

# Homework 8

April 15, 2019

## 1 1

### 1.1 a

First we find  $K_t$  from p. 82 of the text. Since we would prefer to use the global stress instead of net stress, we use the upper curve.  $a/W$  for this chart is  $0.25/7 = 0.0357$ , which means  $K_t = 3$ .

### 1.2 b

We can estimate  $k_f$  using the Peterson method, with  $\alpha = 0.02$  in. for aluminum alloys. This gives

$$q = \frac{1}{1 + \alpha/\rho}$$

with the radius,  $\rho = 0.125$  in.

```
In [1]: import numpy as np
        D = 0.25
        rho = 0.25/2.0 #in.
        alpha = 0.02 #in.
        q = 1/(1+alpha/rho)
        print q
```

0.862068965517

With  $q = 0.862$  we can now find  $k_f$

```
In [2]: Kt = 3.0
        kf = 1+ q*(Kt-1)
        print kf
```

2.72413793103

$$k_f = 2.72$$

### 1.3 c

We can now find the number of cycles to failure using a nominal stress amplitude,  $S_a = k_f S$ . In this case we find the stress as  $S = 30 / (7 * 0.157) = 27.3$  ksi, which gives a nominal stress amplitude of  $S_a = 74.4$  ksi

```
In [3]: P = 30.0 #k-lbs
        W = 7.0
        t = 0.157
        S = P/(W*t)
        print S
        Sa = kf*S
        print Sa
```

```
27.2975432211
74.3622729127
```

This can now be substituted into the equation for the S-N curve using data given on p. 235.

$$S_a = \sigma'_f (2N_f)^b$$

Solved for  $N_f$  gives

$$N_f = \frac{1}{2} \left( \frac{S_a}{\sigma'_f} \right)^{1/b}$$

```
In [4]: sfp = 131.0
        b = -0.102
        Nf = 0.5*(Sa/sfp)**(1/b)
        print Nf
```

```
128.806287448
```

We predict 128.8 cycles to failure in this case.

## 2 2

First we load the given data and plot it

```
In [7]: #load plotting libraries
        from matplotlib import pyplot as plt
        import seaborn as sb
        sb.set(font_scale=1.5)
        %matplotlib inline

        data = np.loadtxt('./hw8.txt')

        ea = data[:,0] #total strain
```

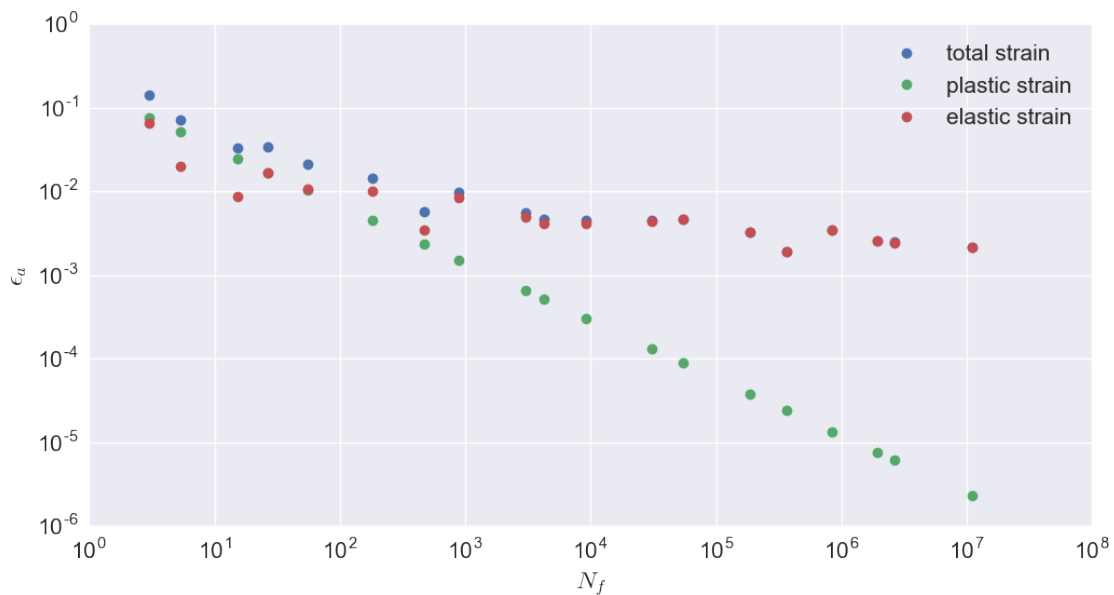
```

epa = data[:,1] #plastic strain
eea = ea - epa #elastic strain
nf = data[:,2] #cycles to failure

plt.figure(figsize=(12,6))
plt.loglog(nf,ea,'o',label='total strain')
plt.loglog(nf,epa,'o',label='plastic strain')
plt.loglog(nf,eea,'o',label='elastic strain')
plt.legend(loc='best')
plt.xlabel('$N_f$')
plt.ylabel('$\epsilon_a$')

```

Out[7]: <matplotlib.text.Text at 0xa3e2668>



To find the constants,  $\sigma'_f$ ,  $b$ ,  $\epsilon'_f$ , and  $c$  we fit linear curves (in the log-log space) to the plastic and elastic strain data.

```

In [8]: from scipy.optimize import curve_fit

def func(x,lsfp,b):
    return lsfp + b*x #log(sfp) + b*log(2Nf)

def func2(Nf,sfp,b):
    return sfp*(2*Nf)**b

#linear fit in log-log domain
popt,pcov = curve_fit(func,np.log10(2*nf),np.log10(epa))
efp = 10**popt[0]

```

```

c = popt[1]
popt,pcov = curve_fit(func,np.log10(2*nf),np.log10(eea))
E = 10.3e3 #ksi
sfp = 10**popt[0]*E
b = popt[1]

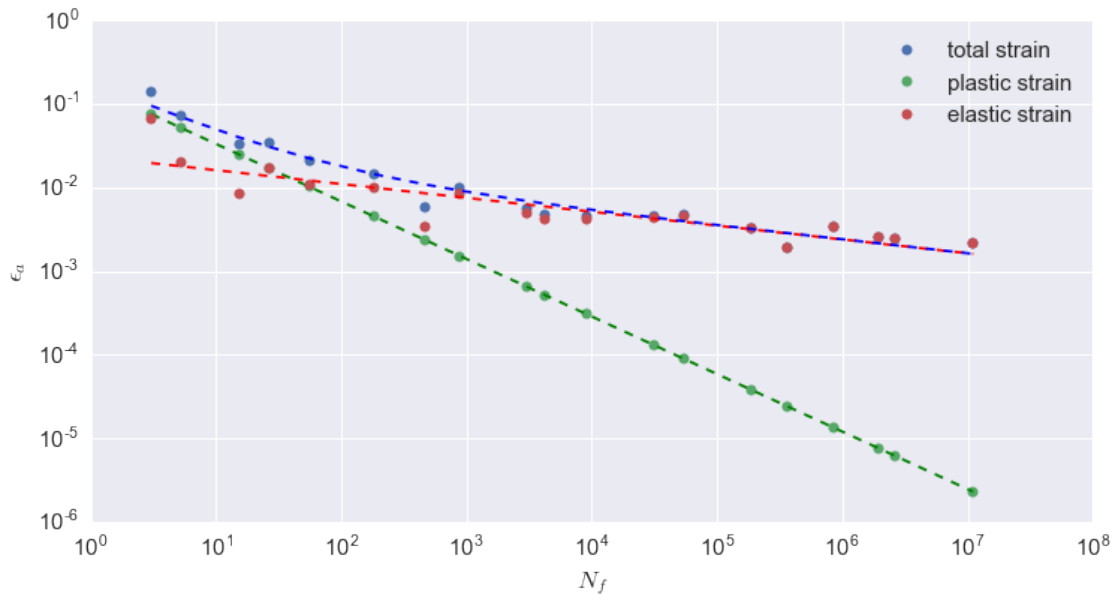
```

```

In [66]: plt.figure(figsize=(12,6))
plt.loglog(nf,ea,'o',label='total strain')
plt.loglog(nf,epa,'o',label='plastic strain')
plt.loglog(nf,func2(nf,efp,c),'g--')
plt.loglog(nf,eea,'o',label='elastic strain')
plt.loglog(nf,func2(nf,sfp/E,b),'r--')
plt.loglog(nf,func2(nf,sfp/E,b)+func2(nf,efp,c),'b--')
plt.legend(loc='best')
plt.xlabel('$N_f$')
plt.ylabel('$\epsilon_a$')

```

Out[66]: <matplotlib.text.Text at 0x1598e940>



We see a good fit, so we now examine the constants

```

In [67]: print sfp, b, efp, c

```

```

273.692934459 -0.165634191231 0.262092470055 -0.688091438879

```

And we find  $\sigma'_f = 273.7$  ksi,  $b = -0.166$ ,  $\epsilon'_f = 0.262$  and  $c = -0.688$ .

### 3 3

We can find the transition life,  $N_t$  by finding the point of intersection between the plastic strain and elastic strain curves. Visually, we would expect it to occur near 20 cycles, but we can solve for it directly.

```
In [68]: Nt = 0.5*(sfp/efp/E)**(1/(c-b))
          print Nt
```

```
39.9550761435
```

And we find  $N_t = 40$

### 4 4

For the Morrow approach we use

$$\epsilon_a = \frac{\sigma'_f}{E} \left(1 - \frac{\sigma_m}{\sigma'_f}\right) (2N_f)^b + \epsilon'_f \left(1 - \frac{\sigma_m}{\sigma'_f}\right)^{c/b} (2N_f)^c$$

For the modified Morrow approach, we use the same equation but only adjust the elastic portion

$$\epsilon_a = \frac{\sigma'_f}{E} \left(1 - \frac{\sigma_m}{\sigma'_f}\right) (2N_f)^b + \epsilon'_f (2N_f)^c$$

And finally, in the Smith, Watson and Topper approach we use

$$\epsilon_a = \frac{1}{\sigma_{max}} \left[ \frac{(\sigma'_f)^2}{E} (2N_f)^{2b} + \sigma'_f \epsilon'_f (2N_f)^{b+c} \right]$$

To find  $\sigma_{max}$ , we add  $\sigma_m$  to the stress amplitude,  $\sigma_a$ .  $\sigma_a$  can be found using the stress-strain curve.

$$\epsilon_a = \frac{\sigma_a}{E} + \left(\frac{\sigma_a}{H'}\right)^{1/n'}$$

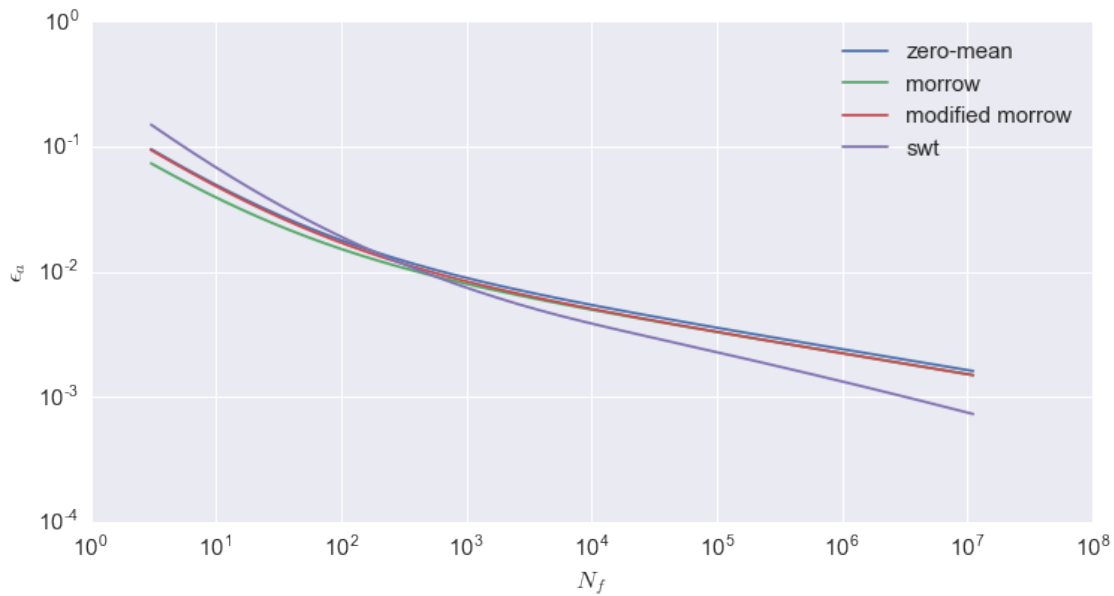
```
In [69]: sm = 20.0 #ksi, mean stress
          Nf = np.logspace(np.log10(min(nf)), np.log10(max(nf)), 200)
          ea_morrow = sfp/E*(1-sm/sfp)*(2*Nf)**b + efp*(1-sm/sfp)**(c/b)*(2*Nf)**c
          ea_mod = sfp/E*(1-sm/sfp)*(2*Nf)**b + efp*(2*Nf)**c
          #numerical solver
          from scipy.optimize import fsolve
          Hp = 142.0
          n = 0.106
          ea_smooth = func2(Nf,sfp/E,b)+func2(Nf,efp,c)
          swt = lambda sa: -ea_smooth + sa/E + (sa/Hp)**(1/n)
          sa = fsolve(swt,func2(Nf,sfp,b))
          smax = sm + sa
```

```

ea_swt = (sfp**2/E*(2*Nf)**(2*b)+sfp*efp*(2*Nf)**(b+c))/smax
plt.figure(figsize=(12,6))
plt.loglog(Nf,ea_smooth,label='zero-mean')
plt.loglog(Nf,ea_morrow,label='morrow')
plt.loglog(Nf,ea_mod,label='modified morrow')
plt.loglog(Nf,ea_swt,label='swt')
plt.xlabel('$N_f$')
plt.ylabel('$\epsilon_a$')
plt.legend(loc='best')

```

Out[69]: <matplotlib.legend.Legend at 0x158c8828>



From these we see that the modified Morrow equation matches the zero-mean data nearly exactly at low-cycles, and converges to the morrow method for higher cycles, the Morrow method itself is almost uniformly lower than the zero-mean data, while the SWT shows a different trend, with an increase in life before the transition region, and a stronger decrease after. Without test data we cannot comment on which is the best fit, but they do provide different estimates.