MULTI-OBJECTIVE GENETIC ALGORITHM FOR MATERIAL PARAMETER OPTIMISATION TO PREDICT HIGH-TEMPERATURE CREEP BEHAVIOUR

J. Choi[1,2,a], L. Bortolan Neto[1], R. Wright[3], J.J. Kruzic[2], O. Muránsky[1,2]

[1] Australian Nuclear Science and Technology Organisation (ANSTO), Lucas Heights, NSW, Australia,
[2] School of Mechanical and Manufacturing Engineering, UNSW Sydney, Sydney, NSW, 2052, Australia,
[3] Idaho National Laboratory, [a] z5208688@ad.unsw.edu.au

Abstract. The study proposes a methodology to predict long-term creep behaviour based on short-term creep data of Alloy 617. The methodology employs a multi-objective genetic algorithm (MOGA) to optimise the material parameters of the Kachanov-Rabotnov (K-R) model. It is shown that the methodology is highly successful in predicting creep behaviour at $800℃$. However, at $900℃$ and $1000℃$, oxidation leads to the atypical accumulation of creep plasticity, which the K-R model cannot account for.

Introduction

Alloy 617 is a nickel-based superalloy with a wide range of high-temperature applications, such as for pipelines in aeroengines [1] and intermediate heat exchangers in nuclear reactors [2]. These systems operate at elevated temperatures and pressures, in which individual components are expected to undergo significant creep damage during their lifetime. The accumulation of creep damage can lead to the unexpected failure of components if left unmanaged, and in turn significantly shorten the life and economic viability of the system. Thus, the ability to predict creep damage is of technological importance for engineers designing such systems.

The Kachanov-Rabotnov (K-R) model [3, 4] was designed to predict high-temperature creep. It stands out from single-point (e.g., Norton's power law [5] and Larson-Miller method [6]) and other multi-point (e.g., Ductility Exhaustion [7] and Stress-Modified Ductility Exhaustion [8]) models, in that it inherently accounts for the multi-regime nature of high-temperature creep, to thus provide improved predictions. The challenge with multi-point models (e.g., the K-R model) is with determining the material parameters. Numerical methodologies, such as linear regression [2], simulated annealing [9], and artificial neural networks (ANN) [10], have been employed with mixed results. For instance, linear regression overly relies on initial parameter values, simulated annealing can be inconsistent and time-consuming, and ANNs are difficult to implement and require large amounts of data to train. Thus, there is interest in employing the multi-objective genetic algorithm (MOGA) for parameter optimisations. The following study proposes the methodology of using the MOGA to calibrate the K-R model by computing its multiple interdependent material parameters. The methodology is demonstrated by calibrating the model using short-term creep data of Alloy 617 produced by the Idaho National Laboratory (INL) [11] and using the calibrated model to predict the alloy's long-term creep behaviour.

Experimental Data

The current study uses the full, uniaxial, creep curves of Alloy 617 from INL, conducted at 800°C (60, 65, 70, $80\ MPa$), $900°C$ (26, 28, 31, $36\ MPa$), and $1000°C$ (11, 12, 13, $16\ MPa$). The predominance of the creep curves in the secondary and tertiary creep regimes justifies using the K-R model to predict the behaviour of the alloy, since the model only accounts for secondary and tertiary creep. Nevertheless, to improve accuracy, we accounted for the primary creep by removing it from the experimental creep curves and implementing a strain offset, $\hat{\varepsilon}_0$, for the predicted curves. For each creep curve, we drew tangents at the minimum creep rate. The values of $\hat{\varepsilon}_0$ for the curves corresponded to the intercepts between the tangents and the vertical axis.

Methodology

The derivation of the K-R model used in this study follows Stewart et al. [12], which involves incorporating Norton's power law [5] into the temperature-dependent K-R constitutive equations. The resulting expression (Eq. 1) defines the K-R model with its material parameters (A, n, M, ϕ, and χ).

$$\varepsilon(t) = A\sigma^n \frac{[1-(\phi+1)M\sigma^{\chi}t]^{\frac{\phi+1-n}{\phi+1}} - 1}{M\sigma^{\chi}(n-\phi-1)} + \hat{\varepsilon}_0 \tag{1}$$

In the study, we defined the four objective functions, $E_{1..4}$, of the MOGA to minimise the mean square errors between the observed and predicted strain (ε), time-to-failure (t_f), strain-to-failure (ε_f), and minimum creep rate ($\dot{\varepsilon}_m$). In other words, when $E_{1..4} \to 0$, then $\int_{t_1}^{\hat{t}_f} \hat{\varepsilon}\, dt - \int_{t_1}^{\tilde{t}_f} \tilde{\varepsilon}\, dt \to 0$, $\hat{t}_f - \tilde{t}_f \to 0$, $\hat{\varepsilon}_f - \tilde{\varepsilon}_f \to 0$, and $\hat{\dot{\varepsilon}}_m - \tilde{\dot{\varepsilon}}_m \to 0$.

Results and Discussion

To demonstrate the methodology, we conducted three sets of ten optimisations using the data at $800℃$, $900℃$, and $1000℃$, to calibrate the K-R model by determining its material parameters (A, n, M, ϕ, and χ). The optimisations calibrated the model with short-term data, and the calibrated model was used to predict the long-term creep behaviour of the alloy. The results of the optimisations are displayed in Fig. 1.

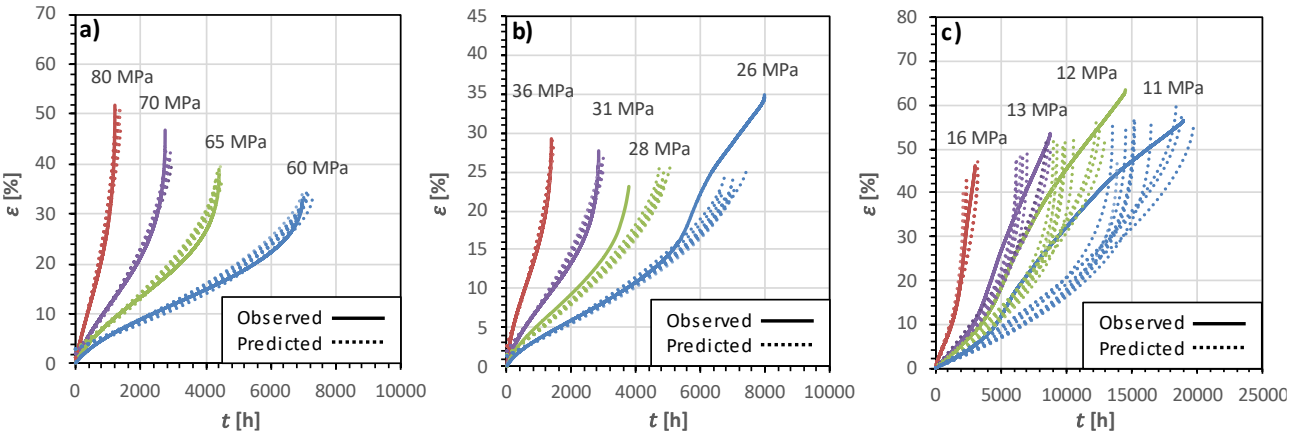

Fig. 1. Results of the optimisation at 800℃ (a), 900℃ (b), and 1000℃ (c), calibrating with short-term creep data (red and purple) to predict long-term creep behaviour (green and blue). Observed and predicted creep curves are displayed as solid and dotted lines, respectively.

Fig. 1a demonstrates that the proposed methodology can predict the long-term creep behaviour at 800℃, accurately and consistently, when the K-R model is calibrated with short-term creep data. In particular, the time-to-failure predictions are of exceptional accuracy. While the strain-to-failure predictions are less accurate, they are always conservative, which is acceptable from an engineering perspective. These results are of technological importance, as in practice, it is easier and less costly to obtain the short-term experimental data (at higher stress conditions) than the long-term experimental data (at lower stress conditions).

However, the predictions at 900℃ (Fig. 1b) and 1000℃ (Fig. 1c) are relatively less accurate and consistent, especially for creep curves conducted with lower stresses. This can be attributed to the changes in the ongoing creep mechanism, thought to be triggered by oxidation at higher temperatures as a result of testing Alloy 617 in air [13]. The cumulative effect of oxidation over the longer creep lives result in unconventional creep behaviour, which manifests itself by atypically shaped creep curves. The K-R model's inability to account for the atypical creep curves thus resulted in the decreased accuracy in the creep predictions at $900°C$ and $1000°C$. Furthermore, since the oxidation is a diffusion-controlled process, the oxidation effect is more pronounced for longer tests, which explains the worse accuracy at lower stresses. That said, it is worth noting that the methodology can still provide indicative time- and strain-to-failure predictions at 900℃ and 1000℃.

Conclusion

In this study, we proposed a methodology that employed a MOGA to determine the material parameters of the K-R model and tested the methodology using INL-produced creep data of Alloy 617. We demonstrated that the methodology could consistently provide accurate and conservative predictions for the time- and strain-to-failure at 800℃. However, the predictions at 900℃ and 1000℃ were less accurate, which we attributed to the alloy's exposure to air. At higher temperatures, the oxidation resulted in atypically shaped creep curves that the K-R model could not account for. Nevertheless, within the limits of the K-R model, the proposed methodology was able to predict the long-term creep behaviour of Alloy 617 using only the short-term creep data. This is of great significance, as it will allow engineers to safely design components in crucial creep-prominent systems, such as in aeroengines and nuclear reactors.

References

[1] Q. Meng, Z. Wang, Creep damage models and their applications for crack growth analysis in pipes: A review, Engineering Fracture Mechanics 205 (2019) 547-576.
[2] K. Kan, O. Muránsky, P.J. Bendeich, R.N. Wright, J.J. Kruzic, W. Payten, Assessment of creep damage models in the prediction of high-temperature creep behaviour of Alloy 617, International Journal of Pressure Vessels and Piping 177 (2019) 103974.
[3] L.M. Kachanov, The Theory of Creep (teoriya Polzuchesti), National Lending Library for Science & Technology1967.
[4] Y.N. Rabotnov, F.A. Leckie, W. Prager, Creep Problems in Structural Members, Journal of Applied Mechanics 37(1) (1970) 249-249.
[5] F.H. Norton, The Creep of Steel at High Temperatures, McGraw-Hill book Company1929.
[6] F.R. Larson, J. Miller, A Time-temperature Relationship for Rupture and Creep Stresses, Transactions of ASME1952.
[7] R. Ainsworth, R5: An Assessment Procedure for the High Temperature Response of Structures, British energy generation Ltd 3 (2003).
[8] M.W. Spindler, The prediction of creep damage in type 347 weld metal. Part I: the determination of material properties from creep and tensile tests, International Journal of Pressure Vessels and Piping 82(3) (2005) 175-184.
[9] C. Stewart, A. Gordon, Analytical method to determine the tertiary creep damage constants of the Kachanov-Rabotnov constitutive model, 2010.
[10] A. Ghatak, P. Robi, Prediction of creep curve of HP40Nb steel using artificial neural network, Neural Computing and Applications 30 (2017) 2953-2964.
[11] K. Sedighiani, M. Diehl, K. Traka, F. Roters, J. Sietsma, D. Raabe, An efficient and robust approach to determine material parameters of crystal plasticity constitutive laws from macro-scale stress–strain curves, International Journal of Plasticity 134 (2020) 102779.
[12] C.M. Stewart, A.P. Gordon, Strain and Damage-Based Analytical Methods to Determine the Kachanov–Rabotnov Tertiary Creep-Damage Constants, International Journal of Damage Mechanics 21(8) (2012) 1186-1201.
[13] D. Kim, C. Jang, W.S. Ryu, Oxidation Characteristics and Oxide Layer Evolution of Alloy 617 and Haynes 230 at 900 °C and 1100 °C, Oxidation of Metals 71(5-6) (2009) 271-293.