

Guidance on methodology for assessment of stress-rupture data —

Part 1: Procedure for derivation of strength values

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Foreword

This Published Document has been prepared under the direction of the Engineering Sector Board. It results from a programme of development and validation activity undertaken by the Creep Rupture Assessment Methodology Panel ISE/73/-/4, with financial support from the Department of Trade and Industry.

Guidance is given for assessment of multi-source, multi-cast, multi-temperature stress rupture data to determine reliable strength values for durations within and beyond the range of the data. The guidance is primarily intended for derivation of stress rupture strength values for inclusion in standards for steels for pressure purposes, and ultimately to form the basis of design strength values in relevant pressure vessel specifications and codes. However, the methodology is equally applicable to provision of rupture strength values for other purposes, and to a wider spectrum of ferrous and non-ferrous materials. The procedure allows for estimation of confidence limits about the predicted strength values.

The procedure exploits recent advances in statistical modelling and desktop computing technology, but requires metallurgical judgement to ensure that model predictions are physically realistic. A large part of the procedure may be implemented using the GLIM¹⁾ program utility macros supplied in Part 2 of this Published Document.

Prior to issue, the procedure was subject to field trials by a number of independent organizations.

It has been assumed in the drafting of this Published Document that execution of its provisions is entrusted to appropriately qualified people.

Summary of pages

This document comprises a front cover, an inside front cover, pages i to iv, pages 1 to 51 and a back cover.

¹⁾ GLIM is a statistical software package supplied by Numerical Algorithms Group Ltd., Wilkinson House, Jordan Hill Road, Oxford OX2 8DR. The copyright for GLIM is owned by the Royal Statistical Society.

Introduction

Creep rupture strength values are determined from assessment of stress rupture data gathered for a number of casts over a range of temperatures. This Published Document defines a method for deriving creep rupture strength values for design and product standards. The method is equally applicable to assessments for other purposes and thereby provides a standard procedure for use by a wide spectrum of practitioners.

The procedure described in this document 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 (e.g. ISO 6303), the new procedure incorporates the following features:

- formal preassessment of 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;
- statistical treatment of variations in data scatter with stress and temperature;
- 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 repeatability and stability of extrapolations; and
- semi-automation, allowing full advantage to be taken of modern desktop computing power, but with ample provision for user intervention.

This procedure develops 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 includes derivatives of the Mendelson-Roberts-Manson (MRM) and Orr-Sherby-Dorn (OSD) models (see Larson and Miller [1], Manson and Haferd [2], Mendelson, Roberts and Manson [3] and Orr, Sherby and Dorn [4]); the MRM equation set forming the basis of the ISO 6303 procedure for assessment of creep rupture data. Two Soviet models (SM1, SM2; see Trunin, Golobova and Loginov [5]) and the Minimum Commitment model (MC; see Manson and Muralidhan [6]) 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; although for use with GLIM routines these should be linear in parameters. Model selection is based primarily on objective criteria but the procedure recognizes the importance of visual inspection of model fits to isothermal data and may require iteration. The procedure incorporates methods for modelling the creep rupture behaviour of both well-behaved and metallurgically active steels²⁾.

This Published Document is in two Parts.

Part 1 contains procedural details for derivation of creep rupture strength values, with guidance on minimum data requirements given in annex A. The statistical background to the procedures is described in annex B and a comprehensive worked example is presented in annex C. Annex D gives an example of a summary report of assessment results. Annex E is a bibliography.

Part 2 of this Published Document 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 that may be implemented using the GLIM statistical modelling package. The macros may be revised from time to time, and users of this document may wish to consult the BS PD 6605 Web Page³⁾ to ensure that they have the latest versions of the software.

1 Scope

This Published Document provides guidance for assessment of multi-source, multi-cast, multi-temperature stress rupture data to determine reliable strength values for durations within and beyond the range of the data. The guidance is primarily intended for derivation of creep rupture strength values for inclusion in standards, and ultimately to form the basis of design strength values in relevant specifications and codes. However, the methodology is equally applicable to providing rupture strength values for other purposes and to a wider spectrum of ferrous and non-ferrous materials.

2 Normative references

The following normative documents contain provisions that, through reference in this text, constitute provisions of this Published Document. For dated references, subsequent amendments to, or revisions of, any of these publications do not apply. For undated references, the latest edition of the publication referred to applies.

BS 3500-1:1969, *Methods for creep and rupture testing of metals — Tensile rupture testing*.

ISO 6303:1981, *Pressure vessel steels not included in ISO 2604 Parts 1 to 6 — Derivation of long-time stress rupture properties*.

²⁾ See 6.2.3.

³⁾ Details of Web Page: <http://www.cas.lancs.ac.uk/bsi6605/>.

BS PD 6525-1:1990, *Elevated temperature properties for steels for pressure purposes — Stress rupture properties*.

BS PD 6605-2, *Computing methods*.

ISO 204:1997, *Metallic materials — Uninterrupted uniaxial creep testing in tension — Method of test*.

3 Symbols and abbreviations

For the purposes of this Published Document, the symbols and abbreviations given in Table 1 apply.

Table 1 — Symbols and abbreviations

Symbol	Quantity
B	broken (test-points)
C	percentage confidence interval
$D, D_{\max}$	reduction in deviance, maximum reduction in deviance
d	deviance
LMn, MRn[0]	Larson–Miller model (see Larson and Miller [1]), i.e. MRM model with $T_0 = 0$, $r = -1$ and $q = 0$
$\ln []$	natural logarithm (i.e. logarithm to base e)
$\log []$	logarithm to base 10
MC	Minimum Commitment model (see Manson and Muraldihan [6])
MHn, MHn[T_0]	Manson–Haferd model (see Manson and Haferd [2]), i.e. MRM model with $r = +1$ and $q = 0$
MHn, MHn[0]	Manson–Haferd model with $T_0 = 0$
MRM	(see Mendelson–Roberts–Manson [3])
MRn, MRn[T_0]	MRM model equation with $r = -1$ and $q = 0$ (simplified MRM)
m	version number of GLIM macro
n	degree of polynomial of $\log [\sigma_0]$ in MHn, MRn and OSDn model equations
n_A	total number of observations
n_I	number of data points at the temperature of interest
OSDn	Orr–Sherby–Dorn model (see Orr, Sherby and Dorn [4])
P	culling percentage in robustness in extrapolation check
PAT	post assessment test ^a
PAT-1	tests of: i) model fit credibility (PAT-1.1); ii) physical realism (PAT-1.2); and iii) model fit derivatives (PAT-1.3)
PAT-2	tests of effectiveness of within-data-range model prediction: i) for all data (PAT-2.1); and ii) for selected temperatures (PAT-2.2)
PAT-3	test of repeatability and stability of extrapolation (specifically PAT-3.1)
q	stress exponent in MRM equation (see Table B.1)
$R_r/T/t$	rupture strength for a given temperature and time (MPa)
r	condition at rupture
r	$(T - T_0)$ exponent in MRM equation (see Table B.1)
S	culling statistic
SM1	Soviet model 1 (see Trunin, Golobova and Loginov [5])
SM2	Soviet model 2 (see Trunin, Golobova and Loginov [5])
$S_{[A-RLT]}$	standard deviation of the residual log times for all data at all temperatures, i.e. $\sqrt{\sum_i (\log [t_r]_i - \log [t_r^*]_i)^2 / (n_A - 1)}$, where $i = 1, 2, \dots, n_A$

^a A number of the analysis checks applied during the course of the procedure originate from the post assessment tests devised by the European Creep Collaborative Committee (see ECCC-WG1, Vol. 5 [7]). The ECCC PATs are a series of acceptability criteria developed to independently test the effectiveness and credibility of the model equation(s) determined by any main assessment procedure.

Table 1 — Symbols and abbreviations (*continued*)

Symbol	Quantity
$s_{[I-RLT]}$	standard deviation for the n_I residual log times at the temperature of interest, i.e. $\sqrt{\{\sum_j (\log [t_r]_j - \log [t_r^*]_j)^2 / (n_I - 1)\}}$, where $j = 1, 2, \dots, n_I$
T	temperature (K in analysis, °C for reporting)
T_{main}	test temperature with the most data points (°C)
$T_{\text{max}}, T_{\text{min}}$	maximum and minimum temperatures for which observed data exist (°C)
$T_{\text{max[app]}}$	maximum application temperature for which predicted strength values are required (°C)
$T_{\text{min[app]}}$	minimum application temperature for which predicted strength values are required (°C)
$T_{\text{max}[x]}, T_{\text{min}[x]}$	maximum and minimum temperatures for which there are $\geq x\%$ data points (°C)
T_x	temperature for which there are $\geq x\%$ broken data points
T_0	constant in MRM model equation set (K in analysis, °C for reporting)
TTP	time–temperature parameter
t	time (h)
t_f, t_c	full and culled isothermal data rupture times at the lowest stress for a given temperature in the robustness of extrapolation test
t_r	observed time to rupture (h)
$t_{r[\text{max}]}$	maximum observed rupture time (h)
t_r^*	predicted time to rupture (h)
UB	unbroken (test points)
α	shape parameter in Weibull (or log-logistic) distribution
$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$	parameters in $\ln [t_r^*] = f(T, \sigma_0)$ model equations
$\gamma_0, \gamma_1, \gamma_2$	parameters in Weibull (or log-logistic) shape parameter equation
η	median of $\ln [t_r]$, $\eta = Md(\ln [t_r] T, \sigma_0) = f(T, \sigma_0)$ (see annex B)
σ_0	initial stress (MPa)
$\sigma_{0[\text{max}]}$	maximum stress in the dataset responsible for specimen rupture (MPa)
$\sigma_{0[\text{min}]}$	minimum stress in the dataset responsible for specimen rupture (MPa)

^a A number of the analysis checks applied during the course of the procedure originate from the post assessment tests devised by the European Creep Collaborative Committee (see ECCC-WG1, Vol. 5 [7]). The ECCC PATs are a series of acceptability criteria developed to independently test the effectiveness and credibility of the model equation(s) determined by any main assessment procedure.

4 Overview

This Published Document describes a procedure for determination of rupture strengths from stress rupture data. The procedure is set out as a flow diagram in Figure 1, and as a set of procedures in Table 2, and comprises four main parts:

- a) an initiation phase, in which the material of interest and the scope of the assessment is specified;
- b) preassessment, in which the acceptability of the data is reviewed;
- c) main assessment of the data, to determine the most appropriate model equation, together with the best-fit coefficients to describe the data; and
- d) post-assessment, in which the extrapolation, repeatability and stability of the selected model is verified, prior to final reporting.

The principal outcome is an optimized model of the stress rupture behaviour, together with a relationship for the selected percentage lower confidence limit. The equations are used to derive the creep strength values corresponding to specified conditions of temperature and rupture time.

5 Initiation phase

5.1 General

Before starting the assessment, the scope should be precisely defined, as well as the objectives of the analysis, and the appropriate test data and associated material pedigree information collated.

NOTE Guidance on test data acceptability criteria and data collation is given in ECCC-WG1, Vol. 3 [8] and ECCC-WG1, Vol. 4 [9].

5.2 Definition of scope

The following information should be defined by the commissioning body:

- a) the material grade for which long term rupture strength values are required;
- b) the specified ranges for chemical composition and heat treatment(s) for the material grade to be assessed;

NOTE 1 For composition ranges, it is customary in assessments to specify the limits for the material grade along with a permissible tolerance to allow for product-to-cast analysis differences. For example, the specified range of 2.0 % to 2.5 % for Cr in 2¼CrMo is extended by 0.1 % at each end of the range to allow for such differences. [For further information, see relevant product standard(s)].

- c) the product form(s) for which data are to be collected;
- d) the implications of restricting the permissible ranges for other related metallurgical properties, e.g. tensile strength at room temperature;
- e) the source of the data.

NOTE 2 The commissioning body should notify whether it supplies the dataset or if the assessor is expected to collate the data, and, in the latter case, if any restrictions on source apply.

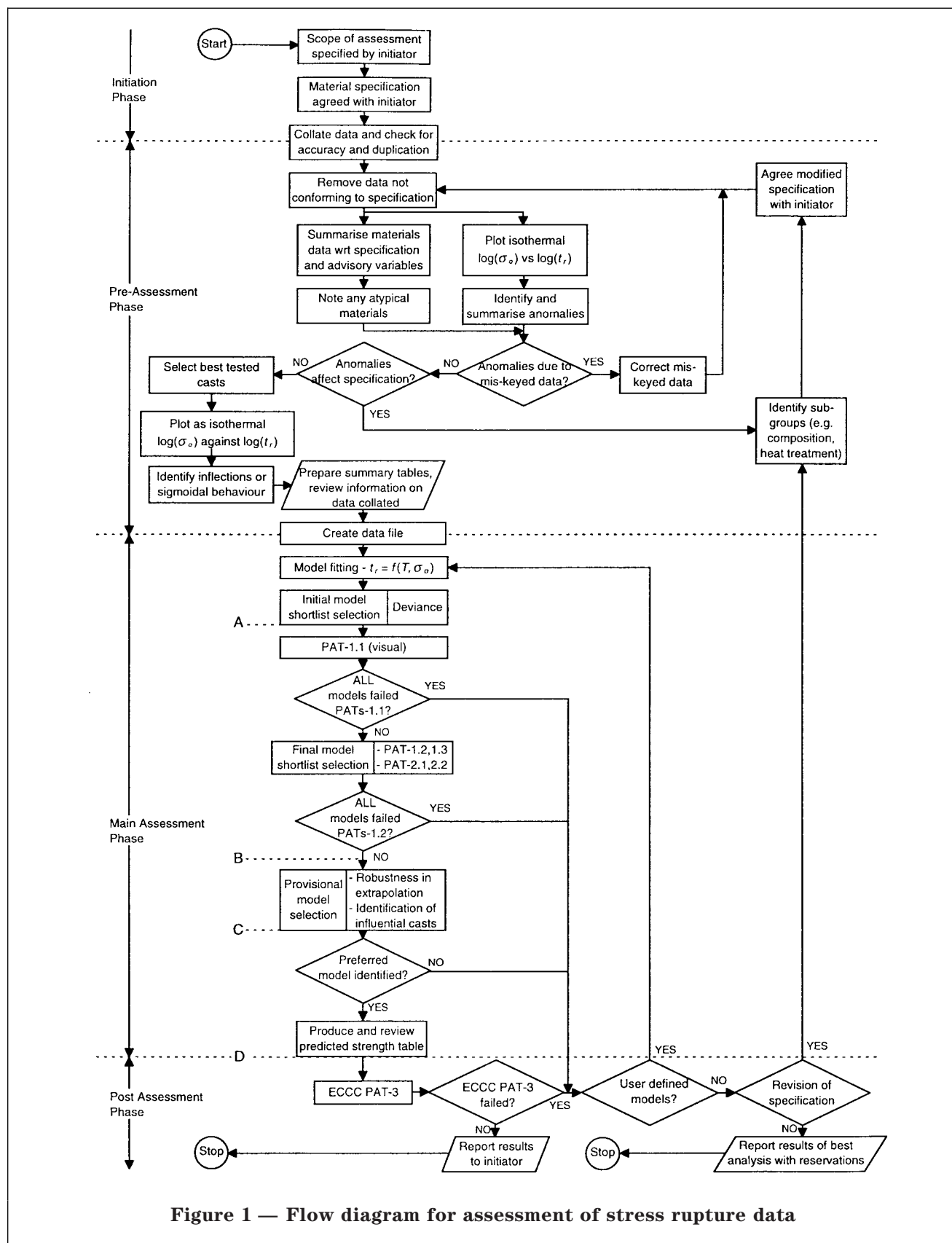


Figure 1 — Flow diagram for assessment of stress rupture data

Table 2 — Stress-rupture data assessment procedure

Step	Clause reference	Figure/table
Initiation phase:		
1) definition of material specification and scope of assessment	5.2	Table C.1
2) data collation	5.3	
Preassessment:		
3) check for accuracy, remove duplicate data	6.1.1	Table C.2
4) remove data not conforming to specification	6.1.2	
5) remove anomalous data	6.1.3	Figure C.1
6) summarize material pedigree data with respect to specification and advisory variables	6.2.2	Table C.3
7) summarize distribution of stress rupture data	6.2.2	Tables C.4 and C.5
8) identify best tested casts	6.2.3	Table C.6, Figure C.2
9) report inflexions, sigmoidal behaviour	6.2.3	
Main assessment:		
10) create data file	4.1 of PD 6605-2, 7.1.1	Annex A of PD 6605-2
11) model fitting	7.1.3, 7.1.4	Table C.7
12) initial model shortlist (deviance)	7.2.1	Table C.8
13) final model shortlist (model fit credibility, physical realism, model prediction within data range)	7.2.2	Table C.8, Figures C.3 to C.6
14) robustness in extrapolation check (provisional model selection)	7.3.1	Tables 2 and C.9
15) identification of influential casts	7.3.2	Table C.9, Figure C.7
16) preferred model selection	7.3	Table C.9
17) produce and review table of predicted strength values	7.4	Table C.10
Post-assessment:		
18) repeatability of extrapolation	8.1	Table C.11
19) alloy class subdivision (if necessary, return to step 4)	8.2	Table 3
20) report results	9	Figure C.8, Table D.1

5.3 Data collation

Collation of failed and unfailed/continuing creep rupture data for the specified material grade should initially be made without strict adherence to the agreed specification. Non-conforming data should be eliminated during preassessment, but may usefully lead to identification of trends during the course of a post-assessment evaluation (e.g. in circumstances in which alloy class subdivision is necessary; Table 2). Collated data should conform to the material pedigree and testing information recommendations in ECCC-WG1, Vol. 3 [8].

NOTE These recommendations include confirmation that the test data have been generated in accordance with an appropriate testing standard (e.g. BS 3500-1, ISO 204).

6 Preassessment

NOTE The main objective of the preassessment phase is to provide an error free, characterized dataset for input into the main assessment.

6.1 Data validation

6.1.1 Duplication

The collated dataset should first be examined for duplicate data entries.

NOTE Duplicate data entries are apparent as simultaneous duplication of information in fields for a) identifier; b) test temperature; c) applied stress; and d) time to rupture. The assessor should produce a table of duplicate test points using a suitable search or sort procedure (see annex C). Care should be taken to ensure that repeat test points are not categorized as duplicate test points, in particular where unbroken specimen data are involved (a suitable format is given in Table C.2). All duplications should be removed from the dataset.



6.1.2 Pedigree

Data that do not conform to the agreed specification should be identified (but not necessarily discarded; see 5.2). Data removed at this stage should be tabulated. Errors in data entry identified during this process should be rectified.

Atypical materials should be identified; e.g. those supplied from large section product forms not prohibited by the specification but with limited data. The specification should be revised with the initiator to remove data associated with such materials, either at this stage or at the time of post-assessment if they are deemed responsible for inadequate model fitting [see 8.2c)].

6.1.3 Anomalies

Anomalous entries in the dataset should be identified; in particular those associated with temperature, stress and time (such anomalies mainly arise due to miskeying during data entry or incorrect unit conversion). The accuracy of failed and unfailed/continuing test data should be confirmed.

NOTE A simple way of detecting anomalies is to isothermally plot $\log [\sigma_0]$ against $\log [t_r]$ data for each temperature, and to visually identify points lying away from the main body of the data, or from other points that belong to the same material cast or batch (see for example Figure C.1).

Care should be taken to ensure that data points are not incorrectly identified as anomalous (such a situation may occur with points lying at data extremes, e.g. the longest broken/unbroken test point at one temperature, in particular just after, or just before, a metallurgical instability becomes apparent). If anomalous data points that cannot be attributed to miskeying or incorrect unit conversion are identified, the data should be tabulated, with explanatory comments if possible.

Large data scatter in plots of $\log [\sigma_0]$ against $\log [t_r]$ may arise if one or more of the ranges specified in the material pedigree is too broad; and if so the specification should be revised with the initiator either at this stage or at the time of post-assessment, if these are deemed responsible for the large data scatter (see 8.2.3).

6.2 Summary statistics

6.2.1 General

The data remaining after validation should be summarized in accordance with recommended tabular structures. In particular, the distribution of the data should be compared with the interim-minimum and target-minimum dataset size requirements recommended in ECCC-WG1, Vol. 5 [7] (see Table A.1).

6.2.2 Dataset summary

The following summary tables should be prepared:

- a table comparing specified and actual ranges of composition, heat treatment, product dimensions, etc. (see for example Table C.3);
- a table showing the extent and distribution of broken and unbroken testpiece data in terms of

temperature and duration (within specific ranges), along with the longest test duration and minimum stress at each test temperature, and some simple summary data statistics (see for example Table C.4);

- a table showing the distribution of casts (or lots) in terms of temperature and duration to provide a check for conformity to 7.4 and Table A.1 (see for example Table C.5).

NOTE 1 Other dataset breakdowns by, for example, steelmaking types, ingot or concast route, or deoxidation practice may also be used.

NOTE 2 It is acceptable to consider data for temperatures within $\pm 2^\circ\text{C}$ of a principal test temperature to be part of the dataset for that temperature (e.g. test data for 649°C may be considered together with data for 650°C).

6.2.3 Best-tested casts

Best-tested casts should be known to enable confirmation that the model fit to the $t_r(T, \sigma_0)$ data is an adequate representation of the behaviour of individual casts [see 7.2.2e)], and to assist in identification of sigmoidal behaviour in $\log [\sigma_0]$ against $\log [t_r]$ curves for one or more temperatures in the dataset.

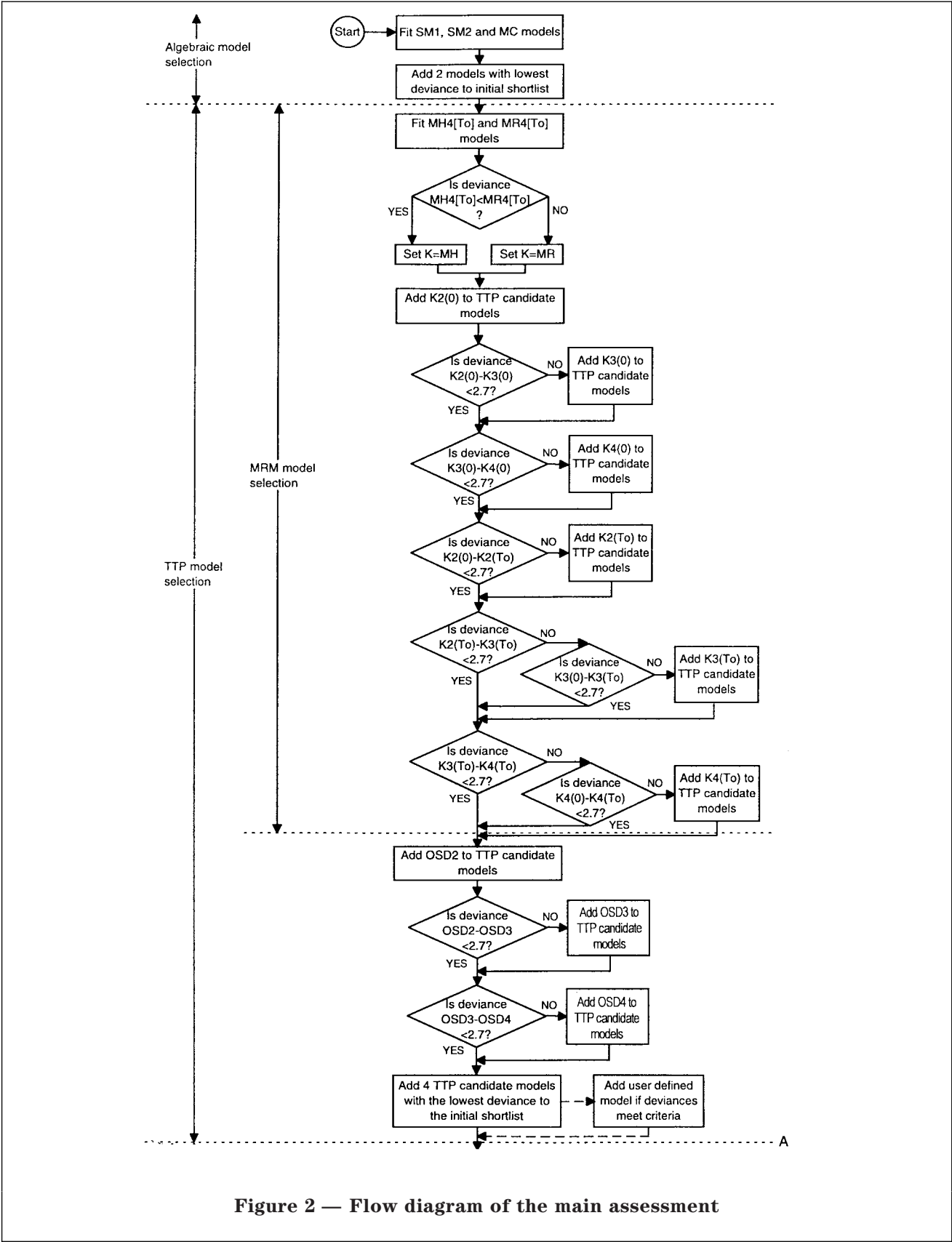
NOTE 1 As a guide, best-tested casts are those for which there are ≥ 5 broken testpiece data points at each of at least three $T_{5\%}$ temperatures (with 2 data points per temperature with rupture durations $> 10\,000$ h). A cast that just fails to conform to this criterion may still be regarded as best-tested if there are ≥ 16 broken testpiece data points in total. For practical reasons, it is recommended that a minimum of three, and a maximum of ten, best-tested casts are selected. It is also recommended to prepare a table showing the distribution of tests in terms of cast identification and temperature as a convenient method of identifying the best-tested casts (see for example Table C.6), particularly if this is performed using a suitable computer-based search technique.

NOTE 2 Inflections and sigmoidal behaviour in $\log [\sigma_0]$ against $\log [t_r]$ curves arise as a consequence of metallurgical reactions leading to variations in strengthening kinetics. Such behaviour may only occur over a limited temperature range and is most readily revealed by examining the trends displayed by single casts (see for example Figure C.2). Best-tested casts provide a view of the $t_r(\sigma_0)$ trends over a range of temperatures and, in particular, an important indication of the extent of sigmoidal behaviour in metallurgically active alloys.

7 Main assessment

NOTE 1 Main assessment is divided into a number of steps (see Table 1). These involve fitting statistical models to the data and checking the physical realism of the alternative formulations. Following this, a shortlist of models is established, initially based on goodness-of-fit criteria, but finally on the results of ECCC PAT-1 and PAT-2 tests (for background see ECCC-WG1, Vol. 5 [7]). One or more provisional models 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 second identifies any individual cast (or casts) that have an undue influence on the assessment, and provides a final selection indicator if more than one provisional model remains after the extrapolation-performance test. These steps help to identify a preferred model that may be used to produce a table of predicted strength values.

NOTE 2 If no preferred model is identified, or if the preferred model subsequently fails the post-assessment test (see 8.1), opportunities are provided for the analyst to investigate a) user defined models; and/or b) criteria for subdividing the dataset, employing the same statistical modelling framework to obtain objective measures of the improvement in fit to the data.



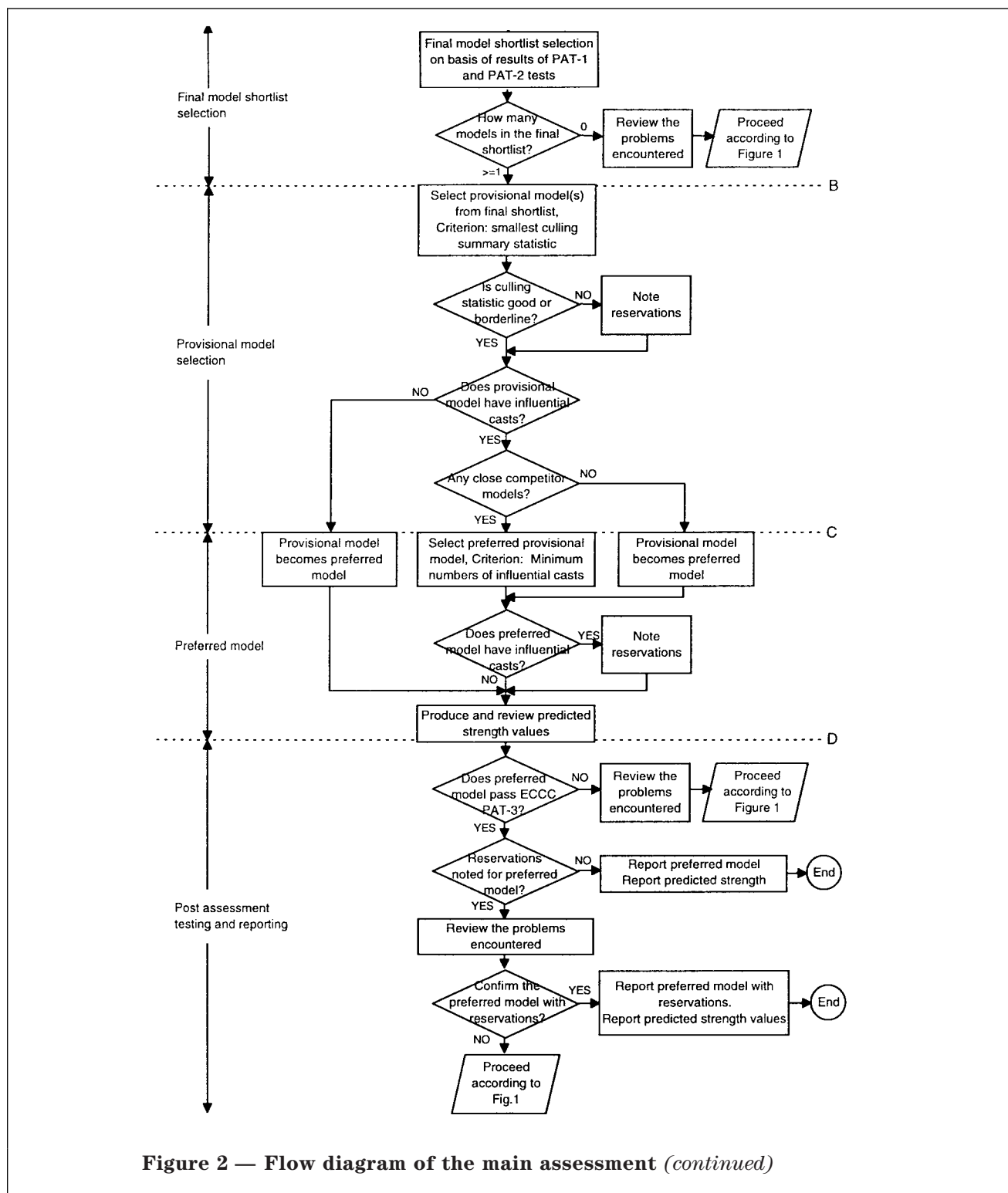


Figure 2 — Flow diagram of the main assessment (continued)

7.1 Fitting the data to candidate models

7.1.1 Data file

On completion of preassessment, a text file containing the data to be evaluated in the main assessment should be created (see 4.1, and annex A of PD 6605-2).

7.1.2 Left censoring

Prior to model fitting, the analyst should consider whether the dataset requires “left censoring”, i.e. removal of the very short failure times that are likely to correspond to failure by a tensile rather than a creep rupture mechanism. One of the following techniques should be used:

- to include all data in the assessment;
- to exclude tests with a short failure time (< 10 h); or
- as in b), but also to exclude all other data points tested at the same temperature and the same or higher stress.

NOTE Technique c) is recommended as this avoids statistical bias, with the data censored on the basis of the explanatory variable rather than the response variable⁴⁾.

7.1.3 Model fitting

The models listed in Table B.1 should be fitted in accordance with the recommendations given in Figure 2. The GLIM macros MODELm.HET or MODELm.BTC⁵⁾ should be used to carry out the model fitting step. A summary table of the model parameters and deviances should be prepared to facilitate model selection (see for example Table C.7).

NOTE The available models include three algebraic equations that do not rely on high order polynomials and a series of TTP (time-temperature parameter) models. The TTP suite of models includes derivatives of the Mendelson-Roberts-Manson (MRM) equation set forming the basis of the ISO 6303 procedure.

7.1.4 MRM models

Derivatives should be considered from a single category in the main assessment.

NOTE 1 MRM derivatives fall into two main categories; one based on the Manson-Haferd (MHn) formulation and the other on what is referred to in this Published Document as the simplified MRM model (i.e. MRn). Selection of the appropriate MRM derivative category for further consideration is based upon which of the MH4 or MR4 model fits gives the lowest deviance (i.e. MH4[T_0] or MR4[T_0] in Figure 2).

Since the models derived from the general MRM equation are not linear in parameters, the parameter T_0 should be estimated before it can be fitted in a generalized linear modelling package such as GLIM¹⁾ (see Table C.7). T_0 should be determined using the GLIM macros FITMHm.HET and FITMRm.HET for the MHn and MRn models respectively.

NOTE 2 The best estimate of T_0 corresponds to the minimum deviance. The recommended range of values of T_0 to be investigated is between $\pm T_{\max}$, where $T_{\max}$ is the maximum temperature (in K) of the dataset. Occasionally, neither the MHn or MRn models display a minimum over a very wide range of temperatures; and if so, T_0 may be taken as zero, i.e. either the MHn or LMn models may be fitted, as appropriate.

7.2 Model selection

7.2.1 Initial shortlist

Following model fitting, an initial shortlist should be constructed (see Table C.7). The flow diagram in Figure 2 should be used to select a variety of model types for the initial shortlist.

NOTE 1 It is recommended that the two best-fitting models are included from the algebraic category and the four best-fitting models included from the TTP suite of equations. 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.

NOTE 2 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 listed above.

7.2.2 Final shortlist

The physical realism and effectiveness of the predicted isothermal lines to model the observed $\log [\sigma_0]$, $\log [t_r]$ data should be assessed for each model in the initial shortlist to provide a final shortlist (see for example Table C.8).

The following tests should be used.

a) Model fit credibility test

The credibility of the model fit over the range of the data should be first visually checked by comparing fitted isothermal $\log [\sigma_0]$ against $\log [t_r^*]$ lines and confidence intervals with the observed $\log [\sigma_0]$, $\log [t_r]$ data. Any reservations should be recorded, and, if there is unequivocal evidence of unsatisfactory fit to the data, the model should be rejected. Reservations recorded at this stage should be reported alongside the final results if the model is subsequently selected as the preferred model. If left censoring has been employed, there should be no expectation that the isothermals tend towards the tensile strength (i.e. become asymptotically horizontal) at lower failure times.

NOTE Appropriate isothermal $\log [\sigma_0]$ against $\log [t_r^*]$ plots are provided by the GLIM macro MODELm.HET (see for example Figure C.3).

⁴⁾ Using GLIM, either a), b) or c) may be specified within the data file (see 4.1 of PD 6605-2). Technique c) is the default condition, and is selected if the others are not preferred.

⁵⁾ “m” defines the version number of the GLIM macro. Guidance on implementation of the GLIM macros is given in PD 6605-2.

As a check on the confidence lines, the analyst should verify that, for example, ~ 2.5 % of the failed points occur at times below the lower 95 % confidence interval (the plots provided by MODELm.HET enable a visual count). A reservation should be recorded if the actual count is less than 75 % of the expected⁶⁾.

b) *Physical realism test*

Physical realism should first be checked by plotting $\log[\sigma_0]$ against $\log[t_r^*]$ isothermal lines at 25 °C intervals from 25 °C below the minimum test temperature to 25 °C above the maximum application temperature⁷⁾ (PAT-1.2, ECCC-WG1, Vol. 5 [7]). Models should be rejected from the shortlist if these isothermal lines: a) cross over; b) come together; or c) turn back for predicted failure times in the range 10 h to 10⁶ h, and for stresses $\geq 0.8\sigma_{0[\min]}$ [isothermal plots are provided by the GLIM macro PATm.HET, e.g. Figures C.4a) and C.4c)]. It should be verified that isothermals are not sigmoidal unless preassessment has identified sigmoidal behaviour.

c) *Model fit derivatives test*

For the same temperatures considered in the physical realism test, the derivative $-\partial \log[t_r^*]/\partial \log[\sigma_0]$ should be plotted as a function of $\log[\sigma_0]$ (PAT-1.3; see ECCC-WG1, Vol. 5 [7]). Provided the steel is not metallurgically active, models should be rejected if these derivatives are < 1.5 for stresses $\leq 0.8\sigma_{0[\min]}$.

NOTE For metallurgically active steels only (identified in preassessment), derivatives < 1.5 are permissible around the points of inflection in the $\log[\sigma_0]$ against $\log[t_r^*]$ isothermal trend lines, provided they exceed 1.5 at $\leq 0.8\sigma_{0[\min]}$.

Plots of the derivatives are provided by the GLIM macro PATm.HET [see for example figures C.4b) and C.4c)].

d) *Within-data-range model fit test (all data)*

To assess the effectiveness of the model to represent the behaviour of the complete dataset, a diagram of $\log[t_r^*]$ against $\log[t_r]$ should be prepared for all observed data (PAT-2.1; see ECCC-WG1, Vol. 5 [7], and, for example, Figure C.5).

The model should be rejected if:

- 1) more than 1.5 % of the $\log[t_r^*]$, $\log[t_r]$ data points fall outside one of the $2.5s_{[A-RLT]}$ boundary lines (where $s_{[A-RLT]}$ is the standard deviation of the residual log times for all the data at all temperatures)⁸⁾;

- 2) the slope of the mean line is less than 0.78 or greater than 1.22⁹⁾; and

- 3) the mean line is not contained within the $\pm \log[2]$ boundary lines between 100 h and 100 000 h.

NOTE Macros are at present unavailable to perform this test and test e). However, both tests may be conveniently implemented in a spreadsheet programme. Further guidance is given in ECCC-WG1, Vol. 5 [7].

e) *Within-data-range model fit test (selected temperatures)*

To assess the effectiveness of the model to represent the behaviour of individual casts, isothermal diagrams of $\log[t_r^*]$ against $\log[t_r]$ should be prepared at temperatures for which there are ≥ 10 % data points (at least at $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$; see for example Figure C.6). In these diagrams, the best-tested casts should be identified (as recommended in PAT-2.2; see ECCC-WG1, Vol. 5 [7]).

Plots of $\log[t_r^*]$ against $\log[t_r]$ for individual casts should have slopes close to unity and should be contained within the $\pm 2.5s_{[I-RLT]}$ boundary lines. In the event of individual casts exhibiting $\partial \log[t_r^*]/\partial \log[t_r]$ slopes of < 0.5 or > 1.5 , and/or with a significant number of $\log[t_r^*]$, $\log[t_r]$ data points outside the $\pm 2.5s_{[I-RLT]}$ boundary lines, a reservation should be noted with respect to the model fit and the pedigree of the material.

The model should be rejected if:

- 1) 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 1.22⁹⁾; and
- 2) the mean line is not contained within the $\pm \log[2]$ boundary lines between 100 h and 100 000 h.

f) *Final selection*

The final shortlist should consist of models conforming to the PAT-1 and PAT-2 model fit tests [i.e., a) to e)]. If none of the models in the initial shortlist conform to the acceptability criteria, see 8.2.

7.3 Preferred model selection

NOTE 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.

⁶⁾ In circumstances in which there is evidence that the Weibull distribution leads to a lower bound confidence interval that is overly conservative, model fitting should be repeated with the log-logistic version of the software, i.e. MODELm.LLG. Only the confidence intervals are affected by using MODELm.LLG. The model fit is unaffected (see annex B).

⁷⁾ The maximum application temperature is the maximum temperature for which predicted strength values are required, and is defined by (or agreed with) the commissioning body.

⁸⁾ For a normal error distribution, almost 99 % of the data points are expected to lie within the $\log[t_r^*] = \log[t_r] \pm 2.5s_{[A-RLT]}$ boundary lines.

⁹⁾ If PAT-2.1(d2)) and PAT-2.2(e1)) are not satisfied at only 1 of 3 temperatures, it is permissible to repeat the test, determining the mean line slope through the data points lying between $t_r = t_{r[\max]}/100$ and $t_r = t_{r[\max]}$. This option is only of potential use when $t_{r[\max]}$ is $> 100\,000$ h.

7.3.1 Robustness in extrapolation

The models passing the acceptability criteria set out in 7.2.2 should first be tested for robustness in extrapolation. The data should be culled by removing *P* % of the data points at the lowest stresses for each temperature¹⁰⁾ (it is recommended that *P* = 30, except for metallurgically active steels, where 15 % culling is more appropriate¹¹⁾). Isothermals from the model fitted to the remaining data points should be compared with isothermals from the model fitted to the whole dataset. The comparison should be made in terms of the differences between estimated failure times at the limit of the total data scatter (the lowest stresses with failed points at each temperature), with and without culling (a culling statistic *S* is defined as the mean square of these differences over all temperatures in the dataset).

NOTE Provisional models are those with a good (or borderline) culling statistic (see Table 3). The provisional preferred model is that with the lowest culling statistic. An unacceptable outcome raises serious doubts about the accuracy of extrapolations from the model. [This is indicative of insufficient data points or too broad a range of metallurgical characteristics in this class of steel (see 8.2).]

Table 3 — Acceptability criteria for robustness in extrapolation

30 % Culling	15 % Culling	Acceptability
$S \leq 0.004$	$S \leq 0.003$	good
$0.004 < S \leq 0.015$	$0.003 < S \leq 0.006$	borderline
$S > 0.015$	$S > 0.006$	unacceptable

An unacceptable outcome should be reported alongside the final results. Using GLIM, the macro CULLm.HET should be used to perform this part of the procedure.

A tabulation of the results from the extrapolation-performance test should be prepared to identify clearly the provisional preferred models (see for example Table C.9).

7.3.2 Identification of influential casts

It should be identified whether any casts have an important individual influence on the provisional model(s), so that this undesirable situation can be avoided, if possible, or reported alongside the final results if inevitable.

NOTE Casts may be influential for two main reasons:

- a) the cast may have a distinctive set of outcomes and may contribute a sufficiently large number of stress-rupture test results for this to have a notable affect on the trend line estimated;

- b) the cast may contribute a high proportion of low stress test results and thereby exert appreciable influence on the trend line at the right side of the data range.

In a), the cast is likely to be influential for any model. In b), the rarer case, the effect is usually less pronounced for models that do not include high order polynomials. It may therefore be possible to avoid the problem by judicious model selection.

A cast should be considered influential if its exclusion causes a change of more than 10 % in the estimated failure time at the lowest failed stress for the temperature examined. Failure times should be compared at three temperatures: $T_{\min[10\%]}$, T_{main} and $T_{\max[10\%]}$. Using GLIM, the macros CASTm.GRA and INFCASTm.HET should be used for this part of the assessment (see for example Figure C.7). The results of the influential cast analysis should be tabulated (see for example Table C.9).

If influential casts are identified for the provisional preferred model, the analysis should be repeated for any close competitor models (provisional models with a summary culling statistic within 50 % of the summary statistic of the preferred model). The provisional preferred model should be replaced by a competitor model if the latter has fewer influential casts.

7.4 Predicted strength tables

As the final step of the main assessment, a table of predicted strength values for the preferred model, based on median and lower confidence interval values, should be produced (see for example Table C.10).

Using GLIM, the stress to cause rupture for a standard series of prespecified times for any temperature should be determined using the macro PREDm.HET (alternatively, PREDAm.HET or PREDBm.HET allow strength values to be determined for user defined linear or logarithmic increments between specified minimum and maximum rupture times; in each case, the software also provides the lower *C* % confidence interval, where *C* is selected by the user¹²⁾).

It is essential that strength predictions based on extended time extrapolations and extended stress extrapolations, as defined by BS PD 6525-1, are identified.

¹⁰⁾ Using the CULLm.HET macro, the level of culling is not always precisely achieved since some data may be “tied” (i.e. may be for the same stress and temperature). In such circumstances, all “tied” data are retained rather than arbitrarily culled.

¹¹⁾ The alloy should be identified as metallurgically active during preassessment.

¹²⁾ In circumstances in which there is evidence that the Weibull distribution leads to an overly conservative lower bound confidence interval [see footnote to 7.2.2a)], predicted strength values should be determined from a log-logistic version of the preferred model using PREDm.LLG, PREDAm.LLG or PREDBm.LLG, as appropriate. Only the confidence intervals are affected by using the log-logistic analysis macros. The model-fit is unaffected (see annex B).