Monitoring power-law creep using the Failure Forecast Method

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A B S T R A C T

Creep is considered to be the life limiting damage mechanism in many load bearing high temperature components. A range of different parameters determine the creep life of a component, many of which are unlikely to be known with sufficient accuracy to enable satisfactory estimation of remnant life. Instead, the integrity of a component should be established through direct measurement of the response of the component to the operating conditions. Creep deformation is shown to be a positive feedback mechanism; an increase in strain leads to an increasing strain rate. It has recently been shown that as a consequence of positive feedback the Failure Forecast Method, a generalised framework for predicting time to criticality based on rates of change of damage, may be applied for remnant life calculations. A range of strain rate based assessments have been proposed in the literature but it is proposed that the Failure Forecast Method unifies many of these techniques and provides additional insight into creep behaviour by virtue of the underlying positive feedback. The methodology has been demonstrated using experiment data sets that are pertinent to creep in high temperature pressure vessels and piping; it is shown that failure times are accurately predicted shortly after the minimum creep strain rate.

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work for rate based remnant life calculation of systems governed by positive feedback. It will be shown that this widely applicable process unifies many of the remnant life predication strategies proposed in the literature. A range of experimental examples that are pertinent to in situ power station monitoring will be given. The third part is discussion focussing on the applicability of strain rate based remnant life estimates to power station components.

2. Power-law creep as a positive feedback mechanism

This section provides a brief description of the underlying strain driven positive feedback in power-law creep; the strain rate is dependent on strain, leading to a self-accelerating time domain behaviour. The following analysis has previously been reported in numerous prior publications [18,32,41,17] though the significance of the positive feedback was not noted. The remainder of the paper will focus on the time where strain rate is increasing, following the point of minimum creep strain rate.

Following from the Norton power law for a given temperature, 
\[ \dot{\varepsilon} \propto \sigma^n \]  
where \( n \) is constant for a range of stresses. As the component deforms the load sustaining cross-section, \( S \), reduces from the previous cross-section, \( S_0 \), with increase in true strain, \( \varepsilon \), according to, 
\[ S = S_0 e^{-\dot{\varepsilon} t}. \]  

Subscript '0' is used to denote a reference state, which does not have to be at the point of minimum strain rate. For the remainder of this study true strain will be used for consistency with this analysis. For a constant load, the stress therefore increases with strain, 
\[ \sigma = \sigma_0 e^{\dot{\varepsilon} t} \]  
and combining Eqs. (2) and (4) gives, 
\[ \dot{\varepsilon} \propto \sigma_0^n e^{\dot{\varepsilon} t} = \dot{\varepsilon}_0 e^{\dot{\varepsilon} t} \]  

It is also argued that the mobile dislocation density is proportional to inelastic strain and that the strain rate is proportional to mobile dislocation density so that, 
\[ \dot{\varepsilon} \propto \varepsilon_0 (1 + C) \]  
where \( C \) is a function of temperature, material characteristics and prior history. Combining Eqs. (5) and (6) gives 
\[ \dot{\varepsilon} = \varepsilon_0 (1 + C) e^{\dot{\varepsilon} t} \approx \dot{\varepsilon}_0 e^{n(\dot{\varepsilon} t)} = \dot{\varepsilon}_0 e^{\dot{\varepsilon} t} \]  
where \( A = n + C \) is introduced for convenience. Clearly \( A > n \) and is frequently \( > 20 \) [41,42]. It is emphasised that this is of course a simplification and does not take into consideration a number of factors including elastic strain (which is assumed to be small) and anelastic strain (following stress changes [43]); the exact form is not critical and is only intended to capture the role of positive feedback. Eq. (7) clearly shows that power-law creep is clearly an extremely strain sensitive positive feedback mechanism. Positive feedback mechanisms are frequently unstable; an increase in strain leads to an increase in the strain rate, this self-accelerating cycle continues until the component reaches criticality and fails. The concept of creep as a positive feedback mechanism is important in remnant life estimation, as shown in the following section.

3. The Failure Forecast Method

3.1. Introduction to the Failure Forecast Method

Following from the work of Fukuzono [23], Voigt [54,55] observed ‘striking generality’ in a range of ‘rate-dependent’ failure mechanisms. He proposed a simple empirical relationship describing the behaviour of a wide range of systems;
\[ \frac{d^2 \Omega}{dt^2} = A \left( \frac{d \Omega}{dt} \right)^n \]  

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**Fig. 1.** Schematic illustration of (a) strain against time and (b) log(strain rate) against time for the creep life of a generic component. It illustrates the model that following primary creep the minimum creep strain rate is observed, which then accelerates due to strain driven positive feedback towards a failure time asymptote.
where \( \Omega \) is an observable metric of damage, \( a \) and \( A \) are ‘constants of experience’ for the situation at hand, and additionally observed that frequently \( a \approx 2 \). It was recently shown that this shared behaviour is a result of underlying positive feedback [11]. Eq. (7) shows that creep is a strain driven positive feedback mechanism, and therefore is expected to be consistent with Voigt’s postulation. Using the chain rule,

\[
\dot{\varepsilon} = \frac{d\varepsilon}{dt} = A \dot{\varepsilon} \dot{\varepsilon}.
\]

(9)

Differentiating Eq. (7),

\[
\frac{d\varepsilon}{d\dot{\varepsilon}} = A \dot{\varepsilon} \dot{\varepsilon} = \dot{\varepsilon}.
\]

(10)

Inserting (10) into (9),

\[
\dot{\varepsilon} = A \dot{\varepsilon} \dot{\varepsilon} = A \dot{\varepsilon}^2
\]

(11)
gives Voigt’s relationship. The relationship provides the foundation for a framework, later termed the ‘Failure Forecast Method’ which has been used extensively in geophysics [14-16,56,29-31,44-46], relating the increase in the rate of damage metrics to the proximity of the asymptotic criticality. Voigt’s postulation is significant as it can be integrated to give remnant life estimates. For \( a > 1 \), Eq. (11) can be integrated to give [55],

\[
\frac{d\varepsilon}{dt} = \left( A(a - 1)(t_f - t) + \left( \frac{d\varepsilon}{dt} \right) \right)^{1-a}.
\]

(12)

where the subscript \( f \) denotes the value at failure time. As the rate at failure is observed to be much larger than the rate earlier on in the component life then it will be assumed that the inverse of the failure strain rate is negligible allowing the simplification,

\[
t_f - t = \frac{1}{A(a - 1) \left( \frac{1}{\dot{\varepsilon}} \right)^{a-1}}.
\]

(13)

This simple general relationship between inverse rate and remnant life is true for a wide variety of positive feedback mechanisms [11]. Eq. (13) is further simplified if \( a \approx 2 \) leading to inverse proportionality between rate and remnant life. It is clear that Eq. (13) arises as a consequence of the underlying positive feedback [11] and is just one example use case for the Failure Forecast Method.

Utilising the Failure Forecast Method for remnant life prediction has been explained in detail in [11], but to aid the explanations of this paper, a brief summary is given here. Voigt’s postulated behaviour is illustrated in Fig. 2 for a range of \( a \) values. Fig. 2(a) shows the familiar increasing rate approaching failure, while Fig. 2(b) shows the decreasing inverse rate as remnant life expires. It is shown that if \( a = 2 \) then there is a linear relationship between inverse rate and time, while if \( a < 2 \) the relationship is ‘concave’ and if \( a > 2 \) then it is ‘convex’. From Eq. (11) \( a \) is expected to be approximately 2, but will not be assumed to be exactly 2. Fig. 2(c) illustrates graphically the intended execution of the technique; plotting the inverse rate against time allows the estimation of the parameters \( A \) and \( a \), which describe the gradient and shape of the inverse rate - time behaviour. The point where inverse rate intersects the x-axis is where the rate tends to infinity and so represents the point of criticality; by projecting the best fitting line the failure time can be estimated. In this regard the inverse strain rate may be considered a metric of integrity which reduces until at failure it reaches 0. In practise, a solver is used to find best fitting estimates of \( a \), \( A \) and \( t_f \) of Eq. (13) to the gathered data.

A number of previous studies have arrived at special cases of the Failure Forecast Method, even if it is not in a form that is immediately obvious, using many different arguments [8,32,40,41]. A number of previous studies have noted the linear relationship between remnant life and inverse creep strain rate; the rationale for this relationship has been argued from many different creep-specific arguments and assumptions. The linear relationship arises from the specific case when assuming \( a = 2 \) in Eq. (13). It is argued here that the relationship is purely a consequence of positive feedback dominating the strain behaviour; the Failure Forecast Method offers an extremely widely applicable [11] methodology that generalises the time domain behaviour of positive feedback mechanisms and encompasses power-law creep.

The Monkman-Grant [34] relation is a special case of Eq. (13) taken at the point of minimum creep strain rate and neglecting the time until the minimum creep rate,

\[
t_f = \frac{1}{A(a - 1)} \left( \frac{1}{\dot{\varepsilon}_m} \right)^{a-1}.
\]

(14)

where conventionally the term \( 1/(a - 1) \) is named the ‘Monkman-Grant’ constant and \( a \) is assumed to be approximately 2 so that the exponent is approximately unity. The description of creep as a positive feedback mechanism, together with the analysis leading to the Failure Forecast Method provides some insight into the Monkman-Grant relation. The Monkman-Grant relation describes the time asymptote that arises from the presence of positive feedback; it is the finite theoretical time taken for the minimum creep rate to accelerate to infinity due to strain dependent positive feedback. From this description the only parameters that determine the creep life are the minimum creep strain rate and the parameter, \( A \), which from Eq. (7), determines the level of positive feedback and therefore how quickly the minimum strain rate will accelerate to failure.

It is also pertinent to add that frequently the product of minimum creep rate and failure time is proposed as being significant and is occasionally referred to as the ‘Monkman-Grant’ ductility [40,59]; this may be seen as a theoretical strain, \( \varepsilon^* \), that would result if strain continued at the minimum rate until failure.

\[
\varepsilon^* \equiv \varepsilon_m a t_f.
\]

(15)

By comparison with Eq. (14) \( \varepsilon^* \) is equivalent to \( 1/A \), by definition linking the minimum creep rate and the time taken to accelerate to failure; it therefore provides a metric of the level of positive feedback (see Eq. (7)). The degree to which \( A \) or indeed \( \varepsilon^* \) may be assumed to be constant for the purpose of relating minimum creep rates to remnant life calculations over a range of conditions clearly depends on whether the positive feedback behaviour is comparable.

The execution of the methodology is important and differs from the strain rate based techniques previously presented in the literature. A key aspect of the Failure Forecast Method is that remnant life is based purely empirically from data for the situation at hand, without assuming the stress state, temperature and material properties. Prager termed a variation on the approach the ‘Omega Method’ [41,42], and it was included in API 579-1/ASME FF51 standard [2]. The ‘Omega Method’ assumes that \( a = 2 \) and also assumes that the parameter \( A \) is known \( a \) priori from estimates of the stress state, temperature and material properties. Not obtaining this parameter from in situ data appears to eliminate the primary benefits of the methodology: that failure prediction can be made without assumptions. It is noted that the \( A \) parameter varies quite widely and will be a function of a range of different variables [2,41]. For the present study it is assumed that measurements are taken using permanently installed sensors allowing the frequent readings that are crucial for accurate rate measurements [11] and improved best-fitting solutions to each of the variables.

3.2. Experimental demonstration of the Failure Forecast Method

Three example experiments will be used in this study to illustrate the Failure Forecast Method; two are intended to capture different aspects pertinent to power station operation: a multiaxially stressed pressurised tube and a long term uniaxial test with a life of 100,000 h. The third dataset has been generated by the authors using a potential drop strain monitoring technique that is proposed for power station use. Background to the three experiments will be given before the results of the Failure Forecast Method are shown.
assuming the potential strain rate at 304 °C as an example for the 2.25Cr-1Mo material.

3.2.1. Internally pressurised tube

The data for this experiment was obtained from the European Commission MatDB database, test specimen identifier bp240 [9]. The test component is a tube of 33 mm outer diameter and wall thickness 2 mm, internally pressurised to 24 MPa, resulting in 180 MPa hoop stress and 90 MPa axial stress. It is composed of 2.25Cr-1Mo (10CrMo9-10) material and tested at 550 °C. The tangential, 'hoop', true strain is shown in Fig. 3. The first and second time derivatives are then calculated by assuming a linear fit over 10 data points and the gradient found by least squares regression; readings are taken every 8 h initially to 15 min at failure.

3.2.2. 100,000 h uniaxial creep test

The data for this experiment was also obtained from the European Commission MatDB database, test specimen identifier ABEI+ [37]. A 304 Stainless Steel (X5 CrNi 18 10) plain cylindrical specimen was crept at 650 °C with constant load initially equating to 60.8 MPa. The strain is shown Fig. 4. As before, the time derivative of strain is calculated by a 10 point least-squares regression, readings are recorded with samples taken every 500–2700 h.

3.2.3. Uniaxial creep test monitored by potential drop sensor

A potential drop strain sensor has been suggested as a simple and robust practical monitoring solution that allows local strain measurement; the method is described in detail in [12,13]. An array of electrodes forming a series of squares is welded on to the surface of a component, as shown in Fig. 5. Orthogonal resistances are measured across each of the squares, indicating the distance between electrodes. As the specimen strains, the squares are deformed and the resistances measured parallel to and orthogonal to the loading direction change; these resistance values can be inverted to give strain as detailed in [12]. The test piece is formed from P91 material and the gauge section has a rectangular cross section of 24 mm × 10 mm and length 40 mm, accommodating an array of 8×5 mm square potential drop sensors. It was tested at 625 °C and 115 MPa.
The strain measured across the 5 mm gauge length of each of the array elements is shown in Fig. 6(a). The time derivative is again calculated using a 10-point linear regression, equating to a time scale of 2 h. The local strain measurements reveal the variation in strain rates along the length of the component, giving improved spatial information. As failure occurred at Element 5, the data for this location is used in subsequent analysis.

3.2.4. Implementing the Failure Forecast Method

Firstly, data prior to the minimum creep strain rate is discarded. Voight’s postulation, Eq. (8), can then be verified by plotting the logarithm of the first and second time derivatives of strain; this is shown in Fig. 7 for each of the three experiments following the minimum creep rate. The linear fit shows that the postulation is consistent with the data. Further, the gradient of approximately 2 is in agreement with the observation that \( \alpha \) is frequently \( \approx 2 \).

Deviation away from the linear relationship is observed in both the 100,000 h and potential drop experiment data sets. In the case of the potential drop example the deviation can be seen to take the form of vertical fluctuations, indicating that the uncertainty may be a consequence of the challenge of measuring second time derivatives. Additionally, the deviation occurs at low strain rates and acceleration; the relative uncertainty in strain acceleration is expected to be relatively large while the acceleration is small.

From Fig. 7 it can be concluded that there is good agreement with Voight’s postulation and further \( \alpha \approx 2 \) is a reasonable approximation, the validity of which will be further explored. As previously mentioned, two approaches will be illustrated in this study; first, a simplified calculation where \( \alpha \) is assumed to be 2, resulting in an assumed linear relationship between remnant life and inverse rate, and second, an approach where \( \alpha \) is not assumed to be 2 and therefore the curvature of the remnant life and inverse rate relationship will also need to be taken into account.

Fig. 8 summarises the results of the Failure Forecast Method. Fig. 8(a)–(c) shows the raw strain-time data again for convenience of comparison. Fig. 8(d)–(f) shows graphically how the remnant life is estimated: a best fitting line (when assuming \( \alpha = 2 \)) or curve (where \( \alpha \) is not assumed to be 2) is found in accordance to Eq. (13). The projection of the best fitting line or curve with the x-axis provides the estimated failure time. In Fig. 8(d)–(f) the best fitting lines and curves are calculated retrospectively for all data following the minimum creep rate in order to illustrate conformity with the predicted behaviour. When im-
Fig. 8. Summary of results for the Failure Forecast Method. Row 1: Strain against time for (a) Internally Pressurised Tube, (b) 100,000 h Uniaxial Creep Test (c) Element 5 of the uniaxial creep test monitored by potential drop sensor. Row 2: Inverse strain rate against time for (d) Internally Pressurised Tube, (e) 100,000 h Uniaxial Creep Test (f) Uniaxial creep test monitored by potential drop sensor. The best fitting lines are calculated retrospectively for the full data set. The projected x-axis intercept gives the failure cycle estimate. Row 3: Estimated failure time calculated using the Failure Forecast Method for (g) Internally Pressurised Tube, (h) 100,000 h Uniaxial Creep Test (i) Uniaxial creep test monitored by potential drop sensor. The vertical red dashed lines indicate the failure time, while the red dotted lines indicate ±10% of the estimated failure cycle. Estimates are only made following the minimum rate. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Implementing the Failure Forecast Method the parameters determining the best fitting lines are refined as each data point is gathered. It is important to reiterate that the estimate of the failure time is refined over time. Initially, with the first few data points there is great uncertainty in the best fitting gradient, and hence where the projected linear fit will intercept the x-axis. As data is accumulated over time the estimate is refined; Fig. 8(g)–(i) shows how the estimated failure time evolves throughout each experiment. It shows that following the initial uncertainty, it can be seen that the failure time estimates converge to within around 10% of the true failure time; even early on in the creep life, where little increase in rate is visually evident in strain-time curves, the failure time can be estimated effectively.

From each experiment it can be seen that by assuming $a = 2$, a more stable failure time estimate is produced as the variability of one less pa-
Fig. 9. Inverse rate against time for the 100,000 h uniaxial creep test. Data is segmented according to visually similar inverse rate – time behaviour, assumed to result from changes in operating conditions. Dotted lines show projected linear fits for each segment, the intercept of the linear regression with the x-axis indicates the estimated failure time that is expected to result from continued operation in those conditions.

4. Discussion

The context of this study is worth re-emphasising. It is understood that the majority of creep related failures in power station components will occur at stress concentrations or welds where analysis based on the formation of microscopic to macroscopic damage is more suitable. Despite this, significant effort is invested in inspecting parent material for volumetric creep damage to manage the risk of creep occurring in deficient material or at points of unexpectedly high stress; this analysis is focused on such cases. The strain rate based methodology is clearly applicable to accelerated uniaxial lab tests in the power-law regime, as demonstrated in this study, but the potential use for power station components requires further consideration. The remainder of this discussion considers the prospects for on-line strain monitoring followed by an analysis of whether Failure Forecast Method is suitable for the assessment of creep damage of power station components.

4.1. On-line strain monitoring of power station components

At present, strain rates of operational power station components are rarely ever collected and reported. Strain rates of the order of 1%/100,000 h might be expected [19,50] and measurements will need to be taken over the decades of operational life typically achieved by components; these two requirements make strain rate monitoring of power station components extremely demanding.

The requirements imply the use of permanently installed sensors. The uncertainty associated with a rate estimate is inversely proportional to the square root of the frequency of individual measurements [11]; with manual inspections measurements may only be obtained during outages (frequently separated by years) while in contrast permanently installed sensors will typically take at least a measurement per day, meaning much more accurate rate estimates are possible. Additionally, when fitting parameters to time domain information, a greater number of data points clearly results in superior estimates. The other advantage in using permanently installed sensors is the suppression of equipment, operator and spatial variability that is a feature of manual point-to-point measurements. If the sensor is permanently installed this variability is eliminated or greatly suppressed.

The factor limiting the use of many monitoring techniques is measurement drift; the readings must be stable to much better than 1%/100,000 h in order to achieve sufficiently accurate strain rate measurements. Dimensional instability between the two reference points of a hypothetical strain sensor may lead to systematic errors constituting drift; in the harsh environment of a power station, oxidation, thermal cycling, rocking on curved surfaces, mechanical interference may all cause minute movement of the sensor. Tied to this requirement is the choice of gauge length, the shorter the gauge length, the greater the influence of dimensional uncertainty becomes; as an example, with a gauge length of 10 mm, a 10μm uncertainty equates to a 0.1% strain error undermining the 1%/100,000 h requirement. For this reason, a longer gauge length is advantageous, but comes at the expense of locational specificity.
A number of techniques have been suggested for in situ strain monitoring over the last few decades [7,25,33,35,38]. The most well-known of these is the capacitance gauge [5,20,22,28,38] which has documented use particularly by Eskom [49] but has otherwise seen limited uptake. Recently the potential drop system included in this study has been proposed for use in power station applications. In both cases where the gauge length is of the order of 10 mm, it has not yet been rigorously demonstrated that they have the required stability in the power station environment over the time scales required. Despite decades of technological development, there does not yet appear to be a universally accepted on-line strain monitoring technique.

### 4.2. Applicability of the Failure Forecast Method for power station components

Although we have demonstrated the methodology on example data that is representative of key aspects of power station operation, it has not yet been demonstrated on plant. The key question determining whether strain rate based assessment is applicable to power station components is whether in non-accelerated power station conditions creep falls within the ‘power-law’ regime where strain dominates material failure. This is a question that does not appear to have consensus, presumably due to the present technological challenge in obtaining satisfactory creep strain data. Deformation maps [3,21] indicate the dominance of different creep mechanisms in different conditions. Viswanathan’s deformation map based analysis concludes that in power station conditions components are expected to fail through intergranular fracture [52] and therefore the development of grain boundary separation is to be expected, while at higher stresses and temperatures (accelerated conditions) failure is expected to be transgranular. This transition also marks the passage from the low stress diffusion dominated regime [10,26,27,36,50] where time-dependent diffusion processes are more dominant and the stress dependence is far less significant, $\dot{\varepsilon} \propto \sigma$, to the higher stress power-law creep, $\dot{\varepsilon} \propto \sigma^n$. This indicates that in the lower stress (non-accelerated) regime the strain dependent positive feedback is very significantly reduced, resulting in much more stable strain behaviour and a less strain accelerated failure. Consequently, strain rate becomes less indicative of the damage mechanism. Despite this the R5 code [6] assumes creep follows power-law behaviour, perhaps due to conservatism. Although the range of experiments in this study show the potential for rate based assessment, it will be necessary to demonstrate the applicability to plant using real data gathered from plant or realistic component tests.

A key assumption in the Failure Forecast Methodology is that the rate at failure is relatively large, and so the inverse rate, indicating remnant life, will approach zero. In each of the experiments used in this study the strain rate at failure is two orders of magnitude greater than the minimum, leading to successful performance of the method, but it is acknowledged that creep curves come in a wide range of forms depending on operating condition and material [58,59]. If this is not the case then failure will appear premature and remnant life estimates will be non-conservative. It is important to make the distinction between ductility and damage tolerance. In the schematic illustration of Fig. 11, one curve has high ductility but shows little strain acceleration before failure, while the other has low ductility yet has a large relative increase in strain rate. While the lower strain rate of the latter is harder to measure, the large relative increase in strain rate makes it more suitable for strain rate based analysis. A number of studies have demonstrated that creep ductility tends to decrease at longer, less accelerated, failure times and

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**Fig. 10.** Estimated failure time having discarded all data prior to 80,000 h.

**Fig. 11.** Illustration of creep strain curves for a component that has a high failure strain but shows little strain acceleration towards failure, and a component that has little strain at failure but a large relative increase in strain rate. Experiment results illustrating these differences can be found in [59].
with increasing multiaxiality, yet these reports do not include strain-time data and therefore do not strictly imply a reduction in relative increase in strain rate. The ‘creep damage tolerance parameter’ [59] aims to quantify the tertiary creep strain that can be sustained before failure, and therefore is indicative of the relative increase in strain rate at failure. Some highly stressed examples are reported where ductility is high but little strain rate acceleration is evident and vice versa [59]. Again, further investigation is required to confirm how much strain acceleration is observed in plant components.

It is important to bear in mind the gauge length of strain measurements when evaluating creep strain-life data. If strain becomes localised then large gauge length measurements may grossly underestimate the local strain; for this reason localised strain measurements such as the potential drop technique used in this paper are advised. It is important to emphasise that the methodology described in this study is not intended to apply to local stress concentrations such as weldments where rupture is apparently premature and ‘brittle’. It may be of interest to note that the Failure Forecast Method is also applicable to creep crack growth, again due to the positive feedback driven damage mechanism [11].

5. Conclusions

Uncertainty in material properties, temperature and particularly stress state make predicting remaining creep life difficult. It is argued that remnant life should be based on observation of the component response to the actual situation at hand and strain rate is a measurable symptom of creep integrity that may be utilised for this purpose.

Present understanding of the creep behaviour of power station steels is necessarily derived from greatly accelerated uniaxial lab tests. In these high stress, high temperature conditions creep is likely to be in the power-law regime. The strain rate in the power-law regime is exceptionally stress sensitive and deformation is driven by dislocation flow; this leads to tremendous strain dependent positive-feedback, leading to unstable self-accelerating strain behaviour.

Strain dependent positive feedback means that the Failure Forecast Method may be used for remnant life estimation. The Failure Forecast Method captures in a general way the strain rate behaviour of creep damage that has been proposed in various subtly different forms in numerous previous publications. The methodology and its positive feedback rationale unifies these different proposals. The methodology is clearly applicable to accelerated uniaxial lab tests in the power-law regime, as demonstrated in this paper and the literature relating to strain rate based methods in the past. Three experiments have been included in this study; two are intended to capture different aspects pertinent to power station operation, multiaxial stress states and long-duration creep life, while the third illustrates the use of a sensor sufficiently robust for power station use. In these three exemplar cases the Failure Forecast Method is shown to be very effective, accurately estimating remnant life shortly after the point of minimum strain rate.

There is significant uncertainty surrounding the strain behaviour of pressure vessels and piping most likely due to the technical challenge of long term monitoring of creep strain in the harsh conditions. The applicability of strain rate based assessment for power station components requires further investigation.

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