

1 **Elevated temperature contact creep and friction of nickel-based superalloys using machine**  
2 **learning assisted finite element analysis**

Sepehr Salari<sup>a</sup>, Farnaz Behnia<sup>b</sup>, Andreas A. Polycarpou<sup>c</sup>, Ali Beheshti<sup>a,\*</sup>

<sup>a</sup> Department of Mechanical Engineering, George Mason University, Fairfax, VA, 22030, USA

<sup>b</sup> Department of Systems Engineering and Operations Research, George Mason University, Fairfax, VA, 22030, USA

<sup>c</sup> J. Mike Walker Department of Mechanical Engineering, Texas A&M University, College Station, TX, 77843, USA

3

**Abstract**

*Nickel-based superalloys with superior thermochemical, mechanical, and tribological properties are highly utilized for critical components in several high temperature applications such as gas turbines and nuclear reactors. Inconel 617, in particular, is considered as one of the main candidate superalloys for tribo-components in very-high-temperature gas-cooled nuclear reactors. Recent findings indicate that this alloy grows unique surface oxide especially in a high-temperature helium environment with distinctive wear, friction, and contact properties. This study investigates the high temperature contact area evolution and frictional behavior of Inconel 617 using finite element simulation and provides predictive models for the contact and friction performance at different normal loads, dwell times, and temperatures. High temperature helium-aged Inconel 617 top surface properties (up to 600 °C) are utilized along with a single asperity-based deformable elastic-plastic contact model under combined normal and tangential loading. Machine learning is used to assist the finite element results and to predict friction coefficient as well as contact area evolution. While a small difference is observed in the instantaneous friction coefficient (no dwell time) for all temperatures, friction coefficient increases considerably with dwell time. This shows that the effect of contact creep for longer dwell times significantly dominates the effect of high temperature variation in basic mechanical parameters such as modulus and yield strength. It is found that increasing temperature and dwell times lead to the friction coefficient increase, yet the dominance of dwell time effects decreases at higher temperatures and loads. While the analysis is presented for Inconel 617, the methodology is easy to be generalized and can be applied to other HT alloys.*

**Keywords:** *Superalloys; Elastic-Plastic-Viscoplastic Contact; High Temperatures; Static Friction; Machine Learning; Artificial Neural Network*

4 **1. Introduction**

5 In view of design demands, providing materials that can withstand high temperature (HT) and its  
6 concomitant HT creep deformation, is vital for the effective and reliable operation of mechanical  
7 components. Advanced nuclear reactors (Wright, 2006a), jet engines (Klocke et al., 2013), and  
8 gas turbines are among several applications that HT creep deformation severely affects their

---

\* Tel.: +1-703-993-5638; E-mail address: abehesh@gmu.edu (Ali Beheshti).

1 performance. Inconel 617 (symbolized as IN617, hereinafter) is one of the advanced materials to  
2 enable higher operating temperatures for many HT applications. In particular, it is among the  
3 main candidate materials for next-generation very-high temperature reactors (VHTR) and high-  
4 temperature gas-cooled reactors (HTGR) due to its excellent mechanical and chemical properties  
5 as well as surface stability. It is mostly to be utilized for controlling rods, valves, and other  
6 contacting pairs in Gen. IV reactors (Cabert et al., 2006; Wright, 2006b, 2006a). Operating under  
7 HT and often long idle conditions, however, makes them susceptible to contact and tribological  
8 challenges (Salari et al., 2022). When it comes to the mechanical contacts and interfaces, the  
9 surface of these components is not perfectly smooth, and contact occurs at small discrete areas  
10 (asperity tips). These microscopic asperities with small contact areas and usually under high  
11 contact stress give rise to the likelihood of contact creep deformation (Feng and Ngan, 2002).  
12 Creep of these contacting asperities relaxes contact stress, increases contact strain, and  
13 subsequently expands the overall contact area. This, in turn, results in a considerable change at  
14 the micro and subsequently macro scales contact and frictional behaviors. This is significant for  
15 the reliable performance and predictable longevity of several reactor mission-critical  
16 components. For instance, this can adversely affect the precise motion of controlling rods in  
17 nuclear reactors (Stanford, 2007). In fact, HT contact creep and self-welding during long idle  
18 intervals causes unpredictable high static friction and often surface damage (Zheng et al., 2020).  
19 The extent of static friction and its predictability is of particular concern for the design and  
20 maintenance as well as control and actuation operations since the material pairs experience high  
21 temperatures and high loads under intermittent movements with long dwell times significantly  
22 affecting frictional and contact behavior (Stanford, 2007).

23 Static coefficient of friction (referred to as COF, hereinafter) and sliding inception phenomena  
24 have been studied since the pioneering work of Coulomb (1785). He proposed a constant COF  
25 being basically the proportionality factor between tangential load and normal load at the sliding  
26 inception. Mindlin developed a COF formula for a spherical contact with elastic Hertzian normal  
27 pressure following the Coulomb friction model: assuming sliding occurs when the entire surface  
28 points reach the shear limit (Mindlin, and Deresiewicz, 1953). Tabor later suggested adhesion  
29 and shear strength of the contact as well as the real contact area as the main elements influencing  
30 the COF (Tabor, 1981). Chang et al. incorporated these elements in their model, and calculated  
31 the friction force of a single asperity while assuming yielding inception as a criterion (Chang et  
32 al., 1988). Using finite element (FE), a semi-analytical solution was developed by Kogut and

1 Etsion (KE model) to provide an empirical expression for the COF of a single asperity based on  
2 the initiation of the yield in the softer component (Kogut and Etsion, 2003). Etsion and his  
3 colleagues (BKE model) later suggested a new approach for determining the sliding inception  
4 by defining relative contact stiffness and considering the contact in full stick condition (Brizmer  
5 et al., 2007). Later, a sliding criterion was developed by Polycarpou and his coworkers (WSP  
6 model) assuming that sliding occurs when shear stress at all contacting points reaches material  
7 bulk maximum shear strength (Wu et al., 2012). Their proposed model was shown to be accurate  
8 for a wider range of loads covering both the KE (low interference) and BKE (high interferences)  
9 models (Wu et al., 2012).

10 Early efforts to describe the observed time dependency of COF suggested it's linked to creep  
11 deformation of asperities at micro-scales (Moore and Tabor, 1952; Rabinowicz and Tanner,  
12 1966; Spurr, 1955). These studies showed an increase in the contact area with dwell time, which  
13 may explain COF increase. However, owing to the multitude of factors influencing the  
14 mechanism, detailed contribution of creep deformation on the sliding inception behavior was not  
15 established. In another study, Malamut et al. (MKE model) numerically studied the effect of  
16 dwell time and normal load on static friction of a creeping elastic-plastic PTFE hemispherical  
17 contact (Malamut et al., 2009). Based on their findings, in addition to the increase in the contact  
18 area, an increase in initial tangential stiffness due to stress relaxation at the contact significantly  
19 influences the tangential load, and consequently, the COF (Malamut et al., 2009). Based on their  
20 best-fit curves to the FE simulations, Malamut et al. suggested an empirical COF for a polymer-  
21 based single asperity at any dwell time and a range of normal loads at room temperature  
22 (Malamut et al., 2009). This model was further evaluated by the experimental work of Kasem et  
23 al. who performed a set of experiments using PTFE spheres to study the effect of dwell time,  
24 normal load, and spherical diameter on the COF (Kasem and Etsion, 2014). Experimental results  
25 showed a comparable course of evolution for COF in comparison to the FE results of MKE in  
26 which COF increases with the dwell time (Kasem and Etsion, 2014; Malamut et al., 2009). It is  
27 worth mentioning that regarding rough surface contact creep, a few attempts were made on  
28 studying friction behavior and the electro-mechanical response of the surface using, for example,  
29 the fractal representation of the surface (see Refs. (Goedecke and Mock, 2010; Rezvanian et al.,  
30 2008)). For a comprehensive review of contact and friction creep studies, the reader is referred to  
31 the recent review by the authors (Salari and Beheshti, 2021).

1 The above-mentioned models described COF evolution for a variety of loads, dwell times, and  
2 material properties, yet a predictive model for contact and friction behavior to incorporate these  
3 parameters, especially, along with temperature variation is lacking in the literature. While this  
4 predictive model is highly beneficial for several HT contact applications, the shortcoming might  
5 be related to the intricacies associated with the development of a comprehensive numerical and  
6 predictive model with complex nonlinearity over wide length, temperature as well as time scales.  
7 The problem, however, can be potentially addressed with the advent of powerful computers and  
8 the FE technique as well as the utilization of advanced machine learning (ML) tools such as  
9 artificial neural networks (ANNs or for simplicity NNs) (Behnia et al., 2020; Deng and Li, 2013;  
10 He et al., 2016; Heidari et al., 2021; Kingma and Ba, 2014; Kumar et al., 2016).

11 Recently, mechanical engineering and, in particular, the tribology community have started to  
12 realize the advantages and efficacy of ML techniques. For example, Thankachan et al. employed  
13 a regression model for optimizing the tribological behavior of hybrid copper surface composites  
14 (Thankachan et al., 2018) whereas Borjali et al. generated a data-driven model that allowed the  
15 prediction of polyethylene wear rate based on several operating parameters (Borjali et al., 2019).  
16 The above attempts showed that NNs-based models can potentially reduce the need for  
17 experimental studies and can also be used to validate the new experimental data. In addition,  
18 Senatore et al. presented a comprehensive view of the main sliding parameters influencing brake  
19 and clutch friction and sliding motion using the NNs method (Senatore et al., 2011). Sattari et al.  
20 developed a machine learning method to predict the intrinsic friction of 2D lubricants by  
21 measuring the surface maximum energy barrier for 2D materials having different structural,  
22 electrical, chemical, thermal and mechanical properties (Sattari Baboukani et al., 2020). [NNs-](#)  
23 [based constitutive models are other applications of NNs which were used along FE simulations.](#)  
24 [Unlike the conventional implementation of plasticity models, NNs do not require special](#)  
25 [integration procedures for implementation in FE analysis \(Hashash et al., 2004\). In another](#)  
26 [study, multiple welding parameters were studied using NNs to predict the tensile strength,](#)  
27 [hardness, and percentage of elongation of the welded alloys \(Khourshid et al., n.d.\). A review on](#)  
28 [advances at the intersection of data science with mechanical deformation simulations has been](#)  
29 [presented by Frydrych et al. \(Frydrych et al., 2021\).](#) The NNs algorithms have also shown the  
30 sensitivity of each input parameter and its influence on the studied parameter for these studies. It

1 is evident that ML algorithms are powerful tools to provide a simple prediction model and are  
2 highly flexible to incorporate different parameters.

3 Let's now turn our attention to tribological components in HTGR/VHTR applications. Due to the  
4 presence of Helium (He) as a coolant with inevitable impurities, the metallic alloys (e.g., IN617)  
5 develop unique surface oxides which significantly influence surface friction, wear, and contact  
6 properties and in turn, impact the performance of the components (Sakaba et al., 2010). In the  
7 authors' previous study, the time-independent and dependent mechanical properties of the oxide  
8 were studied (Salari et al., 2020). Particularly, creep characterization and mechanical parameters  
9 of the oxide under indentation were investigated and extracted. Results showed that while  
10 Young's modulus of the oxide is relatively close to the bulk of IN617 for temperatures up to  
11 600°C, the yield strength, and hardness, in comparison to the bulk material, increase significantly  
12 due to oxidation of the IN617 after aging. The calculated creep parameters, as well as activation  
13 energy, showed that creep of the oxide depends on the diffusion through the grains, unlike the  
14 bulk material in which the main creep mechanism is dislocation climb (Salari et al., 2020; Zhang  
15 et al., 2017). The elevated temperature surface material properties exclusively extracted for He-  
16 aged IN617 by the authors (reported in (Salari et al., 2020)) are used here to model and predict  
17 IN617 oxide contact and COF response at elevated temperatures.

18 The current study investigates the HT contact area and frictional characteristics of a single  
19 asperity from room temperature to 600 °C for the IN617 surface with the assistance of FE  
20 analysis. While this method is presented for the specific material of interest (which its  
21 mechanical properties were extracted from our previous study (Salari et al., 2020)), the  
22 methodology can be applied to other HT alloys and is easy to be generalized. Final simulated  
23 contact area and COF results are used as input data points for a NN algorithm to introduce  
24 comprehensive predictive models based on input values of temperature, load, and dwell time.  
25 While the focus of this study is on modeling HT contact creep and friction, the NNs approach  
26 was used as a powerful tool to come up with an easy-to-use and extendable model and also show  
27 the capability of NN to the mechanics and materials and in particular contact mechanics and  
28 tribology community. Additionally, similar to the MLK, empirical relations for the COF and  
29 contact area (details in Supplementary Information, SI) are introduced and their accuracy are  
30 compared to the NNs.

## 2. Finite element model

In this work, a FE model, within ABAQUS® 2020, was adopted to develop a three-dimensional deformable hemisphere in contact with a rigid flat surface (flattening model). The contact was analyzed with an implicit solver for the normal pre-load (first step) and tangential loading (last step) while a quasi-static approach was chosen to analyze the time-dependent material response (intermediate step) assuming negligible inertia effects (Smith, 2017).

Elastic-plastic-viscoplastic with work hardening properties were assumed for the deformable hemisphere following authors' previous HT indentation study (Salari et al., 2020) on IN617. Adopting properties obtained from common uniaxial creep test in the literature is not available for IN617 oxide and more importantly, even if available for a material, mechanical properties based on indentation creep are more reliable in analyzing contact creep flattening. Hence, all the material properties here are based on our previous measurements (indentation creep) on the oxide surface of aged IN617 (Table 1) (Salari et al., 2020) where IN617 were aged at 950 °C for 100 hours in He to simulate the He-cooled reactor environment. In that study, nanoindentation on the cross-section of the oxide was carried out from room temperature up to 600 °C and load-displacement, as well as creep displacement evolution with time, were obtained. For these measurements, hardness size effect is an important factor to be considered. Based on the extracted hardness and discussion available in Ref. (Salari et al., 2020), consistent results were observed for different loads and temperatures. The extracted results were also validated with other metal oxides in Ref. (Salari et al., 2020) showing good agreements. Following a work hardening model as well as a power-law creep (see Eqs. 1 and 2), raw experimental graphs along with complimentary iterative FE simulations were utilized to obtain the mechanical properties at different temperatures including Youngs' modulus ( $E$ ), Poisson's ratio ( $\nu$ ), yield strength ( $\sigma_y$ ), and strain work hardening exponent ( $n_1$ ). Additionally, time-dependent properties were calculated including creep coefficient ( $A$ ) and creep exponent ( $n_2$ ). For full details please see Ref. (Salari et al., 2020).

$$\sigma_f = \sigma_y \left(1 + \frac{E \times \varepsilon_p}{\sigma_y}\right)^{n_1} \quad (1)$$

$$\dot{\varepsilon} = A \sigma^{n_2} \quad (2)$$

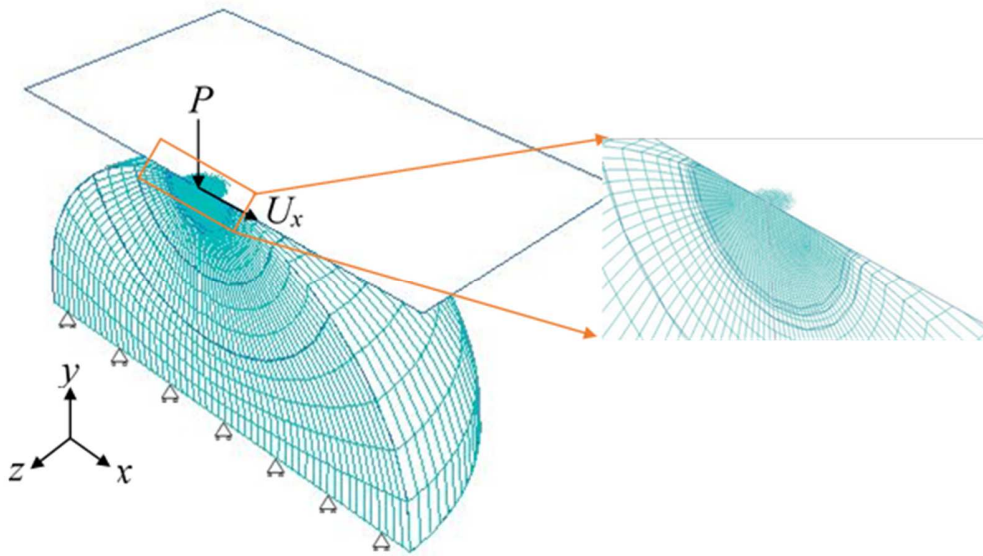
In Eqs. 1 and 2,  $\sigma_f$  and  $\varepsilon_p$  denote the flow stress and strain, respectively and  $\dot{\varepsilon}$  is the creep strain rate.

**Table 1** Mechanical properties of oxide surface of aged Inconel 617 (Salari et al., 2020).

Temperature (°C)	$E$ (GPa)	$\nu$	$\sigma_y$ (GPa)	$n_1$	$A$	$n_2$
25	294.55	0.25	10.28	0.34	3.13E-13	1.71
200	296.10	0.25	6.02	0.22	5.33E-13	1.97
400	297.81	0.25	2.60	0.18	4.75E-12	2.14
600	175.37	0.25	0.13	0.02	1.32E-09	3.51

1

2



**Fig. 1** Schematic representation of the boundary condition and adopted mesh for the hemisphere at the contact.

3

4 To reduce computer cost only half of a hemisphere was modeled and meshed with a total of  
5 75,000 elements of reduced eight-node hexahedral, C3D8R, as shown in **Fig. 1**. The hemisphere,  
6 with a radius of  $R = 1 \text{ mm}$ , was divided into multiple regions to have a gradual mesh size  
7 increase from the contact region. The finest elements were selected near the contact area where  
8 their size was 0.002 times the elements at the bottom to get consistent results for the stress, creep  
9 strain, and contact area. The deformable hemisphere was fully contained at the bottom, and a  
10 symmetry boundary condition was applied for the symmetry plane. Different normal loads were  
11 applied on the rigid flat in the normal direction ( $y$ ) followed by a holding period with a range of  
12 different dwell times,  $t_d$ , from 0 (instantaneous) to 1000 minutes while the load was kept

7

1 constant. For generalization, here we use nondimensional normal load as  $P^* = L/L_c$  where  
 2 normal load,  $L$ , is nondimensionalized with respect to the critical normal load ( $L_c$ ) beyond which  
 3 the contact is no longer elastic. Based on Hertzian solution,  $L_c$ , its associated critical  
 4 interference,  $\omega_c$ , and critical contact area,  $A_c$ , at the onset of yielding are given by:

$$L_c = \frac{4}{3} E^* R^{0.5} \omega_c^{1.5} \quad (3)$$

$$\omega_c = \left( \frac{\pi k H}{2 E^*} \right)^2 R \quad (4)$$

$$A_c = \pi R \omega_c \quad (5)$$

where

$$E^* = \frac{E_i}{1 - \nu_i^2} \quad (6)$$

5 subscript  $i$  relates to IN617 as the elastic modulus for the rigid flat is assumed to be infinity.  $H$   
 6 represents the hardness and  $k$  is the proportionality factor between the maximum contact  
 7 pressure and the hardness at the onset of plastic deformation. Kogut and Etsion proposed a  
 8 relationship ( $k = 0.454 + 0.41\nu$ ) for the calculation of  $k$ . Here, based on the measured average  
 9 Poisson value (0.25) for IN617 oxide,  $k$  was taken equal to 0.55. The range of  $P^*$  (0.5 to 11) and  
 10  $t_d$  (0 to 1000 minutes) were chosen such way that they cover wide deformation regimes—elastic  
 11 (before yielding) to high plastic regimes—and time-dependent creep deformations. It should be  
 12 added that due to large deformations, numerical convergence for higher load values and  
 13 especially under long dwell times was challenging, however, whenever possible the load was  
 14 increased up to  $P^* = 16$ . It should be noted that one of the main benefits of single asperity  
 15 contact models is their ability to be expanded to rough surface models e.g., Greenwood and  
 16 Williamson (GW) based models, simulating entire contact behaviors (Greenwood et al., 1966).  
 17 However, asperity interaction and most importantly asperity merging are not generally valid in  
 18 GW based models and, hence, deformation of an asperity beyond threshold value of  $\lambda = a/R \sim$   
 19 0.4 ( $a$  is the radius of contact area) is not typically considered in asperity contact models  
 20 (Beheshti and Khonsari, 2014, 2012; Jackson and Green, 2005). Accordingly, here, the  
 21 simulations were stopped at large values of  $\lambda$  (more than 0.4). It is believed that beyond this  
 22 threshold asperities are not deformed independently and for many tribological applications, it is  
 23 either unlikely or unacceptable (Greenwood et al., 1966; Jackson and Green, 2005).

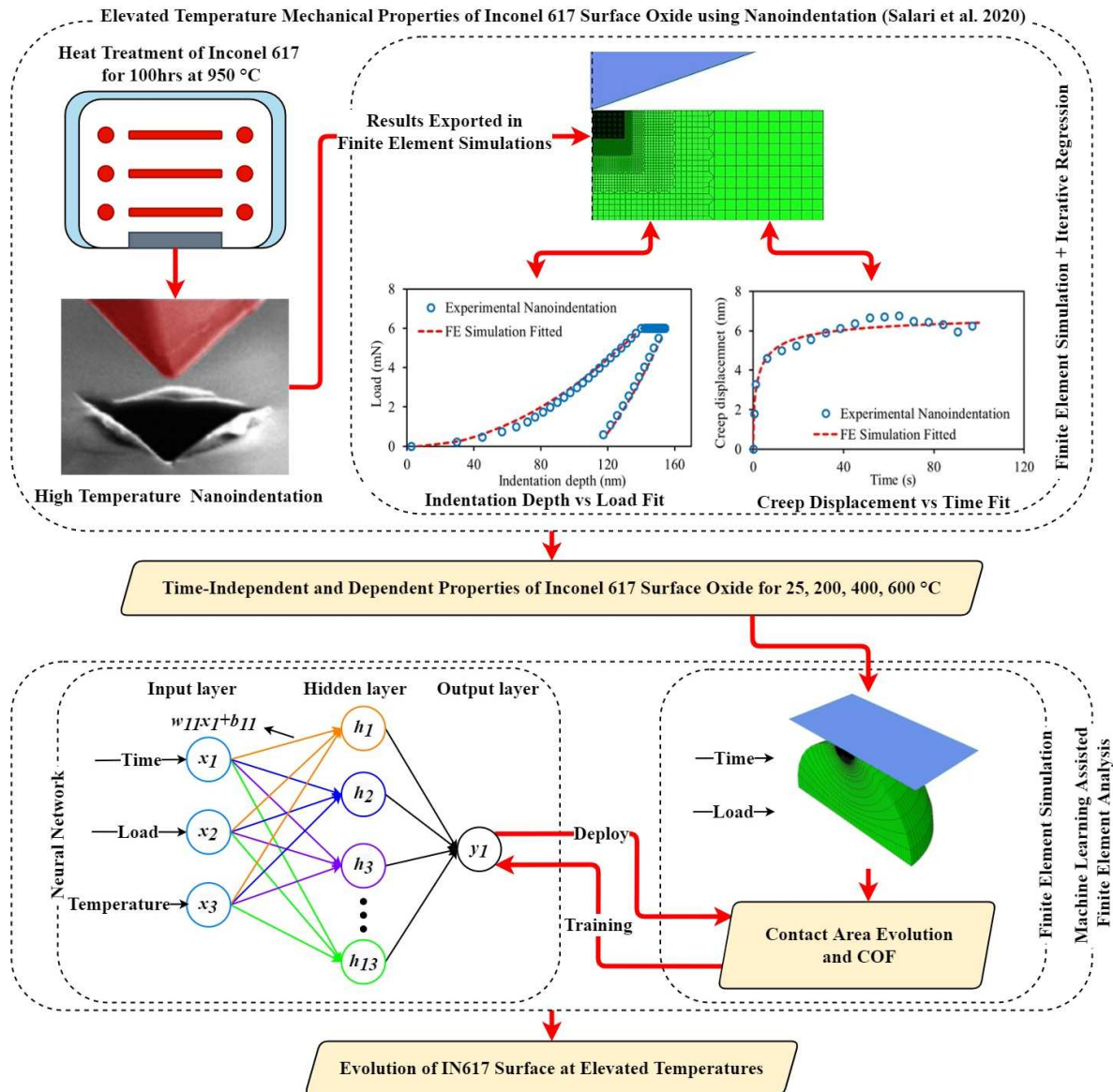
1 Here, first normal load  $P^*$  was applied to the contact followed by the holding period ( $t_d$ ).  
2 Subsequently, a ramp displacement loading ( $U_x$ ) was applied in the tangential direction ( $x$ ) until  
3 “sliding” occurred. The friction for the normal loading is assumed to be negligible (Eriten et al.,  
4 2012), however, for the tangential displacement, a very large local COF was selected for the  
5 entire contact following WSP partial slip approach (Wu et al., 2012) so the input local COF did  
6 not serve as a threshold. Rather, in the WSP model, critical maximum frictional shear stress,  $\tau_c$ ,  
7 was used as the criterion for the local sliding inception.  $\tau_c = \sigma_y / \sqrt{3}$  was selected as contact  
8 maximum shear stress where  $\sigma_y$  denotes the yield strength of the material under investigation  
9 (here, it is the aged IN617 surface yield strength at 25 °C to 600 °C (Salari et al., 2020)). Per the  
10 WSP model, “sliding” happens when shear stress on the entire contact reaches  $\tau_c$ . WSP model  
11 was shown to be valid over large normal interference ranges covering both the KE and the BKE  
12 models (Brizmer et al., 2007).

13 Another important computational parameter for the tangential loading step is the elastic slip (ES)  
14 which should be adjusted for implicit solvers to get converged solution. ES is an elastic  
15 displacement during the stick period that may induce additional elastic slip during tangential  
16 loading (Smith, 2017). It should be mentioned that lower values of ES may give accurate results,  
17 however, the simulations are not computationally efficient. Therefore, to reach the optimum  
18 value for ES, the current FE model was compared and verified against the results reported by the  
19 WSP and MKE models for multiple holding durations and displacements (Malamut et al., 2009;  
20 Wu et al., 2012). Based on the outcome, a value of 0.002 was selected for ES for which the  
21 estimated friction force fell within 5% of WSP and MKE models (Malamut et al., 2009; Wu et  
22 al., 2012). The maximum corresponding tangential load at sliding inception is considered as  
23  $Q_{max}$  and, hence, the COF equals  $Q_{max}$  divided by the constant normal load. In addition the  
24 numerical model requires “creep tolerance” parameter which is a parameter to control the  
25 accuracy of the creep integration at each load increment for the FE software and can be  
26 calculated by selecting an acceptable stress error tolerance,  $\sigma_{err}$ , divided by a typical elastic  
27 modulus,  $E$  (Smith, 2017). In this study,  $\sigma_{err}$  is taken to be 2 MPa. Each FE simulation took  
28 around 1 hour depending on the convergence rate. To come up with sufficient point observations  
29 for the NNs, FE results were used for extended parameters which generated around 1000 data  
30 points taking approximately 2 months.

### 3. Predictive neural network

As discussed above, this paper studies the superalloy contact/friction behavior through FE simulations which is, especially, the first attempt to evaluate contact creep and friction at elevated temperatures. Since the input (temperature, dwell time, and load) and the sought output (COF, contact area) parameters have a nonlinear relationship, achieving a precise comprehensive empirical expression was difficult, and therefore we employed NNs as a feasible alternative. In addition, NNs approach was utilized and introduced as a powerful tool to come up with an easy-to-use and extendable predictive model that can be applied to other tribological and contact models. Here the NNs was used to solve a “regression problem” where the output is predicting the numerical value of the target. To increase accuracy and provide enough data points for the machine learning algorithm, extensive FE simulations were carried out for random  $P^*$  and  $t_d$  in the range of selected parameters for the numerical analysis where final COF and contact area results were augmented to generate sufficient data points of 1000 observation points. NNs algorithms resemble the human brain in two aspects: (i) acquiring knowledge through a learning process, and (ii) storing the knowledge through connection strengths between neurons, known as nodes (Senatore et al., 2011). NNs algorithms can successfully model and predict the non-linearity of the data if suitably trained (Hahnloser et al., 2000). NNs in general consist of three or more layers. The input features are fed into the input layer, the calculations for feature extractions are done in one or more hidden layers, and finally depending on the problem, the output layer predicts or classifies the output. The nodes of each layer can be connected to the different number of nodes of the next layer. In this study, a fully connected (FC) network was used, in which every node in each layer is connected to all the nodes of the next layer. **Fig. 2** shows a simple overview of the present approach, from nanoindentation experiments of the aged oxide (Salari et al., 2020) to the flattening model and the FC neural network with an input layer of 3 nodes, one hidden layer with 13 nodes, and one output node. It should be added again, that all the material properties were based on experimental and complementary numerical analyses of IN617 nanoindentation provided in (Salari et al., 2020). These properties were used to build the FE model which was then employed to get the behavior of the friction and contact area under different load, dwell time, and temperatures. Accordingly, the data that trained NNs was all generated by the FE model. As shown in **Fig. 2** these results were then deployed and trained the

- 1 NNs. It is worth mentioning that there exists no relevant experimental study on the HT contact
- 2 creep and friction.



**Fig. 2** Flow chart representation of the current study from nanoindentation experiments (Salari et al., 2020) to the flattening FE model and the ML algorithm with a 3-layer fully connected neural network.

- 3
- 4 In each layer, several summations and multiplications were performed to calculate the values for
- 5 the next layer. The value of the  $j^{th}$  node in the  $n^{th}$  layer,  $h_j^n$  was calculated by:

$$h_j^n = \sum_{i=1}^m w_{ij} h_i^{n-1} + b_{ij} \quad (7)$$

1 where  $m$  is the number of nodes in the  $(n - 1)^{th}$  layer, and  $w_{ij}$  and  $b_{ij}$  respectively represent the  
 2 weight and the bias of the connection. The goal of the training algorithm is to learn weights and  
 3 the biases for every connection such way that the output of the network has the minimum error.  
 4 However, before feeding the calculated value  $h_j^n$  to the next layer, an activation function was  
 5 called to decide if the node should be activated or not. Activation functions are responsible for  
 6 the nonlinearity characteristic of neural networks. Without activation functions, neural networks  
 7 would be equivalent to linear regression, which may not work for many problems, especially if  
 8 we anticipate our results to behave nonlinearly. Several activation functions can be utilized for  
 9 different problems. In this work, the rectified linear unit (ReLU) function was employed. A  
 10 ReLU function is generally defined as follows (Jain et al., 1996):

$$ReLU: f(\beta) = \begin{cases} \beta & \beta \geq 0 \\ 0 & \beta < 0 \end{cases} \quad (8)$$

11 where  $\beta$  is the output of each layer, and  $f(\beta)$  is the outcome of the ReLU function, used as the  
 12 input for the next layer. A loss function (also called cost or objective function) and an optimizer  
 13 were required to train the neural network. Loss functions were utilized to calculate the error of  
 14 the NNs output whereas the optimizer function was used to update the parameters of the  
 15 network. The Mean Squared Error (MSE) loss function used in this work is given as:

$$MSE = \frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2 \quad (9)$$

16 where  $Y_i$  is the predicted value,  $\hat{Y}_i$  is the true value, and  $N$  is the size of the test data. Here, to  
 17 effectively compare the performance of the two neural networks that are trained for contact area  
 18 and COF predictions, we use Eq. 10 to get the relative error (RE) of each network:

$$RE = \frac{1}{N} \sum_{i=1}^N \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \quad (10)$$

19 The optimizer sets the policy of how the parameters of the network were updated towards the  
 20 goal of optimization. For this purpose, an Adam optimizer was deployed in this work (Kingma  
 21 and Ba, 2014). **The run time for training our NN model was 8.89 minutes (533.201 seconds) and**

1 the model took 0.332 seconds to predict all the test data. The summary of the NNs configuration  
 2 that produces the best regression results is listed in **Table 2** and detailed code descriptions, link  
 3 to the original data (based on the FE simulations) and the constants of the final NNs analysis can  
 4 be found in the SI [document Section S1](#).

*Table 2 Neural Network configuration.*

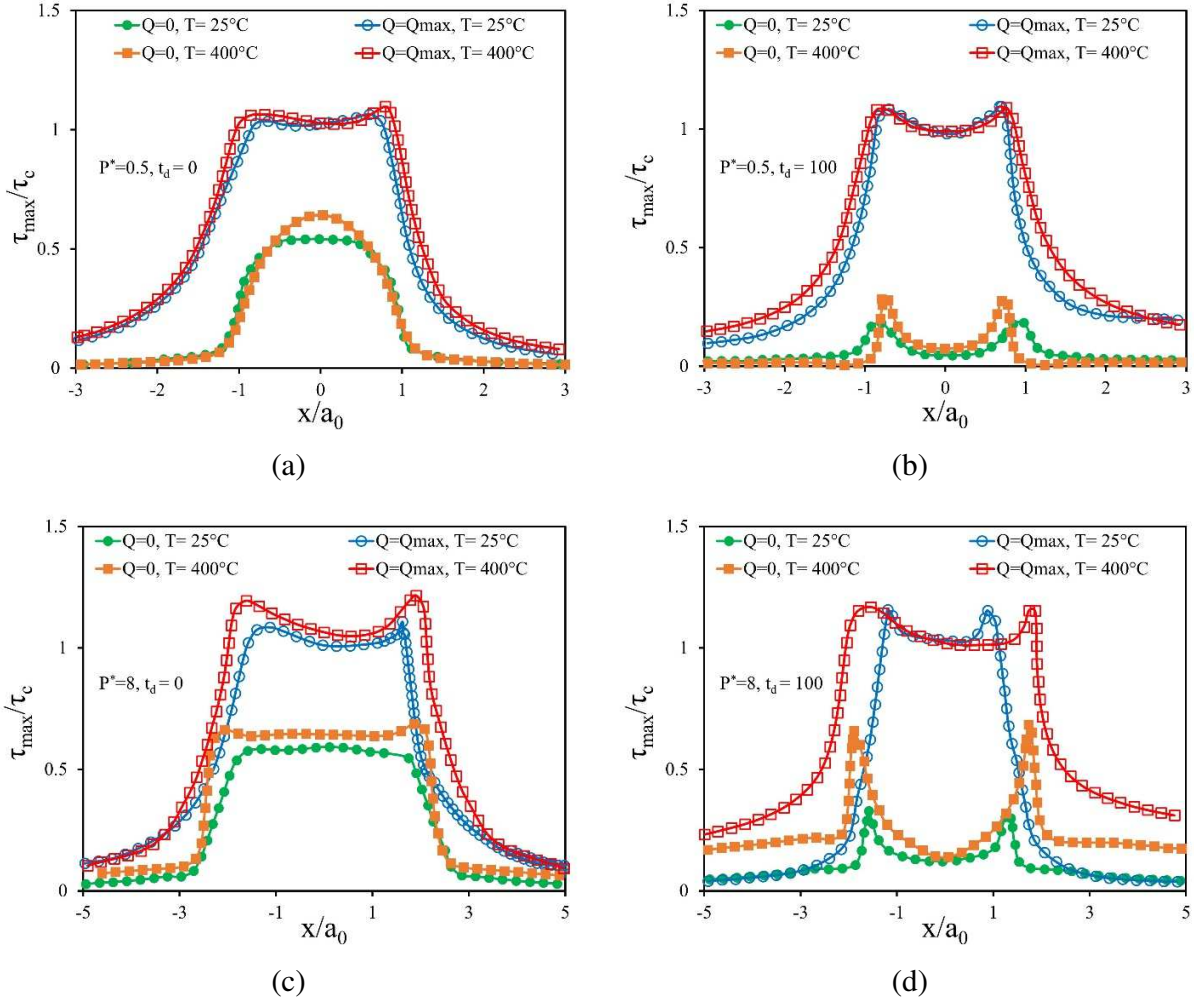
NN Type	Input size	Output size	Hidden layer/Nodes	Activation	Optimizer	Loss function
Fully Connected	3	1	1/13	ReLU	Adam	MSE

## 5 **4. Results and discussion**

### 6 4.1. Maximum shear stress evolution

7 **Fig. 3** shows the evolution of dimensionless maximum shear stress,  $\tau_{max}/\tau_c$ , at the contact  
 8 interface on the hemisphere along the dimensionless symmetry line as tangential load increases  
 9 from zero to its max at the sliding inception. The results are depicted for dimensionless normal  
 10 loads of  $P^* = 0.5$  (Fig. 3a&b) and  $P^* = 8$  (Figs. 3c&d) producing a fully elastic as well as  
 11 elastic-plastic deformation, for  $t_d = 0$  and  $t_d = 100$ , respectively. The shear stress distributions  
 12 are depicted for the beginning of the tangential step while  $Q = 0$  and when the tangential force  
 13 reaches its maximum  $Q = Q_{max}$  at two temperatures of 25 °C and 400 °C. For elastic normal  
 14 loading and while time-dependent deformation is not significant, little difference can be  
 15 observed for  $\tau_{max}/\tau_c$  progress between two temperatures, which may relate to close time-  
 16 independent elastic mechanical properties. Similar to the WSP model for the elastic deformation  
 17 ( $\delta_c = 0.5$ ) of aluminum alloy (Wu et al., 2012), before the initiation of tangential loading, the  
 18 maximum shear is not at the edges of the contact and appears in the middle of the contact area,  
 19 however, this is not the case after a dwell time of 100 min. It should be noted that due to the  
 20 work hardening of the material (following work hardening observed in (Salari et al., 2020)), the  
 21 von Mises stress (or any other equivalent stress) increases beyond the yield stress giving rise to  
 22 the shear stress to go beyond the threshold at some nodes at the contact till shear stress for each  
 23 node at the contact reaches  $\tau_c$ . This is more evident with increased plastic deformation in which  
 24 more work hardening can be seen beyond the equilibrium line  $\tau_{max}/\tau_c = 1$ . When the last node  
 25 at the contact reaches  $\tau_c$ , sliding initiates, and the maximum tangential force or static friction

1 force ( $Q_{max}$ ) is recorded. This is why the maximum shear stresses shows a curved shape with the  
 2 lower value points are the last node reaching the threshold criterion while the leading edges have  
 3 a higher peak due to the longer history of work hardening (Wu et al., 2012).



**Fig. 3** Dimensionless maximum shear stress distributions along the symmetry line on the contact area: (a&b)  $P^* = 0.5$ , and (c&d)  $P^* = 8$ ,  $a_0$  is the contact radius before applying tangential load.

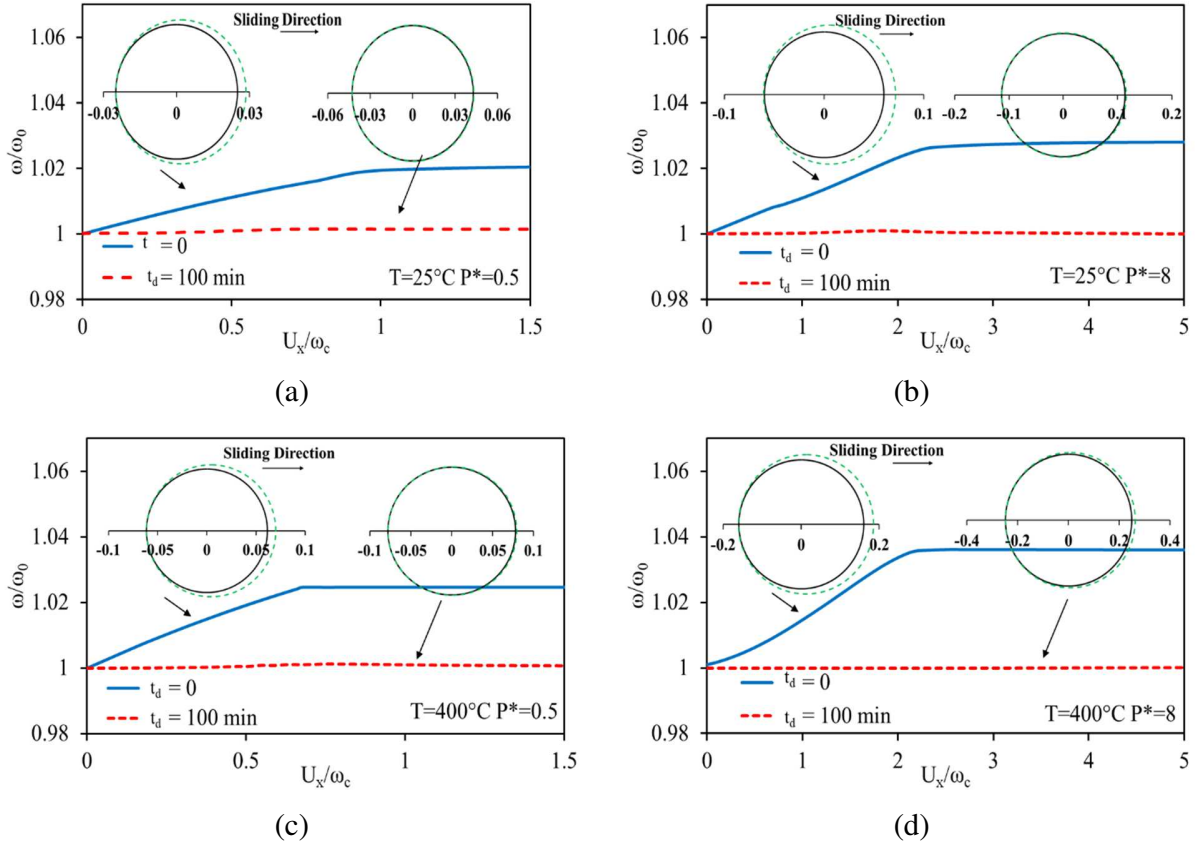
#### 4.2 Time-dependent evolution of contact area and COF

5 **Fig. 4** presents the evolution of the dimensionless normal displacement,  $\omega/\omega_0$ , where  $\omega_0$  is the  
 6 interference before applying a tangential load, with dimensionless tangential displacement for  
 7 two normal loads ( $P^* = 0.5$  &  $8$ ) and temperatures ( $T = 25$  &  $400^\circ\text{C}$ ). Once the load is held for  
 8 a dwell time of  $t_d = 100$  min, the normal displacement stays constant after applying the  
 9 tangential load for both loads and temperatures. This can be related to the already expanded  
 10 contact area that prohibits further expansion of the contact which is aligned with junction

1 growth. The embedded junction growth insets show a 12% to 18% increase for the instantaneous  
2 tangential loading ( $t_d = 0$ ) and like normal displacement, an unnoticeable change after the dwell  
3 times, which is also reported by the FE results of MKE (Malamut et al., 2009). Based on their FE  
4 results, junction growth with tangential loading for a constant normal load of  $P^* = 7$  was 27%  
5 and 13% for zero and 600 s dwell time, respectively. The reported increase in contact area is  
6 higher compare to our study (max 18%) which may relate to different material (polymer) used in  
7 the MKE study (Malamut et al., 2009; Rabinowicz and Tanner, 1966). In their work, junction  
8 growth occurs due to the need to accommodate increasing shear stress with tangential loading  
9 while maintaining the equivalent von Mises stress at the material yield strength since the  
10 mechanical properties considered as elastic- perfect plastic. In our study, due to the work  
11 hardening, the effect of junction growth decreases since there is no requirement to maintain the  
12 equivalent von Mises stress constant and it can increase with increasing strain work hardening.  
13 For the case of zero dwell time, the interference increases when reaching the plateau.  
14 Specifically for higher temperature of 400 °C and  $P^* = 8$  (please note that the insets have  
15 different scales for each load and temperature). It should be noted that the detection of area  
16 growth in FE simulations is affected by relatively large errors due to the finite number of nodes  
17 in the contact interface (Goedecke and Mock, 2009).

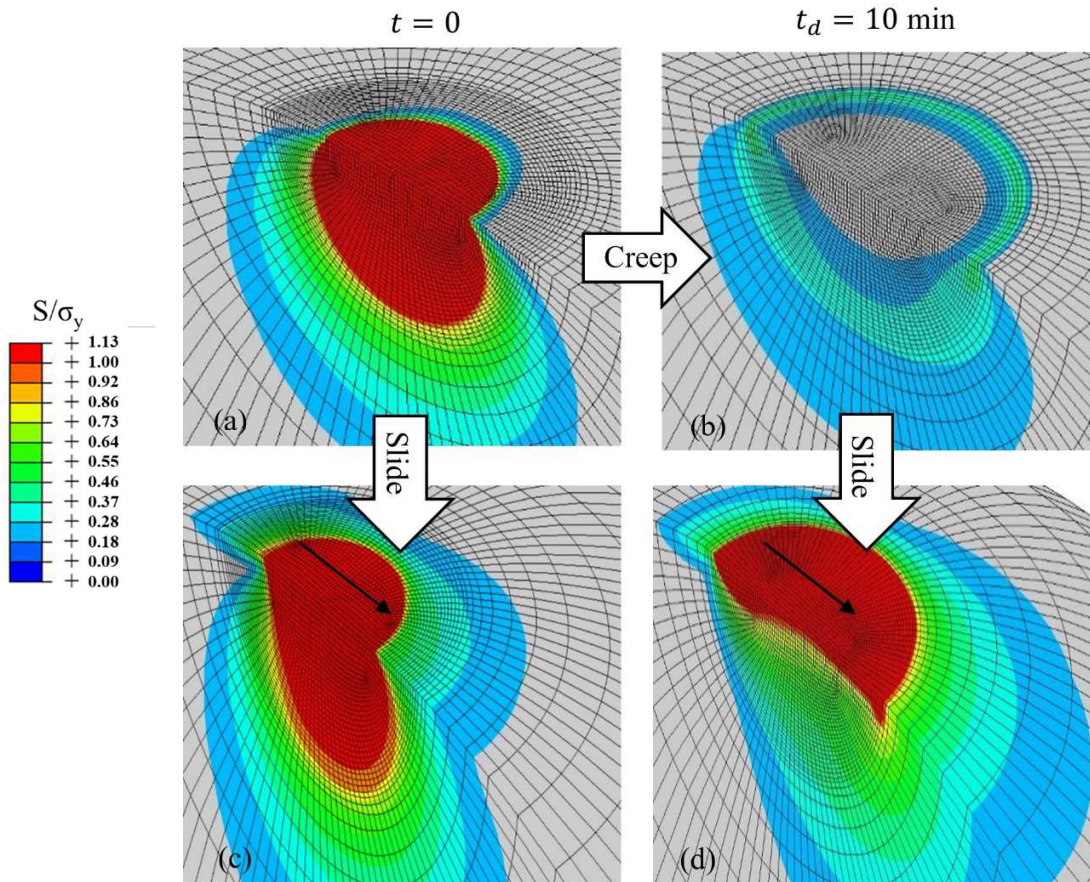
18 Area growth is more noticeable during creep deformation, in which the contact area increases  
19 even after a short period resulting in stress relaxation near the contact associated with normal  
20 pressure loss. **Fig. 5** represents the evolution of von Mises stress near the contact area at 400 °C  
21 showing plastic stress initially under a load of  $P^* = 8$  (Fig. 5a) whereas after a dwell time of 10  
22 minutes the high-stress region completely disappears. Since the area under creep increases,  
23 normal pressure decreases, and subsequently, the equivalent stress at the contact falls below  
24 yield stress and, hence now even more tangential load is required to reach the same equivalent  
25 shear stress criterion ( $\tau_c$ ) necessary for all contact points to initiate sliding. As can be seen, the  
26 plastic zone near the contact reappeared again after the application of tangential loading (Fig.  
27 5b). Before the creep relaxation, the center of the contact is in high contact pressure while the  
28 unaffected surrounding contained and stabilized the region. However, during the creep, this high-  
29 pressure region is no longer restricted resulting in an increase in the contact area due to the  
30 expansion of this region. During this expansion, new shear stress is created by the center material

- 1 pushing the surrounding material aside which can be recognized as peak values near the very
- 2 edge of the contact line with higher von Mises stress (Fig. 3).



**Fig. 4** Dimensionless normal interference versus dimensionless tangential displacement before (blue solid line) and after (orange dashed line) tangential displacement: (a)  $P^* = 0.5$ ,  $T=25^\circ\text{C}$  and (b)  $P^* = 8$ ,  $T=25^\circ\text{C}$ , (c)  $P^* = 0.5$ ,  $T=400^\circ\text{C}$  and (d)  $P^* = 8$ ,  $T=400^\circ\text{C}$ .

3

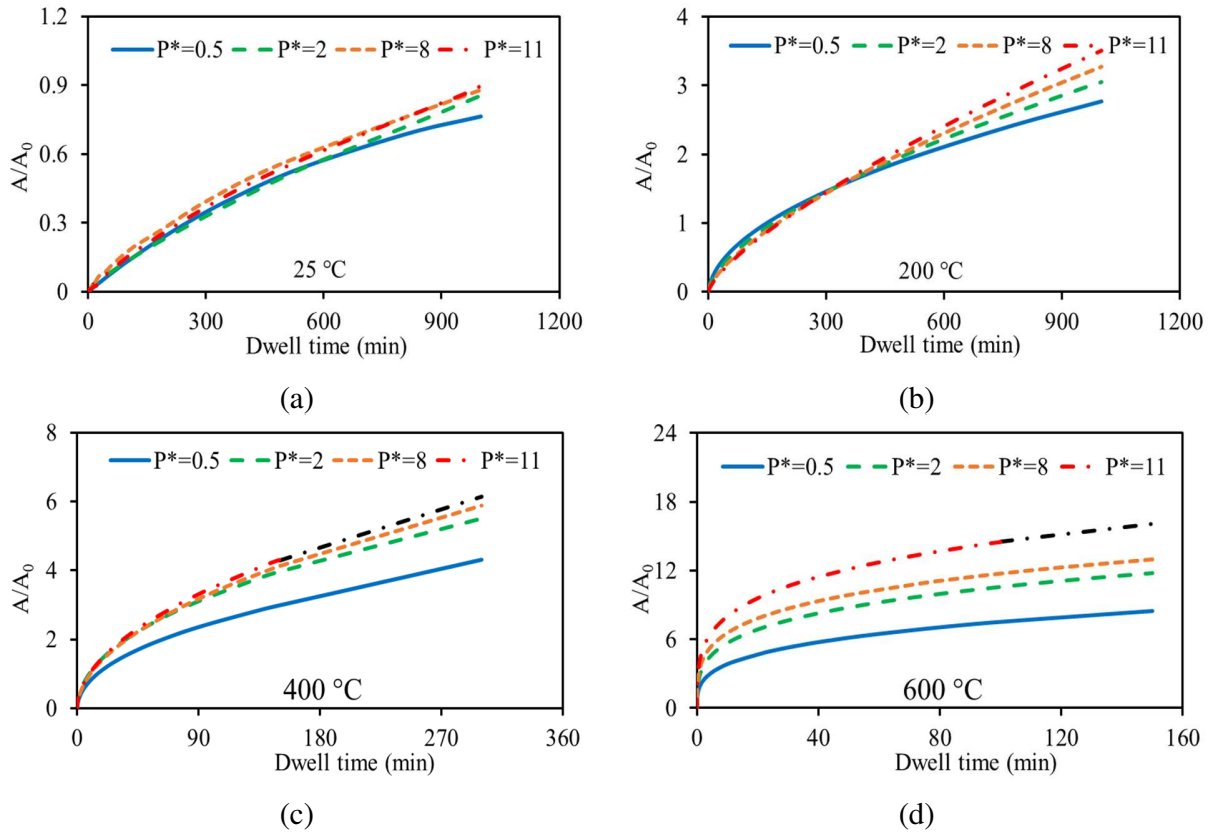


**Fig. 5** Development of dimensionless von Mises stresses,  $S/\sigma_y$ , under a normal load of  $P^*=8$  at  $400\text{ }^\circ\text{C}$  for a)  $t = 0$  and b)  $t = 10\text{ min}$  prior to tangential loading; c) sliding inception after zero dwell time and d) sliding inception after  $t_d = 10\text{ min}$  dwell time (black arrow shows sliding direction in (c) and (d)).

1

2 **Fig. 6** shows the effect of dwell time on the evolution of dimensionless contact areas,  $A/A_0$ , at  
 3 different loads and temperatures where  $A_0$  is the initial contact area right after the application of  
 4 normal loading. It can be observed that by increasing the temperature and dwell time, the  
 5 difference between the dimensionless contact areas for different loadings at each dwell time,  
 6 increases and become more noticeable. As temperature increases, the contact evolution-time  
 7 relation changes from a semi-linear to a power-law curve in which the rate of change, becomes  
 8 almost constant after some time. The steady state condition is reached earlier for higher  
 9 temperatures. This is in agreement to the contact area results of Brot et al. (Brot et al., 2008) and  
 10 Goedecke et al. (Goedecke and Mock, 2009). It should be emphasized that simulations were

1 stopped when the ratio of contact radius over asperity radius ( $a/R$ ) increased beyond 0.412 as  
 2 discussed (Jackson and Green, 2003). Also, for few cases in high loads and dwell times,  
 3 numerical convergence was challenging without easing the ES and creep tolerance, in which  
 4 NNs prediction is used to extend the results. Whenever applicable the black lines show the  
 5 extension of FE analysis using NNs predictions. It should be emphasized that the extrapolatory  
 6 results of NNs were only used for limited cases where FE simulations did not converge. Based  
 7 on the FE results for the contact area and COF evolutions, we expect that the curve would  
 8 continue smoothly and that is actually what was predicted by the NNs for out-of-the-range data.  
 9 In addition, the training points and test prediction points were selected randomly from the FE  
 10 results where there was no relation among the selected points.



**Fig. 6** Evolution of contact area with dwell time for different loads,  $P^*$ , from 25 °C to 600 °C. (As the dimensionless radius of contact ratio,  $a/R$ , reaches 0.4 simulations are stopped and results are extended using NNs by a black line)

11  
 12 **Fig. 7** shows the evolution of total COF,  $\mu$ , for different temperatures and increasing increments  
 13 of dimensionless displacement,  $U_x/\omega_c$  under a constant load of  $P^* = 8$ . Here  $U_x$  is displacement

1 along the “x” axis as shown in **Fig. 1** and  $\omega_c$  is the critical interference based on Hertzian  
 2 calculation (Eq. 4). The COF is calculated by dividing the maximum tangential friction force,  
 3  $Q_{max}$  by the constant normal load. In all temperatures with an increase of dwell time, the COF  
 4 increases, while the rate of increase is more dependent on temperature rather than dwell time.  
 5 For example, at 600 °C, with 10 min of holding, COF increased 4 times while at 25 °C with 1000  
 6 min of holding, COF increased 1.5 times.

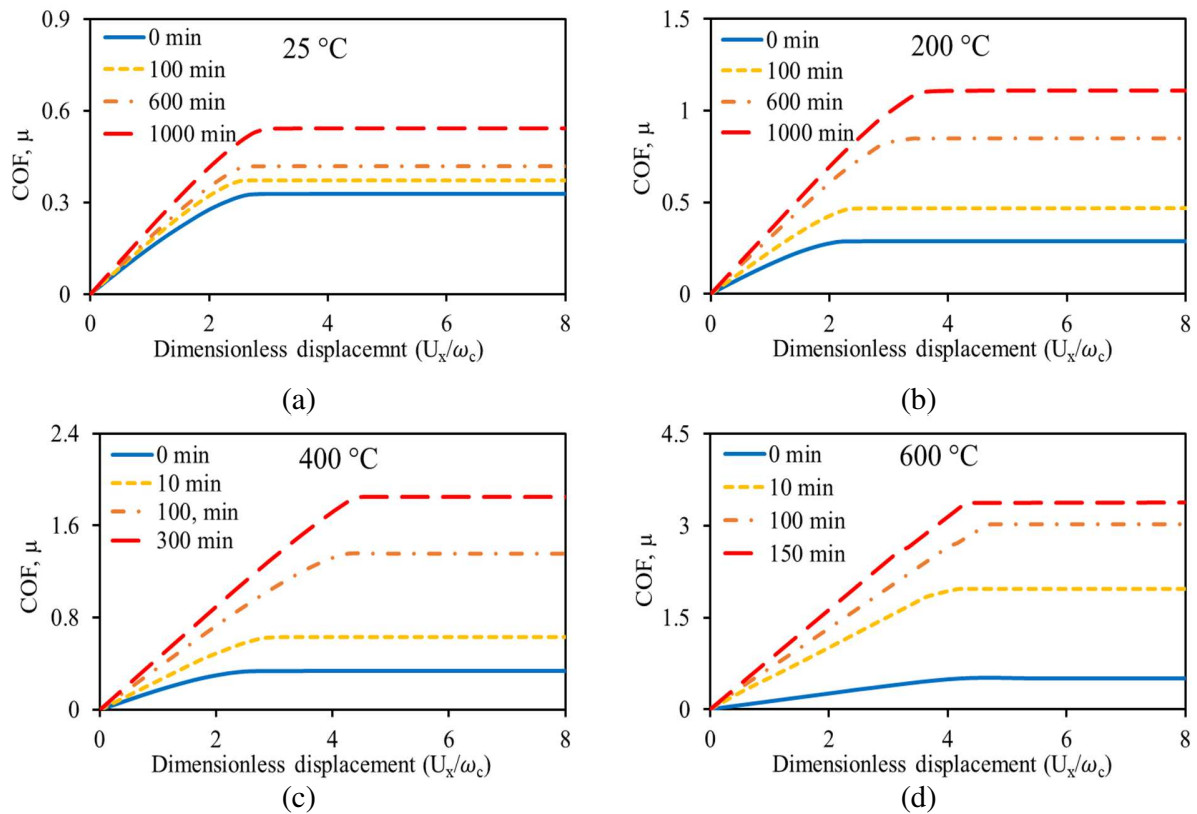
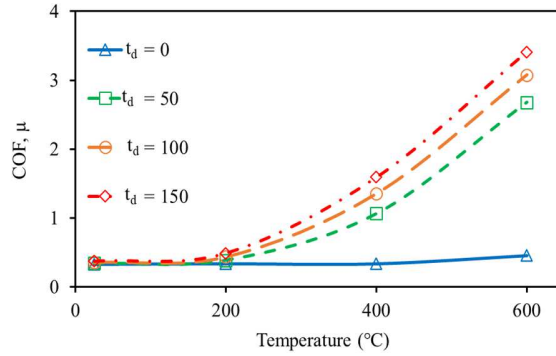


Fig. 7 COF versus dimensionless displacement for different dwell times and temperatures for the load of  $P^* = 8$

7

8 To better show this rate of increase, a comparison between maximum COF (at the verge of  
 9 sliding) at selected temperatures is presented in Fig. 8: Showing that by increasing the dwell time  
 10 and temperature, the total COF increases. The effect of temperature is more significant at  
 11 temperatures higher than 200 °C, which is related to higher creep rate measured for oxide IN617  
 12 at higher temperatures in comparison to room temperature (Salari et al., 2020), increasing the  
 13 contact area (Fig. 6) and relaxing the contact pressure (Fig. 5). With an exception for 600 °C,  
 14 where oxides were observed to exhibit considerable softening, no significant change with  
 15 temperature is seen for dwell time of zero (instantaneous COF), primarily due to the fact that

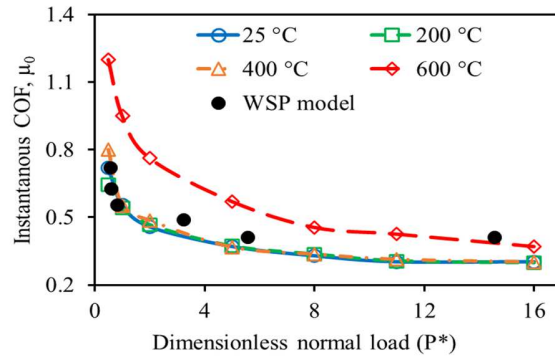
1 time independent material properties change proportionately having slight effect on COF with  
 2 dimensionless nature.



**Fig. 8.** COF evolution for different temperatures and the normal load of  $P^* = 8$  till 150 min of dwell time ( $t_d$ ).

3

4 To better understand the effect of creep deformation on the total COF ( $\mu$ ), we consider it as the  
 5 summation of the instantaneous COF ( $t_d = 0$ ), defined as,  $\mu_0$  and COF increase due to creep,  
 6  $\mu_{cr}$  ( $\mu = \mu_0 + \mu_{cr}$ ). **Fig. 9** presents  $\mu_0$  vs. normal load for all temperatures in comparison to  
 7 WSP. Interestingly, for low dimensionless normal loads and below 400 °C, all the instantaneous  
 8 COFs show similar behavior for increasing dimensionless loads. It is noted that with different  
 9 Poisson's ratios, strain hardening and  $\sigma_y/E$  ratio, COF may differ from conventional models  
 10 (Bhagwat et al., 2017; Brizmer et al., 2007; Wu et al., 2012). Being more ductile at 600 °C, the  
 11 oxide undergoes considerable plastic deformation with strain hardening before sliding. Thus, it  
 12 resists sliding at high plastic strains and increasing COF. This is aligned with the COF results  
 13 reported for Al 2024-T3 as the reference material and with different strain hardening coefficients  
 14 (Bhagwat et al., 2017). Bhagwat et al. showed that for a linear strain hardening material (Al  
 15 2024-T3) with increasing the hardening coefficient the COF increases, however, with increasing  
 16 dimensionless normal displacement (or dimensionless normal load in our case) the COF for all  
 17 hypothetical materials decreases and converges asymptotically (Bhagwat et al., 2017). Similarly,  
 18 harder materials (here  $T < 400$  °C) are unable to achieve a large amount of plastic deformation  
 19 and show little difference in static COF (Bhagwat et al., 2017).



**Fig. 9** Instantaneous COF versus dimensionless tangential displacement for IN617 for different loads and temperatures compared with Wu et al (Wu et al., 2012).

1

2 **Fig. 10** presents ( $\mu_{cr}$ ) for the selected temperatures and dimensionless loads. For all  
 3 temperatures, an increase in  $\mu_{cr}$  can be observed with dwell times. However, their difference  
 4 gradually decreases with increasing temperature and load. This can be related to increasing  
 5 plastic deformation and hardening at the contact for loads beyond the critical load,  $L_c$ . The  
 6 equivalent stress at the contact is higher compared to lower loads which decreases further  
 7 deformation of the contact and required less tangential force to reach the sliding threshold  
 8 (Malamut et al., 2009; Phani et al., 2017; Phani and Oliver, 2016). Similarly, at higher  
 9 temperatures the yield strength decreases, which reduces the tangential force required to reach  
 10 the sliding threshold.

11

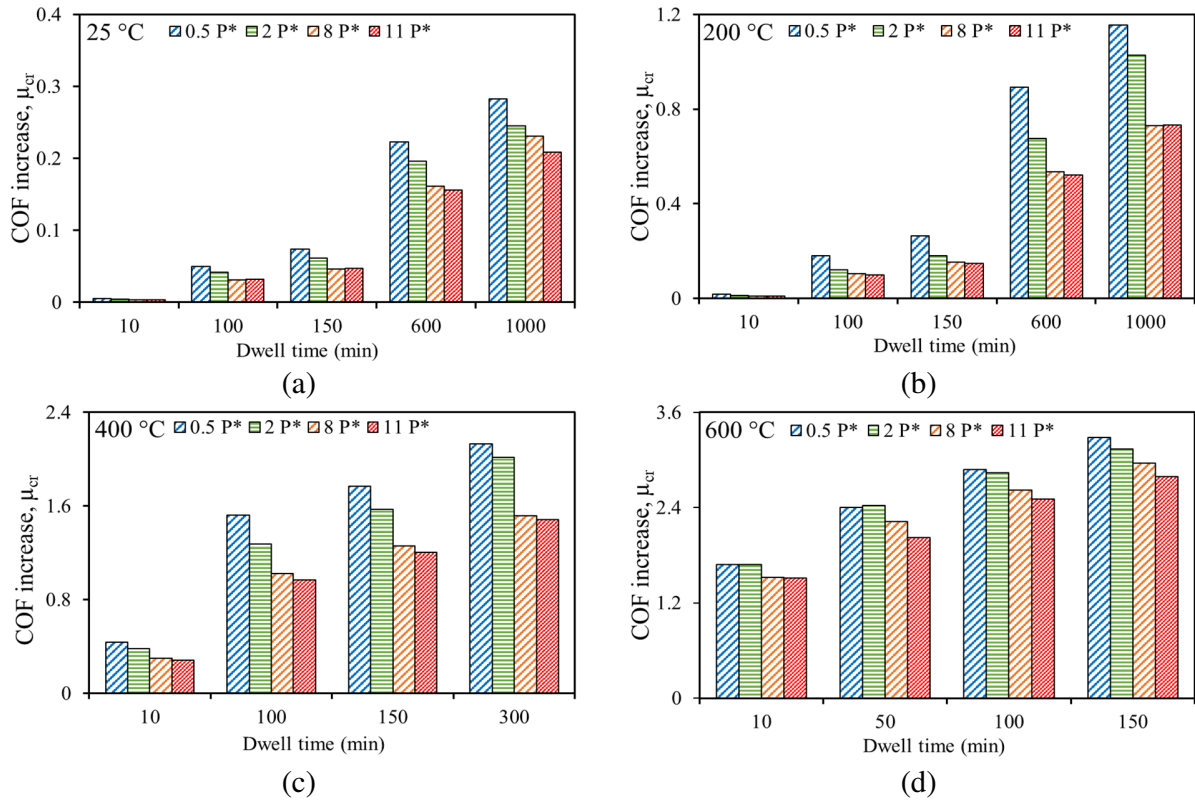
12

13

14

15

16



**Fig. 10** Maximum COF increase due to creep during dwell time for the oxide of aged IN617 at different dwell times and maximum loads for (a) 25 °C (b) 200 °C (c) 400 °C (d) 600 °C.

1

2 The total COF versus the dimensionless normal load for different temperatures is presented in  
 3 **Fig. 11**. It can be seen that as the load increases, the total COF decreases and for all temperatures  
 4 there exist a threshold (approximately  $P^* = 10$ ) beyond which COF levels off, and become  
 5 independent of load. To better compare this threshold COF for each temperature, it is presented  
 6 for different temperatures and loads in **Fig. 12**. As seen, threshold COF changes noticeably for  
 7 temperatures higher than 400 °C with dwell times. Based on these results, it can be argued that at  
 8 higher temperatures like 950 °C if phase transformation does not happen for the oxide, the COF  
 9 will not surpass 2.8 for dwell times of more than 150 min.

10 It is clear that after considerable dwell time, the COF of the asperity increases due to the stress  
 11 relaxation in the contact as well as the evolution of the contact area during creep. While a COF  
 12 of 3 seems to be very high and somewhat exaggerated, values of more than 2 were reported even  
 13 for kinetic COF of IN617 measured through the pin-on-disk configuration at 800 °C (Rahman et  
 14 al., 2019, 2018). The high COF can be related to the mechanical properties of the oxide and more

1 importantly significant creep (Salari et al., 2020). This high COF was also seen for hypothetical  
 2 materials with linear strain hardening (Bhagwat et al., 2017).

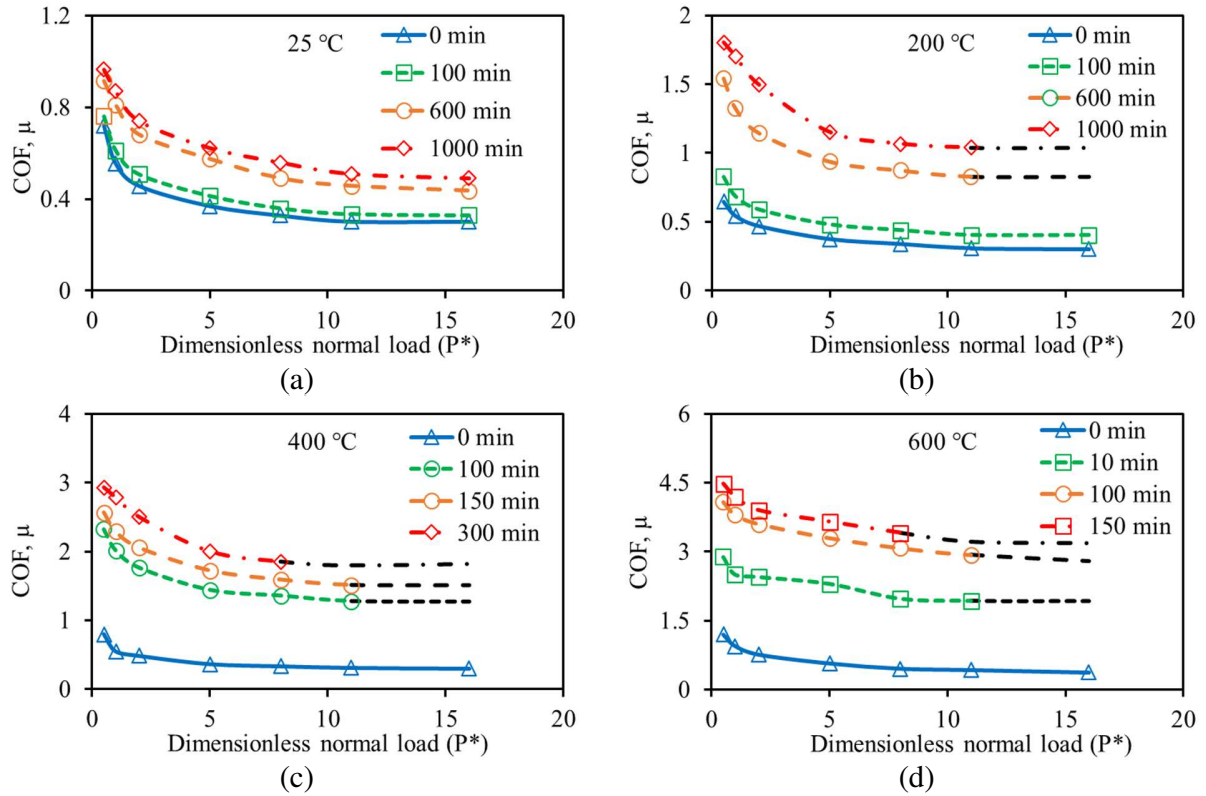


Fig. 11 Total static COF versus the dimensionless normal load for (a) 25 °C (b) 200 °C (c) 400 °C (d) 600 °C

3

4

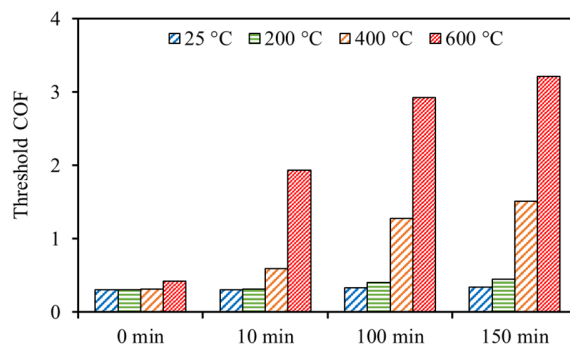
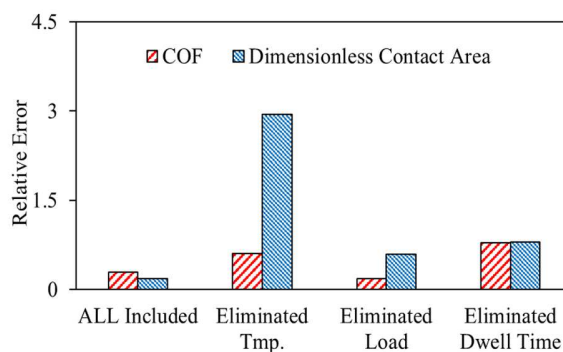


Fig. 12 Threshold COF for different temperatures and dwell times till 150 min.

5

### 4.3 Predictive neural network model

In this work, we trained four separate models to analyze the sensitivity of the NNs for dimensionless contact area and COF to the input parameters (dwell time, temperature, load). The first model is trained by all three input features. The final results for the dimensionless contact area have a MSE of 1.16 and RE of 0.29. The MSE of the NNs for the COF is 0.19 and its RE is 0.18. To compare the performance of the NNs for the two data sets (COF and contact area) RE is a better and consistent measure and is used below. For the second model, we eliminated the temperature feature from the inputs, whereas the REs increase to 2.94 and 0.60 for the dimensionless contact area and COF, respectively, showing that the temperature has a significant role in training a more accurate model for contact area, which is also in agreement with the observations in **Fig. 6**. For the third and fourth models, we eliminated the load and time features from the inputs and obtained the results of REs as follows for the dimensionless contact area and COF, respectively: 0.59 & 0.18 (for the load) and 0.80 & 0.79 (for the time). [Related to the work here, an interesting study was done by \(Bessa et al., 2017\) based on global sensitivity analysis to investigate the effect of each input along with the combine effect of parameters \(two inputs, three inputs, etc.\). The provided sensitivity analysis, discussed in the current study, follows the same concept where the effect of eliminating each input \(load, dwell time and temperature\) along with partial effect of other combined inputs \(here, two inputs\) were explored, concurrently. \*\*Fig. 13\*\* quantitatively shows the relative importance of each input.](#)



*Fig. 13 Sensitivity analysis of each eliminated parameter on contact area and COF to quantitatively determine the relative importance of the inputs.*

The NNs approach was also deployed on each studied temperature separately and the RE was calculated. **Table 3** shows the relative error (RE) calculated for the COF data set as the

1 temperature increases. The RE is relatively higher for lower temperatures. One possibility might  
2 be the much larger contact area at high temperatures that lowers the sensitivity of the FE model  
3 on input parameters.

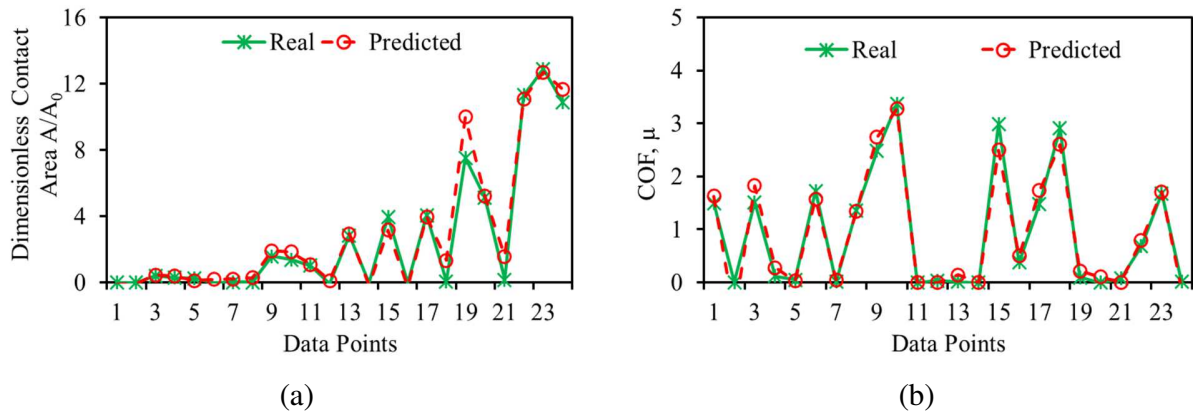
*Table 3 RE calculated for each temperature*

Temperature (°C)	25	200	400	600
RE	0.30	0.25	0.17	0.18

4

5 [Fig. 14](#) shows how well the models performed in predicting the test set for the cases of COF, and  
6 dimensionless contact area. When training the neural network, we divided the data into two sets:  
7 training, and test. The model is trained on the training data and is evaluated on test data to see  
8 how well a fully defined and trained model can work on data entries that are not utilized in the  
9 training process. This evaluation is to make sure the NN model can perform well on the data  
10 training but does not underperform when encountering unseen data. Please note that here we  
11 have three input variables for our prediction model. However, the generality of the proposed  
12 technique and the utilization of NNs make it easily possible to expand to any contact problem  
13 with accurate predictions even having several input variables and high nonlinearity which cannot  
14 be achieved by curve-fitting techniques. [In the general context of contact mechanics and tribology, the NNs make it now possible to expands to models where several input parameters are involved. For example, effects of geometry, coating thickness, graded materials, viscoelasticity, high strain rate, and other highly nonlinear mechanical/material properties can be predicted and framed using NNs.](#) It should also be added that simple regression-based  
19 expressions were not able to predict observed behaviors (especially for contact area) accurately  
20 with reasonable level of error and complexity. This necessitates introducing different sections  
21 and ranges in which empirical equations can be fitted to. To further explore this, we followed the  
22 simple framework presented by the MKE for the COF of PTFE and expanded it using nonlinear  
23 regression analysis to provide a relatively true fit to the FE results of current aged IN617 surface  
24 contact (Malamut et al., 2009) ([see Section S2](#) in SI document for the empirical equations). The  
25 MSE for COF was obtained to be 1.015 which is much higher than the MSE of the NNs (0.19).  
26 A similar method was also attempted for dimensionless contact area where the MSE of 1.54  
27 (compared to 1.16 from NNs training) is obtained. [To further evaluate the NNs outcome, we also](#)

1 conducted the Gaussian process (See Section S3 in the SI file). For the case of Gaussian process,  
 2 the results were better than the analytical (curve-fit) model, but generally less accurate compared  
 3 to the NNs. The relative error for Gaussian was 0.49 for contract area prediction and 0.12 for  
 4 COF compared to that of NNs: 0.29 for contract area prediction and 0.18 for COF.



**Fig. 14** Predicted (a) dimensionless contact area and (b) COF for different loads and temperatures using NN modeling in comparison with real data points from FE simulations.

5

## 6 **5. Conclusion**

7 The contact creep and COF of the oxide of aged IN617 is investigated numerically using FE  
 8 simulation. Based on [the contact area and total COF results](#), a predictive NN algorithm is utilized  
 9 to predict the contact and friction behavior for different normal loads, dwell times, and  
 10 temperatures. Material properties of the oxide for different temperatures are obtained from the  
 11 authors' previous study in which elevated temperature nanoindentation was performed on the  
 12 cross-section of the oxide layer (Salari et al., 2020). The main findings from this study are:

- 13 • Maximum shear stress at the contact shows a curved shape, due to work hardening at the  
 14 contact, while the minimum point at the contact is the last that reaches the sliding  
 15 criterion;
- 16 • Normal interferences during the application of tangential loading show no noticeable  
 17 change after dwell time for all loads, which is related to loss of the plastic zone under the  
 18 normal load and substantial stress relaxation during creep deformation;

- 1       • Behavior of contact evolution with time changes from a semi-linear to a power-law curve  
2       with increasing temperature in which the rate of change, becomes almost constant after  
3       some time;
- 4       • Increasing normal contact load decreases COF at all temperatures and for all dwell times,  
5       which follow general observations for asperity static COF;
- 6       • Due to high nonlinearity of the COF and contact area with input parameters, achieving an  
7       *accurate* and *simple* expression to fit the data is challenging. NNs can easily and readily  
8       solve these issues.
- 9       • [Based on the sensitivity analysis performed by NNs, the prediction model for the contact  
10       area is highly sensitive to temperature and to less extend dwell time. The COF prediction  
11       model is equally dependent on temperature and dwell time. NNs approach is a powerful  
12       tool for predicting both the contact area and COF for the selected range and beyond. The  
13       only challenge to be considered is to provide enough data for the range of training.](#)
- 14       • Understanding the effect of creep on the COF of contacting parts especially at high  
15       temperatures are essential for developing tribological models of the surfaces. This model  
16       can be utilized for the prediction of multi-asperity rough surfaces using, for example,  
17       statistical or fractal-based model; and
- 18       • The utilization of NNs can be expanded for predicting COF and contact area based on  
19       various mechanical, geometrical, load, and dwell times providing a more realistic  
20       prediction of surface behavior [for various contact mechanics and tribology problems.](#)

## 21 **Acknowledgment**

22 This study was supported in part by the U.S. Department of Energy (DOE) under NEUP Project  
23 16-10732 and also partially funded by George Mason University. The authors would also thank  
24 the Office of Research Computing (ORC) team at George Mason University for providing  
25 computational facility.

26

27

28

1

2       **6. References:**

- 3 Beheshti, A., Khonsari, M.M., 2014. On the contact of curved rough surfaces: contact behavior and predictive  
4 formulas. *J. Appl. Mech.* 81. <https://doi.org/10.1115/1.4028426>
- 5 Beheshti, A., Khonsari, M.M., 2012. Asperity micro-contact models as applied to the deformation of rough line  
6 contact. *Tribol. Int.* 52, 61–74. <https://doi.org/10.1016/j.triboint.2012.02.026>
- 7 Behnia, F., Mirzaeian, A., Sabokrou, M., Manoj, S., Mohsenin, T., Khasawneh, K.N., Zhao, L., Homayoun, H.,  
8 Sasan, A., 2020. Code-Bridged Classifier (CBC): A Low or Negative Overhead Defense for Making a CNN  
9 Classifier Robust Against Adversarial Attacks. *arXiv Prepr. arXiv2001.06099*.
- 10 Bessa, M.A., Bostanabad, R., Liu, Z., Hu, A., Apley, D.W., Brinson, C., Chen, W., Liu, W.K., 2017. A framework  
11 for data-driven analysis of materials under uncertainty: Countering the curse of dimensionality. *Comput.*  
12 *Methods Appl. Mech. Eng.* 320, 633–667. <https://doi.org/10.1016/J.CMA.2017.03.037>
- 13 Bhagwat, P., Sista, B., Vemaganti, K., 2017. A computational study of the effects of strain hardening in micro-  
14 asperity friction models. *Tribol. Lett.* 65, 154.
- 15 Borjali, A., Monson, K., Raeymaekers, B., 2019. Predicting the polyethylene wear rate in pin-on-disc experiments in  
16 the context of prosthetic hip implants: Deriving a data-driven model using machine learning methods. *Tribol.*  
17 *Int.* 133, 101–110.
- 18 Brizmer, Kligerman, Etsion, 2007. Elastic–plastic spherical contact under combined normal and tangential loading  
19 in full stick. *Tribol. Lett.* 25, 61–70.
- 20 Brot, C.C., Etsion, I., Kligerman, Y., 2008. A contact model for a creeping sphere and a rigid flat. *Wear* 265, 598–  
21 605.
- 22 Cabet, C., Terlain, A., Lett, P., Guetaz, L., Gentzbittel, J., 2006. High temperature corrosion of structural materials  
23 under gas-cooled reactor helium. *Mater. Corros.* 57, 147–153.
- 24 Chang, W.R., Etsion, I., Bogy, D.B., 1988. Static friction coefficient model for metallic rough surfaces. *J. Tribol.*  
25 110, 57–63. <https://doi.org/10.1115/1.3261575>
- 26 Deng, L., Li, X., 2013. Machine learning paradigms for speech recognition: An overview. *IEEE Trans. Audio.*  
27 *Speech. Lang. Processing* 21, 1060–1089.
- 28 Eriten, M., Polycarpou, A.A., Bergman, L.A., 2012. A physics-based friction model and integration to a simple  
29 dynamical system. *J. Vib. Acoust. Trans. ASME* 134, 1–9. <https://doi.org/10.1115/1.4006182>
- 30 Feng, G., Ngan, A.H.W., 2002. Effects of creep and thermal drift on modulus measurement using depth-sensing  
31 indentation. *J. Mater. Res.* 17, 660–668.
- 32 Frydrych, K., Karimi, K., Pecelerowicz, M., Alvarez, R., Dominguez-Gutiérrez, F.J., Rovaris, F., Papanikolaou, S.,  
33 2021. *Materials Informatics for Mechanical Deformation: A Review of Applications and Challenges. Mater.*  
34 *2021, Vol. 14, Page 5764 14, 5764.* <https://doi.org/10.3390/MA14195764>
- 35 Goedecke, A., Mock, R., 2010. Transient friction effects due to variable normal load in a multi-scale asperity-creep  
36 friction model, in: *STLE/ASME 2010 International Joint Tribology Conference*. pp. 337–339.
- 37 Goedecke, A., Mock, R., 2009. Creep relaxation of an elastic-perfectly plastic hemisphere in fully plastic contact. *J.*  
38 *Tribol.* 131, 1–10. <https://doi.org/10.1115/1.3081978>
- 39 Greenwood, J.A., Williamson, J.B.P., Greenwood, Williamson, 1966. Contact of nominally flat surfaces. *Proc. R.*  
40 *Soc. London. Ser. A. Math. Phys. Sci.* 295, 300–319. <https://doi.org/10.1098/rspa.1966.0242>
- 41 Hahnloser, R.H.R., Sarpeshkar, R., Mahowald, M.A., Douglas, R.J., Seung, H.S., 2000. Digital selection and

- 1 analogue amplification coexist in a cortex-inspired silicon circuit. *Nature* 405, 947–951.
- 2 Hashash, Y.M.A., Jung, S., Ghaboussi, J., 2004. Numerical implementation of a neural network based material  
3 model in finite element analysis. *Int. J. Numer. Methods Eng.* 59, 989–1005. <https://doi.org/10.1002/NME.905>
- 4 He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition, in: *Proceedings of the IEEE  
5 Conference on Computer Vision and Pattern Recognition*. pp. 770–778.
- 6 Heidari, M., Jones, J.H.J., Uzuner, O., 2021. An empirical study of machine learning algorithms for social media bot  
7 detection, in: *2021 IEEE International IOT, Electronics and Mechatronics Conference, IEMTRONICS 2021 -  
8 Proceedings. Institute of Electrical and Electronics Engineers Inc.*  
9 <https://doi.org/10.1109/IEMTRONICS52119.2021.9422605>
- 10 Jackson, R.L., Green, I., 2005. A finite element study of elasto-plastic hemispherical contact against a rigid flat. *J.  
11 Tribol.* 127, 343–354. <https://doi.org/10.1115/1.1866166>
- 12 Jackson, R.L., Green, I., 2003. A Finite Element Study of Elasto-Plastic Hemispherical Contact, in: *International  
13 Joint Tribology Conference*. pp. 65–72. <https://doi.org/10.1115/2003-TRIB-0268>
- 14 Jain, A.K., Mao, J., Mohiuddin, K.M., 1996. Artificial neural networks: A tutorial. *Computer (Long. Beach. Calif.)*  
15 29, 31–44.
- 16 Kasem, H., Etsion, I., 2014. Experimental study of the effect of dwell time and normal load on static friction in  
17 creeping elastic-plastic polymer spherical contact. *Wear* 309, 139–145.  
18 <https://doi.org/10.1016/j.wear.2013.11.006>
- 19 Khourshid, A., El-Kassas, A., of, I.S.-I.J., 2015, undefined, n.d. *Integration between artificial neural network and  
20 responses surfaces methodology for modeling of friction stir welding. academia.edu.*
- 21 Kingma, D.P., Ba, J., 2014. Adam: A method for stochastic optimization. *arXiv Prepr. arXiv1412.6980*.
- 22 Klocke, F., Zeis, M., Klink, A., Veselovac, D., 2013. Experimental research on the electrochemical machining of  
23 modern titanium-and nickel-based alloys for aero engine components. *Procedia Cirp* 6, 368–372.
- 24 Kogut, L., Etsion, I., 2003. A semi-analytical solution for sliding inception of a spherical contact. *J. Tribol.* 125,  
25 499–506. <https://doi.org/10.1115/1.1538190>
- 26 Kumar, A., Irsoy, O., Ondruska, P., Iyyer, M., Bradbury, J., Gulrajani, I., Zhong, V., Paulus, R., Socher, R., 2016.  
27 Ask me anything: Dynamic memory networks for natural language processing, in: *International Conference on  
28 Machine Learning*. pp. 1378–1387.
- 29 Malamut, S., Kligerman, Y., Etsion, I., 2009. The effect of dwell time on the static friction in creeping elastic-  
30 plastic polymer spherical contact. *Tribol. Lett.* 35, 159–170.
- 31 Mindlin, and Deresiewicz, H., 1953. Elastic Spheres in Contact Under Varying Oblique Forces. *J. Appl. Mech.*  
32 *Trans. ASME* 20, 327–344.
- 33 Moore, A.C., Tabor, D., 1952. Some mechanical and adhesive properties of indium. *Br. J. Appl. Phys.* 3, 299.
- 34 Phani, P.S., Oliver, W.C., 2016. A direct comparison of high temperature nanoindentation creep and uniaxial creep  
35 measurements for commercial purity aluminum. *Acta Mater.* 111, 31–38.  
36 <https://doi.org/10.1016/j.actamat.2016.03.032>
- 37 Phani, P.S., Oliver, W.C., Pharr, G.M., 2017. On the Measurement of Power Law Creep Parameters from  
38 Instrumented Indentation. *JOM* 69, 2229–2236.
- 39 Rabinowicz, E., Tanner, R.I., 1966. Friction and wear of materials.
- 40 Rahman, M.S., Ding, J., Beheshti, A., Zhang, X., Polycarpou, A.A., 2019. Helium Tribology of Inconel 617 at  
41 Elevated Temperatures up to 950° C: Parametric Study. *Nucl. Sci. Eng.* 1–15.
- 42 Rahman, M.S., Ding, J., Beheshti, A., Zhang, X., Polycarpou, A.A., 2018. Elevated temperature tribology of Ni

- 1 alloys under helium environment for nuclear reactor applications. *Tribol. Int.* 123, 372–384.
- 2 Rezvanian, O., Brown, C., Zikry, M.A., Kingon, A.I., Krim, J., Irving, D.L., Brenner, D.W., 2008. The role of creep  
3 in the time-dependent resistance of Ohmic gold contacts in radio frequency microelectromechanical system  
4 devices. *J. Appl. Phys.* 104. <https://doi.org/10.1063/1.2953072>
- 5 Sakaba, N., Hamamoto, S., Takeda, Y., 2010. Helium chemistry for very high temperature reactors. *J. Nucl. Sci.*  
6 *Technol.* 47, 269–277.
- 7 Salari, S., Beheshti, A., 2021. Asperity-based contact and static friction with provision for creep: A review. *Surfaces*  
8 *and Interfaces.* <https://doi.org/10.1016/j.surfin.2021.101144>
- 9 Salari, S., Rahman, M.S., Beheshti, A., Polycarpou, A.A., 2022. Elevated temperature nanoscratch of Inconel 617  
10 Superalloy. *Mech. Res. Commun.* 103875. <https://doi.org/10.1016/J.MECHRESCOM.2022.103875>
- 11 Salari, S., Rahman, M.S., Polycarpou, A.A., Beheshti, A., 2020. Elevated temperature mechanical properties of  
12 Inconel 617 surface oxide using nanoindentation. *Mater. Sci. Eng. A* 788, 139539.  
13 <https://doi.org/10.1016/j.msea.2020.139539>
- 14 Sattari Baboukani, B., Ye, Z., G Reyes, K., Nalam, P.C., 2020. Prediction of Nanoscale Friction for Two-  
15 Dimensional Materials Using a Machine Learning Approach. *Tribol. Lett.* 68, 1–14.
- 16 Senatore, A., D'Agostino, V., Di Giuda, R., Petrone, V., 2011. Experimental investigation and neural network  
17 prediction of brakes and clutch material frictional behaviour considering the sliding acceleration influence.  
18 *Tribol. Int.* 44, 1199–1207.
- 19 Smith, M., 2017. ABAQUS/Standard User's Manual, Version 2017. Simulia.
- 20 Spurr, R.T., 1955. Creep and static friction. *Br. J. Appl. Phys.* 6, 402–403. <https://doi.org/10.1088/0508-3443/6/11/306>
- 22 Stanford, M.K., 2007. A review of tribomaterial technology for space nuclear power systems.
- 23 Tabor, D., 1981. Friction—the present state of our understanding.
- 24 Thankachan, T., Soorya Prakash, K., Kamarthin, M., 2018. Optimizing the tribological behavior of hybrid copper  
25 surface composites using statistical and machine learning techniques. *J. Tribol.* 140.
- 26 Wright, R.N., 2006a. Kinetics of gas reactions and environmental degradation in NGNP helium. Citeseer.
- 27 Wright, R.N., 2006b. Summary of studies of aging and environmental effects on Inconel 617 and Haynes 230.
- 28 Wu, A., Shi, X., Polycarpou, A.A., 2012. An elastic-plastic spherical contact model under combined normal and  
29 tangential loading. *J. Appl. Mech.* 79, 51001. <https://doi.org/10.1115/1.4006457>
- 30 Zhang, Y., Mohanty, D.P., Seiler, P., Siegmund, T., Kruzic, J.J., Tomar, V., 2017. High temperature indentation  
31 based property measurements of IN-617. *Int. J. Plast.* 96, 264–281.
- 32 Zheng, Y., Rahman, M.S., Polycarpou, A.A., 2020. Self-welding of Inconel 617 under high-pressure-high-  
33 temperature conditions for nuclear reactors. *Nucl. Eng. Des.* 110941.

34