardised one used regularly viz.

$$P(\sigma) = \frac{\log t - \log t_a}{(T-T_a)^r} \quad (2)$$

The selection of this generalised equation allowed then a single computer program to be written albeit quite complex, to handle and assess the various amounts of information but still flexible enough to represent all types of data characteristics.

The extrapolation method used although not related directly to physical behaviour of the material, is robust enough and practical in performance to give successful extrapolations, as has been proved by subsequent assessments of increasing amounts of data for several steel types in the ISO materials standards series, e.g. Type 316 (18Cr 12NiMo).

In the computerised method (Ref. 4) equation 2 above is solved by re-arranging it as follows:-

$$\log t = \log t_a + (T-T_a)^r \cdot P(\sigma) \quad (3)$$

and by using orthogonal polynomials in log stress this becomes

$$\log t = \log t_a + (T-T_a)^r \sum_{j=1}^{m+1} u_j Q_j(\log \sigma) \quad (4)$$

where σ = stress, u_j = constant, m = highest degree polynomial)

Values of $\log t_a$, T_a and r are determined from the minimisation of the sum of squares of strength values at specific durations using an iterative procedure to produce the best fit 'master' curve defined as those values which give the smallest standard deviations. This is achieved initially by a trial and error sequence based on selected values of r and scanning T_a in 10°C intervals. All combinations of these values are scanned by the computer along with a calculated value for $\log t_a$ for each degree of polynomial.

Based on the assumption that iso-stress curves demonstrate a regular pattern versus temperature, Fig. 2(a), setting, $r = 1$ and $T_a > 0$, gives the Manson Haferd parameter with the computer calculating $\log t_a$ and T_a . Alternatively, if iso stress linearity is $\propto 1/T$ (Fig. 2(b)), this is the Larson Miller parameter when $q = 0$, $r = -1$, and $T_a = 0$. Experience has shown that by setting $r = +1$ or -1 and $T_a = 0$ or some positive value (can neither be negative nor greater than lowest value of T) and with freedom to select the polynomial degree, i.e. accepting the assumptions of Fig. 2, there is sufficient flexibility in the computerised system to reflect the various shapes of isothermal curves encountered.

The obvious drawback to the computerised system is that in some cases the 'best fit' polynomial based master curve, nearly always 4th order, shows reverse curvature which gives non-unique solutions below a certain stress value. This is of particular concern when this occurs within the ranges of stress and temperature of the test data. The operator can overcome this situation by forcing a lower order polynomial curve to be used, accepting that it will not have the best fit statistically.

4 ASSESSMENT PROCEDURE

The overall assessment procedure is step wise with the possibility of reiteration(s) allowed at various stages. The various steps in the assessment procedure are:

4.1 Data Selection

- (i) A specification of material composition, heat treatment and any other parameters relative to the end use, is set, e.g. national/international standard or a more specific restricted case.
- (ii) Data comprising stress rupture test results [stress, temperature, test duration (noting if from an unbroken test) and ductility parameters where available], cast/batch composition, heat treatment, product form - see Appendix 1 for full details which might be available for some or all of the data (see Volume 3 Table 1 for minimum data requirements) are collected and stored in a computer.
- (iii) The data from (ii) are summarised by listing in tabular form, the extent of data at each temperature in terms of number of sources and maximum duration for each test temperature, Tables 1 and 2. It is normal practice at this stage to combine data from near/adjacent temperatures, e.g. ≤ 5 °C apart, usually to accommodate tests from sources using °C and °F. Examples of this would be 538/540, 649/650, 700/704 °C etc. The data in such as Tables 1 and 2 are used to select the temperatures for which isothermal mean curves will be derived. For example, in Table 2 it is indicated which temperatures have been selected for this particular steel type. The choices are generally fairly obvious but for example, 450 °C and 675 °C were not selected despite having long test durations. The reasons in this case were that the data were from only one source, and also were either few in number or showed a limited duration distribution range.

4.2 Isothermal Curves

- (i) Log stress v log duration data plots are produced for all broken and unbroken tests of the selected temperatures. Each plot is examined for broken data points lying outwith the general scatter and also the width of the scatter band at each temperature.

For each outlying data point, the meta data information are re-examined and any association each point has with other data points from the same batch at the same temperature is determined. All conforming data points are retained.

When scatter band(s) are significantly greater than $\pm 20\%$ and/or not regular, e.g. increasing with increasing test duration, the data are re-examined to determine by appropriate means the relevant reason for this behaviour. Where relevant variable is identified, e.g. composition or heat treatment, it is recommended that the data selection process should be restarted based on a revised input specification, either to sub divide the total data selected originally or reduce the data set to one conforming with a revised input specification.

- (ii) Having established the log stress v log time data, a mean curve is determined at each temperature by computerised polynomial fit, using only the data points for broken tests. The

curve range is constrained to the duration range of the data points. Normally a degree 2 curve is found to describe the $\log \sigma / \log t$ relationship at each temperature, but a curve of different degree can be 'forced' if required. The most accurate curve at each temperature is determined by using the least squares method with $\log \sigma$ set as the dependent variable. Although setting $\log t$ as the dependent variable is the correct metallurgical function, the use of $\log \sigma$ as the dependent variable has been found to give a more accurate representation of the data trend for this kind of data.

- (iii) The individual curves are subject to scrutiny both individually with respect to the position of long term unbroken test points (i.e. those not used in curve determinations) and together as a family of curves. This part of the assessment procedure is to rationalise the data before proceeding to the determination of the master curve.

For an individual curve the longer term/lower stress end of the curve may be observed to droop because of lack of data for broken tests in that region - see schematic example in Fig. 3. If unbroken test data are available in the shaded region of Fig. 3, it is considered justified to take these into account and so manually adjust latter part of the curve to higher stress values than given by the equation for the polynomial curve determined by the computer.

All the isothermal curves are judged together as a family, to determine their relative positions. The most common example is as in Fig. 4, which arose from the data in Tables 1 and 2. This is an acceptable situation. However, it can arise that one or more of the isothermal curves is displaced from its respective position, Fig. 5, or shows a different trend from those of adjacent curves, see example in Fig. 3. Corrective actions may be taken to redraw or reset such curves manually if necessary, after taking into account the distribution of the data, cast to cast trends and unbroken test data within each set of data. However, there are occasions when no such remedial action is justified based on the information available. In such cases no changes are made, but due acknowledgement of the effect of such a situation may be necessary when determining the acceptability of the master curve (see 4.3(vi)). Although no strict guidelines can be given to deal with such situations, as in Figs. 3 and 5, experienced operators using metallurgical judgement based on all the data available can determine the degree of adjustment required. This may be one of the iterative steps required after assessment of the 'goodness of fit' of the master curve.

4.3 Master Curve Determination

Having established the most representative family of mean curves, these are now used to provide data for the determination of the master curve (see Section 3).

- (i) From each isothermal curve stress values are derived for selected durations. For up to 10,000 h the values are selected at approximately equal logarithmic increments, e.g. 100, 300, 1,000, 3,000, 10,000 h.

For durations greater than 10,000 h to the longest duration of each curve, the intervals are much smaller in logarithmic increments, though longer in actual duration, e.g. every 10,000 h. Examples from Table 2, for 550 °C, would be stress values at 10,000, 20,000, 30,000 and 40,000 h. Thus weighting is applied automatically to the lower stress values for each

selected temperature, since these are considered to be the most influential particularly at the higher temperatures.

- (ii) The exercise in 4.3(i) generates several sets of data comprising stress, duration and temperature, which form the data input for the determination of the master curve.
- (iii) The computer programme calculates the optimum values for $\log t_a$, T_a and r in equation 4. See Section 3 for the relationship between stress and $P(\sigma)$ (which is the master curve) in terms of orthogonal polynomials in stress viz.

$$P(\sigma) = \frac{\log t - \log t_a}{(T - T_a)^r}$$

$$= u_1 Q_1(\log \sigma) + u_2 Q_2(\log \sigma) \dots u_{m+1} Q_{m+1}(\log \sigma) \quad (5)$$

where σ = stress, u , Q , etc. are constants and m = highest degree of polynomial (usually = 4).

Values of T_a and r (set usually at either +1 or -1) are input and an optimum value of $\log t_a$ determined for each degree of polynomial selected, determined when the residual sum of squares about the master curve is minimised - the standard deviation being used as a measure of the optimum fit.

The computer programme scans all combinations of the values input and by an iteration process selects the best set as determined by the smallest standard deviation. This process can take several steps before the optimised values of the constants are derived. (Note that the coefficients of the polynomial of the $\log \sigma$ terms only have signs that alternate with increasing order of polynomial.)

- (iv) The equation of the master curve (assuming a fourth order polynomial was found to be the optimum in equation) viz $P(\sigma) = a + b \log \sigma + c (\log \sigma)^2 + d (\log \sigma)^3 + e (\log \sigma)^4$ is determined by the computer when plotting the $P(\sigma)$ determined from the optimum value of the constants in equations, as a function of \log stress. An example of such a master curve derived from input data retained from the curves in Fig. 3, is shown in Fig. 6. The equations included in Fig. 6 illustrate the degree of precision given for the values of the constant terms $\log t_a$, a , b , c , d and e . Such precision is found to be necessary to give accurate stress values. The computer programme at British Steel produces the calculated stress values in tabular form for a range of temperatures and durations from 1,000 to 500,000 h. The stress range is equivalent to that of the data input (see 4.3(i)) +10% extension at each end of the range. This is illustrated clearly in Fig. 6.
- (v) Isothermal mean curves are generated from the master curve and compared with the test data at the appropriate temperatures. Examples of such are shown in Fig. 7. This stage is used as a check of the accuracy of the master curve data both with the mean and the overall trend of each isothermal data set which contributed to the master curve data.

If it is determined that some of the derived isothermal mean curves are not representative of the test data, after taking into account the conditions given in 4.2(iii), it is possible to return to at least 4.3(i) to modify the input values to the master curve. This is done in conjunction

with an examination of the respective positions of the data points to the master curve. This examination may lead to the requirement to add more data points to give more weight particularly at the lower stress end of the master curve or to remove data points which are observed to be causing some distortion to the master curve. The latter may arise from a situation such as illustrated in Fig. 5. The master curve determination is then rerun with a revised data input. The results are judged in the same way as above to determine whether an acceptable position has been obtained. Statistical accuracy is not seen as the only parameter to be taken into account.

It is found sometimes that when reverse curvature of the master curve (which is an inherent feature of a fourth order polynomial) occurs within the stress range of the data there is not a unique solution to equation 5, particularly at the low stress end of the curve. Thus stress values cannot be generated from this region of the statistically optimised curve. The options available to try to amend such a situation are, use of additional data or multi-entry of data points at the lower end of the stress range or modification of the order of polynomial used. The latter usually means going to a lower order of polynomial which the computer had already considered, with the given data and rejected in favour of the more statistically accurate higher order polynomial. All of these methods have been used with different degrees of effect on the ultimate result.

Whenever modifications are made, the results are always to be reviewed with respect to the test data such as in Fig. 7.

5 CONCLUSIONS

This document defines the principles and operations involved in the standardised ISO extrapolation procedure, such that it may be used with the minimum of ambiguity.

It is essentially a two stage procedure.

In the first or data reduction stage, isothermal relationships are established between stress, time and temperature. This is a vital stage since without it imbalances in data and spurious, though statistically accurate, results may be allowed to persist into the assessment stage with consequent effect on the end result.

The second stage uses strength values at specific durations from the isothermal curve to determine a log stress/parameter master curve which is determined using $\log t$ as the dependent variable. From the equation of this curve, stress values to at least 500,000 h can be generated for a wide range of temperatures. The stress range is constrained to that of the data set $\pm 10\%$, since it is considered metallurgically inaccurate to allow any greater stress extrapolations.

Operator judgements can be included particularly in the first stage to provide the relevant relationships.

6 REFERENCES

1. British Standard PD 6525 Part 1 1990, 'Elevated Temperature Properties for Steels for Pressure Purposes. Part 1. Stress Rupture Properties'.
2. Annex to International Standard ISO 6303 - 1981E, 'Pressure Vessel Steels Not Included in ISO 2604 Parts 1-6 - Derivation of Long-Time Stress Rupture Properties'. Annex: Method of Extrapolation Used In Analyses of Creep Rupture Data.
3. R.P. Harvey and M.J. May, 'The Application of Time- Temperature Parameters for the Prediction of Long Term Elevated Temperature Properties Using Computerised Techniques', ASTM Materials Engineering Congress 1968, ASM Publication No. D8-100.
4. R.P. Harvey, 'Analysis of Creep Rupture Data for the International Standards Organisation', BISRA Report MG/QF/118/70, June 1970.
5. A. Mendelson, E. Roberts and S.S. Manson, 'Optimisation of Time Temperature Parameters for Creep and Stress Rupture, with Application to Data from German Co-operative Long Time Creep Program', NASA Technical Note NASA TN D-2975, August 1965.

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14.9.94

TABLE 1 DISTRIBUTION OF STRESS-RUPTURE TEST DATA ANALYSED IN TERMS OF TEMPERATURE

Test Temp. °C	Total No. of Data Points	Test Duration, h					
		Up to and Including 10 000	>10 000 to <20 000	>20 000 to <30 000	>30 000 to <50 000	>50 000 to <70 000	>70 000
425	24 (4)	12	2	1 (2)	7 (1)	2	(1)
450	3 (3)	2		(1)	1 (2)		
460	1	1					
475	92 (20)	64	16 (11)	5 (3)	3 (3)	1	3 (3)*
480	1	1					
490	1		1				
500	170 (25)	147 (3)	20 (11)	3 (5)	(5)	(1)	
510	3	3					
520	3	3					
525	111 (18)	75 (1)	18 (3)	7 (7)	2 (4)	5 (1)	4 (2)*
530	3	3					
540	4	4					
550	178 (35)	156 (5)	16 (9)	3 (11)	3 (9)	(1)	
560	3	3					
570	4	4					
575	80 (9)	49 (1)	15 (4)	6	5 (3)	3	2 (1)*
580	4	4					
590	3	3					
600	208 (5)	185 (2)	21 (1)	2 (2)			
610	4	4					
620	9	9					
625	55 (2)	45 (2)	8	1		1	
640	6	6					
650	79 (1)	67 (1)	7	5			
660	5	5					
670	3	3					
675	21	20	1				
680	2	2					
690	1	1					
700	12	11	1				
720	1	1					
740							

N.B Figures in parentheses denote tests still in progress

* Includes tests over 100 000 h (see Table B)

TABLE 2 DISTRIBUTION OF STRESS-RUPTURE DATA ANALYSED IN TERMS OF TEMPERATURE

Test Temp °C	Country													Total	Longest Time To Failure	Fig. No.	
	A	B	C	D	E	F	G	H	I	J	K	L	M				
425			28												28	65 028	
450			6												6	32 857	
460			1												1	1 648	
475			112												112	106 775	1(a)
480			1												1	17	
490			1												1	10 483	
500	21		174												195	26 897	1(b)
510			3												3	3 094	
520			3												3	1 651	
525			123					6							129	108 802	1(c)
530			3												3	1 650	
540			4												4	1 037	
550	30		167					16							213	39 725	2(a)
560			3												3	1 415	
570			4												4	4 927	
575			41				31	17							89	104 504	2(b)
580			4												4	2 029	
590			3												3	736	
600	28		110				44	31							213	26 613	2(c)
610			4												4	6 212	
620			9												9	3 128	
625			10				38	9							57	52 878	3(a)
640			6												6	2 846	
650	11		13				33	23							80	28 288	3(b)
660			5												5	781	
670			3												3	382	
675							21								21	12 186	
680			2												2	1 051	
690			1												1	166	
700			1					11							12	17 683	
720			1												1	397	
740			1												1	47	

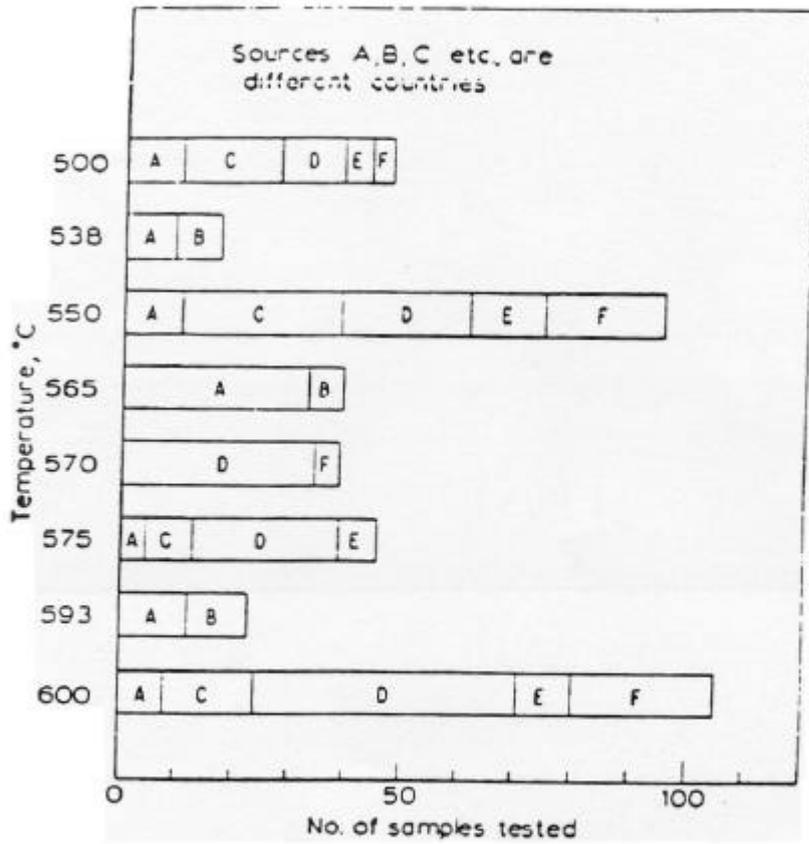
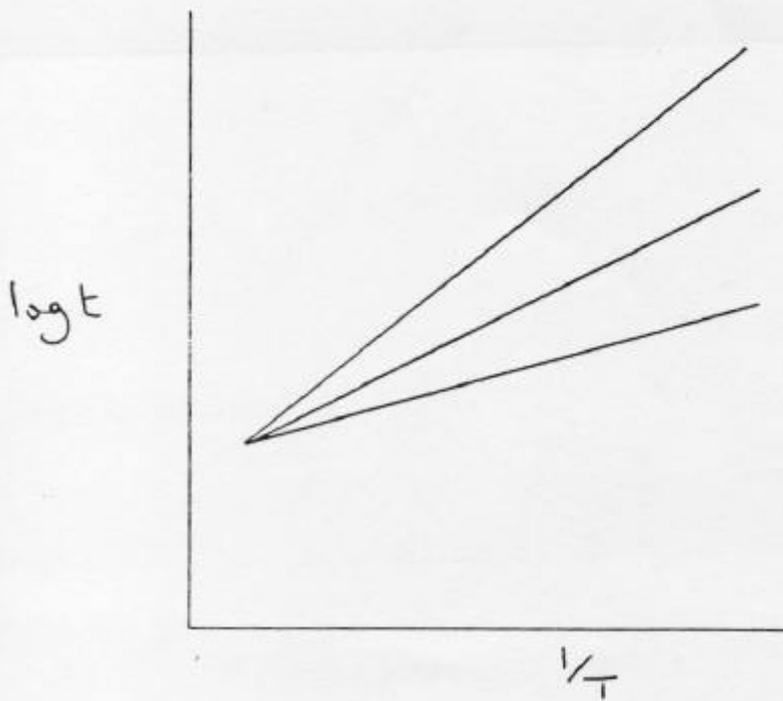
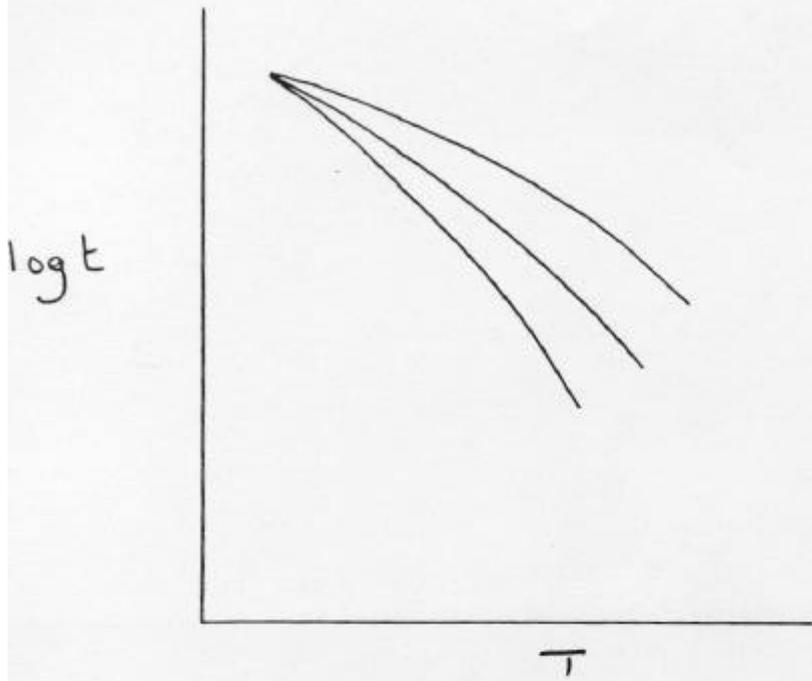


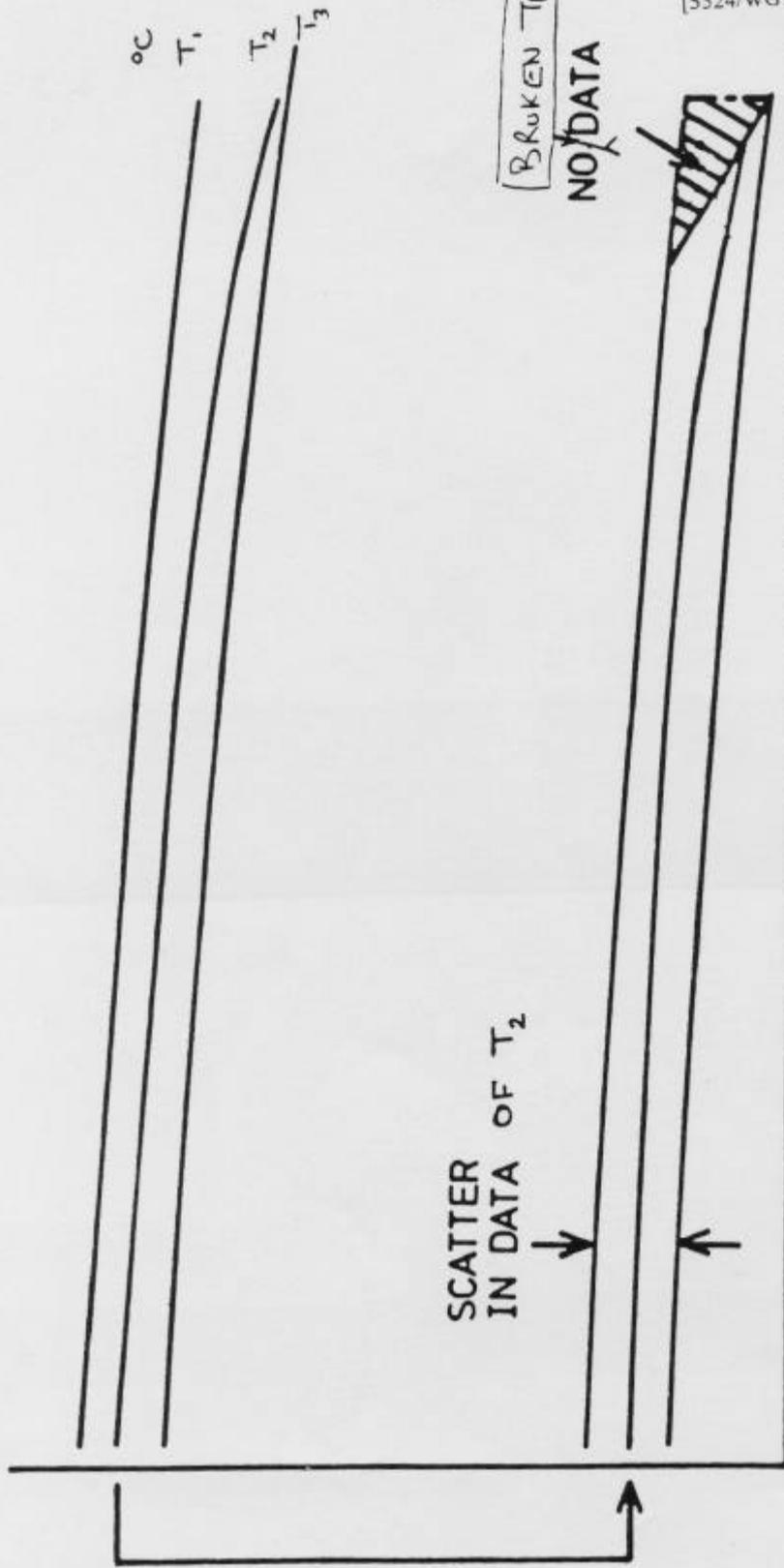
FIG. 1 DISTRIBUTION OF CREEP-RUPTURE DATA ON 2 1/2%Cr-1%Mo STEEL FROM VARIOUS SOURCES



EXAMPLES OF GENERALISED PARAMETER
EQUATION OF MANSON

FIG 2

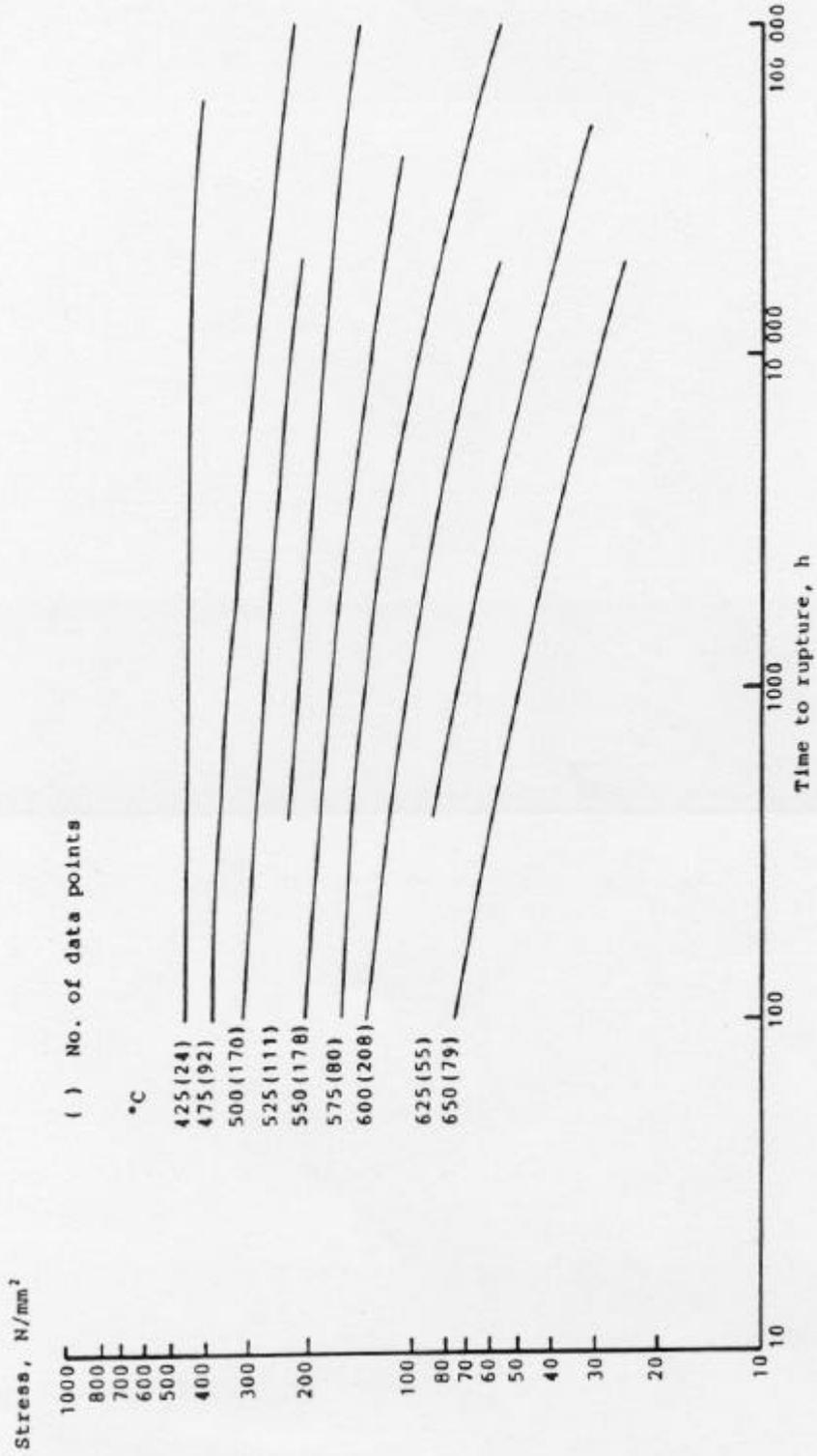
LOG STRESS



LOG TIME

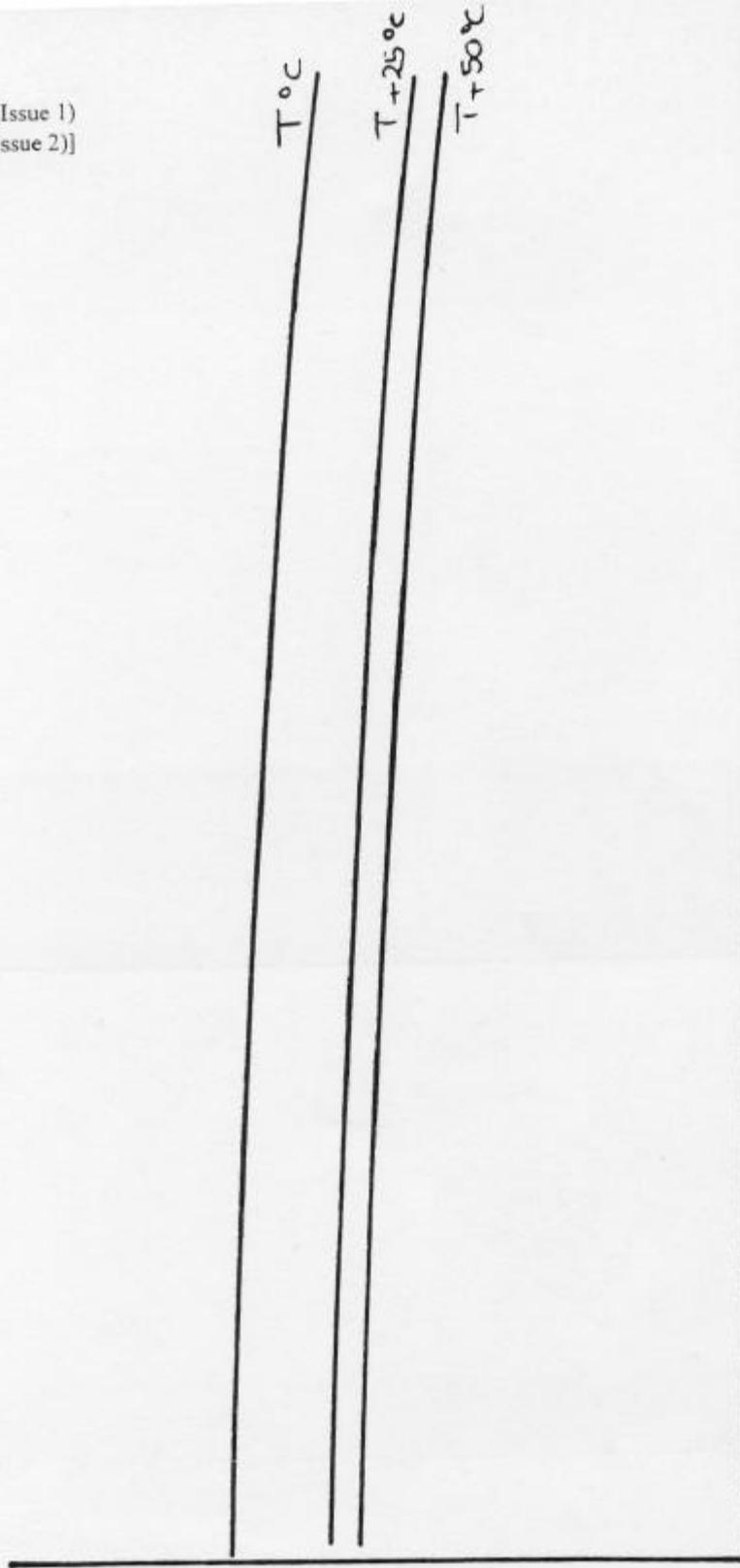
EFFECT OF LIMITED DATA AT LOWER STRESS
VALUES AT T_2

FIG 2



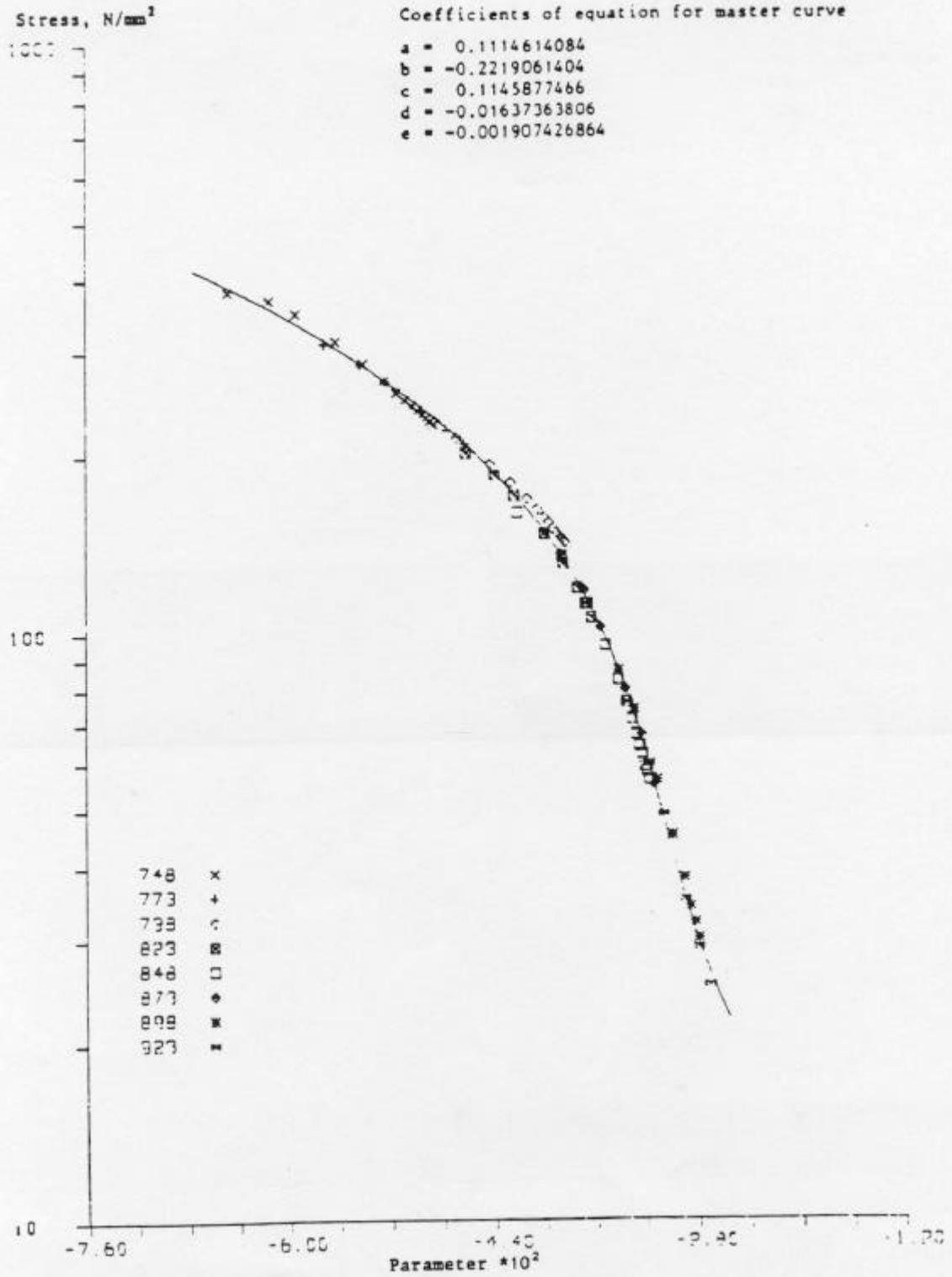
FAMILY OF MEAN CURVES
FIG. 4
(R2/6456)

LOG STRESS



LOG TIME

ISOTHERMAL MEAN CURVES - UNEQUAL SPACING



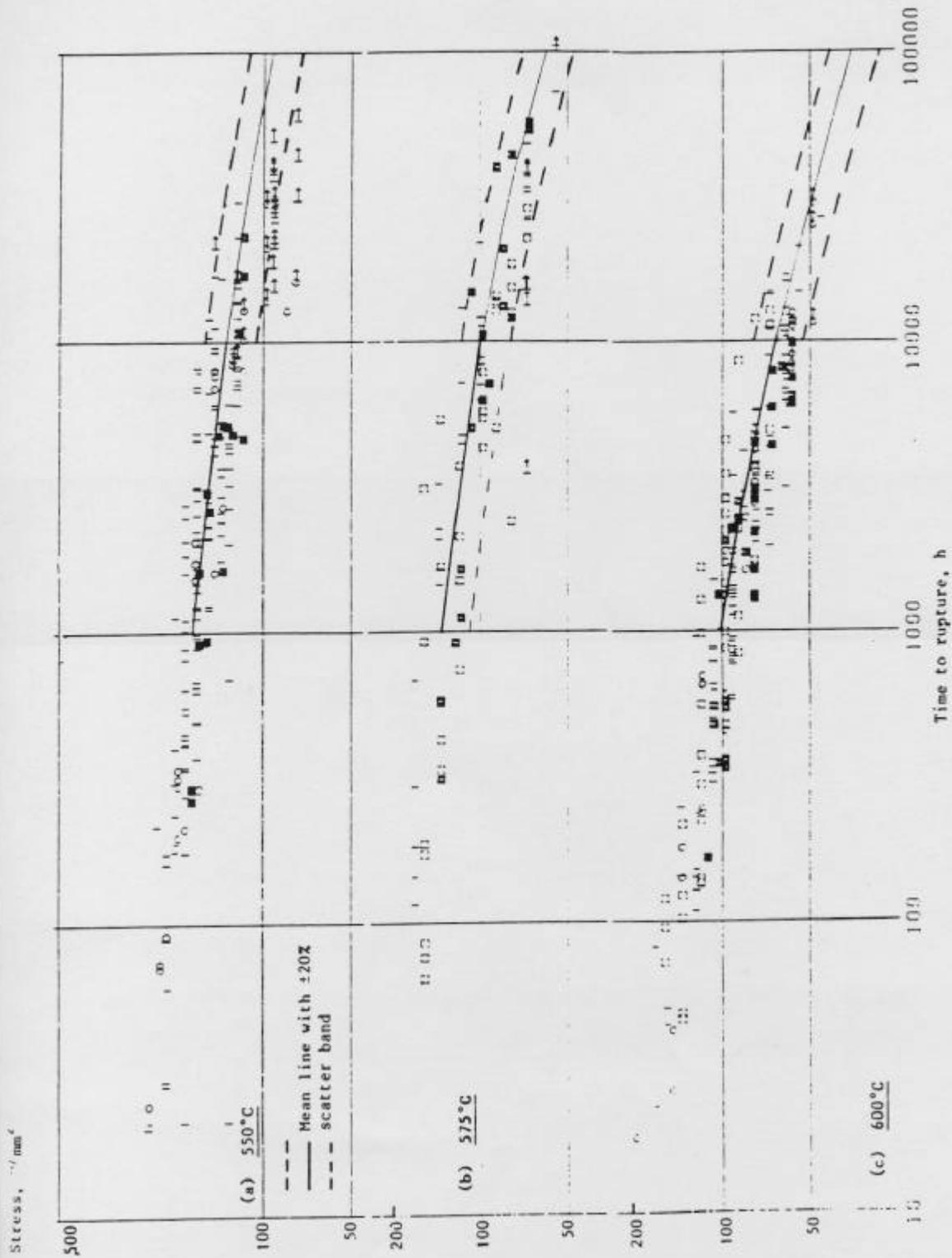
Coefficients of equation for master curve

- a = 0.1114614084
- b = -0.2219061404
- c = 0.1145877466
- d = -0.01637363806
- e = -0.001907426864

$$P(\sigma) = \frac{\log \sigma - 14.172191620}{T - 560} = a + b (\log \sigma) + c (\log \sigma)^2 + d (\log \sigma)^3 + e (\log \sigma)^4$$

MASTER CURVE

FIG. 6



STRESS - RUPTURE DATA -
- 550, 575, 600°C - FIG. 7

Appendix 1. Request form for stress rupture/creep data**1. Manufacturing details**

Cast No.:

Code No.:

Steelmaker:

Testing laboratory:

Steelmaking process, including any secondary process:

De-oxidation practice:

Concast/ingot size:

Concast/ingot weight:

Product form:

Product dimensions:
(Outside diameter and thickness for tube)

Product process route:

2. Chemical composition

(a) State whether information provided is cast or product composition:

(b) Detailed chemical composition data to include*:

C, Si, Mn, P, S, Cr, Mo, Ni, Al, As, B, Bi, Co, Cu, N, Nb, Pb, Sb, Sn, Ti, V, W, Zr.

*Where known.

3. Heat treatment of test sample or piece

- (a) Pretreatments*:
- (b) Austenitizing treatment*:
(Solution treatment)
Actual temperature*:
Time at temperature*:
Cooling medium*:
Cooling rate and temperature range over which measured if controlled cooled*:
- (c) Tempering treatment*:
Actual temperature*:
Time at temperature*:
Cooling medium*:
Cooling rate and temperature range over which measured if controlled cooled*:
- (d) Any subsequent treatments, e.g. post-weld heat treatment(s)*:

4. Test results

- (a) Test piece location,:
e.g. transverse
- (b) Test piece dimensions:
- (c) Elevated temperature stress rupture/creep data:
(to include test temperature, stress, duration, A, Z)
(Please state whether test is completed or test piece unbroken at duration stated.)
(Please state the time to specific creep strain(s) ,
e.g. 0.05 %, 0.1 %, 0.2 %, 0.5 %, 1 %.)
- (d) Testing standard:
- (e) Laboratory accreditation:
- (f) Test atmosphere:

NOTE. Whenever possible, the room and elevated temperature proof and tensile properties for the same batch of material should also be provided.

* Indicate if treatments are works or laboratory treatments.

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APPENDIX D2

ECCC DESA CRDA PROCEDURE DOCUMENT

J Granacher & M Monsees [IfW TU Darmstadt]

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Appendix D2

DESA Assessment Procedure Document for DESA, Version 2.2, 20.2.95

J Granacher and M Monsees

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Overview

The programme DESA is a highly flexible tool for applying time-temperature parametric equations for the assessment of rupture data and creep strength data. A full range of parametric equations may be assessed, comprising a selectable time temperature parameter in combination with a polynomial of a monotonic function of stress σ_0 in the form σ_0^m , $m = 0.1$ to 1 or $\log\sigma_0$. The order of polynomial can range from 2 to 5 and DESA has been prepared for all of these functions to be selectable from a menu. The programme has not yet been used to generate strength values for standards, but has been used for homogeneously as well as inhomogeneously distributed, single heat and multi-heat data sets.

All data are fitted simultaneously, with $\log(\text{time})$ as the dependent variable, and by applying log-normal statistics. Although statistical measures are available to the analyst following the fitting process, these are provided as a guide only. The analyst is expected to use their metallurgical judgement to decide which function best represents the data. Special methods are applied to overcome non-physical behaviour of 2nd and 3rd order polynomials and certain linear and non-linear coefficients can be adjusted manually. These methods can also be used to fit correlated curve families comprising stress rupture curves as well as stress to specific strain curves. Moreover, a temperature dependent time correction is possible to influence the position and slope of isothermal curves in the range of lower temperatures.

In this paper, information is given in chapter 1 concerning the acquisition of DESA and the which hardware and software components are necessary. Further, a guide for the installation of DESA is given. The DESA time-temperature-parameter evaluation method available in DESA 2.2 is described in chapter 2 with the basic equations and details of the statistical methods applied. In chapter 3 a guideline follows giving advice for the use of DESA for creep rupture assessment or creep strength assessment to be carried out with a comprehensive multi-heat data set.

This paper replaces all earlier publications on DESA* distributed within WG1 of ECCC, ie:

The DESA Time-Temperature-Parameter Evaluation Method (Programme DESA 2.01), Doc. ref. 5524/WG1/52, section B, Pages B1 to B18, June 1993.

Leaflet about Programme DESA 2.01, 15.5.94, Doc. ref. 5524/WG1/74, October 1993.

DESA Input Format, IfW TH Darmstadt, 20.9.1993.

DESA Assessment Procedure Document, Version 1, IfW TH Darmstadt, 31.10.94.

* The authors express their thanks to Dr.-Ing. T Preußler who prepared the first version of DESA and to Dr.-Ing. M. Oehl who made valuable contributions to the subsequent development of DESA

1 AVAILABILITY, REQUIREMENTS AND INSTALLATION OF PROGRAMME DESA

DESA is available for data assessment in the frame of ECCC with the agreement of the Forschungsvereinigung Verbrennungskraftmaschinen e.V., c/o Mr Dipl-Ing Geisendorf, Lyoner Str 18, Postfach 71 08 64, D 60 498 Frankfurt/M., Fax (49) 69 6603 673. To obtain DESA, please write or fax a short informal letter to Mr Geisendorf, indicating your interest to obtain DESA application within ECCC. After agreement transmitted from Mr Geisendorf to Institut für Werkstoffkunde (IfW), you can order the programme at the Institut für Werkstoffkunde, Grafenstr. 2, D 64 283 Darmstadt, Germany, Fax (49) 6151 16 5659, Phone (49) 6151 16 2451 in the form of executable binary files. Please fill out the questionnaire annexed and send it with the order to IfW to enable adaptation of the programme for the hardware configuration of your computer. The delivery of DESA includes a detailed handbook written in the German language. The handbook contains example results from a test data set included in the binary files.

The cost for the adaption of the programme is DM 950,-. Additionally a license of DM 805,- must be purchased for the graphical output library, GKS GRAL 74/Vers.3.3, contained in DESA. In the latter amount a value added tax of DM 105.- is included, which can be refunded in the country of destination. All costs are valid for 1995. The total amount of 1,755.-DM has to be submitted to IfW.

The following requirements are to be considered.

Hardware System Requirements: An IBM compatible PC of type 80 386 or higher, numeric co-processor, hard disc, graphic card, printer or plotter

Memory Requirements:

Main storage: 8 MByte

Hard disc space: 6 MByte

Programme Requirements:

Binary files: DESA, CCGMPL, GO32

Operating system: PC-DOS 4.0 or MS-DOS Version 3.1 or higher

Graphic: GKSGRAL 7.4/Ver. 3.3

For the installation of DESA the user should carry out the following actions:

- a) Put the disk #1 into the disk drive.
- b) Start the installation programme INSTALL.BAT. The installation programme needs two variables. The first variable is the name of your disk drive (eg B:) and the second variable is the name of the target partition on the hard disk (eg E:). The installation command for this example is "INSTALL B: E:".
- c) When the installation procedure has been successfully completed, the user has to add the following commands:

```
E:\GTSGRAL\FONTS\VGAIN.T.COM  
SET_GTS FONTS=E:\GTSGRAL\FONTS  
SET DOSX=-SWAPDIR E:\
```

into the file AUTOEXEC.BAT.

Thereafter, the user has to reboot the system.

Important advice: To get a graphic output from DESA neither a memory manager (eg EMM 386 or QEMM 386) nor the RAMDRIVE or SMARTDRIVE utilities may be loaded into memory. The corresponding commands should be removed from the file CONFIG.SYS.

After the actions a) to c) the programme can be started with the command DESA.

2 THE DESA TIME-TEMPERATURE-PARAMETER EVALUATION METHOD

2.1 Introduction

The programme DESA is a tool for calculating mean stress-time curves with stress to a specific strain or rupture stress. The calculation is carried out by means of a model-function based on a stress function and a time-temperature parameter $P(t, \vartheta)$ (Fig.1). Individual test materials as well as classes of materials can be evaluated.

The program requires the results of creep and creep rupture tests as input data, especially the test temperature ϑ , the stress σ_0 and the time t to specific strain or to rupture. The evaluation of the mean curves is based on a multi-linear or multi-non-linear regression analysis of a polynomial master curve, which describes a time-temperature parameter $P(t, \vartheta)$ in dependence of a polynomial of a monotonic stress function $f(\sigma_0)$ as σ_0^m with $0.1 \leq m < 1$ or $\log \sigma_0$. The number M of the coefficients of the polynomial can be chosen between 5 and 2, starting at the maximum number of 5. The stress function and the time-temperature parameter can be selected from a menu. The exponent m has to be selected. The constants of the time-temperature parameter may be determined within the regression analysis or they may be entered manually. Special criterions can be applied to second and third order polynomials. Subsequent to the fitting, the significance of the mean curves is indicated by statistical test values.

After calculating the mean curves, it is possible to review the results in diagrams $\log \sigma_0$ versus $\log t$ as well as in diagrams $\log \sigma_0$ versus $P(t, \vartheta)$. Additionally, the mean curves can be shown in a representation of $\log \sigma_0$ versus ϑ , and of ϑ versus $\log t$ (Fig.2).

2.2 Regression analysis

2.2.1 Multi-linear regression analysis

Often, the evaluation of the data (temperature ϑ (°C), stress σ_0 (MPa), time to specific strain or rupture time t (h)) can be based on an multi-linear regression analysis of a polynomial master curve, which describes a time-temperature parameter $P(t, \vartheta)$ in dependence of a polynomial of the stress function $f(\sigma_0)$

$$P(t, \vartheta) = \sum_{j=1}^M b_j \cdot f(\sigma_0)^{j-1} \quad (1)$$

with $M = 5, 4, 3$ or 2 .

Resolving eq.(1) with respect to the logarithm of time $\log t$ which is in the following written as $\lg t$ and transforming it into notation of regression analysis, one obtains

$$y = B_0 + \sum_{j=1}^M B_j \cdot x_j \quad (2)$$

with the dependent variable $y = \lg t$, the independent variables $x_j = g_j(\vartheta, f(\sigma_0))$ and the coefficients B_j . The determination of the coefficients B_j , $j = 1, M$ is carried out according to the usual methods of multi-linear regression analysis as applied in ¹⁾ and as described by

example in ²⁾³⁾. For $i = 1, N$ data points with the observed values y_i and x_{ij} , eq (2) is written in the form

$$Y_i = B_0 + \sum_{j=1}^M B_j \cdot x_{ij} \quad (3)$$

with Y_i being the estimate of the observed value y_i . Minimizing the sum of squares

$$S^2 = \sum_{i=1}^N (y_i - Y_i)^2 \quad (4)$$

leads to the following condition for the partial derivatives:

$$\partial S^2 / \partial B_j = 0, j = 0, M \quad (5)$$

Equation (5) results in a linear system of $M + 1$ equations to obtain the coefficients B_j . Using the transformations

$$\bar{y} = \frac{1}{N} \cdot \sum_{i=1}^N y_i, \quad \bar{x}_j = \frac{1}{N} \cdot \sum_{i=1}^N x_{ij}, j = 1, M \quad (6)$$

the coefficient B_0 can be calculated according

$$B_0 = \bar{y} - \sum_{j=1}^M B_j \cdot \bar{x}_j \quad (7)$$

The transformations

$$\begin{aligned} \bar{y}_k &= \sum_{i=1}^N (x_{ik} - \bar{x}_k) \cdot (y_i - \bar{y}), \\ \bar{x}_{kj} &= \bar{x}_{jk} = \sum_{i=1}^N (x_{ik} - \bar{x}_k) \cdot (x_{ij} - \bar{x}_j), k = 1, M; j = 1, M \end{aligned} \quad (8)$$

lead to a linear system of M equations for the coefficients $B_j, j = 1, M$

$$\bar{y}_k = \sum_{j=1}^M B_j \cdot \bar{x}_{kj} \quad (9)$$

The inverse matrix

$$\bar{c}_{kj} = \bar{x}_{kj}^{-1} \quad (10)$$

may be determined using the Gauss-algorithm ⁴⁾. Then, the coefficients B_j can easily be calculated by

$$B_j = \sum_{k=1}^M \bar{c}_{jk} \cdot \bar{y}_k \quad \text{with } j = 1, M \quad (11)$$

2.2.2 Statistical data

The quality of the regression analysis may be characterized by statistical data, ie by the standard deviation

$$s = (S^2/(N-M-1))^{1/2} \quad (12)$$

which is calculated from the minimum sum of squares according to eq (4), the number of data points N and the number of coefficients M. Furthermore the coefficient of determination

$$r^2 = \frac{\sum_{i=1}^N (Y_i - \bar{y})^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (13)$$

can be calculated. The 90%-confidence limits may be estimated ²⁾³⁾⁴⁾ according to

$$Y_{5\%}, Y_{95\%} = Y \pm 1,64 \cdot s \quad (14)$$

which means, that a single, additional data point will be determined between the values $Y_{5\%}$ und $Y_{95\%}$ with an estimated probability of 90%. These estimated values are used for the determination of the upper and lower limitations of the scatterband in the $\lg \sigma_0$ versus $P(t, \vartheta)$ diagram.

The test value

$$t_j = B_j / \left(\frac{c_{jj}}{s^2} \right)^{1/2} \quad (15)$$

is calculated to check, if a coefficient is systematically different from zero. If the test value t_j is greater than the value $t_{0,05}(N-M-1)$ of the t- or student-distribution²⁾, the coefficient B_j is different from zero with a probability of 95%.

2.2.3 Non-linear regression analysis

Non-linear regression analysis presumes the same model function, eq (2), as multi-linear regression analysis, but the independent variables $x_j = g_j(\vartheta, f(\sigma_0))$ additionally contain non-linear coefficients C_l , $l = 1, L$. These non linear coefficients are optimized by variations between an upper and a lower limit of each coefficient. For each variation a multi-linear fitting is carried out in which the standard deviation

$$s = (S^2/(N-M-L-1))^{1/2} \quad (16)$$

is determined. The combination of non-linear coefficients C_l which represents the lowest sum of squares S^2 is selected as the optimum solution. Generally, the program DESA uses eq (16) to calculate the value s. If linear or non-linear coefficients are set or in other words are manually entered in DESA, the characteristic value of the regression analysis $N-M-L-1$ is adapted by reduction of L by 1 for each coefficient which is set.

Normally the stress function $f(\sigma_0)$ used in eq (1) is one of the monotonic functions $f(\sigma_0) = \lg \sigma_0$ or $f(\sigma_0) = \sigma_0^m$ with $0.1 \leq m \leq 1$. The second term requires an input of the non linear coefficient m . In this exceptional case, the value L is not changed.

2.3 Model functions

The following time-temperature parameters $P(t, \vartheta)$ can be selected from a menu in the program DESA with $T = \vartheta + 273$:

- Larson-Miller parameter ⁵⁾:

$$P_{LM} = T \cdot (C + \lg t) \quad , \quad (17)$$
with the constant C ;

- Sherby-Dorn parameter ⁶⁾:

$$P_{SD} = \lg t - D/T \quad (18)$$
with the constant D ;

- Manson-Haferd parameter ⁷⁾:

$$P_{MH} = (\lg t - \lg t_a) / (T - T_a) \quad (19)$$
with the constants t_a and T_a ;

- Manson-Brown parameter ⁸⁾:

$$P_{MB} = (\lg t - \lg t_a) / (T - T_a)^R \quad (20)$$
with the constants t_a , T_a and R .

If these parameters are combined with the polynomial of the stress function, eq (1), and the resulting equation is transformed according to eq (2) the following model functions result, which may be applied to calculate mean curves of stresses to specific strain or to rupture.

Based on the Larson-Miller parameter P_{LM} one obtains

$$\lg t = B_0 + \frac{1}{\tau} \cdot \sum_{j=1}^M B_j \cdot f(\sigma_0)^{j-1} \quad (21)$$

with $\tau = (\vartheta + 273) / 1000$ and the Larson-Miller constant $-C = B_0$. The coefficients B_j , $j = 0, 5$ can be determined with multi-linear regression analysis. Moreover it is possible to set the coefficient B_0 manually. In this case, the value L is reduced by 1.

Based on the Sherby-Dorn parameter P_{SD} one obtains

$$\lg t = B_0 + \frac{B_1}{\tau} + \sum_{j=2}^M B_j \cdot f(\sigma_0)^{j-1} \quad (22)$$

with $\tau = (\vartheta + 273) / 1000$ and the Sherby-Dorn constant $D = B_1 \cdot 1000$. The coefficients B_j , $j = 0, 5$ result from multi-linear regression analysis. The constant D may be entered manually. In this case, the value L is reduced by 1.

Based on the Manson-Haferd parameter P_{MH} one obtains

$$\lg t = B_0 + \tau_1 \cdot \sum_{j=1}^M B_j \cdot f(\sigma_0)^{j-1} \quad (23)$$

with $\tau_1 = (9+273-T_a)/1000$ and the Manson-Haferd constants T_a and $\lg t_a = B_0$. The non-linear coefficient T_a is optimized for a parabolic polynomial ($M = 3$), applying stepwise multi-linear regression analysis within the limits $10 \leq T_a \leq T_{\min} - 10$ and $T_{\max} + 10 \leq T_a \leq 3000$. T_{\min} and T_{\max} are the minimum and maximum temperatures which are determined by DESA from the data to be assessed. According to chapter 2.2.3 the optimum of the value T_a is characterized by the lowest sum of squares S^2 . The constant T_a as well as the constant $\lg t_a$ may be entered manually. In this case, the value L is reduced by 1 or 2 respectively.

Based on the Manson-Brown parameter P_{MB} one obtains

$$\lg t = B_0 + \tau_2 \cdot \sum_{j=1}^M B_j \cdot f(\sigma_0)^{j-1} \quad (24)$$

with $\tau_2 = (9+273-T_a/1000)^R$ and the Manson-Brown constants T_a , $\lg t_a = B_0$ and R . The non-linear coefficient T_a is determined as described above for the Manson-Haferd parameter. Additionally the exponent R is optimized within the limits $-1 \leq R \leq 2,5$. According to chapter 2.2.3 that combination of the values T_a , $\lg t_a$ and R is taken, which represents the lowest sum of squares S^2 . Moreover it is possible to enter the constants T_a , $\lg t_a$ and R manually. According to the number of coefficients entered manually, the value L is reduced by 1, 2 or 3.

As a general guideline for the use of the DESA model functions it is recommended to use quadratic or at the most cubic polynomials and to vary the stress function rather than to use higher polynomial degrees. Further it is recommended to use several different functions (and time-temperature-parameters) and to select the function which gives the best data fit in the long term region of data rather than that presenting the lowest standard deviation. If a perfect fit in the long term region is not to obtain one should attain an optimum long term fit for the mean and higher temperatures and subsequently perform a temperature dependent time correction in the region of lower temperatures (see chapter 2.5). In some cases an optimum fit for a family of correlated curves is of interest, eg for the stress - time to rupture - curves and several stress - time to plastic strain - curves. In these cases special forms of the polynomial of the stress function can help to obtain the optimum solution, see the next chapter. A more detailed guideline for the DESA-assessment of multi-heat data is given in chapter 3.

More detailed information about DESA can be found in the DESA-handbook⁹⁾ which is however written in the German language.

2.4 Special form of polynomials of stress function

Special evaluation methods can be carried out with model functions, eq (21) to (24) with polynomials of third ($M = 4$) and second ($M = 3$) order. In a $f(\sigma_0)$ versus P diagram, model functions with a polynomial of third order are characterized by a point of inflection at stress σ_w (Fig.3a). Additionally, they may have two vertices at stresses σ_{E1} and σ_{E2} (Fig.3b). Model functions with a polynomial of second order are always characterized by a vertex at stress σ_E and parameter P_E (Fig.3c). The vertex or vertices of a master curve should normally be situated outside the data points with a sufficient distance. If the regression analysis does not fulfill this condition the model function can be adapted by fixing the σ_0 -coordinate of the point of inflection or of the (vertex) vertices and the regression analysis is repeated under this special

condition. For a second order polynomial it is also possible to fix simultaneously the σ_0 - and the P-coordinate of the vertex.

Supposing a third order polynomial ($M = 4$, Fig.3a, b), the coordinates of the point of inflection can be calculated according to

$$f(\sigma_w) = -b_3/3 \cdot b_4 \quad (25)$$

and the coordinates of the vertices according to

$$f(\sigma_{E1}) = (-b_3 + D^{0.5}) / 3 \cdot b_4 \quad (26)$$

$$f(\sigma_{E2}) = (-b_3 - D^{0.5}) / 3 \cdot b_4 \quad (27)$$

with $D = 3 \cdot b_2 \cdot b_4 - b_3^2 > 0$. If the coordinate σ_w is fixed, the model function according to eq. (1) results in

$$P(t, \vartheta) = b_1 + b_2 f(\sigma_0) + b_3 f(\sigma_0)^2 \left(1 - \frac{f(\sigma_0)}{3 \cdot f(\sigma_w)}\right) \quad (28)$$

If the coordinates σ_{E1} and σ_{E2} of the vertices are fixed, the model function results in

$$P(t, \vartheta) = b_1 + b_2 \cdot f(\sigma_0) \cdot \left(1 - \frac{S \cdot f(\sigma_0)}{2 \cdot F} + \frac{f(\sigma_0)^2}{3 \cdot F}\right) \quad (29)$$

with $S = f(\sigma_{E1}) + f(\sigma_{E2})$ and $F = f(\sigma_{E1}) \cdot f(\sigma_{E2})$. Third order polynomials may particularly be used for the evaluation of materials, which show S-shaped curves in the $\lg \sigma_0$ versus $\lg t$ diagram (example Fig.4) and in this special case the inflection point can be situated inside the data points.

For a second order polynomial ($M = 3$, Fig.3c), the σ_0 -coordinate of the vertex is determined according to

$$f(\sigma_E) = -b_2/2 \cdot b_3 \quad (30)$$

If the coordinate σ_E is fixed the model function results in

$$P(t, \vartheta) = b_1 + b_2 \cdot f(\sigma_0) \cdot \left(1 - \frac{f(\sigma_0)}{2 \cdot f(\sigma_E)}\right) \quad (31)$$

For third and second order polynomials, the regression analysis is carried out on the basis of eq (28), (29) or (31), which are combined with a time-temperature parameter according to eq (17), (18), (19) or (20) and transformed into an equation for the value $\lg t$.

Concerning the regression analysis, a second order polynomial with a fixed σ_E -coordinate of its vertex is equivalent to a linear fitting ($M=2$) and may be interpreted as a master curve with defined "curvature". For test values of inferior quality this kind of defining the curvature can be more suitable than a linear regression analysis ($M = 2$) with a definition of the curvature by variation of the exponent m of the stress function $f(\sigma_0) = \sigma_0^m$. Details will be given below.

Additionally, it may be of interest for a second order polynomial with a fixed σ_E -coordinate of the vertex to define the "slope" of the master curve. This is possible by an additional fixing of the coordinate P_E of the vertex (Fig.3c).

Placing the value P_E in eq (31), the expression

$$b_2 = 2 (P_E - b_1)/f(\sigma_E) \quad (32)$$

is obtained. Combining eq (29) and (32), the model function

$$P(t, \vartheta) = b_1 + 2(P_E - b_1) \frac{f(\sigma_0)}{f(\sigma_E)} - (P_E - b_1) \left(\frac{f(\sigma_0)}{f(\sigma_E)} \right)^2 \quad (33)$$

is derived, which has a fixed vertex position $(P_E, f(\sigma_E))$. If the model function is specified in such a extensive manner, it is convenient, to enter the constants of the time-temperature parameter manually. Then, only the coefficient b_1 of eq (29) had to be determined from the data points. Transforming eq (33) with respect to b_1 , the following expression is obtained:

$$b_1 = P_E + \frac{P - P_E}{(1 - f(\sigma_0)/f(\sigma_E))^2} \quad (34)$$

In this case, the regression analysis is reduced to a determination of the mean value \bar{b}_1 for all data points:

$$\bar{b}_1 = \frac{1}{N} \sum_{i=1}^N b_1(\vartheta_i, \sigma_{0i}, t_i) \quad (35)$$

with b_1 according to eq (34) and the time-temperature parameter according to eq (17), (18), (19) or (20). After the determination of the coefficient \bar{b}_1 according to eq (35), eq (33) is transformed into the model function according to eq (21), (22) (23) or (24).

Partial fixing (σ_E) or total fixing (σ_E, P_E) of the vertex of a master curve is convenient, if stresses to several specific strains have to be simultaneously interpreted for one material or in other words, if a "curve family" of correlated curves has to be fitted. In most of this cases the number of test values for stresses to reach the lower specific strain values is relatively small. Then the slope of the correspondent mean curves probably does not match well with the mean curves for the higher specific strain values if a normal regression analysis is performed with "free" coefficients b_1 , b_2 and b_3 . An example of such a fixing procedure is shown in ¹⁰⁾, Fig.5. Normally the fixing is accompanied by fitting the course of $\sigma_E \varepsilon_p$ -curves and if necessary $P_E - \varepsilon_p$ -curves (Fig.6). The procedure of fixing the curvature and the slope by fixing the vertex (σ_E, P_E) is comparable with a graphic evaluation method, where it is possible to transfer experiences from curves with sufficient number of test values to curves with an insufficient number of test values. However, a trial should be always given first to fix only the value $f(\sigma_E)$.

Nevertheless, it is possible, that single curves of a set do not run parallel, due to different centres of gravity of the test values, eg Fig.7. In this case it is possible to enter the coefficient b_1 manually, too.

In any case and especially, if fixing of coefficients of a master curve or of a set of master curves is carried out, the interpretation of the test values should be visually checked in the $\lg \sigma_0$ versus $\lg t$ diagram as recommended in DIN 50 118, appendix C and especially the fit of the long term data should be considered in this case.

2.5 Temperature dependent time correction

This correction is developed to overcome a principal disadvantage of time temperature parameters, ie the often too strong slope of isothermals in the range of the lowest test temperatures. This is due to a stress and temperature dependent course of creep exponent n , which cannot be considered by the parameter if the temperature and thus stress range is relatively large and if different creep mechanisms are existing in this range. As an example, for low alloy ferritic or bainitic steels, there is often a change in slope between the 450°C-region and the 500°C-region and higher.

The correction method developed is based on the experience (Fig.8) that the deviation of the measured data points with time t from the calculated DESA points with time t' can be described by

$$t/t' = c \cdot t'^d \quad (36)$$

The constants c and d can be determined in DESA by regression analysis for any test temperature which presents a sufficient number (≥ 5) of data points. If the constants are plotted against temperature ϑ in the range ϑ_{\min} to ϑ_{\max} of the data (Fig.9a, b), the value $c = 1$ and $d = 0$ should be attained for the higher temperatures until ϑ_{\max} . If this is not the case, the model function should be further improved (see guideline for the use of DESA, chapter 3). If finally the conditions $c < 1$ and $d > 0$ are fulfilled in the region near ϑ_{\min} , a temperature range $\vartheta_{\min a}$ to $\vartheta_{\min b}$ has to be selected, between which the temperature correction shall be carried out. In this temperature range the fit of the data by the corrected isotherms is to be checked. To this purpose, eq (36) is modified to

$$t^* = (c \cdot t')^{1/(1-d)} \quad (37)$$

with corrected time t^* . As a result of this check, the coefficient $d_{\max} = d(\vartheta_{\min a})$ is adjusted to give an optimum interpretation at least to the slope of the correspondent isotherm and further $d(\vartheta_{\min b}) = 0$ is set. Now the coefficient $d(\vartheta)$ is interpolated between $\vartheta_{\min a}$ and $\vartheta_{\min b}$ by a 3rd degree parabola

$$d = d_0 + d_1 \cdot \vartheta + d_2 \cdot \vartheta^2 + d_3 \cdot \vartheta^3 \quad (38)$$

with the conditions $d(\vartheta_{\min a}) = d_{\max}$, $d(\vartheta_{\min b}) = 0$, $dd/d\vartheta(\vartheta_{\min a}) = 0$ and $dd/d\vartheta(\vartheta_{\min b}) = 0$, ie with horizontal tangents at the ends of range $\vartheta_{\min a}$ to $\vartheta_{\min b}$ (Fig.9d). In the next step, the optimum values of coefficient d are calculated with eq (36) and with d from eq (38). For the resulting values of c (Fig.9c) again the fit of data points by the corrected isotherms is checked and if necessary, the coefficient $d(\vartheta_{\min a}) = d_{\min}$ is further adjusted. On this basis the coefficient $d(\vartheta)$ is interpolated between $\vartheta_{\min a}$ and $\vartheta_{\min b}$ by

$$c = c_0 + c_1 \cdot \vartheta + c_2 \cdot \vartheta^2 + c_3 \cdot \vartheta^3 \quad (39)$$

- facility to save a user configurable sequence of temperatures within the data set of a material for the output of isotherms or for the temperature dependent time correction (see chapter 2.5),
- tabulation of results as isotherms, isostats, isochrones and master curves of the parametric model function,
- facility to allow discrete values of stress, time or temperature to be calculated from the model function.

Some improvements to be realized within the medium term concern:

- facility to fix additionally to the stress value σ_w the parameter value P_w of an inflection point of a cubic polynomial (see chapter 2.4),
- improved charts to include title, axes labels, curve labels or style key, data point style key and comment box into the graphical DESA-output.

Further improvements to be realized within longer time concern:

- reduction in repetitive data input sequences when calculating model functions,
- batch processing facility for calculating model functions,
- introduction of additional pre- and post-assessment facilities into DESA (see ¹¹⁾ and chapter 3),
- an English version of DESA with an English handbook.

Some of the above mentioned future improvements of DESA are available at present from the programmes ZDESA and PASAC associated to DESA. These programmes have direct access to the DESA input data and to the model functions determined in DESA. ZDESA tabulates isotherms for given temperature and time values. The isotherms are calculated with a model function determined in DESA. PASAC plots isotherms in 25°C-steps from ϑ_{\min} - at maximum 25°C until ϑ_{\max} + at maximum 25°C. Further, PASAC performs the calculations and graphical presentations of the post-assessment criteria as defined in Vol.5 of ECCC ¹³⁾. Examples of PASAC-results are to be seen in ¹¹⁾. ZDESA and PASAC are available on request from IfW.

3 GUIDELINE FOR THE USE OF DESA FOR MULTI-HEAT DATA ASSESSMENT

3.1 Purpose of the guideline and data pre-assessment

The guideline relates to the assessment of a stress-time-temperature-multi-heat data set which contains at least more than 3 unique test materials (heats). The time is either rupture time or time to a specific plastic or creep strain. For the assessment, DESA contains a practically infinite number of possible model functions, as is shown in chapter 2. The purpose of this guideline is to give help to a user of DESA who is a material expert to come quickly to an optimum creep or rupture data assessment on the basis of a multi-heat data set. For this, the steps in chapter 3.2 are recommended, which are restricted to a single data type, either rupture data or data for a unique specific strain value.

The data set should previously be submitted to a data pre-assessment which assures a sufficient data homogeneity. Three different pre-assessments are of interest.

In a first pre-assessment regarding the pedigree data it should be assured that the data characterizing the manufacturing of the material and the product as well as the chemical composition, heat treatment, structural properties and mechanical short term properties are within the specifications of the material type of interest. This aspect should be addressed without DESA.

In a second pre-assessment regarding the distribution of the test parameters, ie. temperature and stress and the resulting characteristic time, eg rupture time it should be checked whether these data are uniformly distributed for all unique test materials. This ideal goal is only approximated in the normal case. An indication that the data homogeneity is sufficient can be concluded from the observation that the maximum test time is sufficiently long for several temperatures covering a relevant part of the temperature range which is typical for the test material, eg Table 3. To reduce regression pinning, the data can be diluted in regions of relatively high data density. A simple method is being developed by IfW at present. If this method will be successful it will be included into DESA.

In a third pre-assessment the scatter of the test results, i.e. of the characteristic time is to be considered. It is proposed to perform a first assessment with DESA, preferably according to the general guideline described at the end of chapter 3, ie with a simple time-temperature-parameter eg P_{LM} (eq (17)) and a quadratic polynomial of stress function σ_0^m with $m = 0.1$ or 0.5 . On this basis one should consider the data points in the $\log\sigma_0$ -parameter-diagram. If a greater part of the data of a unique test material is outside the mastercurve with parameters $P(T_m, \lg t \pm 1.64 s)$, ie approximately outside the 90%-confidence limits (T_m being the mean temperature of the long term data range and s being taken from eq (12)) all data of that unique material should be removed from the whole data set. If a single data point is outside the range $P(T_m, \lg t \pm 2.58 s)$, ie approximately outside the 98%-confidence limits, the data point can assumed to be an outlier and can be removed from the data set.

After these pre-assessment steps the DESA assessment can go on as described in the next chapter. Other considerations concerning the scatter of test results are part of the post-assessment¹³⁾ to be performed after the DESA assessment.

3.2 Stepwise DESA assessment

The DESA assessment is recommended to be performed in the following steps which are part of a DESA pre-assessment carried out with selected unique material data sets and a DESA main assessment carried out with the whole data set to be considered.

Step 1. From the whole data set of the steel type, the three best tested unique materials (heats) have to be chosen for the DESA pre-assessment. "Best tested heat" means a heat tested over the usual stress-time-temperature range of the steel type with a uniform data distribution up to the longest time at least at a lower, a mean and a higher temperature and as a recommendation but not mandatory at a high extrapolation temperature down to a stress corresponding to the lowest stress at the highest long term temperature. The easiest way to determine these heats is to examine a listing of the data and to plot the data points of selected heats with DESA in the form of logarithmic stress time diagrams. At the same time, the minimum stress $\sigma_{0 \min}$ and the longest time t_{\max} of the data field can be determined.

If sufficient well tested heats are available and if, from a previous data preassessment or by a comparison of the data, small systematic differences between the selected individual heats are known, eg differences in chemical composition, heat treatment or creep rupture strength values, heats with typically different properties should be chosen as the three best tested heats.

Step 2. For each of the three best tested heats, an optimum model function should be determined. For that, one should begin with the Larson-Miller-parameter and the Manson-Haford-parameter and a quadratic polynomial of the stress functions $f(\sigma_0) = \sigma_0^{0.5}$, $\sigma_0^{0.25}$, $\sigma_0^{0.1}$ and $\log \sigma_0$, ie with 8 different model functions. In the regression analyses performed with DESA and the 8 functions, no parameter constants or polynomial coefficients may be set. For the Manson-Haford-parameter the case $T_a < T_{\min}$ should be selected. As a result of each of the $3 \cdot 8 = 24$ calculations, a stress parameter diagram with the calculated master curve and a stress time diagram with the calculated isothermal (rupture or stress to specific strain) curves should be plotted with DESA. Depending on the experiences of the material expert with eg similar materials, the number of different model functions can be reduced below 8.

Step 3. For each of the three best tested heats, the best of the individual model functions should now be determined. Two conditions are to be fulfilled. The first and in most cases trivial condition is, that there is a good data fit in the whole data range. This condition includes that the stress σ_E of the vertex of the master curve is at least below 80% of the minimum stress $\sigma_{0 \min}$, however a value of 10% or smaller is recommended. Due to the use of a stress function $f(\sigma_0) = \sigma_0^m$ this cannot in all cases be examined in the parameter diagram or in the stress time diagram. However, the stress σ_E is printed out by DESA. If the first condition is fulfilled in both points, one can proceed to examine the second condition described in the next but one paragraph.

In a few cases, a systematic misfit may appear at all $\log \sigma_0$ - $\log t$ -isothermals for all functions. Then, the polynomial should be replaced either by a linear function of $\log \sigma_0$ (if rather linear isothermals appear) or by a cubic polynomial of the stress function $f(\sigma_0)$ (if rather isothermals with an inflection point appear). With the new model functions the calculation should be repeated and the first condition reexamined. After that, one can take over the relatively best

model functions and proceed to examine the second condition below. Also in this stage of the assessment, outliers can be detected and removed.

The second condition is, that there is a good data fit in the long term range, ie in the range between the maximum test time t_{\max} and the time $t_{\max}/10$. This should be examined in the stress time diagram by observing the interpretation of the long term data points. The best fit is a uniform interpretation across the greatest possible temperature range, ideally for all long term isothermals supported by data points. If an optimum fit is not possible for all temperatures the best fit for the mean and higher temperatures should be attempted and the temperature dependent time correction (see chapter 2.5 and step 10) can be applied later. An example of a DESA pre-assessment is demonstrated in Table 4, more examples are to be seen in ¹¹⁾. The decision about the best data fit has to be visually made at the moment. A numerical method is being developed by IfW and will be introduced in DESA if it works well.

Step 4. Now the best model function types for the three best tested heats have to be compared to each other. If the parameter type, the polynomial degree and the type of the stress function $f(\sigma_0)$, for which condition 2 of point 2 is at best fulfilled, are the same for three or at least two of the heats, the correspondent type of model function should be carried over for the creep rupture data assessment and one can proceed to step 5. If the latter is not the case or if none of the model functions examined up to now shows an acceptable data fit, the regression analysis can be repeated from step 2 but with the Manson-Brown- and Sherby-Dorn-parameters. If that gives no better solutions or if the expert omits this way, the function type used for a similar steel or a similar steel type or the relatively best Larson-Miller-type model function should be carried over. In this way, the DESA-preassessment is finished and one can proceed to step 5.

Step 5. The optimum model function type resulting from step 4 can be applied now to the whole steel type data set. Again no parameter constants or polynomial coefficients may be set for the regression analysis with DESA. However, to ensure the best model function is selected for the steel type one should again try some variations of the model function. It is recommended to keep at first the parameter type and to change the stress function by taking the next higher and the next lower stress exponents $\log \sigma_0$ corresponding in this sense to a lower exponent. That means by example if the start from step 4 was with $\sigma_0^{0.1}$ the stress functions $\sigma_0^{0.25}$ and $\lg \sigma_0$ should be taken. If this change is only possible in one direction two steps in this direction can be made. For all three cases again stress parameter and stress time diagrams should be plotted.

Step 6. For the results of step 5 it is necessary to reexamine if the first and second conditions of step 3 are fulfilled, ie if the rather trivial fit in the whole data range and the more decisive fit in the long term data range between t_{\max} and $t_{\max}/10$ are acceptable. If the fit becomes better for a stress function varied, further variations if possible should be examined, ie $\sigma_0^{0.5}$ in the example given above. With the best stress function then a variation of the parameter should be made. Instead of the Larson-Miller-parameter the Manson-Haford-parameter should be taken, the same is recommended for the Manson-Brown-parameter, whereas instead of the Manson-Haford-parameter or the Sherby-Dorn-parameter one should take the Larson-Miller-parameter. Select the optimum parameter and make finally slight variations of the parameter constants. At least one variation of this type should be made, if up to here only three variations were made. However, depending on the experiences of the materials expert e.g. with similar steel types, the number of variations can be reduced.

To the first assessment of step 6 a quality index of 1 is attributed. For each further assessment with the first and the second condition of step 3 fulfilled, this index is increased by 1, kept constant or decreased by 1, when the fit becomes better, equal or worse than in the preceding assessment. To assessments which do not fulfill the first and second condition of step 3 no quality index is given. An example of a DESA main assessment according to steps 5 and 6 is demonstrated in Table 5.

Step 7. To the 1 to at maximum 4 assessment(s) with the highest quality index or indices a temperature dependent time correction may be applied if this seems to be useful (refer to Section 2.5). Finally the best of the 1 to 4 solutions has to be determined according to the second condition of step 3 observing the long term data fit in the whole temperature range. Thereafter, the DESA main assessment usually is finished. An example of the assessment according to step 7 is demonstrated in Table 6, details are described in ¹¹⁾.

Step 8. The results of the best method can now be submitted to the post assessment acceptability criteria described in ¹³⁾. These criteria can be applied by example via the programme PASAC (chapter 2.7). If from there a reassessment is recommended, one should begin at step 6 with a varied stress function. However, for an assessment with culled data one should begin from step 1 ¹¹⁾.

A short overview on the stepwise DESA procedure is given in Table 7.

3.3 Final remarks on DESA multi-heat assessment

According to the experiences gained up to now with the WG1 creep rupture working data sets of steels 2.25Cr1Mo, 12CrMoVNb, 18Cr11Ni and alloy 31Ni20CrAl, collected within ECCC, WG1 ¹⁴⁾, the recommended stepwise DESA assessment leads to the best possible interpretation of a multi-heat data set. If the results of the 4 best creep rupture data assessments from step 7 on the above mentioned 4 materials are compared to the mean thereof the scatter of the rupture stresses $R_{m 100000}$ (for $t_{r \max}$ 100,000 h) was always below 7% ¹¹⁾, if the temperatures for long term use of the material were considered.

Depending on the experience of the DESA user some steps can be abbreviated. As an example it can be recommended to take the same type of model function if another steel type is assessed which is similar in composition or in structure. If difficulties with DESA are experienced or if improvements for this guideline are found please do not hesitate to contact IfW via the address given in chapter 1.

To give a better support to the decision about the best fit of long term data, a post-assessment procedure is being in development in IfW. The procedure considers the deviation of predicted and measured time values in the long term range, evaluates the level and the trend of prediction for different temperature ranges and determines a number for the quality of prediction in the long term range.

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Table 1. DESA input variables

Input variable	Content	Format	Example
WSKOM	comment for the steel type	A40	10 CrMo 9 10, luftvergütet
TPE(1 to 9), Tm	headline characterizing the time to specific strain and to rupture	10 A4	0.02, 0.05,....t _m
no	consecutive no. of a single test material	I3	1
name	test material identifier	A6	7K
rec	no. of records for the current test material	I3	26
com	comment for the current test material	A40	Prüfzeichen TE
DATEN (1 to 1000,1)	test temperature(°C)	F10.2	500.00
DATEN (1 to 1000,2)	applied stress (MPa)	F10.2	196.00
DATEN (1 to 1000, 3 to 12)	time to specific strain, rupture time -1.00 stands for: time is not available	F10.2	-1.00 195.00...

Kommentar: 10 CrMo 9 10, luftvergütet
 Dehngrenzen: 0.02 0.05 0.1 0.2 0.5 1.0 2.0 5.0 10. tm
 NR: 1 NAME:7K REC: 26 BEM:Prüfzeichen TE

500.00	196.00	-1.00	195.00	320.00	520.00	880.00	1300.00	1900.00	2400.00	2600.00	3400.00
500.00	157.00	-1.00	260.00	530.00	1030.00	1850.00	3500.00	6000.00	9300.00	11500.00	13500.00
500.00	123.00	-1.00	-1.00	280.00	1600.00	13000.00	52000.00	100000.00	180000.00	-1.00	-1.00
500.00	98.10	-1.00	2700.00	6000.00	12000.00	50000.00	140000.00	-1.00	-1.00	-1.00	-1.00
550.00	309.00	-1.00	-1.00	-1.00	-1.00	-1.00	67.00	71.00	73.00	76.00	82.00
550.00	196.00	-1.00	-1.00	-1.00	-1.00	-1.00	70.00	110.00	185.00	260.00	420.00
550.00	157.00	-1.00	-1.00	-1.00	40.00	100.00	180.00	310.00	550.00	650.00	950.00
550.00	123.00	-1.00	-1.00	-1.00	87.00	265.00	680.00	1700.00	3300.00	4200.00	5000.00
550.00	98.10	-1.00	-1.00	90.00	280.00	1050.00	2650.00	7000.00	13000.00	15500.00	17500.00
550.00	78.50	-1.00	75.00	290.00	950.00	4100.00	12000.00	23500.00	35000.00	38500.00	42000.00
550.00	58.90	-1.00	170.00	700.00	3300.00	20000.00	51000.00	65000.00	-1.00	-1.00	-1.00
575.00	245.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	17.00	19.50	22.00	26.00
575.00	157.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	53.00	170.00	250.00	350.00
575.00	123.00	-1.00	-1.00	-1.00	-1.00	75.00	230.00	430.00	850.00	1030.00	1300.00
575.00	98.10	-1.00	-1.00	-1.00	36.00	133.00	250.00	600.00	1530.00	2300.00	2900.00
575.00	78.50	-1.00	20.00	63.00	160.00	620.00	2000.00	4300.00	12500.00	22000.00	25000.00
575.00	61.80	-1.00	-1.00	83.00	250.00	2800.00	5300.00	13500.00	33000.00	39000.00	42000.00
575.00	49.10	-1.00	75.00	290.00	1300.00	8800.00	14500.00	27000.00	-1.00	-1.00	-1.00
575.00	39.20	-1.00	105.00	470.00	5900.00	15000.00	30000.00	55000.00	-1.00	-1.00	-1.00
500.00	342.00	-1.00	-1.00	-1.00	-1.00	58.00	72.00	86.00	106.00	121.00	150.00
500.00	309.00	-1.00	-1.00	67.00	94.00	150.00	189.00	242.00	315.00	336.00	450.00
500.00	246.00	-1.00	73.00	170.00	307.00	453.00	581.00	671.00	820.00	930.00	1050.00
450.00	320.00	37.00	100.00	180.00	330.00	720.00	5000.00	8000.00	8800.00	9200.00	10000.00
450.00	278.00	50.00	220.00	3500.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
450.00	240.00	220.00	1380.00	13000.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
450.00	220.00	270.00	5000.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00

NR: 2 NAME:7P REC: 12 BEM:Prüfzeichen UF

500.00	309.00	-1.00	-1.00	-1.00	-1.00	77.00	115.00	177.00	301.00	320.00	370.00
500.00	245.00	-1.00	-1.00	-1.00	100.00	259.00	446.00	654.00	1002.00	1401.00	1800.00
500.00	196.00	-1.00	-1.00	50.00	125.00	800.00	2000.00	5200.00	11000.00	12500.00	14500.00
500.00	157.00	-1.00	28.00	150.00	870.00	3800.00	12500.00	29000.00	63000.00	-1.00	-1.00
500.00	123.00	-1.00	73.00	400.00	2500.00	22000.00	58000.00	-1.00	-1.00	-1.00	-1.00
550.00	196.00	-1.00	-1.00	-1.00	-1.00	36.00	130.00	230.00	280.00	320.00	480.00
550.00	123.00	-1.00	-1.00	-1.00	115.00	480.00	1000.00	2100.00	5200.00	6300.00	8200.00
550.00	78.50	-1.00	-1.00	270.00	1400.00	7800.00	21000.00	27000.00	37000.00	42500.00	46000.00

Table 2. Example of the first part of a DESA input data set

Table 2a		Steel type : 12 CrMoVNb					Total number of data points
Total No. of individual heats : 33		Type of data : f.					
Heat No.	Maximum time (1000 h) for a temperature (°C) of						
	425	450	475	500	550	600	
GBCR				94.8	48.8		14
GBCS				55.7	41.5		13
GBGC			50.3		37.0	43.9	17
GBLD			57.3		68.2	52.8	16
GBCJ				21.0	53.2		11
GBCK				128.1	74.7		12
GBLN			59.9		81.2	52.8	16
GBME			83.9		100.5	9.4	15
GBF409		12.7		21.5	13.0		8
GBF629		20.8		16.6	9.7		7
GBB630		16.5		26.5	18.9		9
GBF384					59.0		5
GBF401					36.4		5
GBF404					41.8		5
D320B		28.4		71.1	92.2	36.1	20
D126				112.2	85.5		14
D127				55.9	57.6		8
D128				66.6	129.2		3
D130					15.0		4
D132					4.4		2
D440E					7.5	15.3	7
D440N	0.8			24.9	64.0	24.3	11
D562A					50.1	28.1	8
D562B					23.7	25.0	9
D563					35.3		2
D564					26.5		3
D320I				14.3	17.7	10.2	9
D320C					7.1	15.3	7
D320C		19.3		88.7	66.2	13.5	16
D320D		1.3		90.7	72.0	13.0	14
D320H				3.2	1.2	1.2	6
D320K				1.3	1.7	2.0	6
D51B					66.4		3
all							310

Table 3. Maximum rupture times for the main test temperatures and total number of rupture points of the individual heats of steel 12 CrMoVNb (X 19 CrMoVNbN 11 1), after ¹¹⁾

Heat	Ass. No.	Parameter *) P	Stress function log σ_0 or $\sigma_0^{(n)}$	Optim. para. constants	σ_{min} / σ_E (MPa)	Standard deviation s	Good data fit in the *) hole range long term ra.	Best model function	opt. model function
A11 data	1	LN	m = 0.5	C = 17.59	1 033	0.137			
	2		0.25	C = 17.56	79 072	0.142			
	3		0.1	C = 17.61	<10 ⁻⁶	0.143	X		
	4		log σ	C = 17.65	0.865	0.141	X		
	5	MH	m = 0.5	lgta=11.77 Ta=482	-1 649	0.120	X	X	
	6		0.25	lgta=12.08 Ta=470	0.906	0.119	X	X	X
	7		0.1	lgta=12.93 Ta=437	11.2	0.119			
	8		log σ	lgta=13.98 Ta=369	18.2	0.121			

*) LN: Larson-Miller, MH: Manson-Haferd, SD: Sherby-Dorn, MB: Manson-Brown combined with a quadratic polynomial of the stress function

Table 4. Results of a DESA pre-assessment according to step 1 to 4 at one (D7ZT) of the 3 best tested heats of 2.25Cr 1Mo-steel, after ¹¹⁾

All data	Assessment No.	1	2	3	4	5	6	7	8
	Parameter *)	MH	MH	MH	MH	LM	LM		
	Stress function x)	$\sigma^{0,25}$	$\sigma^{0,1}$	$\sigma^{0,5}$	$\lg\sigma$	$\sigma^{0,1}$	$\sigma^{0,1}$		
	Optim. par. const.	$\lg ta=22,01$ $Ta = 43$	$\lg ta=22,18$ $Ta = 32$	$\lg ta=22,99$ $Ta = 1$	$\lg ta=23,01$ $Ta = 1$	$C = 15,98$	$C = 18$ set		
	$\sigma_{0 \min}: 22 \text{ MPa}, \sigma_E$	-0,0009	5,6	29 962	13,0	0,0049	0,027		
	Good da- ta fit in	hole range	X	X		X	X	X	
	long t.ra.		X			X	X		
	Quality index	1	2	+))	1	2	2		

*) LM: Larson-Miller, MH: Manson-Haferd, SD: Sherby-Dorn, MB: Manson-Brown combined with a quadratic polynomial of the stress function +) first and second condition of step 3 are not fulfilled

Table 5. Results of a DESA main assessment according to steps 5 and 6 at 2.25Cr 1Mo-steel, after 11)

All data	Assessment No.	1 main time corr.		2 main time corr.		5 main time corr.		6 main time corr.	
	Parameter *)	MH	T 450/500	MH	T 450/500	LM	T 450/500	LM	no time corr.
	Stress function x)	$\sigma^{0,25}$	d 0,06/0	$\sigma^{0,1}$	d 0,07/0	$\sigma^{0,1}$	d 0,03/0	$\sigma^{0,1}$	performed
	Optim. par. const.	$\lg ta=22,01$ $Ta = 43$	T 450/500	$\lg ta=22,38$ $Ta = 322$	T 450/500	$C = 15,98$	T 450/500	$C = 18$ set	
	$\sigma_{0 \min}: 22 \text{ MPa}, \sigma_E$	-0,0009	c 0,8/1	5,559	c 0,7/1	0,0049	c 0,9/1	0,027	
	Good da- ta fit in	hole range	X	X		X		X	X
	long t.ra.				X		X		X
	Quality		best-3		best-2		best		best-1

*) LM: Larson-Miller, MH: Manson-Haferd, SD: Sherby-Dorn, MB: Manson-Brown combined with a quadratic polynomial of the stress function +) first and second condition of step 3 are not fulfilled

Table 6. Results of a DESA main assessment according to step 7 at 2.25Cr 1Mo-steel, after 11)

DESA	Step	Procedure
pre-assessment	1	Select the 3 best tested heats
	2	Apply up to 8 model functions to the 3 heats
	3	Select the best *) model function for each heat
	4	Select the best model function type from step 3
main assessment	5	Apply the best function to the hole data set and vary twice the stress function
	6	Select the best *) model function from step 5 and attribute a quality index 1, vary once more the stress function and thereafter the parameter, vary slightly the constants of the best *) parameter, increase or decrease the quality index for a better *) or worse function +)
	7	Apply a temperature dependent time correction if necessary to the 1 to 4 functions from step 6 with the highest quality indices, select the function (with or without time correction) presenting the best long term data fit
post-assessment	8	Submit the results of the best model function from step 7 to the post-assessment criteria, repeat if necessary from step 6 to improve the model function or from step 1 with culled data
*) best model function (or parameter) is characterized by - a good fit in the hole data range - the best fit in the long term data range ($t_{\max}/10$ to t_{\max}) +) no quality index is given to an insufficient data fit		

Table 7. Overview on the recommended DESA procedure for the assessment of a multi-heat data set comprising temperature, stress and resulting time to rupture or to given strain

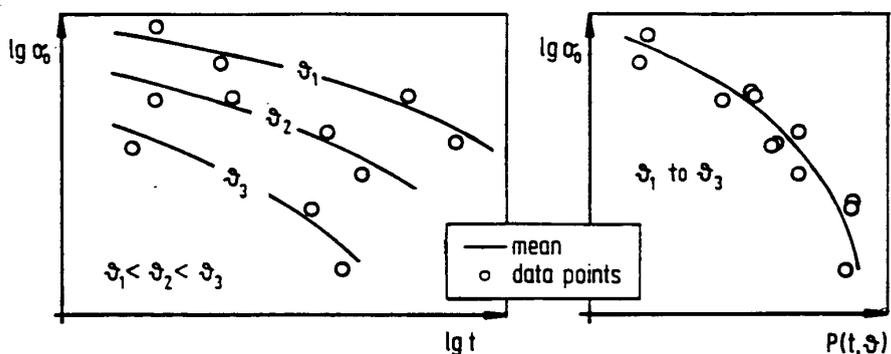


Fig. 1. Time dependency of stresses to reach a specific strain or of rupture stresses in the $\log \sigma_0$ versus $\log t$ -diagram and in the $\log \sigma_0$ versus $P(t, \vartheta)$ -diagram

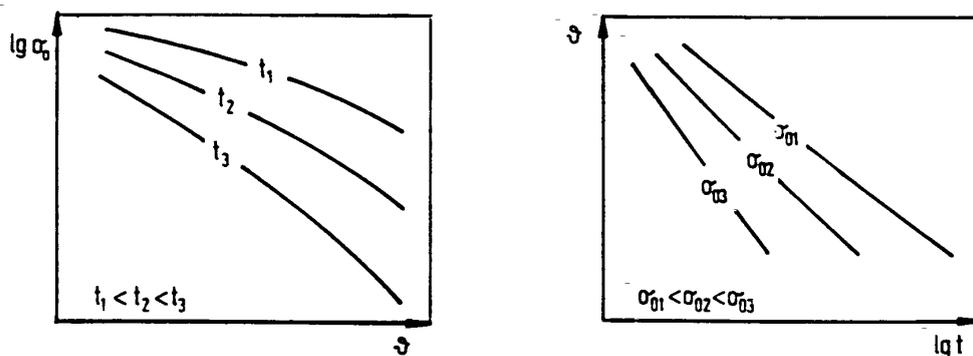


Fig. 2. Representation of mean curves in a $\log \sigma_0$ versus ϑ -diagram and in a ϑ versus $\log t$ -diagram

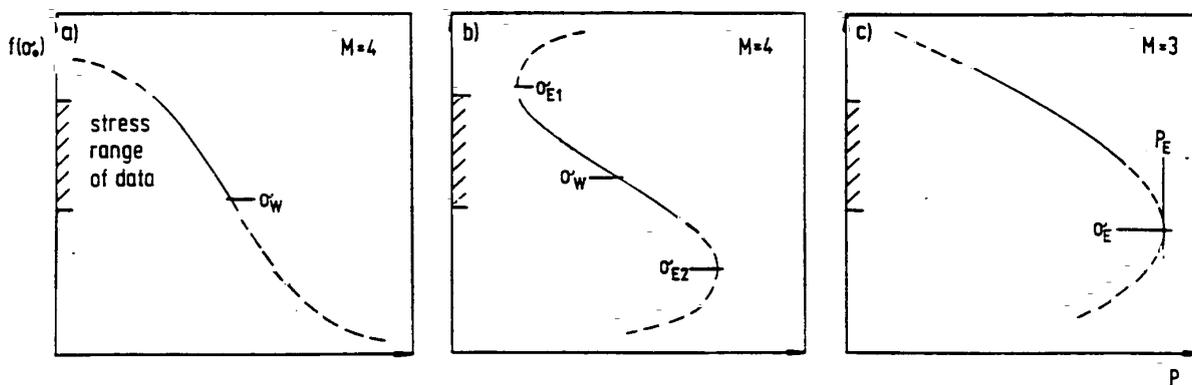


Fig. 3. Model function of a third order polynomial with a point of inflection (a) and additional vertices (b) and model function of a second order polynomial with vertex (c)

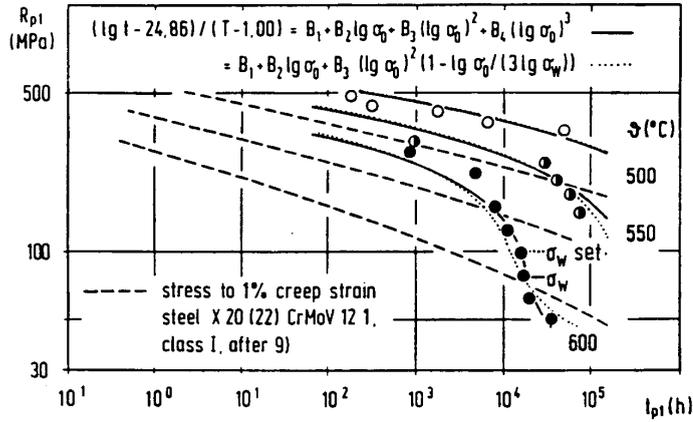


Fig. 4. Evaluation of a material, which shows S-shaped curves in the $\log \sigma_0$ versus $\log t$ -diagram with a third order polynomial, 11Cr-1Mo-0.3V-Nb-N-steel, σ_0 is the stress to 1 % strain

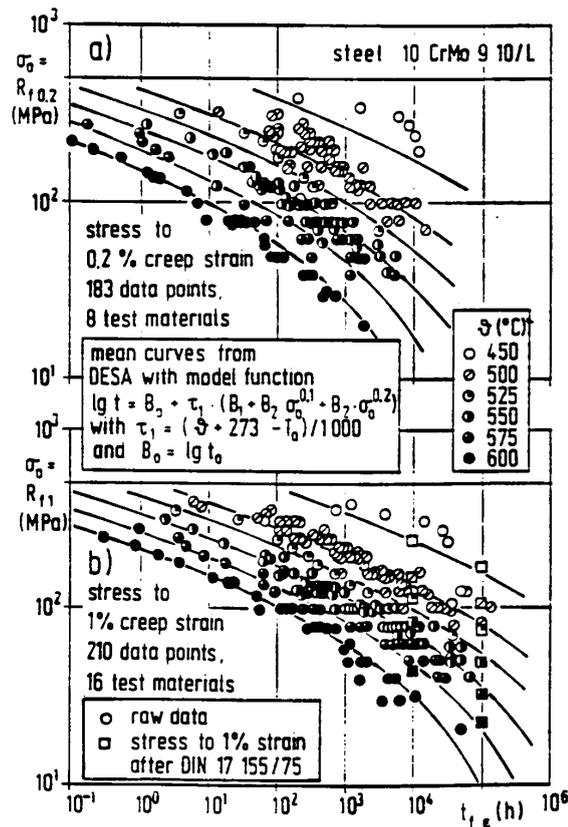


Figure 5. Scatter band evaluation of creep data for 0.2% strain (a) and 1% strain (b) and comparison of the resulting isostrain curves with values from DIN 17 155/75, steel 2.25Cr-1Mo, austenized, aircooled and tempered, after ⁹⁾

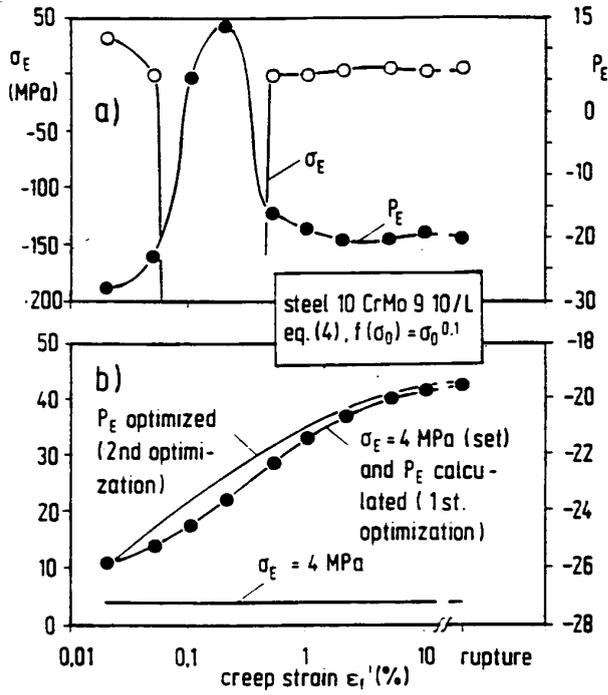


Figure 6. Strain dependency of the coordinates of the vertices of the isostrain master curves (a) resulting from regression analyses and (b) after optimization, steel 2.25 Cr-1 Mo, air cooled

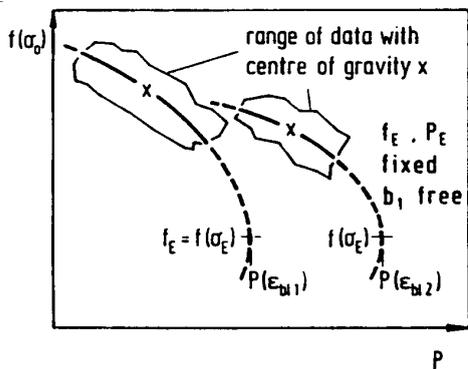


Fig. 7. Example for the influence of different centres of gravity x of test values on adjacent master curves

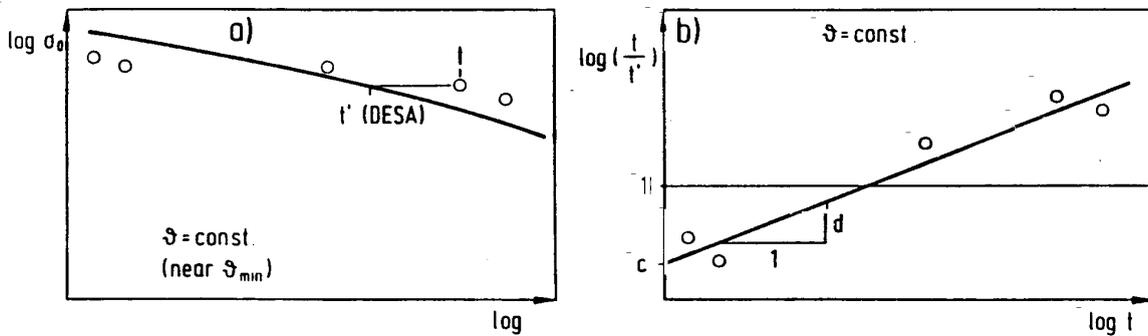


Fig. 8. Principle of the temperature dependent time correction in the log stress-log time-diagram (a) and in a log (t/t')-log t-diagram (b)

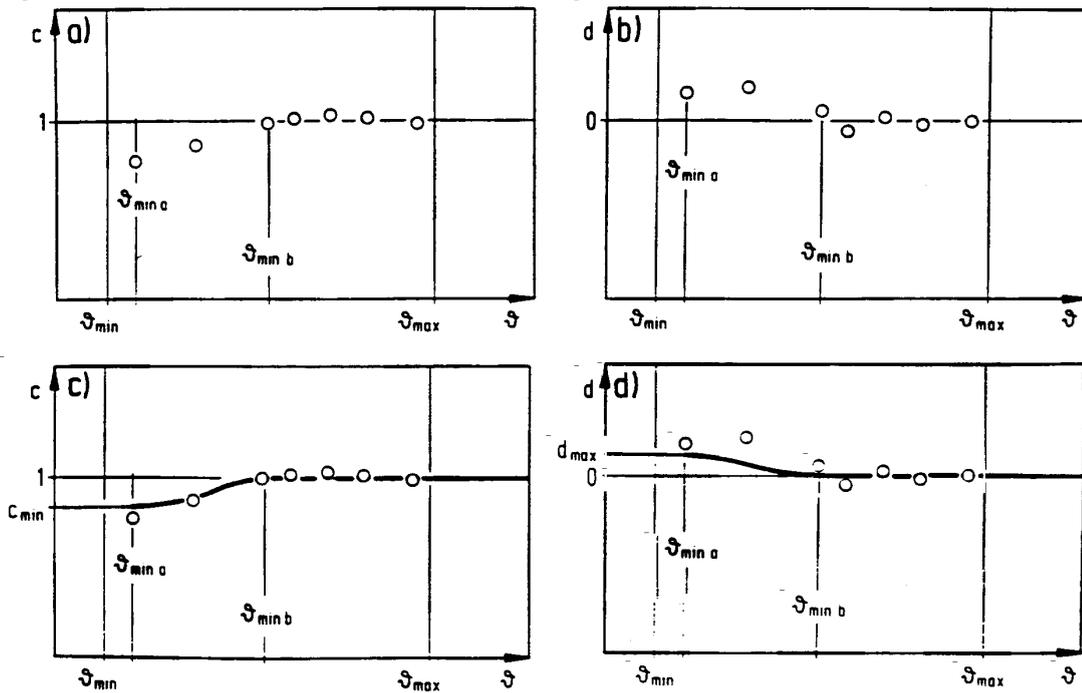


Fig. 9. Scheme of temperature dependent time correction with eq. (36) to (39)

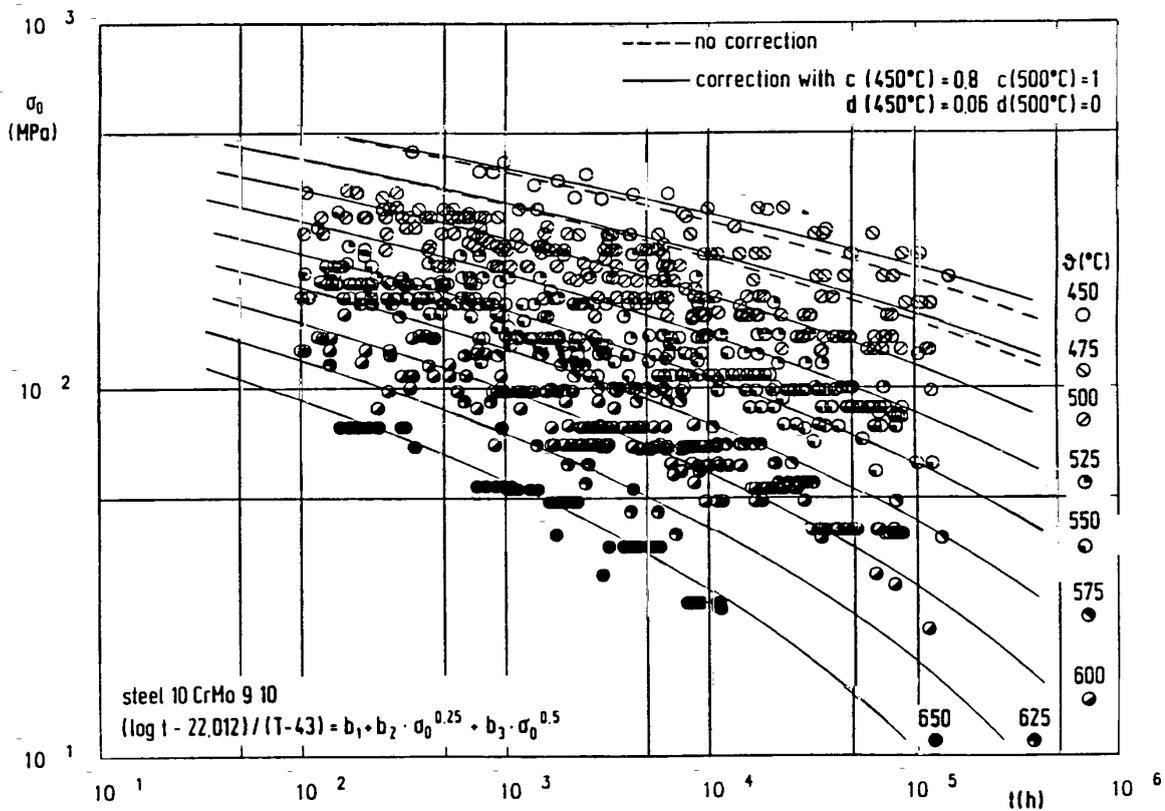


Fig. 10. Example of a temperature dependent time correction of the rupture curves of steel 2.25Cr1Mo in the temperature range of 450 to 500 °C, after 11)

6. Annex

Questionnaire for the Adaption of the Programme DESA to an existing Hardware configuration *)				
IBM-compatible computer, CPU	<input type="checkbox"/> 80 386	<input checked="" type="checkbox"/> 80 486		
Main storage	<input checked="" type="checkbox"/> 8 MB	<input type="checkbox"/>		
Hard disc space	<input checked="" type="checkbox"/> 160 MB	<input type="checkbox"/>		
5 1/4" floppy drive	<input checked="" type="checkbox"/> 1,2 MB			
3 1/2" floppy drive	<input checked="" type="checkbox"/> 1,44 MB			
Graphic card	<input checked="" type="checkbox"/> Herkules	<input type="checkbox"/> EGA	<input checked="" type="checkbox"/> VGA	
Numeric Data Processor	<input checked="" type="checkbox"/> available			
Line Printer	<input checked="" type="checkbox"/> Kyocera	<input type="checkbox"/>		
Plotter	<input checked="" type="checkbox"/> Kyocera	<input checked="" type="checkbox"/> HP7550A		
Printer Port	<input checked="" type="checkbox"/> LPT1	<input type="checkbox"/> LPT2	<input type="checkbox"/> COM1	<input type="checkbox"/> COM2
Plotter Port	<input type="checkbox"/> LPT1	<input type="checkbox"/> LPT2	<input type="checkbox"/> COM1	<input checked="" type="checkbox"/> COM2
No. of PC's with DESA	<input type="checkbox"/>			
*) <input type="checkbox"/> Standard configuration of the IfW				

Please mark or add your configuration and send this form with your address back to

Institut für Werkstoffkunde
Herrn Dr.-Ing. J. Granacher
Grafenstrasse 2

D-64 283 Darmstadt
Fax (49) 6151 165659

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APPENDIX D3

BS PD6605 CREEP RUPTURE DATA ASSESSMENT PROCEDURE

S R Holdsworth[§], C K Bullough[§] & J Orr[✽]

**[§] ALSTOM Power
[✽] CORUS**

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APPENDIX D3

BS PD6605 CREEP-RUPTURE DATA ASSESSMENT PROCEDURE

S R Holdsworth, C K Bullough & J Orr

1. INTRODUCTION

The following appendix reviews the essential features of the BS PD6605 procedure for the assessment of multi-source, multi-cast, multi-temperature creep-rupture data to determine reliable strength values for durations within and beyond the range of the experimental $t_r(T, \sigma_0)$ data. Full details are given in [1].

The procedure is based on rigorous statistical principles but requires metallurgical judgement to ensure that model predictions are physically realistic. Whilst retaining continuity with older deterministic methods (eg. [2]), the new procedure incorporates the following features:

- formal pre-assessment of the stress-rupture data available for the specified material,
- a wide selection of $t_r(T, \sigma_0)$ models enabling the effects of temperature and stress on time to rupture to be analysed simultaneously,
- state-of-the-art statistical treatment of variations in data scatter with both stress and temperature,
- the routine inclusion of unfailed test data in each analysis without subjective judgements,
- confidence intervals on time to rupture,
- independent checks on physical realism, goodness of fit and the repeatability and stability of extrapolations, and
- semi-automation, allowing full advantage to be taken of modern desk top computing power, but with ample provision for user intervention.

This procedure develops upon a formal statistical modelling of creep-rupture data, providing a decision making framework within which a preferred model may be selected. Candidate models are available from two categories of equations classified as TTP (time-temperature-parameter) and Algebraic. The TTP suite of equations include derivatives of the Mendelson-Roberts-Manson (MRM) and Orr-Sherby-Dorn (OSD) models [3-6]. Two Soviet models (SM1 and SM2 [7]) and the Minimum Commitment ($A=0$) model (MC [8]) make up the Algebraic category. The three Algebraic equations do not rely on high order polynomials and have been shown to be effective in modelling creep-rupture behaviour for a variety of materials. There is also the ability to employ user-defined equations. Model selection is based primarily on objective criteria but the procedure recognises the importance of visual inspection of model fits to isothermal data and may require iteration. To this end, ECCC recommendations [9-12] form an integral part of the PD6605 procedure.

BS PD6605 is in two parts [1]. Part 1 contains the procedural details for the derivation of creep rupture strength values; with a) guidance on minimum data requirements, b) information on the statistical background and c) a comprehensive worked example given in appendices. Part 2 provides a description of the computing methods available to support the new procedure and is accompanied by a diskette containing a suite of program utility macros to implement the procedure using the GLIM statistical modelling package¹.

¹ GLIM is a statistical software package supplied by Numerical Algorithms Group Ltd, Oxford, on behalf of the Royal Statistical Society

2. NOTATION

The notation listed below are those referred to in this appendix which are not defined in ECCC Volume 2 [9].

C	percentage confidence interval
LMn, MRn[0]	Larson-Miller model [3], ie. MRM model with $T_o = 0$, $r = -1$ and $q = 0$
MC	Minimum commitment model [8]
MHn, MHn[T_o]	Manson-Haferd model [4], ie. MRM model with $r = +1$ and $q = 0$
MH0n, MHn[0]	Manson-Haferd model with $T_o = 0$
MRM	Mendelson-Roberts-Manson [5]
MRn, MRn[T_o]	MRM model equation with $r = -1$ and $q = 0$ (simplified MRM)
n	degree of polynomial of $\log[\sigma_o]$ in MHn, MRn and OSDn model equations
OSDn	Orr-Sherby-Dorn model [6]
P	culling percentage in <i>Extrapolation-Performance</i> test
SM1	Soviet Model 1 [7]
SM2	Soviet Model 2 [7]
T_o	constant in MRM model equation set ($^{\circ}\text{K}$ in analysis, $^{\circ}\text{C}$ for reporting)
TTP	Time-Temperature-Parameter
$\beta_0, \beta_1, \beta_2,$ $\beta_3, \beta_4, \beta_5$	model parameters in $\ln[t_r^*] = f(T, \sigma_o)$ model equations (see Table 1)

3. OVERVIEW

The procedure is set out in the overall flow diagram (Fig.1), and comprises four main phases:

- 1 An initiation phase in which the material of interest and the scope of the assessment is specified,
- 2 Pre-assessment in which the acceptability of the data is reviewed,
- 3 The main-assessment of the data to determine the most appropriate model equation, together with the best-fit coefficients to describe the data, and
- 4 Post-assessment in which the repeatability and stability of the selected model is assessed, prior to final reporting.

The principal outcome is an optimised model of the stress rupture behaviour together with a relationship for the selected percentage lower confidence limit. These equations are used to derive the creep strength values corresponding to specified conditions of temperature and rupture time. Further background information is given in [13].

4. INITIATION PHASE

Before starting the assessment, it is necessary to precisely define the scope and objectives of the analysis and to collate the appropriate test data and associated material pedigree information. The guidance given on test data acceptability criteria and data collation is largely based on ECCC Volumes 3 and 4 [10,11].

The collation of failed and unfailed/continuing creep rupture data for the specified material grade is initially made without strict adherence to the agreed specification. Non-conforming data are eliminated during pre-assessment, but may usefully lead to the identification of trends during the course of a post assessment re-evaluation. The data collated should meet the material pedigree and testing information requirements recommended in ECCC Volume 3 [10].

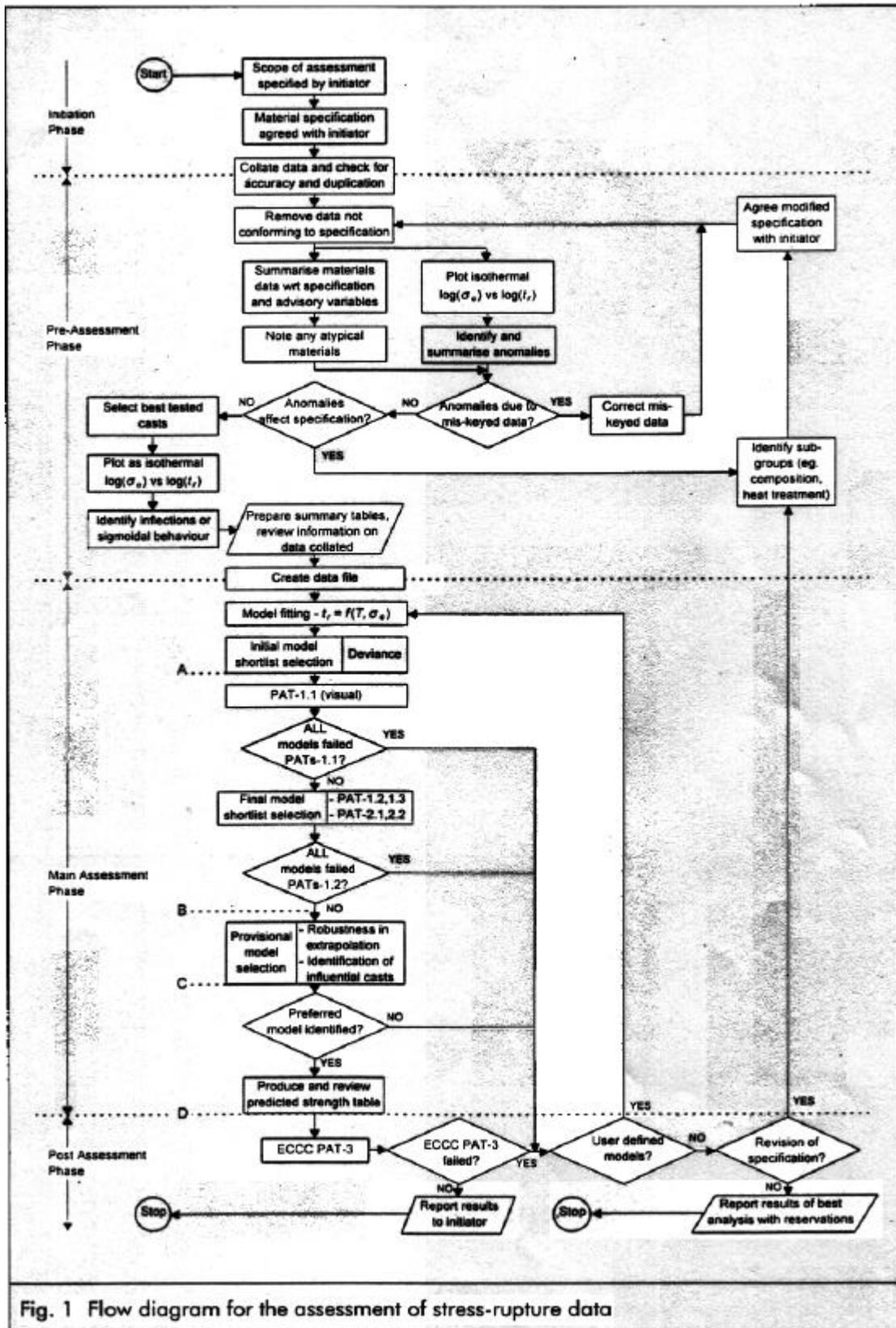


Fig. 1 Flow diagram for the assessment of stress-rupture data

5. PRE-ASSESSMENT

The main objective of the pre-assessment phase is to provide an error free, characterised dataset for consideration in the main assessment. This is achieved during a series of data validation actions and by the preparation of a number of summary statistics tabulations.

5.1 DATA VALIDATION

The collated dataset is first examined for duplicate data entries. These are apparent as simultaneous duplication of information in fields for i) identifier, ii) test temperature, iii) applied stress and iv) time to rupture. All duplications are removed from the dataset.

Those data which do not conform to the agreed specification are identified (for possible future reference) prior to being discarded. Errors in data entry identified during this process are rectified.

All anomalous entries in the dataset are identified, in particular those associated with temperature, stress and time. Care is required to ensure that data points are not incorrectly identified as being anomalous.

Large data scatter in isothermal $\log[\sigma_o]$ vs $\log[t_r]$ plots may arise if one or more of the ranges specified in the material pedigree is too broad. There is the opportunity to revise the specification with the initiator either at this stage or at the time of post assessment if these are deemed responsible for the large data scatter.

5.2 SUMMARY STATISTICS

The data remaining after validation is summarised in accordance with recommended tabular structures. In particular, the distribution of the data is compared with the interim-minimum and target-minimum dataset size requirements recommended in ECCC Volume 5 [12].

A knowledge of the best-tested casts is required (a) to enable the analyst to confirm that the model fit to the $t_r(T, \sigma_o)$ data is an adequate representation of the behaviour of individual casts, and (b) to assist in the identification of sigmoidal behaviour in $\log[\sigma_o]$ vs $\log[t_r]$ curves for one or more temperatures in the dataset.

The preparation of a table showing the distribution of tests in terms of cast identification and temperature is a convenient method of identifying the best-tested casts, particularly if this is performed using a suitable computer based search technique.

6. MAIN-ASSESSMENT

6.1 OVERVIEW

The Main Assessment is divided into a number of steps (Fig. 2). These involve fitting statistical models to the data and checking the physical realism of the alternative formulations. Following model fitting a shortlist of models is established, initially based upon goodness-of-fit criteria, but finally on the results of PAT-1 and PAT-2 tests. One or more provisional model(s) are chosen from the final shortlist and two selection tests are provided for this purpose. The first provides a simple measure of extrapolation performance when part of the dataset is removed. The role of the second is to alert the analyst to any individual cast (or casts) which have an undue influence on the assessment, and to provide a final selection indicator if more than one provisional model remains after the extrapolation-performance test. These steps will usually identify a preferred model which should then be used to produce a table of predicted strength values.

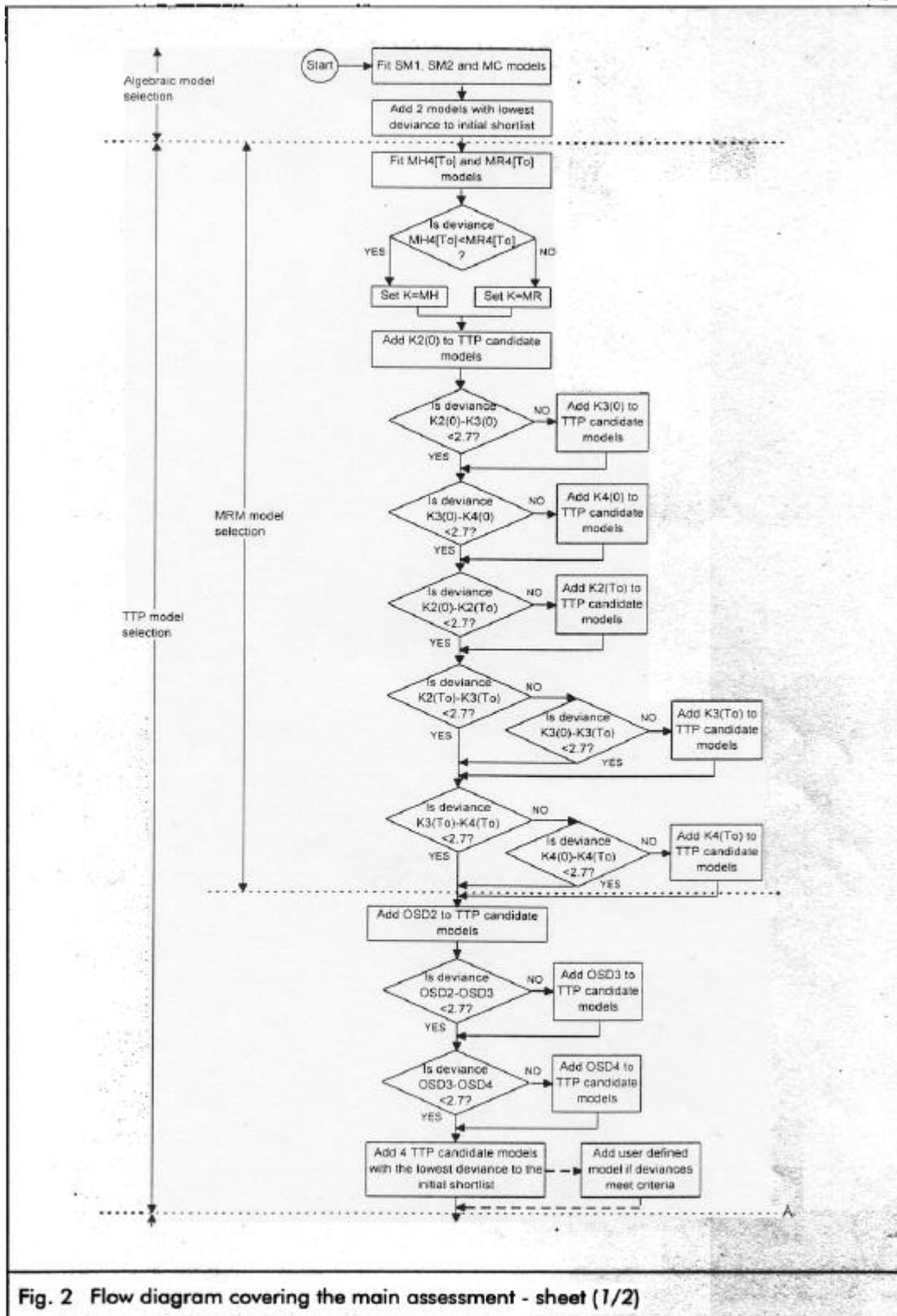


Fig. 2 Flow diagram covering the main assessment - sheet (1/2)

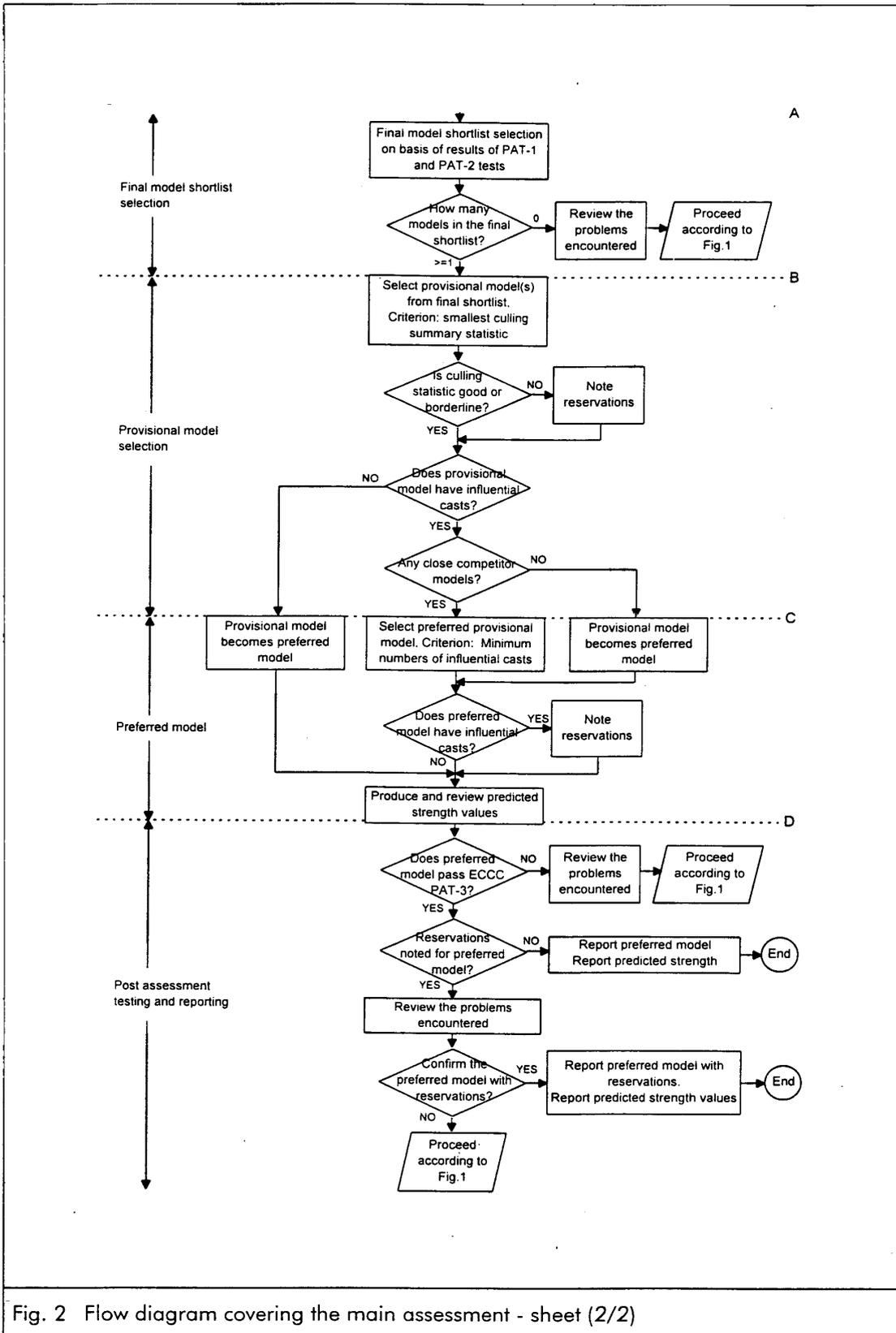


Fig. 2 Flow diagram covering the main assessment - sheet (2/2)

In the event of no preferred model being identified or of the preferred model subsequently failing the post assessment test, opportunities are provided for the analyst to investigate (i) user defined models and/or (ii) criteria for subdividing the dataset, employing the same statistical modelling framework to obtain objective measures of the improvement in goodness-of-fit.

6.2 FITTING THE DATA TO CANDIDATE MODELS

On the completion of pre-assessment, a text file containing the data to be evaluated in the main assessment is created.

Within the software supplied, three options are available for left censoring very short duration test data. These are: (i) not to censor, (ii) to exclude tests with a short failure time of <10 hours, or (iii) as (ii) but also to exclude all other data points tested at the same or higher stress at the same temperature (to avoid statistical bias by simply censoring the dependent variable).

All the models listed in Table 1 are fitted according to the guidance given in Fig. 2. In Table 1, σ_o is the stress, T is the temperature, and $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$, and T_o are the parameters to be estimated. A summary table of the model parameters and deviances is prepared to facilitate model selection [1].

MODEL	TREND EQUATION	CODE
Soviet Model 1	$f(T, \sigma_o) = \beta_0 + \beta_1 \log[T] + \beta_2 \log[\sigma_o] + \beta_3/T + \beta_4 \sigma_o/T$	SM1
Soviet Model 2	$f(T, \sigma_o) = \beta_0 + \beta_1 \log[T] + \beta_2 \log[\sigma_o]/T + \beta_3/T + \beta_4 \sigma_o/T$	SM2
Minimum commitment, A=0	$f(T, \sigma_o) = \beta_0 + \beta_1 \log[\sigma_o] + \beta_2 \sigma_o + \beta_3 \sigma_o^2 + \beta_4 T + \beta_5/T$	MC
Mendelson-Roberts-Manson	$f(T, \sigma_o) = \{ \sum_{k=0}^n \beta_k (\log[\sigma_o])^k \} (T - T_o)^n / \sigma_o^{-9} + \beta_5$	MRM
Simplified MRM [‡]	$f(T, \sigma_o) = \{ \sum_{k=0}^n \beta_k (\log[\sigma_o])^k \} / (T - T_o) + \beta_5 \quad (n = 2,3,4)$	MRn
Larson-Miller [‡]	$f(T, \sigma_o) = \{ \sum_{k=0}^n \beta_k (\log[\sigma_o])^k \} / T + \beta_5 \quad (n = 2,3,4)$	LMn
Manson-Haferd [‡]	$f(T, \sigma_o) = \{ \sum_{k=0}^n \beta_k (\log[\sigma_o])^k \} (T - T_o) + \beta_5 \quad (n = 2,3,4)$	MHn
Manson-Haferd with $T_o=0$ [‡]	$f(T, \sigma_o) = \{ \sum_{k=0}^n \beta_k (\log[\sigma_o])^k \} \cdot T + \beta_5 \quad (n = 2,3,4)$	MH0n
Orr-Sherby-Dorn	$f(T, \sigma_o) = \sum_{k=0}^n \beta_k (\log[\sigma_o])^k + \beta_5/T \quad (n = 2,3,4)$	OSDn

[‡] these models derive from the Mendelson-Roberts-Manson (MRM) suite of equations

6.3 MODEL SELECTION

6.3.1 Initial short list

Following model fitting, an initial shortlist is constructed. The flow diagram in Fig. 2 leads the analyst to select a variety of model types for the initial shortlist. These typically include the two best fitting Algebraic models and the four best fitting TTP models. The criteria given in the flow diagram ensure that lower-order polynomials in the TTP suite of equations are represented in the shortlist to compete with higher order polynomials. This is because higher order polynomials have better goodness of fit properties than lower order polynomials but may not perform well in extrapolation.

User defined models may also be included in the initial shortlist if their deviance is within or below the range of deviances of the six models shortlisted above.

6.3.2 Final short list

The physical realism and effectiveness of the predicted isothermal lines to model the observed $\log[\sigma_0], \log[t_r]$ data is assessed for each model in the initial short list to provide a final short-listing. This is achieved using ECCC PAT-1 and PAT-2 [12].

6.3.3 Preferred model selection

The preferred model is identified on the basis of information from two selection tests. The *Extrapolation-Performance* test is the main indicator. However, the *Influential-Cast* evaluation provides the final selector in the event of more than one provisional model emerging from the first test.

In the *Extrapolation-Performance* test, the data are culled by removing P% of the data points at the lowest stresses for each temperature (similar in principle to PAT-3.2 [12]). Typically, P is 30% except for metallurgically active steels where 15% culling is more appropriate². The software generates a culling statistic indicating the acceptability of the model in terms of 'robustness-in-extrapolation'. An unacceptable outcome raises serious doubts about the accuracy of extrapolations from the model.

It is important to identify whether any casts individually have an important influence on the provisional model(s) so that this undesirable situation can be avoided if possible or reported alongside the final results if inevitable. Casts may be influential for two main reasons. Firstly, the cast may have a distinctive set of outcomes and contribute a sufficiently large number of stress-rupture test results for this to have a notable affect on the trend line estimated. Secondly, the cast may contribute a high proportion of the low stress test results and thereby exert appreciable influence on the trend-line at the right hand side of the data range. In the former case, the cast is likely to be influential for any model. However, in the latter (rarer) case, the effect will usually be less pronounced for models which do not include high order polynomials. It may therefore be possible to avoid the problem by judicious model selection.

A cast is considered to be influential if its exclusion causes a change of more than 10% in the estimated failure time at the lowest failed stress for the temperature being examined. Failure times are compared at three temperatures, ie. $T_{min[10\%]}$, T_{main} and $T_{max[10\%]}$ using the software supplied.

6.4 PREDICTED STRENGTH TABLES

The final step of the main assessment is to produce a table of predicted strength values for the preferred model. The software generates various options of predicted strength tables along with lower C% confidence intervals where C is selected by the user.

Strength predictions are qualified in terms of extended time extrapolations and extended stress extrapolations, defined in accordance with [12,14].

7. POST-ASSESSMENT

The preferred model becomes the adopted model if it meets the requirements of the ECCC PAT-3.1 test [12]. A stress-based culling test has already been performed as part of the main assessment (ie. in the *Extrapolation-Performance* test) and consequently the execution of PAT-3.2 is unnecessary at this stage.

² The alloy should have been identified as being metallurgically active during pre-assessment.

It is possible that, as a result of the foregoing procedure, none of the models investigated provide a wholly adequate representation of the data (Fig. 1). This situation may arise from a number of circumstances, each of which must be addressed differently.

There may be insufficient data points or the range of variables tested is too restricted. There is no analytical solution to this problem and additional testing is the only way forward to determine fully acceptable strength values without attached reservations.

The available models may be insufficiently flexible to describe the observed behaviour. A better description may be achieved by specifying a more flexible model; in particular formulisms which allow greater sensitivity to temperature. There is the opportunity to implement own-user-defined models in the software supplied. Alternatively, it may be necessary to restrict the assessment to a narrower range of temperatures or to sub-divide the data into two or more temperature ranges.

The inability to determine an acceptable model-fit may be due to too broad a range of metallurgical characteristics being encompassed by the specification or testing conditions. In this case, the data can be divided into two or more classes on the basis of metallurgical properties and/or cast features. The characteristics which result in the greatest reduction in deviance are those which should be considered for subdividing the class of alloy, thereby producing more homogenous classes. A software implemented deviance test is provided to assist in alloy class sub-division.

An example of the results of a successful PD6605 assessment is shown in Fig.3.

8. REPORTING

The output of a BS PD6605 assessment is a comprehensive reporting package more than meeting the requirements of ECCC Volume 5. The reporting package is illustrated in the worked example.

9. REFERENCES

- 1 BS PD6605; "Guidance on methodology for the assessment of stress rupture data", 1998.
- 2 ISO 6303-1981E; "Pressure vessel steels not included in ISO 2604 Parts 1-6 - Derivation of long-time stress rupture properties", Annex: "Method of extrapolation used in analyses of creep rupture data".
- 3 F R Larson & J Miller; "A time-temperature relationship for rupture and creep stress", Trans ASME, 1952, 74, 765.
- 4 S S Manson & A M Haferd; "A linear time-temperature relation for extrapolation of creep and stress rupture data", NASA TN 2890, 1953.
- 5 A Mendelson, E Roberts & S S Manson; "Optimisation of time-temperature parameters for creep and stress-rupture, with application to data from German co-operative long time creep program", NASA Technical Note: NASA-TN-D-2975, 1965, August.
- 6 R L Orr, O D Sherby & J E Dorn; "Correlation of rupture data for metals at elevated temperatures", Trans. ASM, 1954, 46, 113.
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- 8 S S Manson & U Muralidhan; "Analysis of creep rupture data for five multi-heat alloys by minimum commitment method using double heat term centring technique", Research Project 638-1, EPRI CS-3171, 1983, July.

- 9 ECCC-WG1 Recommendations Volume 2; "Terms and terminology for use with stress rupture, creep and stress relaxation: Testing, data collation and assessment", ECCC Document 5524/MC/23 [Issue 5], Edited: J Orr, Publ. ERA Technology Ltd, Leatherhead, September 1996.
- 10 ECCC-WG1 Recommendations Volume 3; "Acceptability criteria for stress-rupture, creep and stress relaxation data", ECCC Document 5524/MC/30 [Issue 3], Edited: J Granacher & S R Holdsworth, Publ. ERA Technology Ltd, Leatherhead, October 1996.
- 11 ECCC-WG1 Recommendations Volume 4; "Guidance for the exchange and collation of creep rupture, creep strain-time and stress relaxation data for assessment purposes", ECCC Document 5524/MC/68 [Issue 2], Edited: C K Bullough & G Merckling, Publ. ERA Technology Ltd, Leatherhead, October 1996.
- 12 ECCC-WG1 Recommendations Volume 5; "Guidance for the assessment of creep rupture, creep strain and stress relaxation data", ECCC Document 5524/MC/38 [Issue 3], Edited S R Holdsworth, Publ. ERA Technology Ltd, Leatherhead, October 1996.
- 13 S R Holdsworth & R B Davies; "A recent advance in the assessment of creep rupture data", Proc. SMiRT Post Conf. Seminar on Intelligent Software Systems in Inspection and Life Management of Power and Process Plants, Paris, August 1997.
- 14 BS PD 6525 Part 1: 1990; "Elevated temperature properties for steels for pressure purposes; Part 1 - Stress rupture properties", [Amendment 2], February 1994.

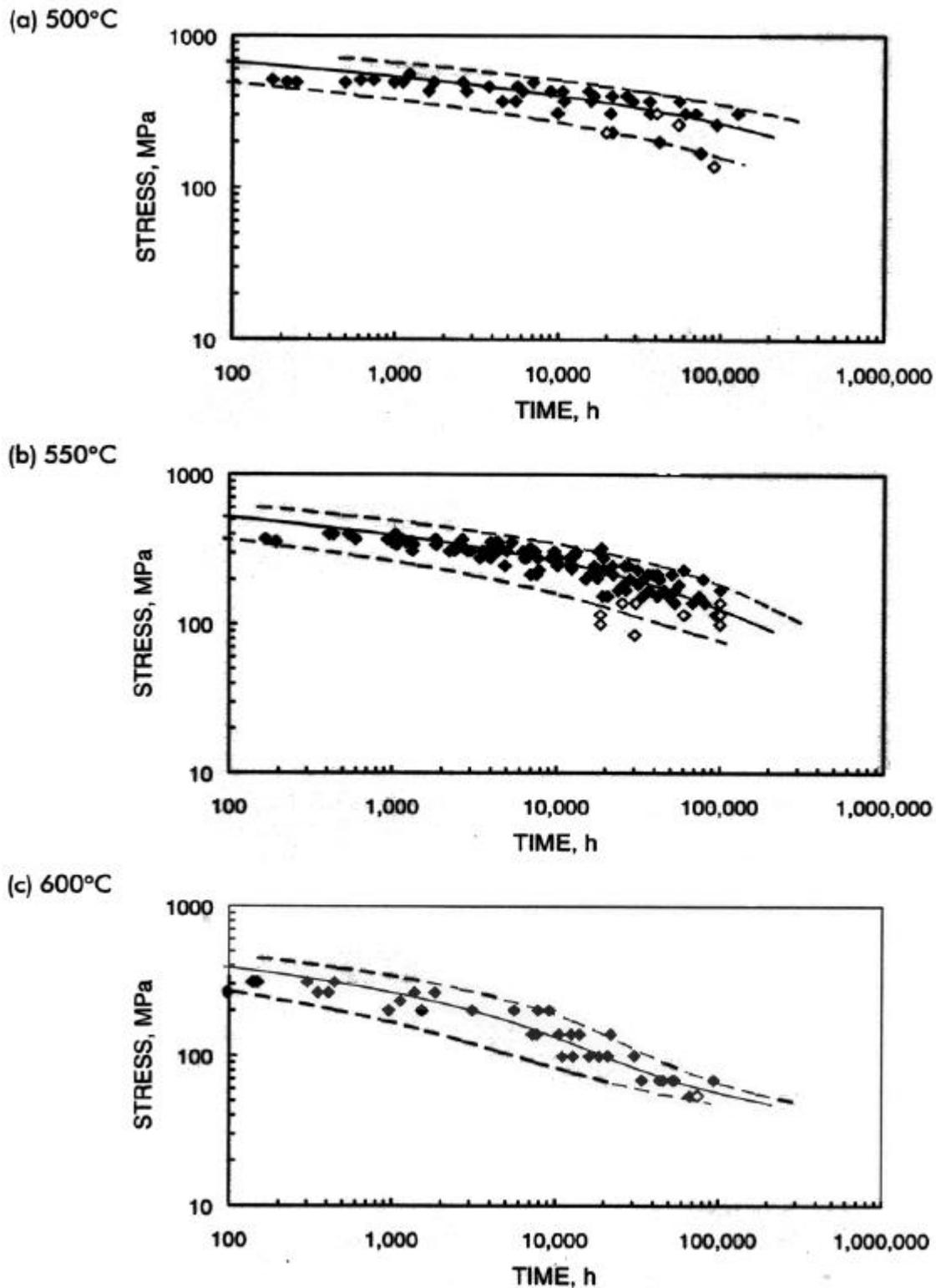


Fig.3 Isothermal plots of creep rupture data for a 12Cr alloy at 500, 550 and 600°C showing model fit lines and 95% confidence intervals (solid points - failed data, open points - unfailed data)

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APPENDIX D4

**ECCC PROCEDURE DOCUMENT FOR GRAPHICAL MULTI-HEAT AVERAGING AND
CROSS PLOTTING METHOD**

J Granacher & M Schwienheer [IfW TU Darmstadt]

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ECCC – WG1 - Procedure Document on Graphical Multi-Heat Averaging and Cross Plotting Method

Document of 05.04.2001

Approved by the Arbeitsgemeinschaften fuer warmfeste Stähle und Hochtemperaturwerkstoffe

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1. Introduction

The graphical assessment of creep rupture data is the eldest method which was generally used before numerical assessment methods, i.e. time temperature parameter methods and computer based procedures were introduced. The time expenditure for the graphical method is relatively high. However, as an advantage, the assessor wins an intimate knowledge about the creep rupture data. Another advantage is the high flexibility of the method. This is of special importance when metallurgical unstable materials are considered which may show sigmoidal isothermal curves.

Due to the flexibility of the graphical method, the different needs of assessment and different laboratory traditions, there exist many variants, which can not all be described in this document. The following description is limited to the problem to assess time to plastic strain data and time to rupture data of a steel type or steel grade, which was creep rupture tested on a sufficient number of individual materials (heats, casts). The aim is to determine the average behaviour of that steel type or steel grade in the temperature, stress and time ranges being of interest and covered by data.

The data needed for a graphical assessment are similar to those for numerical assessments. These are for any individual material tested:

- the pedigree data characterizing the chemical composition, production process and heat treatment and other relevant conditions as test piece position within the material, see Vol. 4 ,
- the test data which are test temperature T , stress σ_0 , times to plastic strain $t_{p0.2}$, $t_{p0.5}$, t_{p1} , t_{p2} and rupture time t_u .

A pre-assessment has to be carried out according to chapter 2.3 of Vol. 5.

The post assessment tests (PAT's) recommended for numerical assessments, are differently to be applied to the graphical method. Whereas the PAT's 1 and 2, which concern the evaluation of the assessed curves and their deviations from the original data points, shall be

introduced into the graphical method after a certain transition time, the PAT 3, which compares extrapolations from the full data set and reduced data sets can not be fully applied. However, a reduced post assessment procedure seems to be applicable and is proposed for the future.

2. Graphical Averaging and Cross Plotting Method

The below described Graphical Averaging and Cross Plotting Method has been used for many years, especially in Germany^{1) 2) 3)} but also in Austria and other countries for the assessment of creep and rupture data to produce the creep strength and rupture strength values reported in DIN- and EN-standards. The method is subdivided into individual assessment steps. The following description refers to a flow chart (Fig. 1) and to schematical diagrams which explain individual steps. Beside the references^{1) to 3)}, references^{4) to 5)} were used.

2.1 Data Selection

The experimental data have to be evaluated to examine whether they fulfill a chosen material specification in national or international standards or one chosen by another authorised organisation. Any individual material (heat, cast) of the alloy considered has to be examined, whether the main alloying elements, the production, the heat treatment and the mechanical properties at room temperature are situated in the frame of the specification. It has to be checked whether the distributions of yield strength or rupture strength values at room temperature suggest a subdivision of the material into different grades, which have to be separately assessed. Finally, data from individual materials of a material grade are to be removed if they are outside the specification accepted. This procedure corresponds to the pre-assessment points (i) and (ii) of chapter 2.3, Vol 5⁶⁾.

2.2 Isothermals of the Individual Materials

For any individual material selected for a material grade and for any test temperature, the time to specific plastic strain or to rupture data points are plotted into a $\log \sigma_0 - \log t$ - diagram. The scaling of the axes shall assure a good resolution and may not be changed during an assessment. A creep strength or rupture strength curve (isothermal) is graphically drawn which equalizes the deviations between the individual data points (Fig. 2). Data points which are close to a specific strain or near rupture can support the assessment. Further, comparisons between the creep strength curves and the rupture curve can support the

assessment and effect small adjustments. Such a "curve family assessment" is characteristic for the graphical method. It can also be carried out with numerical methods but needs special programs and additional effort. Moreover, the numerical methods can be too rigid for a successful application in all cases⁷⁾. However, instead of the graphical determination of the isothermals a computerized polynomial least squares fit can be applied at that stage of the assessment if a visual control of the isothermals confirms a good data interpretation. For a final assessment of property values, the isothermals may not be prolonged by more than a factor of 3 beyond the longest experimental time.

2.3 Determination of Strength Values of the Individual Materials

From the isothermals of the individual materials (Fig. 2) the values of creep strength or rupture strength were determined for characteristic time values of $t_i = 3 \cdot 10^3$, 10^4 , $3 \cdot 10^4$, 10^5 and $3 \cdot 10^5$ h. These strength values are plotted in a linear or a logarithmic scale against temperature T for each individual time value (Fig. 3). Further, individual isochronous curves $\sigma_{0k}(T)$ are drawn which equilibrate all data points of the correspondent individual materials.

2.4 Average Strength Values from the Individual Materials

From the correlated data points in the $\sigma_0(\log \sigma_0) - T$ - diagrams (Fig. 3) for each characteristic time value t_i an arithmetic (or logarithmic) average is determined and an average isochronous curve $\sigma_0^*(T)$ is graphically drawn through the average data points. The logarithmic average should be preferred because creep rupture stresses present a standard distribution in the logarithmic scale rather than in the linear scale.

For each characteristic time value t_i , the average curves $\sigma_0^*(T)$ and the individual curves $\sigma_{0k}(T)$ are compared to each other and the average curve is adjusted if necessary. This is a first internal assessment test (IAT 1) which is typical for the graphical method but untypical for numerical methods, which need post assessment tests after completion of the assessment. IAT 1 corresponds in some way to PAT 2.2 in Vol. 5. If large deviations appear between the average curve and the individual curves, the original data are re-examined, whether an explanation for the deviations can be derived, which influences the average. For acceptable small deviations, a comparison of average curves for adjacent time values is made (Fig. 4), which can lead to additional adjustments. This is a second internal assessment test (IAT 2), which assures continuously spaced isochronals in the stress-temperature-time-space, as is aimed in another way in PAT 1 of Vol. 5. Finally, the isochronous average points are retransferred into a $\log \sigma_0 - \log t$ - diagram and average isothermals are drawn (Fig. 5). The

resulting average data points are retransferred into Fig. 4. If they do not sufficiently agree to the original average curves, these data points are retransferred into the diagrams of Fig. 3 and readjusted considering again the isochronals of the individual materials. This internal assessment test (IAT 3) corresponds partly to PAT 1 (assuring sound curve families by cross plotting) and partly to PAT 2.2 comparing individual and average isochronals.

The result is always a data fit $\sigma_0^*(t,T)$ based on cross plotted average isochronals and isothermals which are originally derived from average strength values from the individual materials.

If the assessment is performed for different strength values, i.e. rupture strength and creep strength values, the demonstrated assessment steps can be performed in parallel for the different strength values. The $\sigma_0^*(T,t)$ -values of Fig. 4 and 5 can be compared for all plastic strain values treated and for rupture and if necessary they can be improved. For the first time this procedure can be performed at the end of point 2.4. Preferably it is performed at the end of point 2.6, as described in chapter 2.6.

2.5 Isothermals from Direct Scatterband Analysis

Besides the use of average stress values from the individual materials, point 2.2 to 2.4, the graphical method provides a direct scatterband analysis which is based on isothermal data sets containing each the data from all individual materials. This branch of the assessment is again performed for the rupture strength and/or for one or more creep strength values. The time to strain or to rupture data points for all individual materials are plotted for each temperature in a $\log \sigma_0 - \log t$ - diagram (Fig. 6). Through the isothermal data points a directly determined average isothermal $\sigma_{0d}^*(T)$ is graphically drawn which equilibrates the data points and which, in the case of a final assessment of property values, again may not exceed the longest experimental time beyond a factor of 3.

For a reduced post assessment test which approximates PAT 3.1 of Vol. 5, each second data point in the range t_{max} to $t_{max}/10$ is removed (Fig. 7) and from each reduced isothermal data set a second average isothermal is drawn. From each of these a strength value $\sigma_{0d}^*_{red}$ is read of at the smaller value of 300 000 h or $3 \cdot t_{max}$. These strength values are reserved for a later comparison in point 2.6.

In relation to the isothermals which were directly averaged from the full data set, a scatterband width of the individual data points is determined which is approximately $\pm 20\%$ in the normal case. In a special version of the method the lower scatterband limit is set to -20% of the average with the consequence, that the average isothermals may have to be re-

adjusted. This special version is connected to design rules which suppose the lower scatterband limit to be situated 20 % below the average. In general, the scatterband width of rupture data is assumed to be larger than that of the correspondent time to strain data. For data points outside the scatterband, the test data are re-examined. When an individual material is characterized by outliers, the data selection process has to be repeated with a revised input specification, and the assessment has to be repeated. This comparison between the original data points on the one hand and the directly determined isothermals on the other hand is a further internal assessment test (IAT 4) which corresponds in some way to PAT 2.1 of Vol. 5.

To avoid unnecessary assessments, the direct scatterband analysis can precede the assessments of points 2.3 and 2.4, if relatively large deviations are detected during the assessment of the isothermals of the individual materials according point 2.2.

2.6 Comparison of the Average Strength Values from the Individual Materials and the Direct Scatterband Analysis

The average values σ_0^* resulting from point 2.4 are compared to the average values σ_{0d}^* from point 2.5. This is the internal assessment test IAT 5. If the agreement is unsatisfactory, the assessment has to be re-examined and the $\sigma_{0d}^*(t,T)$ -values in Fig. 6 as well as the $\sigma_0^*(T,t)$ -values in Fig. 3 and 4 have to be re-adjusted considering the best possible fit to the original data points in these Figures. Thereafter the internal assessment test IAT 5 has to be repeated. If these values and the correspondent curves are in a good agreement, additional comparisons have to be performed between the average curves of creep strength (if determined) and rupture strength (Fig. 8), as yet indicated in the end of chapter 2.4. These curves are judged as a family to avoid them crossing over, or converging in an unrealistic manner. Also from these comparisons according to the internal assessment test IAT 6 small adjustments may be derived if necessary. The $\sigma_0^*(T,t)$ -values in Fig. 8 have to be adjusted and to be transferred into Fig. 4 to repeat the IAT's 5 and 6.

Finally the post assessment tests PAT 1 and 2 (chapter 2.4 of Vol. 5) can be applied. This will need computer based data sets and will not be necessary before the transition time of 5 years (chapter 1). PAT 3.1 can be applied even now in a specific form by comparing the final $\sigma_0^*_{3 \cdot 10^5 T}$ -values from Fig. 4 to the $\sigma_{0d}^*_{red 3 \cdot 10^5 T}$ -values from the time reduced isothermal data sets (Fig. 7). If the differences at the main temperatures exceed $\pm 10\%$, the assessment has to be repeated. Else, the assessment is finished and the averaged isochronous curves $\sigma_0^*(T)$ deliver the property values of creep strength $R_{pE t T}$ or rupture strength $R_{u t T}$ of the material grade assessed.

2.7 Comments on Internal and Post Assessment Tests

As compared to the post assessment tests PAT 2 of Vol. 5, a typical feature of the internal assessment tests IAT of the graphical method is, that the decisions about "large, small or medium deviation" and "good or insufficient agreement" are left to the graphical assessor who is conscious of the specific scatter of the data to be assessed.

The post assessment tests of Vol. 5 were introduced to evaluate and if necessary to improve the results of computer supported numerical assessment. These are derived from model functions which are to a certain degree pure formal. If such model functions are used, several decisions are made automatically or are the result of minimum square fits which can only to a limited degree be mastered in the sense that the most probable long term strength values result. In these cases post assessment tests clearly are of great value. However, at a graphical assessment, several internal assessment tests are yet performed during the assessment itself (Fig. 1) and appropriate adjustments are included in the method itself and therefore have not to be applied after the final results are submitted to a post assessment test. Therefore, in the past, experienced graphical assessors did not feel the necessity to apply the PAT's of Vol. 5 on graphical assessments.

As the physical realism of the predicted isothermal lines is concerned, this is checked during the graphical assessment. The fit of the isothermals over the data range (PAT 1.1) and no cross over, come together or turn back (PAT 1.2) is guaranteed by the cross plotting and comparison procedures. The same is valid for a reasonable slope of the isothermals (n -value). A realistic slope of the isothermals is always to be expected from a graphical procedure, whereas a computer supported model function can produce erroneous slopes. Moreover, the graphical method is, as earlier mentioned, the best adapted one to draw sigmoidal isothermals when this is necessary.

As the effectiveness of model prediction within the range of input data is concerned (PAT 2.1 and 2.2), this is assured in the graphical assessment by the repeated comparisons between t^* -data (average data) and t -data (individual materials experimental data) which are performed in the internal assessment tests. So the PAT's 2.1 and 2.2 are performed during the graphical assessment itself. If one of these PAT's is violated the reason is a bad data situation which can not be improved by another graphical assessment but only by a re-examination of individual material data, which is part of the graphical method.

As the repeatability and stability of the extrapolations is concerned (PAT 3.1 and 3.2), the graphical assessment considers the special action of the long term data on the extrapolation to a much larger degree than is possible with any minimum square fit which has to consider all data at once over the full time range. Moreover, the cross plotting of isochronous data against

temperature assures an optimum time temperature correlation which is superior to a formal time temperature parameter, which has to be invariable over the full data range. Whereas cull tests make sense for the formal computer based procedures this is not the case for the graphical assessments. Here the isothermals are determined beginning at the short time end. When the curves are being continued up to the longer times, the influence of the additional data points onto the slope of the isothermals is continuously observed which is the actual sense of a culling technique. So as is indicated in [Fig. 9](#) a cull test is implicitly realized during the graphical assessment.

However, an important point favours the introduction of the PAT's into the graphical assessment method. This is the generation of numbers characterizing the quality of the assessment. It is proposed therefore, that the PAT's 1 and 2 will be introduced into the graphical assessment method after a transition time of 5 years, i.e. from year 2006. It is assumed that after that time original data as well as assessment results will be available in digitalized form. In connection with special programs as DESA-PAT⁸⁾, which are going to be prepared, the application of the PAT's 1 and 2 will be relatively easy then. The full introduction of the PAT's 3.1 and 3.2 into the graphical method would prohibit the application. The introduction of the simplified PAT 3.1 into 2.6, Fig. 1 seems to be sufficient.

3. Special Characteristics of the Graphical Multi-Heat-Assessment

A special facility of the graphical method is, that an inhomogeneous heat situation in which a restricted number of heats presents only short time data or data at a reduced number of temperatures, can be equilibrated, as demonstrated in [Fig. 10](#). The graphical assessor is able to prolong the isothermal of material 3 and thus to avoid the "error" of the numerical procedure to average 3 curves at shorter times and 2 curves at longer times. This situation which is typical for multi-heat data and can produce serious assessment errors, is not commented in Vol. 5. With numerical procedures the situation can at best be used to give a warning⁷⁾. Another but difficult and problematic way is to equilibrate the data by a data reduction. Another way is to hope that the situation may be "statistically equilibrated". However, this has been refuted in⁷⁾. So, a main advantage of the graphical assessment as compared to a numerical assessment is, that an unequilibrated number of individual materials at different temperatures and time values can be balanced to a certain degree.

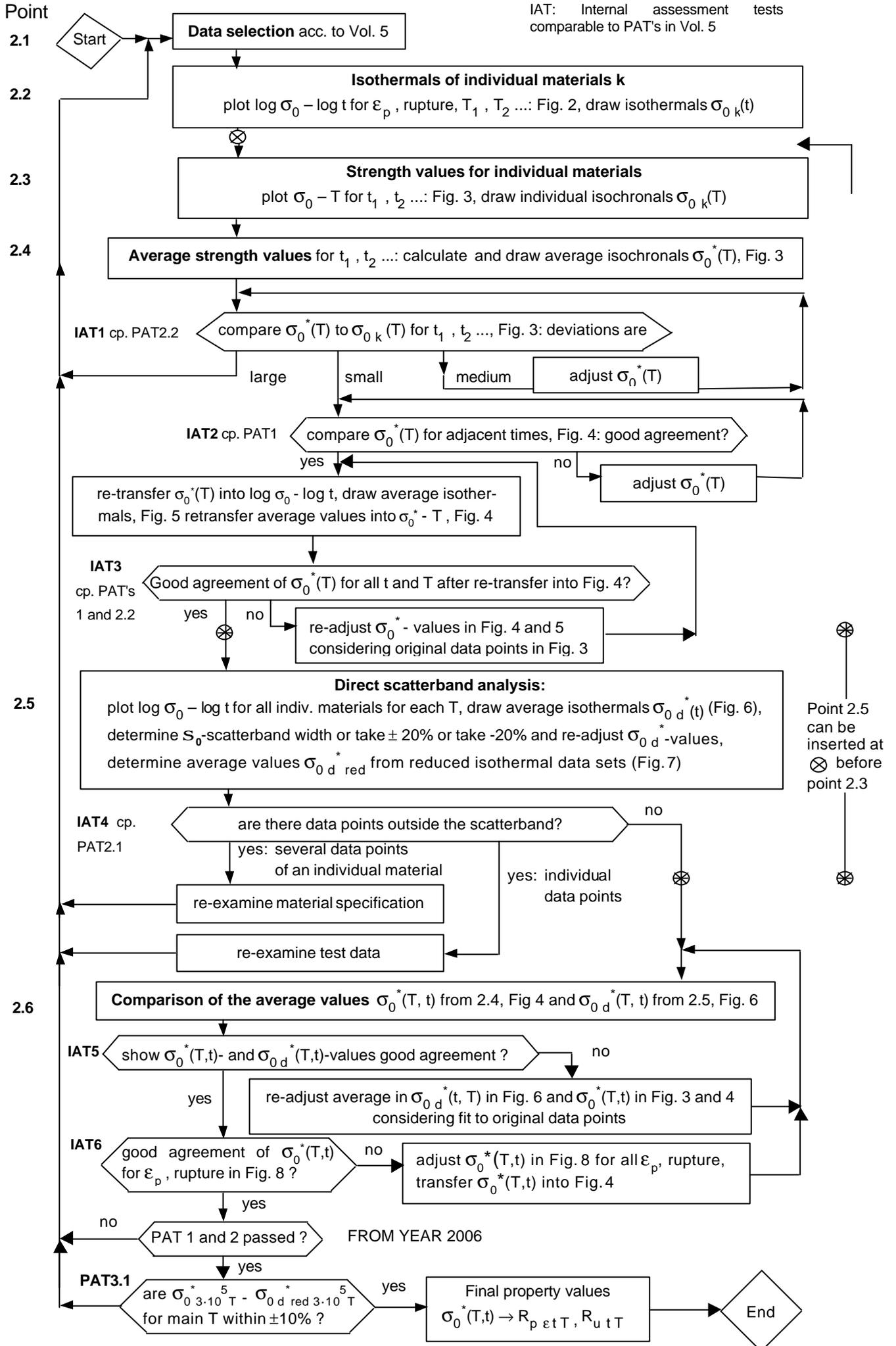
Another, yet repeatedly mentioned advantage of the graphical method is, that it is of special advantage if apparently sigmoidal isothermals curves are to be assessed. With numerical methods this is possible in principle but very difficult, especially in cases, where the sigmoidal behaviour does not follow the time temperature parameter used for the assessment.

Another yet mentioned feature of the graphical method is that the limit of "good agreement" is not automatically defined by a value like a calculated standard deviation. On the contrary "good agreement" can be defined by the assessor in dependency of the material, heat and data situation. This is an advantage for the evaluation of the assessment results which is not submitted to a inflexible regulation.

A special problem of the graphical assessment method is the high time expenditure which is necessary. However, this does not need to be a disadvantage because it gives the assessor a better insight into the data situation. For the future, a computer aided graphical method would be of interest which releases the assessor from the extensive cross plotting and averaging work but leaves to him to adapt the curves to the experimental data. However, the development of such a method is difficult, because interactive procedures have to be realized on the computer.

4. References

- 1) Ergebnisse deutscher Zeitstandversuche langer Dauer, Ed.: Verein Deutscher Eisenhüttenleute in Zusammenarbeit mit der Arbeitsgemeinschaft für warmfeste Stähle und der Arbeitsgemeinschaft für Hochtemperaturwerkstoffe, 1969, Verlag Stahleisen mbH, Düsseldorf, Germany.
- 2) Ergebnisse deutscher Zeitstandversuche langer Dauer an Stahlgußsorten nach DIN 17 245 – Warmfester ferritischer Stahlguß – , Ed.: Forschungsvereinigung Warmfeste Stähle (FVW) und Forschungsvereinigung Verbrennungskraftmaschinen e.V. (FVV), Bericht FVW/FVV Nr. 1-86, Juli 1986, Düsseldorf, Germany.
- 3) Ergebnisse deutscher Zeitstandversuche langer Dauer an den hochwarmfesten Legierungen X40 CoCrNi 20 20 (Typ S-590) und X12 CrCoNi 21 20 (Typ N-155), Ed.: Forschungsvereinigung Hochtemperaturwerkstoffe (FVHT) und Forschungsvereinigung Verbrennungskraftmaschinen e.V. (FVV), Bericht FVHT/FVV Nr. 2-87, August 1987, Düsseldorf, Germany
- 4) Bandel, G. und Gravenhorst, H.: Verhalten warmfester Stähle im Zeitstandversuch bei 500 bis 700 °C, Teil II. Auswertungsverfahren, Archiv Eisenhüttenwes. 28 (1957), P. 253/258.
- 5) Bendick, W., Haarmann, K. and Wellnitz, G.: Evaluation of Design Values for Steel P91, Proc. of ECSC Information Day on the Manufacture and Properties of Steel 91 for the Power Plant and Process Industries, 5. Nov. 1992, Düsseldorf, Germany.
- 6) Vol. 5 [Issue 3], Appendix B1, P. B1.8/B1.9 .
- 7) Granacher, J., Schwienheer, M.: Assessment of Sub-size Creep Rupture Data Sets with and without Creep Strain Data, Doc. Ref. 0509/WG1/105, 2000.
- 8) Granacher, J., Möhlig, H.: Manual for Program DESA P for the Post Assessment Tests on Creep Rupture Data, IfW TUD, to be published.



Point 2.5 can be inserted at \otimes before point 2.3

Fig. 1. Flow chart of the graphical averaging and assessment method

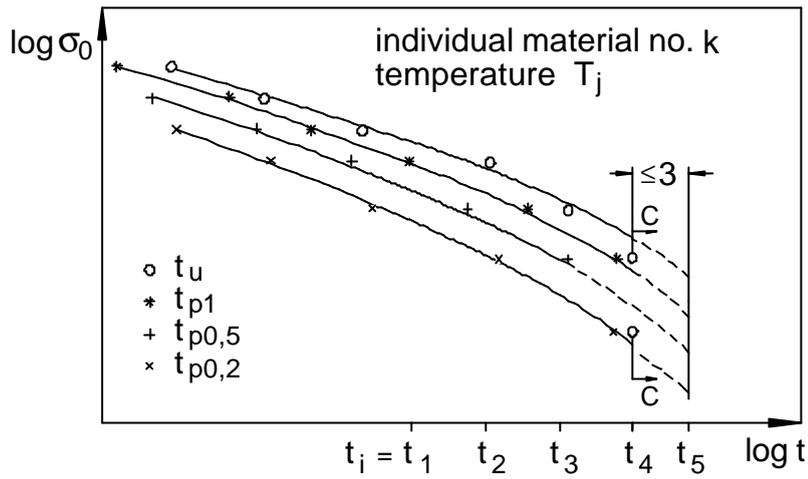


Fig. 2. Scheme of logarithmic stress time plot for an individual material and for constant temperature T

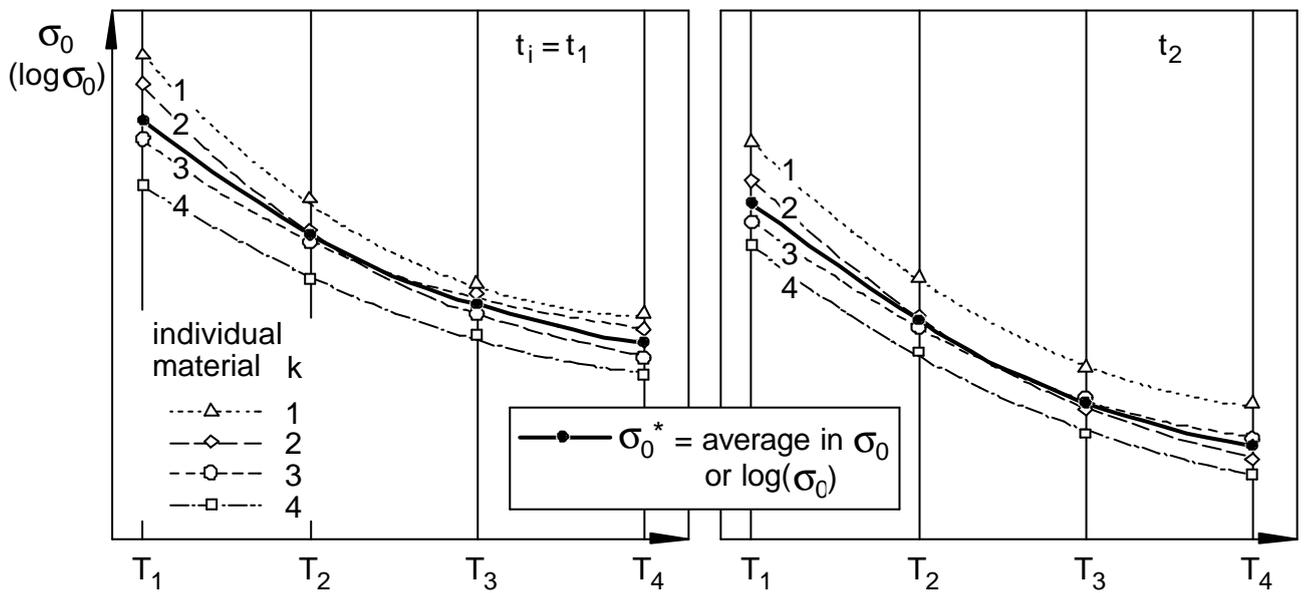


Fig. 3. Scheme of stress against temperature diagrams for characteristic time values $t_i = t_1, t_2 \dots$

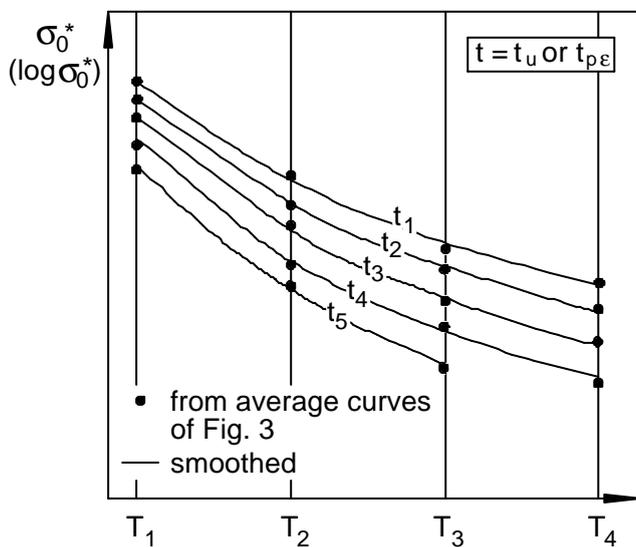


Fig. 4. Scheme of a stress temperature diagram with average $\sigma_0^*(T)$ curves for characteristic time values t_1 to t_5

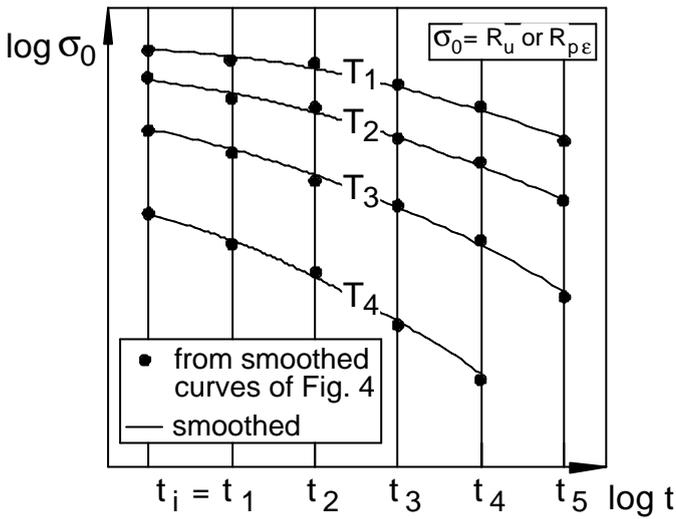


Fig. 5. Scheme of a stress time diagram with average isothermals

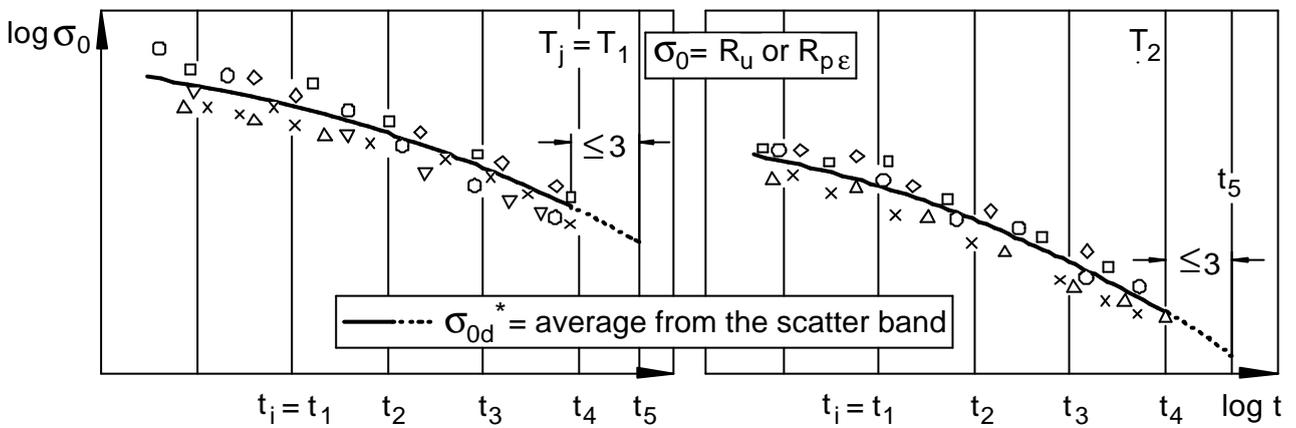


Fig. 6. Scheme of a data analysis derived from isothermal scatterbands for the temperatures T_1, T_2, \dots

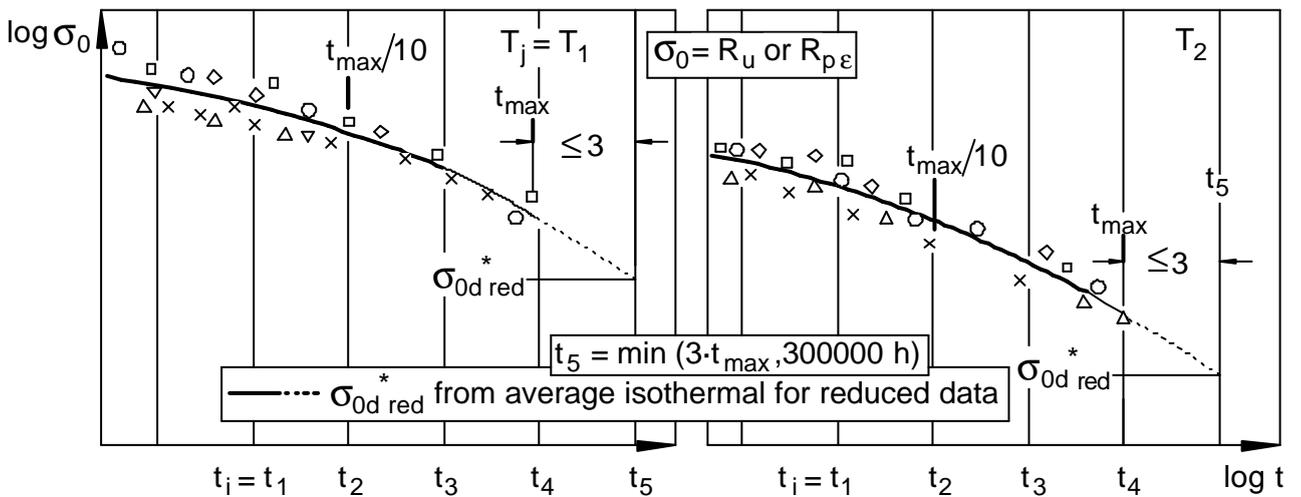


Fig. 7. Scheme of the determination of the strength values $\sigma_{0 \text{ red}}^*$ from the average isothermals of the reduced data sets for the temperatures T_1, T_2, \dots

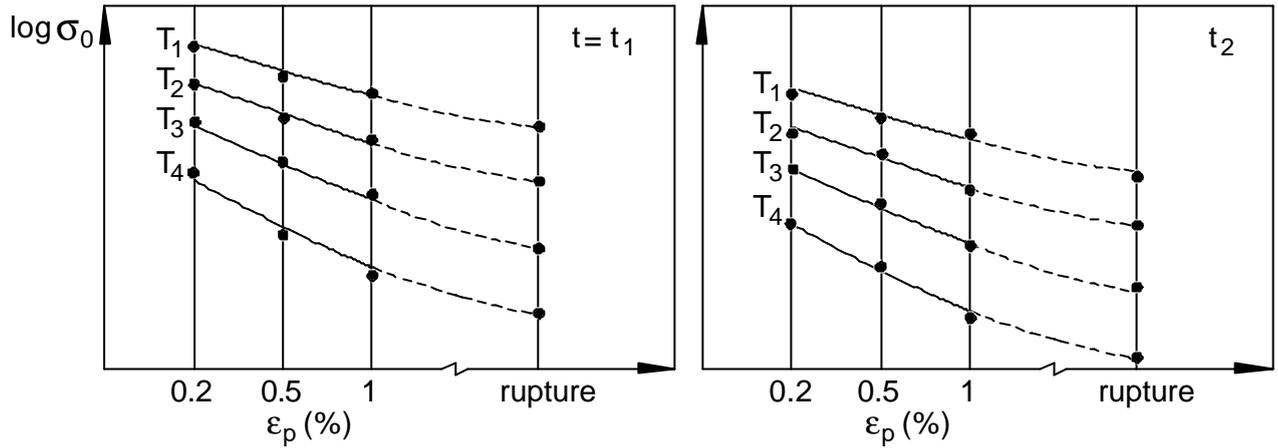


Fig. 8 Scheme of equilibrating rupture strength and creep strength values for specific times t_1, t_2, \dots

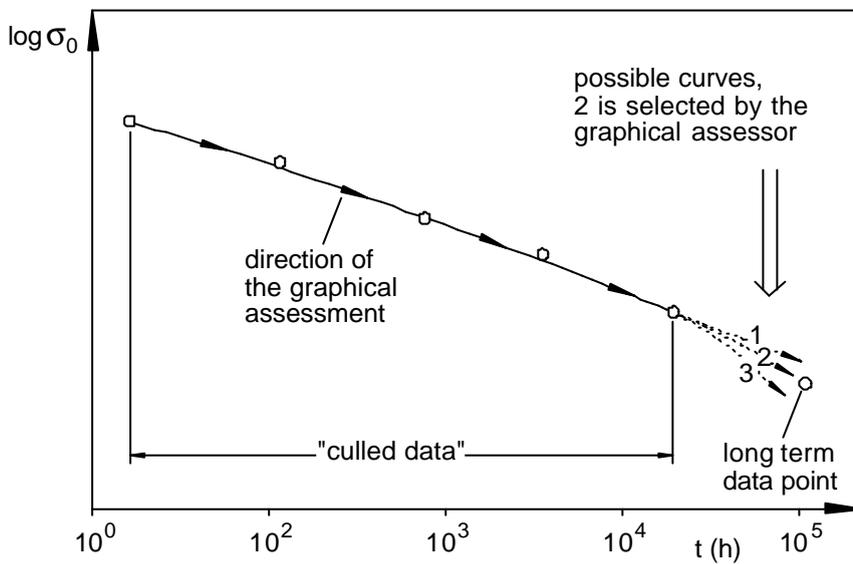


Fig. 9. Scheme of a typical "cull situation" during a graphical assessment

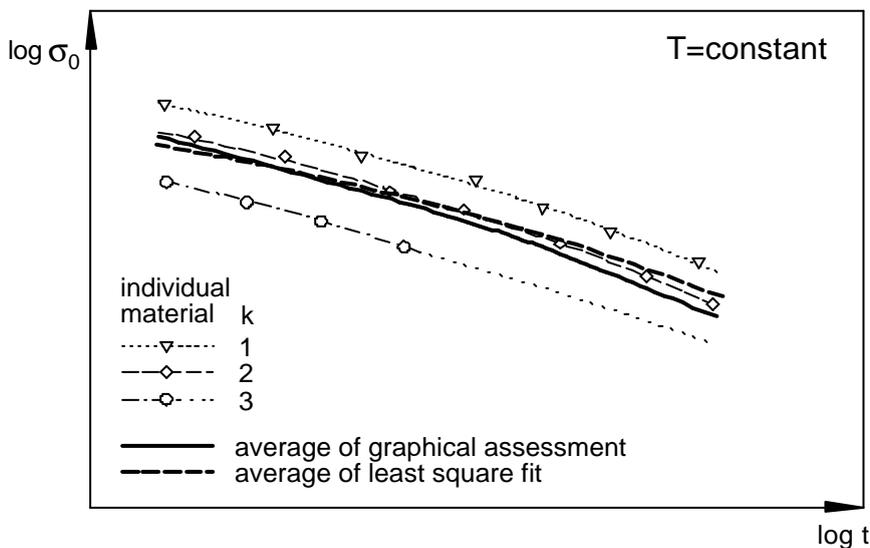


Fig. 10. Scheme of an inhomogeneous heat situation in a logarithmic stress time diagram

APPENDIX E1

**RECOMMENDED FORMAT FOR CREEP RUPTURE DATA ASSESSMENT REPORTING
WITH WORKED EXAMPLE**

C K Bullough [ALSTOM Power]

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APPENDIX E1

RECOMMENDED FORMAT FOR CREEP RUPTURE DATA ASSESSMENT REPORTING WITH WORKED EXAMPLE

CK Bullough (European Gas Turbines¹)

E1.1 INTRODUCTION

Appendix E1 describes the standard format to be adopted for reporting the results of a single creep rupture data assessment (CRDA) performed according to ECCC-WG1 Guidelines. The recommended format is illustrated with an example (Section E1.5), which includes information on how the WG1 Post Assessment Tests may be implemented. A simple checklist is also provided which will permit the rapid review of the assessment. Detailed information on how some aspects of the work were performed is included in the form of Implementation Notes (to be found towards the end of this Appendix).

It is intended that standard formats for creep strain and stress relaxation data assessment will be recorded in later issues of Volume 5.

E1.2 INFORMATION TO BE RECORDED

Three basic types of information are to be reported: i) textual description of the main points of the assessment; ii) tabular information including, for example, specification and derived strength values; and iii) figures that contain graphical plots of the data, "acceptability criteria" etc. Regarding the content of the report, the following principles should be noted:

i) Terms and Terminology

The standard reporting format uses the terminology defined in ECCC-WG1 Volume 2², and the content of the report should also use these definitions. In particular, the classification of "mandatory", "recommended" and "optional" (marked M, R and O respectively) has been adopted without change if it has already been stipulated in other ECCC WG1 Volumes.

ii) Data Quality

The data used for the assessment should conform to the requirements in ECCC-WG1 Volume 3³, any deviations of data from those guidelines or lack of information regarding conformance should be clearly indicated, and consequences evaluated.

¹ This document was partly prepared whilst the author was employed at ERA Technology Ltd.

² ECCC-WG1 Recommendations Volume 2; "Terms and terminology for use with stress-rupture, creep and stress relaxation; testing, data collation and assessment", ECCC Document 5524/MC23 [Issue 4] Edited: J Orr, 29-9-95.

³ ECCC-WG1 Recommendations Volume 3; "Data Generation. Acceptability Criteria for Stress-Rupture, Creep and Stress Relaxation Data", ECCC Document 5524/MC30 [Issue 2] Edited: J Granacher and SR Holdsworth, 29-9-95.

iii) Collation and Exchange

Where relevant, the collation and exchange procedures described in ECCC-WG1 Volume 4⁴ will have been followed to ensure that the scope and quality of the information supplied for the assessment is sufficient. A brief description of the collation and exchange procedure should be made which, in particular indicates any deficiencies that may have affected the assessment results.

iv) Data Assessment Procedure

The contents of this section are defined in the Recommendations Section of this Volume. One key aspect of the report is that it should contain details of the procedure that was followed (unless adequately described in an ECCC CRDA procedure document, Appendix D), and any variations that were introduced by the assessor. Moreover, decisions that were arrived at on the basis of tests applied to the data, or at the discretion of the assessor should be adequately reported. The aim is to demonstrate how the assessment was performed in sufficient detail that there would be no significant differences in the results arrived at by an independent assessor following the report. The report should also detail the equipment used since minor variations in equipment and software packages may, possibly, affect results.

E1.3 ACCEPTANCE OF REPORT

It is the responsibility of the organisation commissioning the data assessment to ensure that work has been performed to the ECCC WG1 Guidelines (primarily the Recommendations section of this Volume), and reported in a satisfactory manner. Within ECCC, the organisation commissioning the work will ordinarily be the Working Group 3.x, and the final responsibility for ensuring the report is satisfactory will therefore reside with that Group, and its Convenor. However, it is anticipated that the ECCC WG1 Guidelines will be used much more widely (such as within individual industrial organisations, and by national/European standards committees). In that circumstance, it is recommended that the commissioning organisation state clearly to whom the final results should be reported, and examined according to ECCC WG1 Guidelines.

A checklist is provided at the end of Section 1.5 that summarises the recommended format (in particular the post assessment tests) in order to aid the review of reported results.

⁴ ECCC-WG1 Recommendations Volume 4; "Guidance for the Exchange and Collation of Creep Rupture and Creep Strain-Time and Stress Relaxation Data", ECCC Document 5524/MC/68 [Issue 1] Edited: CK Bullough and G Merckling. 29-9-95.

Section / Contents	Requirement
Section 3. Main Assessment.	
The following information shall be recorded in Section 3 in sufficient detail to permit others to reproduce the analysis.	
3.1 The predictive equations used to fit the data.	R
3.2 The error distribution. Measures of goodness of fit [mandatory, where available]*.	R[M]*
3.3 The method of estimation.	R
3.4 A record of any data conditioning or further removal of data (eg. outliers or other data).	R
3.5 In relation to the procedure, a record of decisions taken by the assessor together with any supporting statistical data or other evidence.	R
3.6 A table containing the assessed mean strength values and an indication of its range of acceptable use.	R
3.7 A table recording measures of coefficients goodness of fit, and confidence intervals.	R
Section 4. Post Assessment Acceptability Criteria.	
The following information regarding the performance of the post assessment acceptability criteria shall be included in Section 4.	
4.1 $\log \sigma_o$ vs. $\log t_r^*$ plotted isothermally, together with the raw data, and statement regarding the credibility of the fit. [Recommendation 5, Section 2.4, PAT-1.1]	M
4.2 Isothermal plots of $\log \sigma_o$ vs. $\log t_r^*$ at 25°C intervals from 25°C below the minimum test temperature to 25°C above the temperature for which predicted strength values are required and to durations of 10h to 1,000,000h or beyond, and stresses down to $0.8\sigma_{o,min}$ or below. A statement regarding whether the predicted isothermal lines a) cross-over, b) come-together, or c) turn-back [Recommendation 5, Section 2.4, PAT-1.2]	M
4.3 The derivative of the predictive model, n' ($= -\partial \log t_r^* / \partial \log \sigma_o$) plotted at 25°C intervals from 25°C below the minimum temperature to 25°C above the temperature for which predicted strength values are required. A statement whether the values of n' are ≥ 2 . [Recommendation 5, Section 2.4, PAT-1.3]	M
4.4 Plots of predicted time vs. observed time (all data), together with lines defining the ideal and boundary lines. A statement regarding outliers, the slope and location of the line. [Recommendation 5, Section 2.4, PAT-2.1]	M
4.5 One plot of standardised residuals vs. $\log t_r$ for all input data, together with a linear regression line.	O
4.6 One plot of standardised residuals vs. $\log t_r^*$ for all input data, together with a linear regression line.	O
4.7 One plot of standardised residuals vs. $\log \sigma_o$ for all input data, together with a linear regression line.	O
4.8 One plot of standardised residuals vs. T or all input data, together with a linear regression line.	O
4.9 Isothermal plots of predicted time vs. observed time (identifying the best tested casts), together with lines defining the ideal and boundary lines. A statement regarding outliers, the slope and location of the line. [Recommendation 5, Section 2.4, PAT-2.2]	M

Section / Contents	Requirement
4.10 A repeat assessment of the data sets following a random cull of 50% of the data between $t_{r[\max]}/10$ and $t_{r[\max]}$. A statement regarding the repeatability of strength predictions at $T_{\min[10\%]}$, T_{main} , and $T_{\max[10\%]}$. [Recommendation 5, Section 2.4, PAT-3.1]	M
4.11 A repeat assessment of the data sets following a random cull at each of the main stress temperatures of 10% of the lowest stress data between. A statement regarding the repeatability of strength predictions at $T_{\min[10\%]}$, T_{main} , and $T_{\max[10\%]}$. [Recommendation 5, Section 2.4, PAT-3.2]	[M]
4.12 The results of the post assessment acceptability criteria summarised in a table.	R
<u>Section 5. Conclusions</u>	
The following information shall be provided.	
5.1 A statement describing whether or not the results meet the ECCC WG1 Guidelines.	M
5.2 A statement clarifying which strength values are to be proposed to the commissioning organisation (eg. ECCC WG3.x), together with any restrictions as to their use.	M

E1.5 AN EXAMPLE REPORT OF A CREEP RUPTURE DATA ASSESSMENT USING THE STANDARD REPORTING FORMAT AND CHECKLIST

CK Bullough

An Assessment of the Creep Rupture Properties of Type 304H Steel Using the DESA 2.01 Assessment Procedure⁵

Section 1. Introduction

An assessment of the rupture properties of Type 304H stainless steel has been performed by ERA Technology on behalf of the European Creep Collaborative Committee, Working Group 1. The objectives of the assessment were to examine the reproducibility of the assessment procedure, and to provide information on the post assessment acceptability criteria. Other assessments were performed on the same data set using the same, and different assessment procedures, and a comparison of the results is recorded in ECCC WG1 Volume 5 Appendix C.

The assessment performed by ERA used the DESA 2.01 computer programme under the following conditions.

- Permission to use the DESA 2.01 programme was obtained from Forschungsvereinigung Verbrennungskraftmaschinen e.V., and the programme was configured by Dr M Monsees of IfW Darmstadt.
- The assessment procedure was defined "Guideline for the use of DESA, Version 2.01 for creep rupture data assessment" dated 25.04.94⁶ and the use of the programme was defined in "Anwenderhandbuch für das Programm DESA 2.01" dated 02.11.92 (a translation of that document was provided by Dr SR Holdsworth of GECA, Rugby). The procedure was followed without known deviation. An optional correction to the slope of the line at low temperatures was not selected.
- The software was mounted on a 468DX 33MHz PC, with the DOS 6.0 operating system. Excel 5.0 was used in conjunction to: i) format the data prior to input; ii) perform the post assessment acceptability criteria; iii) obtain the mean strength values from the master equation.

Section 2. Data Collation and Pre-Assessment.

Data were collated by ECCC WG1 and termed a "WG1 Working Data Set". The data were distributed to the participants of ECCC WG1 in the form of an ad-hoc Excel 4.0 format spreadsheet file, with the detail shown below. Note that the data were distributed prior to the completion of ECCC WG1 work on optimum format for data collation and exchange.

⁵The information used in this example was first reported in ECCC WG1 document ref. 5524/WG1/112 Issue 2 (RM Cotgrove and CK Bullough), 1994.

⁶Since the assessment was completed the procedure has been updated, and is recorded in Appendix D of this Volume.

Name	Extension	Size	Date	Time
T304HDAT	XLS	212,992	21/04/95	17:50

The material pedigree information were not generally distributed for confidentiality reasons. Hence it was impossible to state whether or not the data meet the material pedigree and testing requirements stipulated in ECCC WG1 Volume 3.

Rupture data were identified by country and by material identifier, no sub-division of the data was performed during the assessment. Table E1.1 records the specification to which the material was collated. Table E1.2 records the distribution of the data with respect to temperature, duration and source. [See *Implementation Note E1.1 for suggestions for preparing Table E1.2.*⁷ There were more than 10% of the data at 600, 650 and 700°C and between 5 and 10% of the data at 550 and 649°C. All of the data were used in the assessment, and no data conditioning or reduction techniques were followed. However, two test points had neither rupture life nor unbroken test duration (320D at 450°C and 551MPa, and 320I at 550°C and 230MPa) and were therefore omitted from the assessment.

The longest duration broken and unbroken tests were, respectively, 110,806h (cast 121A tested at 700°C and 31MPa) and 150,000h (cast 121B tested at 500°C and 158MPa). The lowest stress to cause failure was 10MPa (cast 121A tested at 800°C). No further data rejection, re-organisation or reduction was performed.

The first stage of the method requires that several models are fitted to the data of three best-tested casts (termed "dominant" casts in the procedure document for DESA 2.01). No clear guidance was given in the DESA 2.01 procedure for selecting those casts (except to choose the best-tested casts). The "dominant" or "best-tested" casts were chosen by identifying the number of tests at each temperature for each cast, Table E1.3. [See *Implementation Note E1.2*] Cast 121A had the greatest number of test data, and was therefore selected as the "main cast". The following casts were also chosen to be representative: 121B and 3518.

Initial visual checks of isothermal $\log \sigma_0$ vs. $\log t_r$ plots of the data did not indicate any requirement for separation or rejection of either of groups of data, or of individual points.

Section 3. Main Assessment.

The DESA 2.01 assessment procedure is based on fitting a variety of predictive models to the three dominant casts, one of which is then fitted to the total data set (broken points only). A normal error distribution in logarithm of time was assumed throughout, and each model was fitted by multiple linear regression methods.

The most general form of the model is given by Equation 1.

$$\log t_r^* = P(\sigma_0)(T - T_a)^R + \log t_a \quad \dots(1)$$

where

t_r^* is the predicted life, $P(\sigma_0)$ is a function of stress, T is the temperature, and T_a , t_a and R are constants.

The function in stress takes the form of a polynomial, up to order 5, of either the logarithm of stress or stress raised to a power. The *model* is therefore similar in form to that resulting to other time-

⁷ Implementation Notes are recorded at the end of Section 1.5, following the figures.

temperature-parameter assessment procedures (such as the ISO:6303 procedure) *except* that the function in stress has several more options.

In the first stage of the assessment, a combination of different models were fitted to the data of each of the three dominant casts. These models were those of Larson Miller, Manson Brown, Sherby Dorn and Manson Haferd, with 3rd order polynomials of 4 stress functions. The models with the lowest standard deviations (the best "goodness of fit"), and which were judged to be the most appropriate visually, were as follows.

Cast	No of Data	Model	Stress function	Std. Deviation
3518	20	Manson Haferd	$P(\sigma_o)=f(\sigma_o^{0.25})$ 3rd order	0.08918
121A	33	Manson Haferd	$P(\sigma_o)=f(\sigma_o^{0.1})$ 3rd order	0.20185
121B	27	Sherby Dorn	$P(\sigma_o)=f(\log\sigma_o)$ 3rd order	0.18080

Plots of the predictive model and the raw data were also output from DESA that confirmed the adequacy of the fits. Two of the best tested casts had the same model (Manson Haferd) and therefore this model type was initially selected for further investigation.

The Manson Haferd model was applied to the total data set (broken points) and, as stated in the procedure, a number of different stress functions were investigated, in order to find the model with the lowest residual sum of squares. In addition, all other model forms were re-investigated. The following predictive model was found to give the best fit to the data (lowest standard deviation), and the suitability of the model was confirmed visually with a plot of the model upon the raw data.

Cast	No of Data	Model	Stress function	Std. Deviation
All	796	Larson Miller	$P(\sigma_o)=f(\sigma_o^{0.6})$ 3rd order	0.45215

The mean strength values at specified times were obtained by numerical solution of the above equation within an Excel 5.0 spreadsheet, Table E1.4. [See *Implementation Note E1.3.*] As a general guide, the strength values should not be used beyond 3 x the longest duration exceed by the data points from 5 casts at temperatures within 25°C of that specified. (See Recommendations section, point 9 (footnote) for more detailed guidance). The predictive model is plotted in isothermal form in Figure E1.1. Full details of the model and other statistical parameters are given in Table E1.5.

Section 4. Post Assessment Acceptability Criteria.

The post assessment acceptability criteria have been performed according to ECCC WG1 Volume 5 Issue 2 guidelines. [Implementation Notes 1.4 to 1.6 are appended to this Example, and illustrate how the Post Assessment Tests were performed in practice.]

Physical Realism of Predicted Lines

The first test of the physical realism of predicted isothermal lines, PAT-1.1, is to visually confirm that the predicted model adequately represents the behaviour of the data. This test was performed by preparing Figure E1.2 [See *Implementation Note 1.4*], from which it can be seen that the mean line does indeed adequately represent the data.

The second test, PAT-1.2, is to plot the model over a range of temperatures and stresses slightly exceeding that for which it might be used to prepare strength values. The model is plotted in Figure 1.3 for predicted lifetimes from 1 to 1,000,000 hours, and above 8Nmm^{-2} ($= 0.8\sigma_{o\text{min}}$) at temperatures from 375°C to 925°C in 25°C steps (in fact, PAT-1.2 only requires that it is plotted to

25°C above the temperature for which predicted strength values are required). It can be seen that the isothermal lines do not cross over, come together, or 'turn back'.

The third test, PAT-1.3, was prepared by plotting the values of the derivative of the model, $\partial \log t_r^* / \partial \log \sigma_o$, as a function of $\log \sigma_o$ at temperatures of 375°C to 925°C in 25°C steps, Figure E1.4. (Again, PAT-1.3 only requires that the derivative is plotted to 25°C above the temperature for which predicted strength values are required). The derivative was never greater than -2, and remained in the range $-2.4 > \partial \log t_r^* / \partial \log \sigma_o > -30$ for the range of stresses from 8Nmm⁻² to 500Nmm⁻².

Effectiveness of Model Prediction within Range of Input Data

The first test of the effectiveness of model prediction with the range of the input data is to examine the behaviour of the entire data set, PAT-2.1. The basis of the test is to plot the predicted life vs. the observed life, and to examine the spread of test points, and the slope of the mean line. [See *Implementation Note 1.4.*] The results of the test are indicated in Figure E1.5, and a summary of the derived test statistics are recorded in the Checklist Part 2. There are 9 points having standardised residuals of greater than +2.5, and one point with a standardised residual of less than -2.5. Compared to the total population of (failed) points of 796, these numbers are equivalent to percentages of 1.13%, and 0.1%, respectively, both of which are less than the test criterion of 1.5%. The slope of the mean line is calculated as 1.0028, which lies within the test criteria of 0.78 to 1.22. From Figure E1.5 it may be seen that the mean line is contained within the $\pm \log 2$ boundary lines between $100h \leq t_r \leq 3 * t_{r[\max]}$.

Informative plots of standardised residuals vs. $\log t_r$, vs. $\log t_r^*$, vs. $\log \sigma_o$ and vs. T are shown in Figure E1.6. They indicate that for three of the plots the slopes of the trend lines are approximately horizontal and that the residuals are reasonably equally balanced either side of the mean line. However, for the plot of standardised residuals vs. $\log t_r$, the slope is 0.649, which is unusually high.

The second test, PAT-2.2, has as its basis plots of predicted life vs. the observed life of *individual casts at the main test temperatures* (ie. those with more than 10% of the data points). Isothermal plots at 550, 600, 649-650 and 700°C were prepared, and the main and best-tested casts identified, by means of symbols and lines, Figure E1.7 and Figure E1.8. A summary of derived test statistics is also shown in the Checklist Part 2. None of the casts had slopes which lay outside of the limits ≤ 0.5 and ≥ 1.5 , or a significant number of points outside of the $\pm 2.5 S_{[I-LRT]}$ boundaries, and therefore there was no requirement to examine their pedigree, or to consider the need for changing the specification.

As part of PAT-2.2, the slope of the mean line and its position are also considered. The slope is contained within the limits 0.78 and 1.22, and its position is within the $\pm \log 2$ boundaries in the range $100h \leq t_r \leq 3 * t_{r[\max]}$. Therefore, the predicted model passes PAT-2.2.

Repeatability and Stability of Extrapolations

The first test of credibility of extrapolation is performed by randomly culling 50% of the data between $t_{r[\max]}/10$ and $t_{r[\max]}$ (11,080 hours to 110,800 hours), and then by comparing the predicted strength values at 300,000h with those obtained without culling, PAT-3.1. This procedure was performed in Excel 5.0 using the Excel random number generator to provide a value of between 0 and 1. Those points that were in the range 11,080 hours to 110,800 hours and had a value of the random number below 0.5 were removed from the data set. This was not exactly 50% owing to the small sample size. [See *Implementation Note 1.6.*] The data were then re-assessed using the standard procedure. The same predictive model was chosen to represent the data, but several types of stress function were re-examined.⁸ The predicted $R_{r/300,000h}$ strength values at T_{main} , $T_{\text{min}\{10\%}}$, and $T_{\text{max}\{10\%}}$ are recorded in

⁸ This part of the example was prepared before it was agreed in WG1 that the re-assessment should be begun from the very start of the procedure.

the Checklist Part 2, from which it may be seen that they are, indeed, reproduced to within 10% of those obtained from the data set without culling.

To perform the second test, PAT-3.2, 10% of the data were removed at the lowest stress from each of the main test temperatures, and the assessment repeated using the standard procedure (but see footnote 8). The predicted $R_{r/300,000h}$ strength values at T_{main} , $T_{min[10\%]}$, and $T_{max[10\%]}$ are recorded in the Checklist Part 2, from which it may be seen that they are, indeed, reproduced to within 10% of those obtained from the data set without culling. Type 304 steel is not known to be metallurgically unstable at long times, therefore meeting the requirements of PAT-3.2 is Mandatory for this assessment.

Section 5. Conclusions

A creep rupture data assessment has been performed on a WG1 Working Data Set of Type304H steel, using the DESA 2.01 Assessment Procedure. The procedure has been performed to ECCC WG1 guidelines (Volume 5, Issue 2), except that there was insufficient information to perform part of the pre-assessment. The post-assessment tests have been performed as stipulated (except for a minor deviation in performing PAT-3.1 and PAT3.2, due to their recent revision). The results of the assessment pass the post assessment tests.

The recommended strength values from this work, marked in the manner described by Recommendations section, point 9 (footnote), are shown as shaded region of Table E1.4.

**Checklist for ECCC WG1 Creep Rupture Data Assessment
Part 1: Content of Report
(Type 304H Steel Using the DESA 2.01 Assessment Procedure)⁹**

Section / Contents	Requirement	Location in Report	Comments
<u>Section 1. Introduction</u>			
1.1 Commissioning, objectives and relationship.	R	Section 1	
1.2 CRDA References, and any modifications.	M	"	
1.3 Local implementation.	R	"	
<u>Section 2. Data Collation and Pre-Assessment.</u>			
2.1 Record of exchange files.	M	Section 2	
2.2 Conformance with ECCC WG1 Vol 4	R	"	Files did not conform.
2.3 Conformance with ECCC WG1 Vol 3	M	"	Information unavailable
2.4 Specification and summary statistics (table).	M	Table E1.1	
2.5 Distribution of rupture data (table).	M	Table E1.2	
2.6 A record of the main and best tested casts.	M	Table E1.3	
2.7 Groups of data rejected or separated and explanation.	M	Section 2	None rejected
2.8 Single points rejected and explanation.	M	Section 2	320D at 450°C/ 551MPa - no duration 320I at 550°C/230MPa - no duration
2.9 Any data re-organisation or data reduction.	M	Section 2	None.
<u>Section 3. Main Assessment.</u>			
3.1 Predictive equations.	R	Section 3 Table E1.5	
3.2 Error distribution.	R[M]*	Section 3	
3.3 Method of estimation.	R	Section 3	
3.4 Any data conditioning or further treatment.	R	"	None performed
3.5 Deviations from written procedure.	R	"	None (but deviates from new procedure in Appendix D).
3.6 A table of mean strength values.	M	Table E1.4	
3.7 Table recording coefficients, goodness of fit, and confidence intervals.	R	Table E1.5	confidence intervals not determined

⁹ An empty copy of this checklist is included later in this Appendix. A copy is also contained on the diskette distributed with Volume 4.

Section / Contents	Requirement	Location in Report	Comments
3.7 Table recording coefficients, goodness of fit, and confidence intervals.	R	Table E1.5	confidence intervals not determined
Section 4. Post Assessment Acceptability Criteria.			
4.1 Credibility of predictive model: model and data plotted isothermally. [PAT-1.1]	M	Section 4	See also Figures E1.1 and E1.2
4.2 Credibility of predictive model: model plotted at 25°C intervals to 1,000,000h and $0.8\sigma_{\min}$. [PAT-1.2]	M	Section 4 Figure E1.3	
4.3 Credibility of derivative, n' plotted at 25°C intervals to 1,000,000h and $0.8\sigma_{\min}$. (record minimum value at end of checklist.) [PAT-1.3]	M	Section 4 Figure E1.4	
4.4 Model prediction all data (predicted time vs. observed time) [PAT-2.1]	M	Section 4 Figure E1.5	
4.5 Plot of standardised residuals vs: $\log t_r$.	O	Section 4 Figure E1.6	Slope of line is unusually high.
4.6 " " vs. $\log t_r^*$.	O	"	
4.7 " " vs. $\log \sigma_o$.	O	"	
4.8 " " vs. T.	O	"	
4.9 Model prediction, data of "best tested" casts (predicted time vs. observed time) [PAT-2.2]	M	Section 4 Figure E1.7 Figure E1.8	
4.10 50% cull between $t_{r[\max]}/10$ and $t_{r[\max]}$. [PAT-3.1]	M	Section 4 Table E1.6	
4.11 10% cull of the lowest stress data. [PAT-3.2]	[M]	Section 4 Table E1.6	
4.12 Summary results of PATS.	R		See latter part of this checklist
Section 5. Conclusions			
5.1 Conformance with ECCC WG1 Volume 5 Guidelines.	M	Section 5	
5.2 Strength values proposed, and restrictions.	M	Section 5 Table E1.4	

**Checklist for ECCC WG1 Creep Rupture Data Assessment
Part 2: Summary of Numerical Values**

Quantity	Symbol	Value(s)	Comments		
Total no. broken points	-	796	Required for PAT-2.1		
Lowest test temp. °C, Highest test temp. °C		400 (UB) 899	Required for PAT-1.2, PAT-1.3		
Main test temperature	T_{main} $T_{min[10\%]}$ $T_{max[10\%]}$	650 550 700	Required for PAT-2.2, PAT3.1, PAT3.2		
Lowest test stress (failed points), Nmm^{-2}	$\sigma_{o,min}$ $0.9*\sigma_{o,min}$ $0.8*\sigma_{o,min}$	10 9 8	Required for PAT-1.2, PAT3.2 and for strength table		
Longest duration (failed points), h	$t_{r[max]}$ $t_{r[max]}/3$	110806 332418	Required for PAT3.1, PAT-3.2		
Best tested cast Main casts			See table E1.3, first 12 selected		
Predicted rupture life at i) T_{main} ii) $T_{min[10\%]}$ iii) $T_{max[10\%]}$		$R_{r/300,000h}$ 43.4 106.2 25.9	Required for PAT3.1, PAT-3.2, may use $R_{r/300,000h}$ instead of $R_{r/300,000h}$ if $t_{r[max]} < 100,000h$		
Post Assessment Tests			Crite- rion	Pass/ Fail	Comments
PAT 1.1 Model and Data	-	-	Visual check	P	
PAT 1.2 Model to 1,000,000h, $0.8\sigma_{o,min}$	-	-	not cross-over not converge no turn-back	P P P	
PAT 1.3 Derivative of model, $\geq 0.8*\sigma_{o,min}$	min. n max. n	2.17 26.9	(≥ 2) -	P	(At 800°C)
PAT 2.1 Model prediction, all data.	$\% > +2.5.S_{[A-RLT]}$ $\% < -2.5.S_{[A-RLT]}$ mean slope mean line	1.13 0.13 1.0026	≤ 1.5 " $> 0.78,$ < 1.22	P P P P	From Figure E1.5
PAT 2.2 Model prediction, best tested casts at: i) T_{main} ii) $T_{min[10\%]}$ iii) $T_{max[10\%]}$	$\% > 2.5.S_{[I-RLT]}$ mean slope mean line cast behaviour		≤ 1.5 $> 0.78,$ < 1.22 $\pm \log 2$	P P P	
PAT 3.1 50% cull on t_r , observed life at: i) T_{main} ii) $T_{min[10\%]}$ iii) $T_{max[10\%]}$	no. removed	75 $R_{r/300,000h}$ 40.7 99.9 24.2		- P P P	See Table E1.6
PAT 3.2 10% cull on σ_o , observed life at: i) T_{main} ii) $T_{min[10\%]}$ iii) $T_{max[10\%]}$	no. removed	79 $R_{r/300,000h}$ 45.2 109.7 27.4		- P P P	See Table E1.6

Table E1.3 The main and best tested casts of the Type 304H steel data set.

IDENT	No. of rupture points at specific temperatures °C																				Grand Total							
	400	482	500	538	550	585	586	570	593	600	620	621	625	649	650	670	677	700	704	720		732	750	766	800	816	871	899
Grand Total	6	18	5	57	9	22	3	30	174	2	1	21	77	184	3	1	118	7	3	19	13	2	14	5	1	1	796	
121A		6		4					6					7			6											33
121B		7		3					4					6			4											27
3518									6					6			5				3							20
3516									5					5			6				3							19
3517									6					5			5				3							19
3527									5					8			6											19
5544			1					5			1		6			1							2		1		1	18
3504									4								6				3							17
5527						5							6							6								17
0024				5					6				5															16
121BY									8				7															15
0022				5					6				4															15
121M		5		5					4				4															14
0001				6					4				4															14
3542									4				6				4											14
3548							3		3		2		4		3					3								14
3550									4				5				5											14
0021				5					4				4															13
3531									4				5															13
3536									4				5															13
3541									4				5															13
3501									5				4															12
3532									4				5															12
3537									4				5															12
3538									3				5															12
5530						4							4							4								12
0003				5					2				4															11
0054									3				3											3				11
3502									5				3															11
3503									4				4															11
3520									4				4					3										11
5501	4							3					4						2									11
5526						4							4							3						2		11

Shaded columns are those temperatures with failed points of more than 10% of the total data population.

Table E1.4 Predicted mean strength values at specific durations

Temp °C	Stress (MPa) to rupture at durations (h)										
	1,000	3,000	5,000	10,000	30,000	50,000	100,000	150,000	200,000	250,000	300,000
450	410.1	381.0	366.8	347.0	314.3	298.6	277.1	264.5	255.6	248.8	243.2
475	376.4	344.1	328.5	306.8	271.6	255.2	233.3	220.9	212.2	205.7	200.4
500	340.4	305.0	288.1	265.1	229.2	213.2	192.6	181.1	173.4*	167.5*	162.9*
525	302.2	264.6	247.2	224.2	190.0	175.4	157.1	147.2	140.5*	135.6*	131.6*
550	263.0	224.9	208.1	186.5	155.9	143.2	127.6	119.2	113.6*	109.5*	106.2*
575	224.5	188.3	172.9	153.8	127.4	116.6	103.5	96.5	91.8*	88.3*	85.5*
600	188.9	156.2	142.8	126.3	103.9	94.9	83.8	77.9	73.9	71.0	68.7*
625	157.6	129.1	117.7	103.7	84.7	77.0	67.7	62.6	59.3	56.8	54.8*
650	131.0	106.6	96.8	84.9	68.8	62.3	54.3	50.0	47.2*	45.0*	43.4*
675	108.8	87.9	79.6	69.4	55.6	50.1	43.2	39.5	37.1*	35.3*	33.8*
700	90.3	72.4	65.2	56.5	44.6	39.8	33.9	30.8*	28.7*	27.1*	25.9*
725	74.7	59.3	53.1	45.6	35.4	31.2	26.2	23.5*	21.7*	20.4*	19.3*
750	61.7	48.3	43.0	36.4	27.6	24.0	19.7	17.4	15.9	14.8	13.9
775	50.6	39.0	34.3	28.7	21.1	18.0	14.3	12.4	11.1	10.2	9.5 ¹
800	41.2	31.1	27.0	22.2	15.6	13.0	9.9 ¹	8.3 ¹	7.3 ¹	6.5 ¹	5.9 ¹
825	33.2	24.4	20.9	16.7	11.1	8.9 ¹	6.4 ¹	5.1 ¹	4.3 ¹	3.7 ¹	3.2 ¹

Notes

1. There are only limited test data below 500°C and above 800°C, see Table E1.2.
2. Data marked thus: 6.5¹, are below the minimum test stress.
3. The strength values at more than 3 x the longest test duration (see point 9 of recommendations) are marked by an asterisk: 20.4*
4. Only shaded values are to be recommended for consideration for standardisation, with the above qualifications. (Values may also be rounded down to the nearest integer.)

Table E1.5 Model, coefficients and statistical measures of goodness of fit.

Predictive Model

$$\log t_r^* = P(\sigma)(T - T_a)^R + \log t_a$$

$$P(\sigma_o) = a + b.f(\sigma_o) + c.f(\sigma_o)^2 + d.f(\sigma_o)^3 + e.f(\sigma_o)^4$$

$$f(\sigma_o) = \sigma_o^{0.6}$$

Where:

$T_a = 0$
 $R = -1$
 $\log t_a = -12.894299$
 $a = 21309.925$
 $b = -594.183$
 $c = 16.726$
 $d = -0.212$
 $e = 0$

No. data = 796
 Variance = 161.714798
 Std Dev = 0.452154 (sample standard deviation, n-5)

Table E1.6 Predicted mean strength values at 300,000 hours (PAT3.1, PAT3.2)

Stress (MPa) to rupture at 300,000h						
Temp °C		Main Assessment	PAT 3.1 Results	%Diff	PAT 3.2 Results	%Diff
450		243.2	232.5	4.40	249.7	-2.67
500		162.9	153.8	5.59	168.3	-3.31
550	T_{min}	106.2	99.9	5.93	109.7	-3.30
600		68.7	64.5	6.11	71.1	-3.49
650	T_{main}	43.4	40.7	6.22	45.2	-4.15
700	T_{max}	25.9	24.2	6.56	27.4	-5.79
750		13.9	12.9	7.19	15.1	-8.63
800		5.9 ¹	5.4	8.63	6.8	-15.06

Notes

Pass criterion is less than 10% deviation from main assessment results at main test temperatures.

Figure E1.1 Predicted mean strength values and data plotted isothermally (Part 1)
 (broken points: squares, unbroken points: crosses)

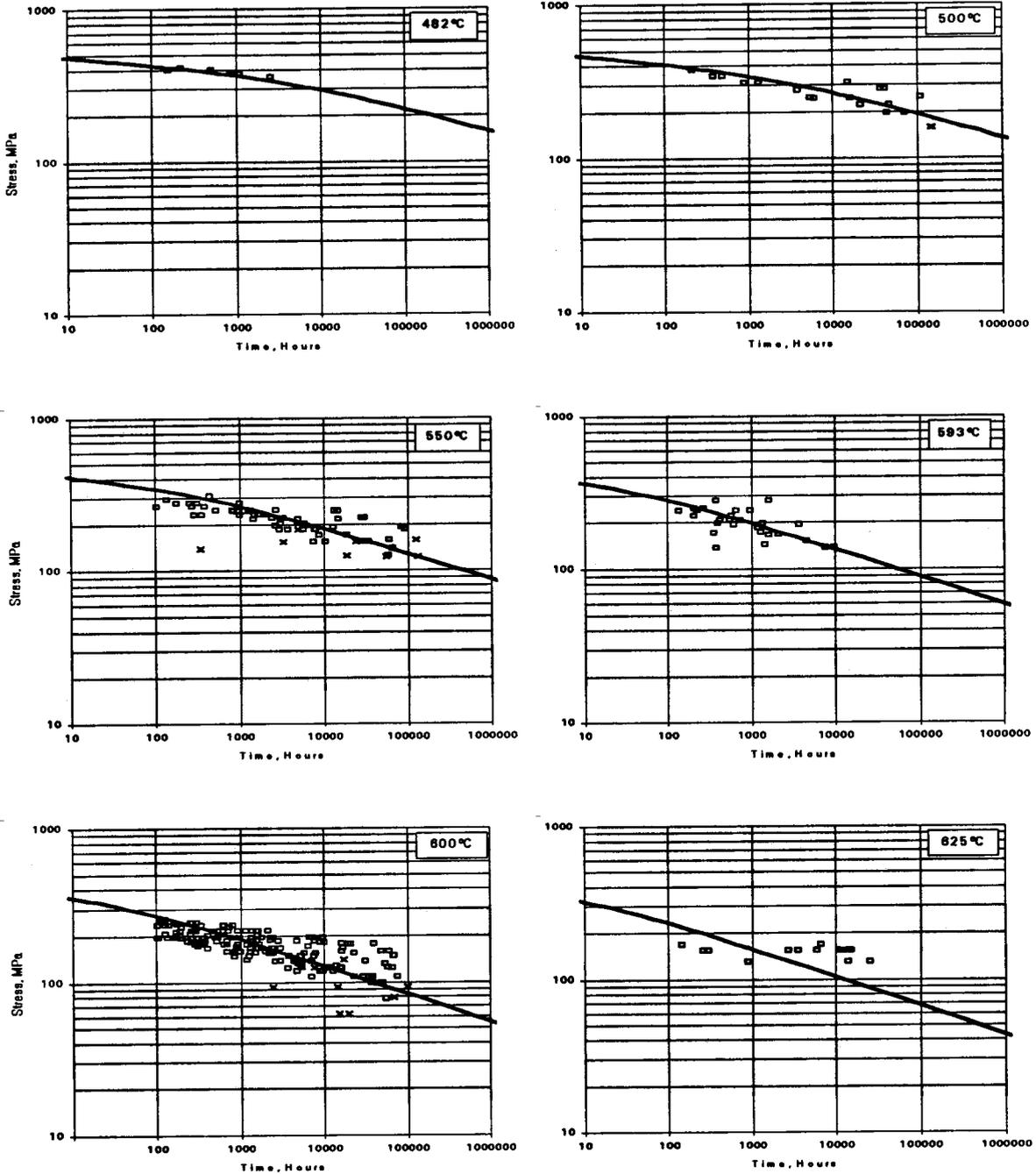


Figure E1.2 Predicted mean strength values and data plotted isothermally (Part 2)
(broken points: squares, unbroken points: crosses)

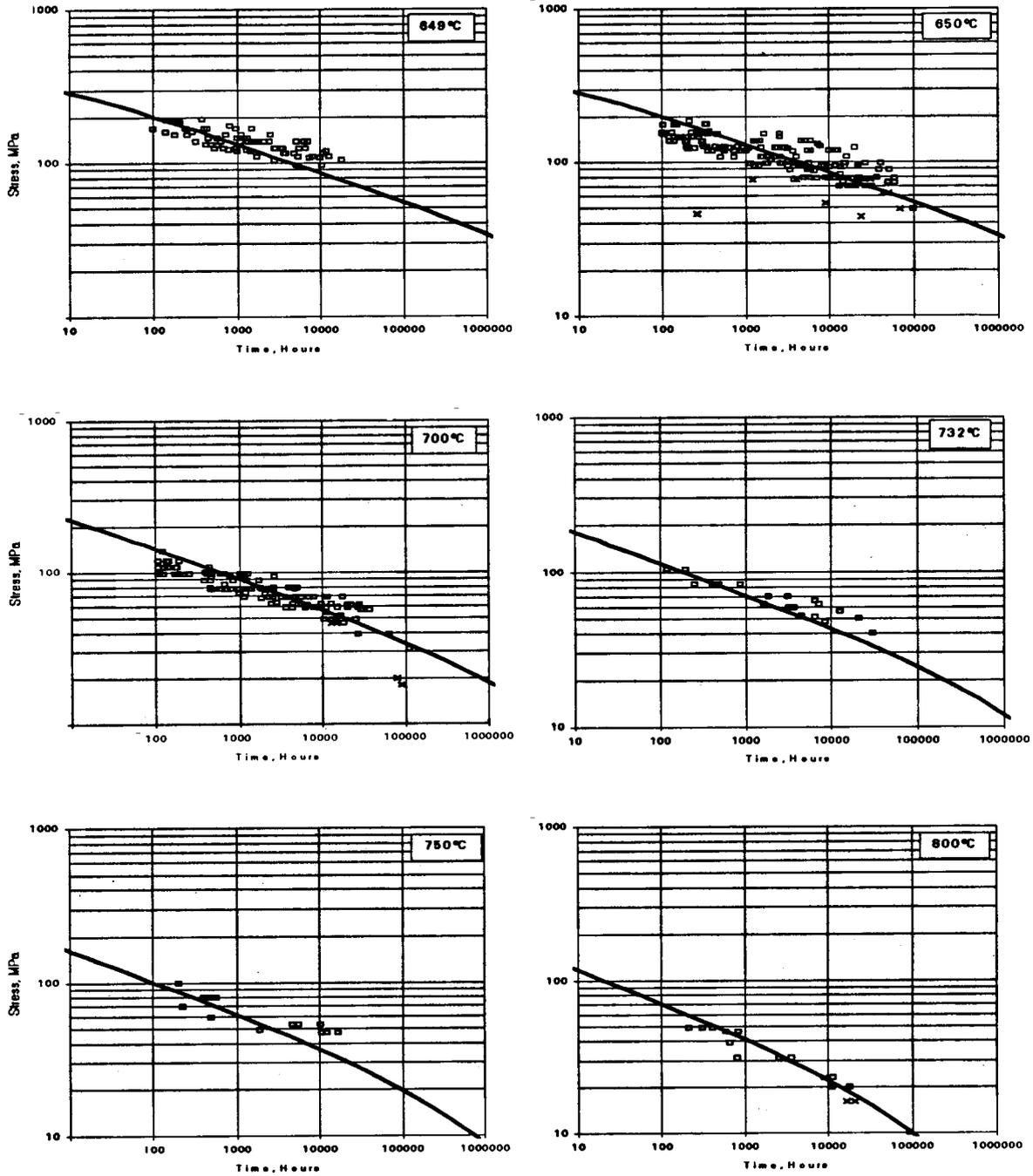


Figure E1.3 Predicted rupture behaviour from 375° to 925°C in 25°C steps (PAT-1.2)

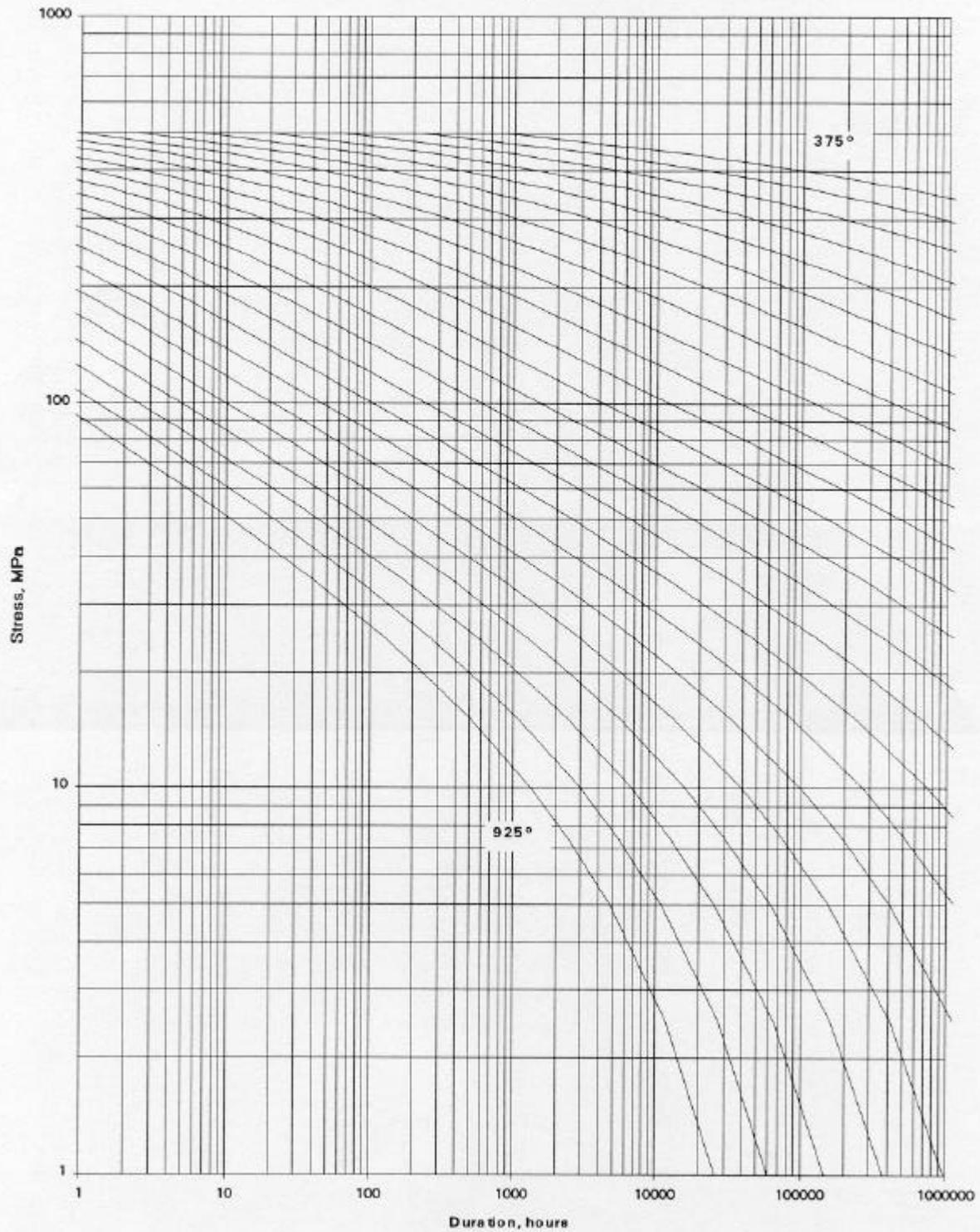


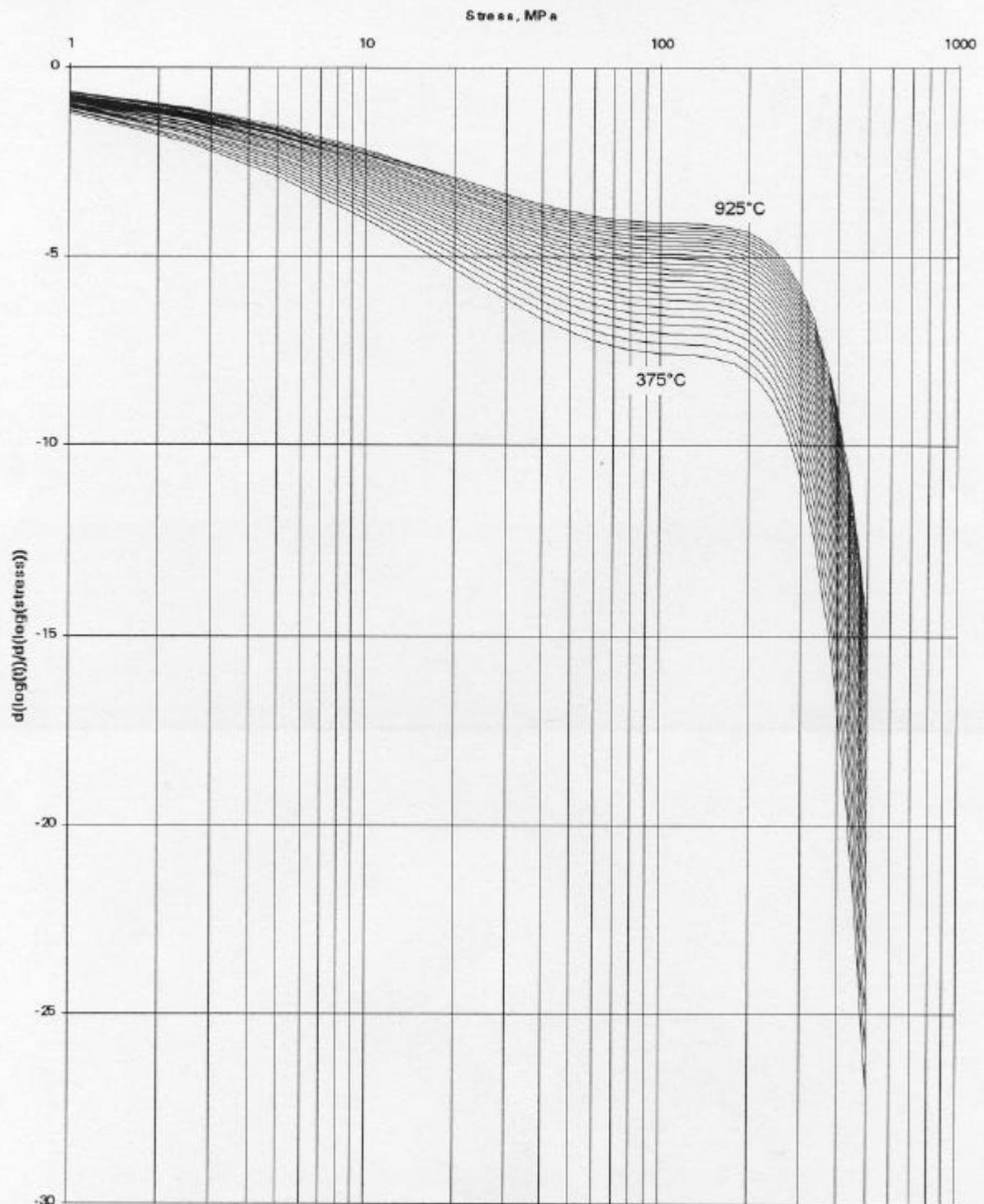
Figure E1.4 Predicted values of $\partial \log t_r^* / \partial \log \sigma_0$ from 375° to 925°C in 25°C steps (PAT-1.3)

Figure E1.5 Predicted life versus observed life for the entire data set (PAT-2.1)

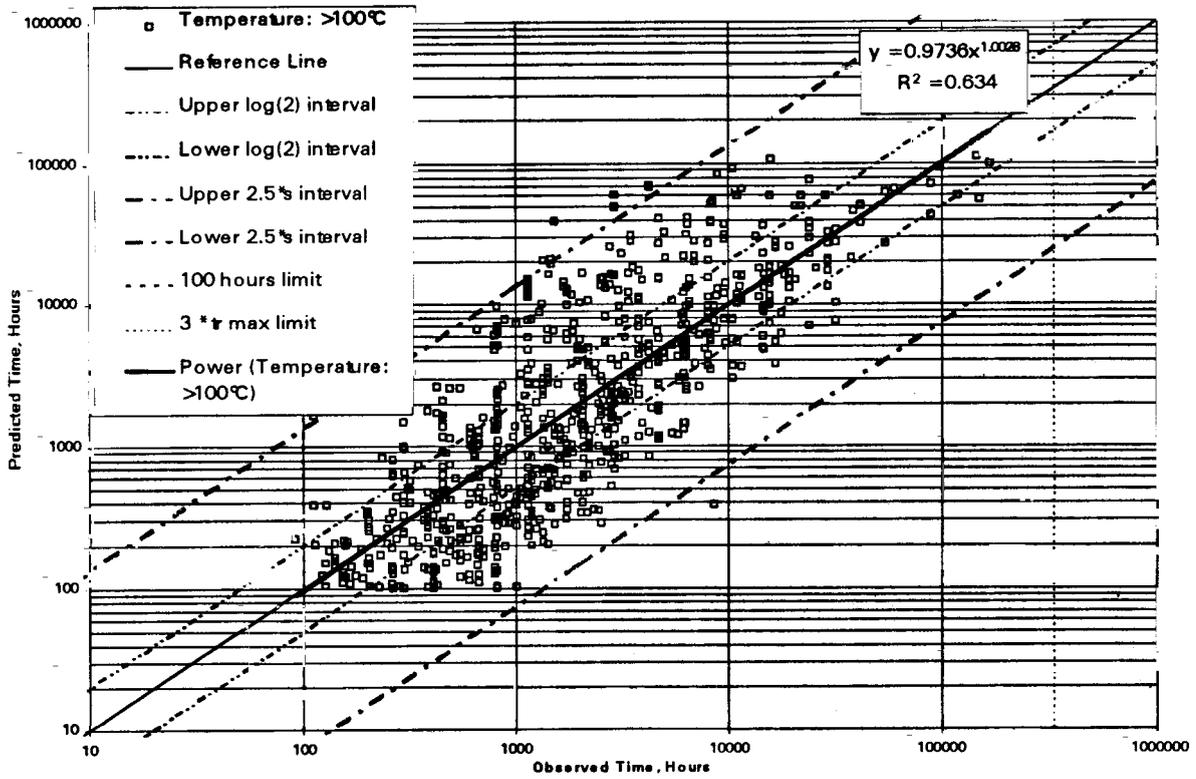
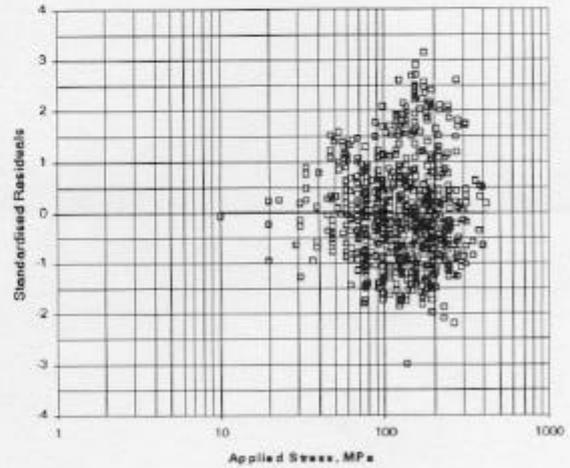
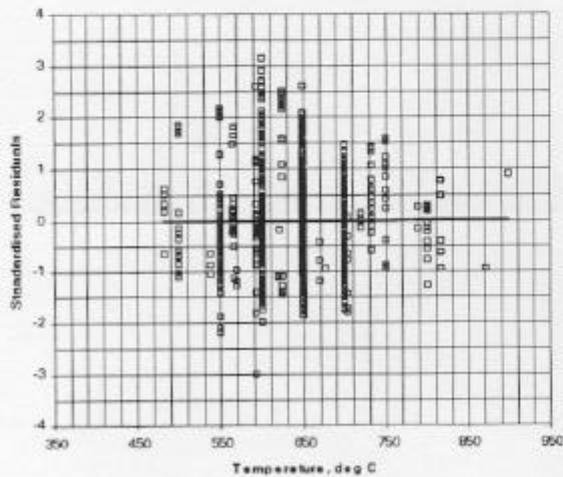
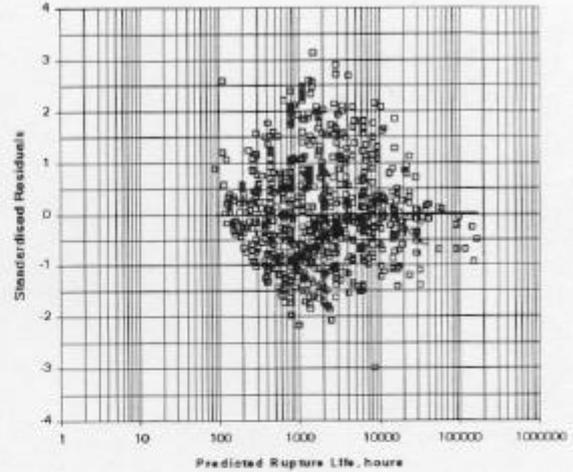
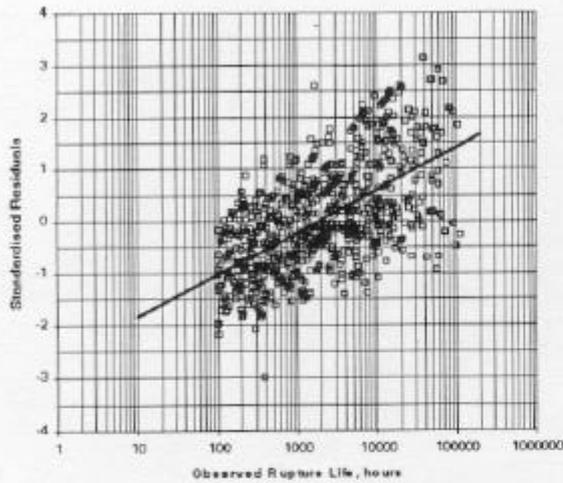


Figure E1.6 Standardised residuals of the entire data set versus: i) observed life; ii) predicted life; iii) temperature; iv) stress



Top Left: Regression Line: $A\text{-SLRT} = 0.813686 \cdot \log tr + -2.661001$
 Top Right: Regression Line: $A\text{-SLRT} = 0.005433 \cdot \log tr + -0.023303$
 Bottom Left: Regression Line: $A\text{-SLRT} = 0.000044 \cdot \text{Temperature} + -0.03388$
 Bottom Right: Regression Line: $A\text{-SLRT} = -0.025027 \cdot \log \text{stress} + 0.047165$

Total rupture points: 796

Sum $A\text{-SLRT} > 2.5$ is: 10

$A\text{-SLRT} > 2.5$ is: 1.26 % of broken points

Figure E1.7 Predicted life versus observed life for the data set at the main test temperatures, identifying the best tested casts (PAT-2.2) (Part 1.)

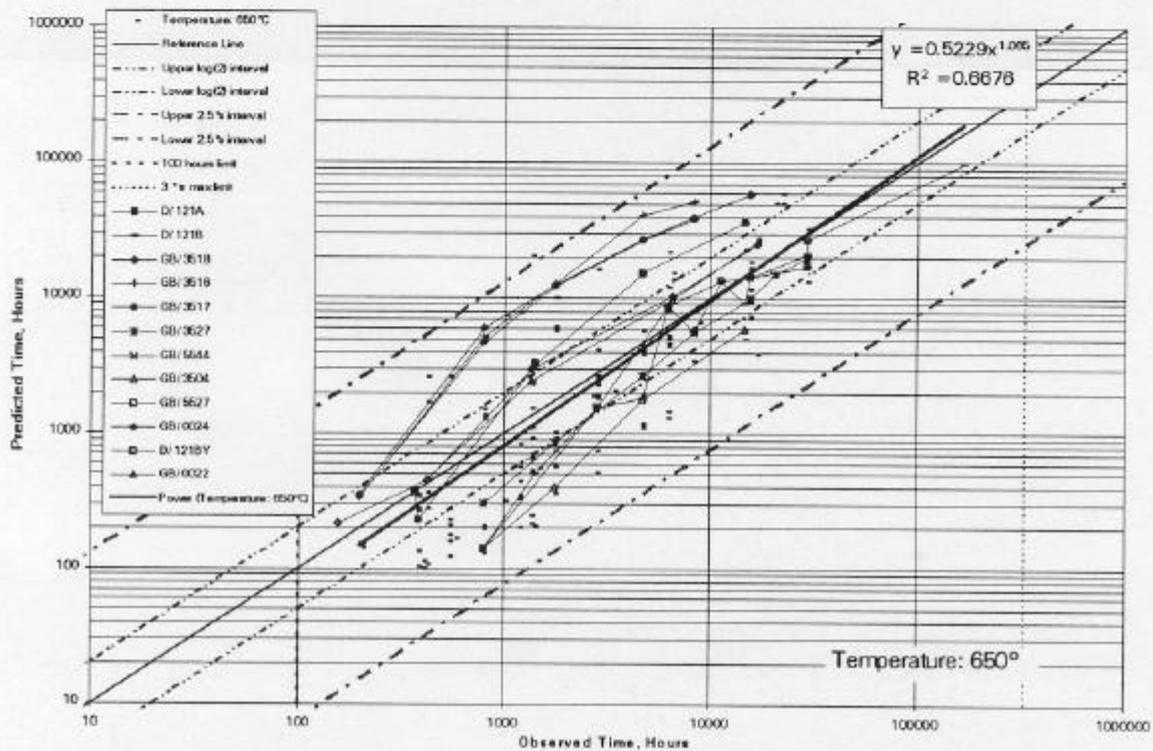
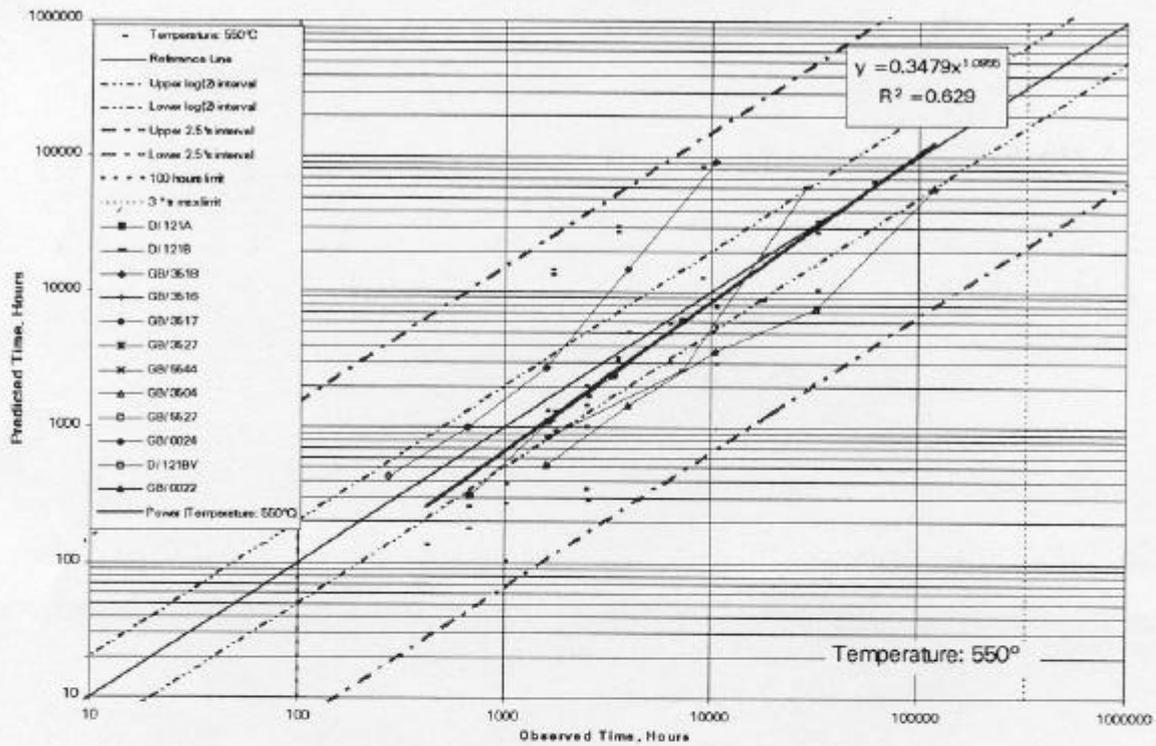
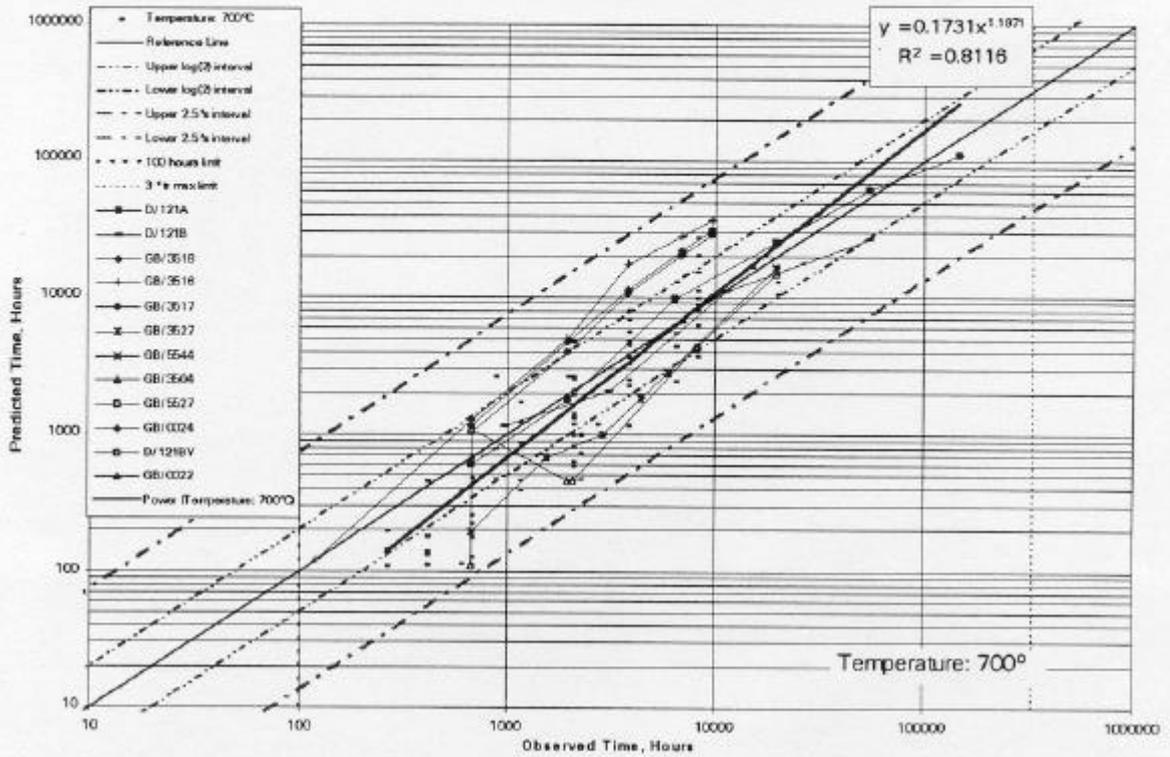


Figure E1.8 Predicted life versus observed life for the data set at the main test temperatures, identifying the best tested casts (PAT-2.2) (Part 2).



IMPLEMENTATION NOTE E1.1 : ANALYSIS OF DISTRIBUTION OF RUPTURE DATA

Recommendation 3, Section 2.3 ii) of ECCC WG1 Volume 5 Guidelines states that the statistical distribution of rupture data should be produced, such as that shown in Table E1.2. For small data sets (less than 50 points, say) this table could be produced by manual methods. Computerised methods are advised for larger data sets, since these may sometimes exceed more than 1,000 points and manual methods would be too time consuming.

The essential component of a computerised method is to automatically produce a *frequency table* (sometimes also called a *cross-tabulation* or *pivot table*), which relates the number of data points (and t_{rmax} , σ_{min}) to the test temperature, test duration and source of data. The following relates how table E1.2 was prepared using Microsoft Excel 5.0 pivot tables.

- i) the rupture data were first organised into columns, with separate columns for source of test results (ECCC WG1 Volume 2 Section 0), test temperature, applied stress, unfailed test duration and failed test duration.
- ii) an Excel 5.0 pivot table was then prepared using the entire rupture data set. The test temperature was assigned to the *row label*; the source of the test results to the *column label*; and the count of failed test data to the *data label*. The pivot table was produced, and copied to another location for later combination with other pivot tables.
- iii) the procedure in step ii) was repeated, except that this time no *column label* was selected, and the "maximum of the failed test duration" was entered into the *data label*.
- iv) the procedure in step iii) was repeated except that the "minimum of the specified applied stress" was entered into the *data label*.
- v) the distribution of rupture data with respect to temperature and duration was achieved using a coding variable. Thus, all data with durations of less than 10Kh were given a code of 1, all data with durations between 10-20Kh were given a code 2, and so on. (In practice, this was achieved with a spreadsheet formula). Next, a pivot table was produced as before, but with the coding variable placed in the *column label*, and the count of failed test data in the *data label*.
- vi) a similar procedure to that in step v) was followed to produce a pivot table of the count of unfailed test data.
- vii) as a final step, the data from the various pivot tables were combined and formatted. The number of failed test points expressed as a percentage of total data set was calculated using a simple formula, and added to the table's right hand side.

Once the spreadsheet pivot tables have been prepared in the manner described above, they may be re-used with any other rupture data set, requiring only that the database range is re-entered, and the pivot tables refreshed before they are re-combined and re-formatted.

IMPLEMENTATION NOTE E1.2 : IDENTIFYING THE MAIN AND BEST TESTED CASTS

Recommendation 3, Section 2.3 iv) of ECCC WG1 Volume 5 Guidelines states that the 'main' and 'best tested' casts should be identified. The data from these casts is compared against the predictive model (or strength values) of the main assessment in the post assessment tests. The following guide is given in the Recommendations Section:

- i) the main cast has the most test points at the most temperatures;
- ii) the best tested casts are those for which there are ≥ 5 broken testpiece data points at each of at least three $T_{[5\%]}$ temperatures (with ≥ 2 /temperature having rupture durations $> 10,000$ h). A cast which just fails to meet this criterion, may still be regarded as a best-tested cast if there are ≥ 16 broken testpiece data points total.

This guide may be followed by manually searching through the lists of rupture data. In this circumstance, it will be helpful to sort the data with respect to cast identity. (This procedure will be eased if a 'nested sort' with respect to cast identity [ascending], temperature [ascending] and stress [descending] should be performed, in advance.)

Alternatively, the frequency table approach described in Implementation Note E1.1 may be adapted to provide the information required. The following description relates how table E1.3 was prepared using Microsoft Excel 5.0 pivot tables.

- i) the rupture data were first organised into columns, with separate columns for source of test results and cast identity (ECCC WG1 Volume 2 Section 0), test temperature, applied stress unfailed test duration and failed test duration.
- ii) an Excel 5.0 pivot table was then prepared using the entire rupture data set. The cast identity was assigned to the *row label*, the temperature to the *column label*; and the count of failed test data to the *data data label*.
- iii) the pivot table produced in step ii) was then copied, and the rows sorted with respect to the row totals. For convenience, rows where the totals were 10 or less were deleted, and the table reformatted.

From Table E1.1, the main test temperature (T_{main}) has already been identified as 650°C, and those temperatures with more than 5% of the testpiece population ($T_{[5\%]}$) have been shown to be 550°C, 600°C, 649°C, and 700°C. The casts with the greatest number of test points are (in decreasing order) 121A, 121B and 3518. An examination of their rupture data indicates long term tests at T_{main} and $T_{[5\%]}$. Preferably, the best tested casts would be chosen from different sources, but data were only available from two sources for this data set.

**IMPLEMENTATION NOTE E1.3 : THE GENERATION OF STANDARD
STRENGTH TABLES FROM PREDICTIVE MODELS**

The final output of a creep rupture data assessment is a summary table of design strength values. For a relatively few procedures (for example, the German Averaging and Cross Plotting Method, Appendix B) the design strength values are obtained directly. For the majority of procedures however, the initial output from the assessment procedure is a mathematical relation often termed a "predictive model", which relates the predicted rupture life t_r to a function of temperature, T , and applied stress, σ_o . To obtain strength values from the predictive model and two situations may arise:

- i) simple "algebraic" predictive models may be manipulated to yield σ_o as a direct function of T and t_r , from which strength values are readily computed.
- ii) more complex predictive models, including the majority of time-temperature-parameters involving polynomial functions in stress, must be solved by numerically since it is impossible to isolate σ_o as a direct function of T and t_r .

Numerical solution of the time-temperature-parameters might appear, at first sight, to be a daunting process. A table of strength values typically contains six temperatures and ten durations. At each of the sixty combinations of temperature and duration, a solution of the predictive model must be obtained in an iterative fashion by altering the value of stress until the predicted time agrees with the specified duration. With practice, this operation can be performed manually to an acceptable accuracy, but will take about an hour to complete the entire strength table. The procedure can be fully automated, however, using the nonlinear solution capabilities of statistical or spreadsheet programmes. An example Microsoft Excel 5.0 spreadsheet application is described in the following, that was used to prepare the strength values shown in Table E1.4.

It has been shown that the majority of the time-temperature-parameters conform to the Mendelson-Roberts-Manson general form indicated in Equation (1) (see also appendix B).

$$P(\sigma_o) = \frac{\sigma_o^q (\log t_r^* - \log t_a)}{(T - T_a)^R} \quad (1)$$

Only exceptionally is the value of q other than 0, therefore Equation (1) is usually simplified and rearranged, to that shown in Equation (2).

$$\log t_r^* = P(\sigma_o)(T - T_a)^R + \log t_a \quad (2a)$$

$$\text{where } P(\sigma_o) = a + b.f(\sigma_o) + c.f(\sigma_o)^2 + d.f(\sigma_o)^3 + e.f(\sigma_o)^4 \quad (2b)$$

$$f(\sigma_o) = \sigma_o^w \text{ or } \log \sigma_o \quad (2c)$$

A spreadsheet was prepared incorporating the main elements listed below.

- i) strength table: a table labelled with the temperatures and durations at which strength values are required, together with approximate "starting values" of the numerical solution (these may typically range from 500MPa at the shortest duration/highest temperature to 100MPa at the longest duration/lowest temperature).

- ii) coefficients table: cells containing values of the coefficients obtained from the creep rupture data assessment procedure, together with an appropriate choice of the values of r and T_a (if not otherwise specified) in order for Equation (2) to represent the appropriate model form.
- iii) time-temperature-parameter equations: cells containing the formulae necessary to estimate the predicted time, t_r , from Equation (2) and values in the coefficients table, and the values supplied for solution from the numerical solutions table (see below).
- iv) numerical solutions table: cells containing a single set of the temperature and duration values and approximate starting value of strength, taken from those in the strength table. In this table, the sum of the squares of the difference between the specified duration, t_s , and the predicted time t_r is also entered as a formula.

To obtain a single strength value, a set of values of temperature duration and starting value of strength were copied from the strength table to the numerical solutions table. Next the 'Solver' (non-linear solutions) module was activated from the menu, with the target cell reference entered that contains the sum of squares of $(t_s - t_r)$ and the 'minimise' option selected. The cell reference to be adjusted was that in the numerical solutions table which initially contained the starting value of strength. All other aspects of the Solver module were left at their default values, and the numerical solution process begun. On completion, the cell that initially contained the starting value, contained the estimate of strength. Provided the final value of sum of squares of $(t_s - t_r)$ was acceptably small, the strength value was copied back to the appropriate location in the strength table.

The process was repeated for the other values in the strength table. An Excel macro was written to automate the procedure.

This procedure may also be adapted for the numerical solution of other non-linear creep rupture predictive models, and indeed a wide variety of predictive models for other types of test data.

IMPLEMENTATION NOTE E1.4 : PHYSICAL REALISM OF PREDICTED LINES**PAT 1.1, PAT1.2, PAT1.3**

The primary objective of the first group of ECCC WG1 Post Assessment Tests (PATs), which are applied the results of a creep rupture data assessment, is to evaluate the physical realism of the predicted behaviour within reasonable limits of temperature, stress and duration. There are likely to be several ways in which this group of PATs may be applied, but it is the purpose of this implementation note to indicate how they may be applied to the results arising from the use of common time-temperature-parameters.

PAT-1.1

Very often, PAT-1.1 will already have been performed as part of the assessment, since it merely requires that the analyst examine the predicted and observed behaviour over the range of the data. Conventional isothermal $\log \sigma_0$ versus $\log t_r$ axes are chosen to display the data. If the assessment procedure does provide plots of predicted and observed behaviour, they may be simply constructed, in a spreadsheet for example. The following procedure was used to prepare Figures E1.1 and E1.2 in the worked example.

- i) A table of the rupture data was prepared, with columns for the independent variables temperature (T), initial applied stress (σ_0), and the dependent variable, rupture life (t_r). The data were sorted with respect to temperature, and stress(descending). The data for each temperature were plotted on a separate spreadsheet chart, with the "log axes" option selected. The unfailed test duration, (t_{UB}) was included in a fourth column, and different symbols were used to plot these durations.
- ii) The coefficients of the parametric equation shown in Table E1.5 was entered into a separate location of the spreadsheet, and the temperatures of interest entered as column headings in a table. In a further column, a range of stresses (from 500 to 1MPa) was entered. For each pair of temperature and stress, there was therefore one cell in the table. In that cell, the parametric equation together with the coefficient values and the values of temperature and stress was used to calculate the predicted rupture life. The predicted rupture lives were then plotted upon the same figures as the observed rupture life.

Note that the analyst should examine the figures carefully, particularly at temperatures for which there are more than 5% of the data, to ensure that the predicted life generally falls within the middle of the data. It is also appropriate to consider whether or not unfailed test data are adequately represented by the predicted line. If there are a lot of unfailed data *beyond* the predicted line, then the prediction is likely to be conservative, for example.

PAT-1.2

The second of the PATs in this group, PAT-1.2, aims to show that physically realistic behaviour is predicted when the function is slightly extrapolated beyond the region of the data. The tools required to produce Figure E1.3 in the worked example, were very similar to those used to confirm the credibility of the predicted behaviour with the observed data, PAT-1.1. In essence, it is merely necessary to replace the range of temperatures considered in stage ii) with those stated in PAT-1.2, and to plot the predicted lives on the same axes.

PAT-1.3

The third of the PATs, PAT-1.3, is based on the observation that the slope of the rupture curve on isothermal $\log \sigma_o$ versus $\log t_r$ axes is expected to fall within well-known limits. At short durations, the curve tends to the horizontal and $-\partial \log t_r^* / \partial \log \sigma_o$ tends to a large value of 30 or more. At long durations, the curve becomes increasingly inclined and $-\partial \log t_r^* / \partial \log \sigma_o$ tends to a value of 5 or less. The criterion for PAT-1.3 is based on the fact that $-\partial \log t_r^* / \partial \log \sigma_o$ should never fall below 2. Figure E1.4 in the worked example was prepared in the following way.

- i) The table of predicted lives based on a range of temperatures and stresses, that was prepared for PAT-1.2 was copied into a new spreadsheet. The function of predicted life was replaced with that for $\partial \log t_r^* / \partial \log \sigma_o$ by noting that the derivative of the parametric equation (Equation 1) is that given in Equation 2.
- ii) The value of the function was plotted versus stress on linear/log axes for each of the temperatures of interest.

$$\log t_r^* = P(\sigma_o)(T - T_a)^R + \log t_a \quad (1a)$$

$$\text{where } P(\sigma_o) = a + b.f(\sigma_o) + c.f(\sigma_o)^2 + d.f(\sigma_o)^3 + e.f(\sigma_o)^4 \quad (1b)$$

$$f(\sigma_o) = \sigma_o^m \text{ or } \log \sigma_o \quad (1c)$$

$$\begin{aligned} \partial \log t_r^* / \partial \log \sigma_o = \\ (b.f(\sigma_o) + 2.c.f(\sigma_o)^1 + 3.d.f(\sigma_o)^2 + 4.e.f(\sigma_o)^3).g(\sigma_o).(T - T_a)^R + \log t_a \end{aligned} \quad (2a)$$

$$\text{where } g(\sigma_o) = \sigma_o^m \text{ or } 1 \quad (2b)$$

Note that the analyst should examine the plot of $\partial \log t_r^* / \partial \log \sigma_o$ to ensure that the value of the derivative is less than -2, even at $0.8 \cdot \sigma_{o[\min]}$ (8MPa in the worked example) to ensure that the PAT-1.3 criterion is passed.

**IMPLEMENTATION NOTE E1.5 : EFFECTIVENESS OF MODEL PREDICTION WITHIN RANGE
OF INPUT DATA - PAT 2.1, PAT2.2**

The primary objective of the second group of post assessment tests (PATs) is to test how well rupture life is predicted with regard to the input data. The mandatory parts of the two tests are closely related, with PAT-2.1 examining the behaviour of the entire data set, and PAT-2.2 examining the behaviour at the main test temperatures. The author's experience suggests that it is advisable to prepare one set of tools that will perform both PATs. The major difference between the two tasks is largely one of presentation, with PAT-2.2 additionally requiring that the best-tested casts (10 casts) are identified.

The main elements used in Microsoft Excel 5.0 to prepare the Figures (E1.5, E1.6 and E1.7) and data to perform PATs 2.1 and 2.2, were as follows.

- i) A spreadsheet was prepared that contained the tabulated rupture data, with separate columns for the independent variables temperature (T), initial applied stress (σ_0), and the dependent variables, rupture life (t_r) and unfailed test duration, (t_{UB}). (See also Implementation Note E1.4 for a description of a similar table, these two tables may be combined if desired).
- ii) Alongside each rupture point, the predicted life (t_r^*) was calculated from the predictive equation and coefficients, together with the raw residual error ($\log t_r - \log t_r^*$), and the square of the raw residual error, $(\log t_r - \log t_r^*)^2$.
- iii) In a separate sheet, spreadsheet database functions (termed "advanced filter" in Excel 5.0) were used to *extract* the data from the first sheet, at specified temperatures, or for all temperatures.
- iv) The standard deviation, s_{A-LRT} or s_{I-LRT} was calculated by using the spreadsheet SUM function to sum the square of the raw residual error, $(\log t_r - \log t_r^*)^2$, and the COUNT function to count the number of data, and the formulae:

$$s_{A-LRT} = \sqrt{\frac{\sum_{j=1}^n \{\log t_r - \log t_r^*\}_j^2}{n-1}} \quad T = \text{all temperatures} \quad (1a)$$

$$s_{I-LRT} = \sqrt{\frac{\sum_{j=1}^n \{\log t_r - \log t_r^*\}_j^2}{n-1}} \quad (1b)$$

The standardised residual log time (termed either "A-SLRT" for all data, or "I-SLRT" at a specific temperature) was calculated by dividing the raw residual error ($\log t_r - \log t_r^*$) by the value of s_{A-LRT} or s_{I-LRT} as appropriate.

PAT-2.1

To perform PAT-2.1, it was necessary merely to plot the predicted and observed time on log-log axes, and add the reference 1:1 line, vertical lines at 100 hours and $3 \cdot t_{r[\max]}$ (=332,000 hours), and lines displaced from the 1:1 line constructed by the simple formulae:

$$\log t_r^* = \log t_r \pm \log 2 \quad (2a)$$

$$\log t_r^* = \log t_r \pm 2.5 \times s_{A-LRT} \quad (2b)$$

Further, a power law function (Excel trendline) was fitted through the predicted time vs. observed time data, of the form shown in Equation 3, yielding the values of the slope required for PAT-2.1's numerical criteria.

$$t_r^* = a \cdot t_r^b \quad (3a)$$

$$\log t_r^* = \log a + b \cdot \log t_r \quad (3b)$$

The analyst should use this plot and derived information to demonstrate that the assessment results pass the mandatory requirements of PAT-2.1.

The *recommended* aspects of PAT-2.1, that is plots of standardised residuals vs. observed life, $\log t_r$; vs. predicted life, $\log t_r^*$; vs. stress, $\log \sigma_o$ and vs. temperature, T are readily prepared using the same extracted table of data described above, see Figure E1.6.

PAT-2.2

To perform PAT-2.2, the extracted data (point iii) were obtained at one of the main test temperatures and the isothermal standard deviation, s_{I-LRT} , and the isothermal standardised residual log time calculated, as described above. A separate chart was used to plot the data, and the limits (prepared with s_{I-LRT} instead of s_{A-LRT} in Equation 2b) applied as described previously.

In a separate sheet, however, the data for the best tested casts were each extracted for the chosen temperature (again using Excel's "advanced filter" option) into separate tables, and these data added to the chart using different symbols and lines.

**IMPLEMENTATION NOTE 1.6 : REPEATABILITY AND STABILITY EXTRAPOLATIONS -
PAT3.1, PAT 3.2**

The objective of the third group of post assessment tests is to test the repeatability and stability of the predicted behaviour. This is done by removing a small amount of data from the data set, and entirely repeating the assessment procedure. A comparison is made between the strength results at either 300,000 hour duration or 3 times the longest test duration, whichever is shortest. In PAT-3.1, data are removed by random culling (removal) of 50% of the long-term data points (on the basis of observed life). In this way it provides a test of the assessment procedure to slight changes in the long-term data population, as sometimes occurs due to the eventual failure of long-term tests. In PAT-3.2, lowest stress data are removed from the main test temperatures. Since it is those data that generally dominate the long-term fit, PAT-3.2 tests the ability of procedure to provide accurate long-term extrapolation.

The actual repeat assessment will be covered by the assessment procedure documentation, for example, Appendix D. Therefore, the following description only addresses the process of culling the data set.

PAT-3.1

In common with other procedures to implement the post assessment tests, the first stage of PAT-3.1 is to produce a table of the rupture data (that is, temperature, initial stress, observed life and predicted life). To cull 50% of the long-term data from the data set used in worked example, it was then necessary to identify which observed lives fell within the range $t_{r[\max]}$ and $t_{r[\max]}/10$. For the present data set, this is the range 110,806 hours to 11,081 hours, respectively. One approach was to re-order the data with respect to decreasing observed life. A random number generator (the RAND() function in Microsoft Excel 5.0) was then introduced into the column adjacent to those data with observed lives within the stated range. The RAND() function produced values in the range 0 to 1, and in the first instance (that reported in the worked example) data with values less than 0.5 were identified and removed.

In all but very large data sets, it is unlikely that the RAND() function will provide a set a values whose median value is exactly 0.5. Therefore, selection of data below this value for culling will quite often lead to a percentage of the data set other than 50% being removed. For that reason, a variation of this approach is to determine the median value from the random numbers, and to delete those whose values for below the median value.

PAT-3.2

The removal of 10% of the lowest stress data from each of the main test temperatures is relatively straight-forward. In the worked example, the table of rupture data were first sorted with respect to temperature and stress. Taking 600°C as an example, there were 174 failed test data in the original data set. 10% of this number is therefore 17.4, and therefore 17 of the lowest stress data points at 600°C were then identified and removed from the data set. This process was repeated at the other main test temperatures.

**Checklist for ECCC WG1 Creep Rupture Data Assessment
Part 1: Content of Report**

Section / Contents	Requirement	Location in Report	Comments
<u>Section 1. Introduction</u>			
1.1 Commissioning, objectives and relationship.	R		
1.2 CRDA References, and any modifications.	M		
1.3 Local implementation.	R		
<u>Section 2. Data Collation and Pre-Assessment.</u>			
2.1 Record of exchange files.	M		
2.2 Conformance with ECCC WG1 Vol 4	R		
2.3 Conformance with ECCC WG1 Vol 3	M		
2.4 Specification and summary statistics (table).	M		
2.5 Distribution of rupture data (table).	M		
2.6 A record of the main and best tested casts.	M		
2.7 Groups of data rejected or separated and explanation.	M		
2.8 Single points rejected and explanation.	M		
2.9 Any data re-organisation or data reduction.	M		
<u>Section 3. Main Assessment.</u>			
3.1 Predictive equations.	R		
3.2 Error distribution.	R[M]*		
3.3 Method of estimation.	R		
3.4 Any data conditioning or further treatment.	R		
3.5 Deviations from written procedure.	R		
3.6 A table of mean strength values.	M		
3.7 Table recording coefficients, goodness of fit, and confidence intervals.	R		

Section / Contents	Requirement	Location in Report	Comments
Section 4. Post Assessment Acceptability Criteria.			
4.1 Credibility of predictive model: model and data plotted isothermally. [PAT-1.1]	M		
4.2 Credibility of predictive model: model plotted at 25°C intervals to 1,000,000h and $0.8\sigma_{\min}$. [PAT-1.2]	M		
4.3 Credibility of derivative, n' plotted at 25°C intervals to 1,000,000h and $0.8\sigma_{\min}$. (record minimum value at end of checklist.) [PAT-1.3]	M		
4.4 Model prediction all data (predicted time vs. observed time) [PAT-2.1]	M		
4.5 Plot of standardised residuals vs: $\log t_r$.	O		
4.6 " " vs. $\log t_r^*$.	O		
4.7 " " vs. $\log \sigma_v$.	O		
4.8 " " vs. T.	O		
4.9 Model prediction, data of "best tested" casts (predicted time vs. observed time) [PAT-2.2]	M		
4.10 50% cull between $t_{r[\max]}/10$ and $t_{r[\max]}$. [PAT-3.1]	M		
4.11 10% cull of the lowest stress data. [PAT-3.2]	[M]		
4.12 Summary results of PATS.	R		
Section 5. Conclusions			
5.1 Conformance with ECCG WG1 Volume 5 Guidelines.	M		
5.2 Strength values proposed, and restrictions.	M		

**Checklist for ECCC WG1 Creep Rupture Data Assessment
Part 2: Summary of Numerical Values**

Quantity	Symbol	Value(s)	Comments		
Total no. broken points	–		Required for PAT-2.1		
Lowest test temp. °C, Highest test temp. °C			Required for PAT-1.2; PAT-1.3		
Main test temperature	T_{main} $T_{min[10\%]}$ $T_{max[10\%]}$		Required for PAT-2.2, PAT3.1, PAT3.2		
Lowest test stress (failed points), Nmm^{-2}	σ_{min} $0.9*\sigma_{min}$ $0.8*\sigma_{min}$		Required for PAT-1.2, PAT3.2 and for strength table		
Longest duration (failed points), h	$t_{r[max]}$ $t_{r[max]}/3$		Required for PAT3.1, PAT-3.2		
Best tested cast Main casts					
Predicted rupture life at i) T_{main} ii) $T_{min[10\%]}$. iii) $T_{max[10\%]}$.		$R_{r/300,000h}$	Required for PAT3.1, PAT-3.2, may use $R_{r/300,000h}$ instead of $R_{r/300,000h}$ if $t_{r[max]} < 100,000h$		
Post Assessment Tests			Criterion	Pass/Fail	Comments
PAT 1.1 Model and Data	-	-	Visual check		
PAT 1.2 Model to 1,000,000h, $0.8\sigma_{min}$	-	-	not cross-over not converge no turn-back		
PAT 1.3 Derivative of model, $\geq 0.8*\sigma_{min}$	min. n max. n		(≥ 2) -		
PAT 2.1 Model prediction, all data.	$\% > +2.5.S_{[A-RLT]}$ $\% < -2.5.S_{[A-RLT]}$ mean slope mean line		≤ 1.5 $> 0.78,$ < 1.22 $\pm \log 2$		
PAT 2.2 Model prediction, best tested casts at: i) T_{main} ii) $T_{min[10\%]}$. iii) $T_{max[10\%]}$.	$\% > 2.5.S_{[I-RLT]}$ mean slope mean line cast behaviour		≤ 1.5 $> 0.78,$ < 1.22 $\pm \log 2$		
PAT 3.1 50% cull on t_r , observed life at: i) T_{main} ii) $T_{min[10\%]}$. iii) $T_{max[10\%]}$.	no. removed	$R_{r/300,000h}$		-	
PAT 3.2 10% cull on σ_o , observed life at: i) T_{main} ii) $T_{min[10\%]}$. iii) $T_{max[10\%]}$.	no. removed	$R_{r/300,000h}$			

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APPENDIX F

**NEW RECOMMENDATIONS FOR MINIMUM STRESS RUPTURE DATASET SIZE
REQUIREMENTS**

S R Holdsworth [ALSTOM Power]

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APPENDIX F

NEW RECOMMENDATIONS FOR MINIMUM STRESS RUPTURE DATASET SIZE REQUIREMENTS

S R Holdsworth

BACKGROUND AND INTRODUCTION

The following note considers the minimum size requirements for a stress-rupture dataset to be suitable for the provision of strength values for Design and Product Standards. This is in response to a growing concern that existing requirements are rarely met in practice. In order to evaluate the situation, the statistics for a number of the large datasets recently assessed by the European Creep Collaborative Committee (ECCC) have been examined.

The main purpose of the requirements are to ensure that the cast-to-cast (and ideally any alloy producer) variability in the properties of the alloy under investigation is fully represented, in particular in the long term regime within which the data has significant influence on strength values determined as a result of extended extrapolation.

Having determined that existing minimum dataset requirements are generally unsuitable for randomly generated inhomogeneously distributed stress rupture datasets, alternative requirements are proposed.

EXISTING DATASET SIZE REQUIREMENTS

Target-minimum

TM1. Current ECCC guidance for a target-minimum dataset size follows that given in reference [1], i.e. data are required for:

- ≥ 6 casts at ≥ 3 temperatures at intervals of 25-50°C, with
- ≥ 5 tests per cast per temperature for t_u up to $\geq 40\text{kh}$ or $\geq t_{\text{Des}}/3$ (different s_o)
see also Table 1 (column 3, rows 9-12), requirement referred to as 'TM1'

These 'fully-characterised' cast requirements were defined to enable ISO6303-defined extended-time extrapolations to be adopted, i.e.

Extended time extrapolations are those beyond x3 the test duration exceeded by data points from 5 casts at temperatures within 25°C of that specified

In a specifically designed data collection activity, such a dataset could be established with a total of 90 tests

TM2. Recently, a more relaxed target-minimum requirement has been defined in reference [2], i.e. data are required for:

- ≥ 6 casts at ≥ 2 temperature, with
- ≥ 5 tests per cast per temperature for t_u up to $\geq 35\text{kh}$ or $\geq t_{\text{Des}}/3$ (different s_o)
see also Table 1 (column 4, rows 9-12), requirement referred to as 'TM2'

TM3. A third target-minimum requirement is introduced, i.e. in which data are required for:

- ≥ 6 casts at ≥ 1 temperature, with
- ≥ 5 tests per cast per temperature for t_u up to $\geq 35\text{kh}$ or $\geq t_{\text{Des}}/3$ (different s_o)
see also Table 1 (column 5, rows 9-12), requirement referred to as 'TM3'

Interim-minimum

Current ECCC guidance for an interim-minimum dataset size also follows that given in reference [1]. The same requirement is also specified in reference [2], i.e. data are required for:

- ≥ 3 casts at ≥ 3 temperatures at intervals of 50-100°C, with
- ≥ 3 tests per cast per temperature for t_u up to ≥ 10 kh (different s_o)
see also Table 1 (column 2, rows 9-12), requirement referred to as 'Interim'

LARGE DATASET STATISTICS

Table 1 summarises the statistics for 8 large ECCC datasets. For each of these, the last three columns list the number of temperatures for which data has been collated, the number of observations and the maximum test duration.

The first column in Table 1 lists 8 alloys for which creep-rupture datasets have been assembled for assessment within ECCC.

Columns 2 to 6 contain information relating to the number of casts for which data has been collected for the 8 alloys. Columns 2 to 5 respectively give the numbers of casts characterised according to the 'Interim', TM1, TM2 and TM3 definitions given above. Column 6 gives the total number of casts.

Column 2 gives the number of casts which meet the interim-minimum requirements. For each material, the number of casts in the dataset meeting the 'Interim' requirements significantly exceeds the minimum.

Column 3 gives the number of casts which meet the TM1 target-minimum (current ECCC) requirements. There is only one material for which there is a sufficient number of 'fully-characterised' casts in the dataset to meet the TM1 requirement.

Significantly, there are 3 materials with data from over 120 casts and with $\gg 1500$ data points which do not meet the TM1 requirement, i.e. there are insufficient 'fully-characterised' casts.

Column 4 gives the number of casts which meet the TM2 target-minimum (EN12952) requirements. Fifty percent of the datasets meet this requirement.

One of the datasets involving $\gg 120$ casts and $\gg 1500$ data points does not meet the TM2 requirement.

Column 5 gives the number of casts which meet the TM3 requirements. All the large datasets meet this requirement.

Reducing the number of tests per cast per temperature to '4' from '5' does not significantly change the picture given by Table 1.

OBSERVATIONS

The three target-minimum options considered in Table 1 are based on a requirement for ≥ 6 'fully characterised' casts (as defined in columns 3-5 in rows 2-4 of lower part of table). In accordance with reference [1], a current ECCC recommendation is that rupture strengths may be cited without qualification provided they are not the result of extrapolation beyond $\times 3$ the

test duration to which there are data points from 5 casts. With this in mind, it is proposed to reduce the 'fully characterised' cast number requirement to ≥ 5 .

RECOMMENDATIONS

It is proposed that the original ECCC recommendation concerning the requirements for a target-minimum dataset (i.e. TM1) continues to be acknowledged as an ideal (Table 2). A well organised testing strategy could provide a dataset to meet these requirements with 90 tests.

Failing this, a target-minimum requirement based on TM2 is acceptable (but with ≥ 5 'fully characterised' heats), providing there are $N_{OBS} \geq 300$ originating from ≥ 10 casts at $N_{TEMPS} \geq 5$ covering the range $T_{MAIN} \pm \geq 50^\circ\text{C}$ (Table 2).

Ideally, there should be data for ≥ 5 heats at T_{MAIN} , $T_{MAIN} + 50^\circ\text{C}$ and $T_{MAIN} - 50^\circ\text{C}$.

Failing this, a target-minimum requirement based on TM3 is also acceptable (but with ≥ 5 'fully characterised' heats), providing there are $N_{OBS} \geq 500$ originating from ≥ 20 casts at $N_{TEMPS} \geq 5$ covering the range $T_{MAIN} \pm \geq 50^\circ\text{C}$ (Table 2).

Ideally, there should be data for ≥ 5 heats at T_{MAIN} , $T_{MAIN} + 50^\circ\text{C}$ and $T_{MAIN} - 50^\circ\text{C}$.

REFERENCES

- 1 ISO6303, 1981, 'Pressure vessel steels not included in ISO 2604, Parts 1 to 6', International Standards Organisation.
- 2 EN12952, 2001, 'Water tube boilers and auxiliary installations - Part 2: Materials for pressure parts of boilers and accessories', European Standard

SRH/25.7.03

Table 1 Number of Interim-minimum (Interim) and Target-minimum (TM1, TM2 and TM3) Casts in Large ECCC Datasets

ALLOY	NUMBER OF CASTS					N_{TEMPS}	N_{OBS}	$t_{u,max}$ kh
	Interim	TM1	TM2	TM3	Total			
12MoCrV6-2-2	42	1	6	20	126	9	1912	140
10CrMo9-10	29	16	21	27	98	23	1017	141
X10CrMoVNb9-1	17	-	2	10	141	36	1713	84
X10CrWMoV9-2	10	-	-	7	42	19	817	42
X19CrMoVNbN11-1	10	1	5	9	33	6	360	129
X2CrNi18-9	15	2	8	14	96	24	843	111
X10CrNiMoMnNbVB15-10-1	16	2	12	15	198	20	1591	179
X5NiCrAlTi31-20	15	-	2	10	33	12	552	79
No. of characterised casts	≥ 6	≥ 6	≥ 6	≥ 6				
$t_{u,max}(T)$	$\geq 10\text{kh}$	$\geq 40\text{kh}$	$\geq 35\text{kh}$	$\geq 35\text{kh}$				
No. of testpieces	$\geq 3\text{tps}$	$\geq 5\text{tps}$	$\geq 5\text{tps}$	$\geq 5\text{tps}$				
N_{TEMPS}	≥ 3	≥ 3	≥ 2	≥ 1				
ECCC / EN 12952	ECCC	ECCC	EN					

Table 2 Alternative Dataset Size Requirements

<i>INTERIM-MINIMUM REQUIREMENTS</i>	<i>TARGET-MINIMUM REQUIREMENTS</i>		
	<i>Original (TM1)</i>	<i>TM2</i>	<i>TM3</i>
		For datasets with ≈ 300 observations, originating from ≈ 10 casts, at ≈ 5 temperatures covering the range $T_{\text{MAIN}} \pm \approx 50^{\circ}\text{C}$	For datasets with ≈ 500 observations, originating from ≈ 20 casts, at ≈ 5 temperatures covering the range $T_{\text{MAIN}} \pm \approx 50^{\circ}\text{C}$
<p>For ≥ 3 casts, there should be $t_u(T, s_0)$ observations from:</p> <ul style="list-style-type: none"> ➤ ≥ 3 tests at each of ≥ 3 temperatures, at intervals of 50 to 100°C - ≥ 3 tests per temperature (different s_0) with $t_{u, \text{max}} \geq 10\text{kh}$ 	<p>For ≥ 6 casts, there should be $t_u(T, s_0)$ observations from:</p> <ul style="list-style-type: none"> ➤ ≥ 5 tests at each of ≥ 3 temperatures in the design application range at intervals of 25 to 50°C - ≥ 4 tests per temperature (different s_0) with $t_u \leq 40\text{kh}$ - ≥ 1 test per temperature with $t_{u, \text{max}} \geq 40\text{kh}$ 	<p>For ≥ 5 casts, there should be $t_u(T, s_0)$ observations from:</p> <ul style="list-style-type: none"> ➤ ≥ 5 tests at each of ≥ 2 temperatures in the design application range at an interval(s) of 25 to 50°C - ≥ 4 tests per temperature (different s_0) with $t_u \leq 35\text{kh}$ - ≥ 1 test per temperature with $t_{u, \text{max}} \geq 35\text{kh}$ 	<p>For ≥ 5 casts, should be $t_u(T, s_0)$ observations from:</p> <ul style="list-style-type: none"> ➤ ≥ 5 tests at ≥ 1 temperature(s) in the design application range (at intervals of 25 to 50°C) - ≥ 4 tests per temperature (different s_0) with $t_u \leq 35\text{kh}$ - ≥ 1 test per temperature with $t_{u, \text{max}} \geq 35\text{kh}$
<p><i>Predicted strength values determined from an Interim-minimum dataset shall be regarded as tentative until the data requirements defined in one of the Target-minimum columns are obtained</i></p>			