sv fitting

September 25, 2024

```
[]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit
from matplotlib.backends.backend_pdf import PdfPages
```

1 Normal Swift-Voce fitting

```
[]: def analyze_sv_fit(file_path, strain_column, stress_column, title,_
      # Load data in
        data = pd.read_csv(file_path)
        strain = data[strain_column].dropna().values
        stress = data[stress_column].dropna().values
    # Define the Swift-Voce equation
        def swift_voce(strain, alpha, A, epsilon_0, n, k0, Q, beta):
            swift_term = alpha * A * (epsilon_0 + strain) ** n
            voce_term = (1 - alpha) * (k0 + Q * (1 - np.exp(-beta * strain)))
            return swift_term + voce_term
     # Initial guesses for parameters [alpha, A, epsilon_0, n, k0, Q, beta]
        initial_guess = [0.5, 500, 0.01, 0.2, 300, 200, 10]
    # Fit the curve
        params, _ = curve_fit(swift_voce, strain, stress, p0=initial_guess,_
      →maxfev=20000)
     # Extract fitted parameters
        alpha, A, epsilon_0, n, k0, Q, beta = params
     # Plot the experimental data and the fitted curve
        fitted_stress = swift_voce(strain, *params)
        plt.scatter(strain, stress, label='Experimental Data', color='red')
        plt.plot(strain, fitted_stress, label='Fitted Curve', color='blue')
        plt.xlabel('True Strain')
        plt.ylabel('True Stress')
```

```
plt.title(title)
   plt.legend()
   plt.show()
# Print fitted parameters
   print(f'Fitted Parameters:\nAlpha: {alpha: .4f}\nA: {A:.4f}\nEpsilon_0:__

¬{epsilon_0:.4f}\n'
      f'n: {n:.4f}\nK0: {k0:.4f}\nQ: {Q:.4f}\nBeta: {beta:.4f}\n')
# Calculate error metrics
   mse = np.mean((stress - fitted_stress) ** 2)
   rmse = np.sqrt(mse)
   mae = np.mean(np.abs(stress - fitted_stress))
   r_squared = 1 - np.sum((stress - fitted_stress) ** 2) / np.sum((stress - np.
 →mean(stress)) ** 2)
    # Print error metrics
   print(f'Error Metrics:\n'
          f'MSE: \{mse:.4f\}\n'
          f'RMSE: {rmse:.4f}\n'
          f'MAE: \{mae:.4f\}\n'
          f'R-squared: {r_squared:.4f}')
# Extended strain for comparison (you might want to adjust this range)
    extended_strain = np.concatenate((strain, np.arange(strain[-1] + 0.01, 2.
 \hookrightarrow 01, 0.01)))
   extended_stress = swift_voce(extended_strain, *params)
   plt.scatter(strain, stress, label='Experimental Data', color='red')
   plt.plot(extended_strain, extended_stress, label='Fitted Curve',_

color='blue')

   plt.xlabel('True Strain')
   plt.ylabel('True Stress')
   plt.title(f"{title} extended")
   plt.legend()
   plt.show()
    # Export stress and strain values
   stress_difference = stress - fitted_stress
    # Create a DataFrame with the required columns
    df = pd.DataFrame({
        'Experimental Strain': strain,
        'Experimental Stress': stress,
        'Fitted Stress': fitted_stress,
        'Stress Difference': stress_difference
    })
```

```
extracted_strain = np.arange(0.1, 3.01, 0.01)
extracted_stress = swift_voce(extracted_strain, *params)
df2 = pd.DataFrame({
    'Extended Strain': extracted_strain,
    'Extended Stress': extracted_stress,
})

# Save the DataFrame to an Excel file with the file name based on the_
\title` argument

output_file_path = f"{title}_stress_strain_comparison.xlsx"

with pd.ExcelWriter(output_file_path) as writer:
    df.to_excel(writer, sheet_name='Comparison', index=False)
    df2.to_excel(writer, sheet_name='Extended Fit', index=False)

print(f"Data has been exported to {output_file_path}")

"""
return params
```

2 Modified Swift-Voce fitting with damping value for high strain

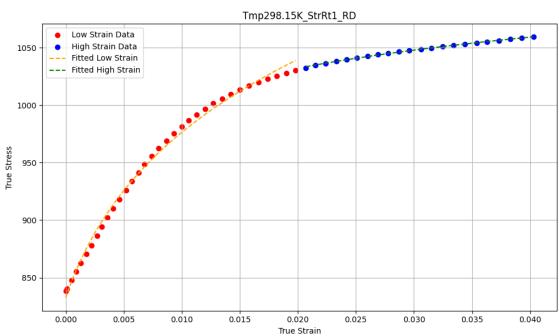
```
[]: def analyze_msv_fit(file_path, strain_column, stress_column, title,_
      ⇔initial guess=None):
         # Load data
         data = pd.read_csv(file_path)
         strain = data[strain_column].dropna().values
         stress = data[stress_column].dropna().values
         # Define the Modified Swift-Voce equation
         def modified_swift_voce(strain, A, B, n, K, epsilon0, alpha, beta):
             swift_part = A * (strain + epsilon0) ** n # Swift law
            voce_part = K * (1 - np.exp(-B * strain)) # Voce law
            damping = (1 - np.exp(-alpha * strain)) / (1 + beta * strain) #__
      → Damping term
             return swift_part + voce_part * damping
         # Initial guesses for parameters [A, B, n, K, epsilon0, alpha, beta]
         if initial_guess is None:
             initial_guess = [1500, 20, 0.2, 2000, 0.02, 0.3, 5] # Default values if_
      ⇔not provided
         # Adjusted bounds to limit parameter values
         bounds = ([500, 0, 0, 500, 0, 0], [5000, 50, 1, 5000, 0.2, 1, 20])
         # Separate data into low and high strain regions
         low_strain = strain[strain < 0.02]</pre>
```

```
low_stress = stress[strain < 0.02]</pre>
  high_strain = strain[strain >= 0.02]
  high_stress = stress[strain >= 0.02]
  # Fit the curve for low strain data
  params_low, _ = curve_fit(
      modified_swift_voce, low_strain, low_stress, p0=initial_guess,__
⇒bounds=bounds
  # Fit the curve for high strain data
  params_high, _ = curve_fit(
      modified_swift_voce, high_strain, high_stress, p0=initial_guess,_
⇒bounds=bounds
  )
  # Extract fitted stress values
  fitted_low_stress = modified_swift_voce(low_strain, *params_low)
  fitted_high_stress = modified_swift_voce(high_strain, *params_high)
  # Plot experimental and fitted curves
  plt.figure(figsize=(10, 6))
  plt.scatter(low_strain, low_stress, label='Low Strain Data', color='red')
  plt.scatter(high_strain, high_stress, label='High Strain Data', __
⇔color='blue')
  plt.plot(low_strain, fitted_low_stress, color='orange', linestyle='--',u
⇔label='Fitted Low Strain')
  plt.plot(high_strain, fitted high_stress, color='green', linestyle='--',u
⇔label='Fitted High Strain')
  plt.xlabel('True Strain')
  plt.ylabel('True Stress')
  plt.title(title)
  plt.legend()
  plt.grid(True)
  plt.tight_layout()
  plt.show()
  # Print fitted parameters for both regions
  print(f'Fitted Parameters for Low Strain (<0.02):\n'</pre>
        f'A: {params_low[0]:.4f}, B: {params_low[1]:.4f}, n: {params_low[2]:.

4f}, '
        f'K: {params_low[3]:.4f}, Epsilon_0: {params_low[4]:.4f}, '
        f'Alpha: {params_low[5]:.4f}, Beta: {params_low[6]:.4f}')
```

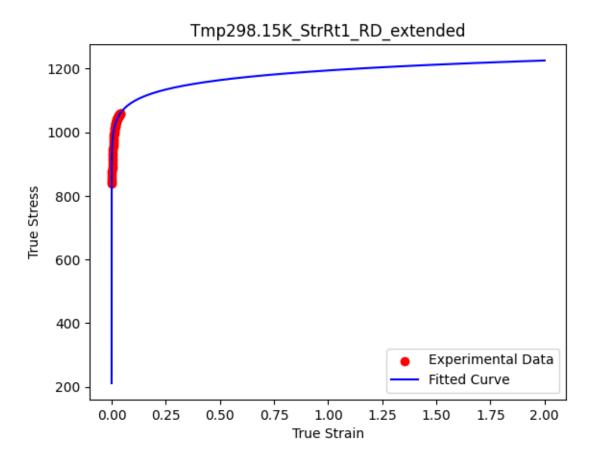
```
print(f'Fitted Parameters for High Strain (>=0.02):\n'
          f'A: {params_high[0]:.4f}, B: {params_high[1]:.4f}, n:__
 ⇔{params_high[2]:.4f}, '
          f'K: {params_high[3]:.4f}, Epsilon_0: {params_high[4]:.4f}, '
          f'Alpha: {params_high[5]:.4f}, Beta: {params_high[6]:.4f}')
    extended_strain = np.concatenate((strain, np.arange(strain[-1] + 0.01, 2.
 ⇔01, 0.01)))
    extended_stress = modified_swift_voce(extended_strain, *params_high)
    plt.scatter(strain, stress, label='Experimental Data', color='red')
    plt.plot(extended_strain, extended_stress, label='Fitted Curve', __

¬color='blue')
    plt.xlabel('True Strain')
    plt.ylabel('True Stress')
    plt.title(f"{title}_extended")
    plt.legend()
    plt.show()
    return params_low, params_high
condition = 'Tmp298.15K_StrRt1_RD'
analyze_msv_fit('data/Exp_FC_StrRtDpn_TmpDpn_Tmp298.csv', condition + '_E', _
 ⇔condition + '_S', condition)
```



Fitted Parameters for Low Strain (<0.02):

```
A: 1581.8136, B: 18.7997, n: 0.1114, K: 1891.1069, Epsilon_0: 0.0031, Alpha: 0.0000, Beta: 19.9786
Fitted Parameters for High Strain (>=0.02):
A: 1194.0092, B: 14.7818, n: 0.0373, K: 759.6380, Epsilon_0: 0.0000, Alpha: 0.0000, Beta: 6.3350
```



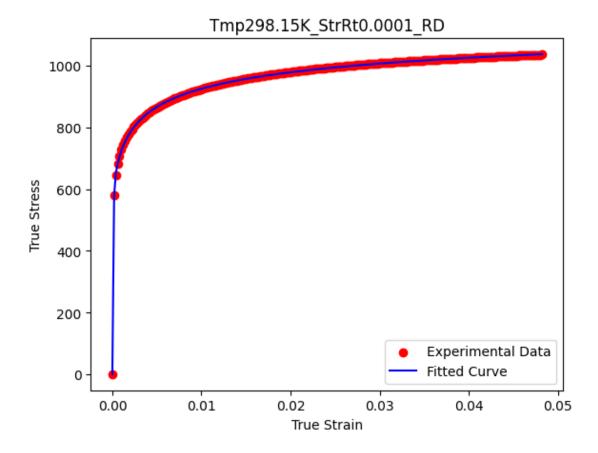
```
[]: (array([1.58181360e+03, 1.87997462e+01, 1.11411675e-01, 1.89110690e+03, 3.14836951e-03, 7.70761622e-13, 1.99786230e+01]), array([1.19400920e+03, 1.47817668e+01, 3.72508750e-02, 7.59638004e+02, 6.16173973e-21, 6.07998938e-30, 6.33500171e+00]))
```

3 Plot of all strain rate at RT and parameters relationship

```
[]: params = [] #store all parameters
params_name = ['alpha', 'A', 'epsilon_0', 'n', 'k0', 'Q', 'beta']
```

```
conditions = ['Tmp298.15K StrRt0.0001 RD', 'Tmp298.15K StrRt0.0001 DD', 'Tmp298.
 415K_StrRt0.0001_TD', 'Tmp298.15K_StrRt0.001_RD', 'Tmp298.15K_StrRt0.001_DD',
 ⇔01_DD', 'Tmp298.15K_StrRt0.01_TD', 'Tmp298.15K_StrRt0.1_DD', 'Tmp298.

¬15K_StrRt0.1_TD','Tmp298.15K_StrRt1_RD']
#conditions = ['Tmp77.15K StrRt0.0001 RD']
for condition in conditions:
   params.append(analyze_sv_fit('data/Exp_FC_StrRtDpn_TmpDpn_Tmp298.csv',_
 for i in range(7):
   plt.figure(figsize=(8, 5)) # Create a new figure for each plot
   plt.plot(conditions, [p[i] for p in params], marker='o')
   plt.xlabel('Conditions')
   plt.xticks(rotation=60)
   plt.ylabel(params_name[i])
   plt.title(params_name[i] + ' of Each Condition')
   plt.tight_layout() # Adjust layout to prevent label cut-off
   plt.show() # Display the plot
```

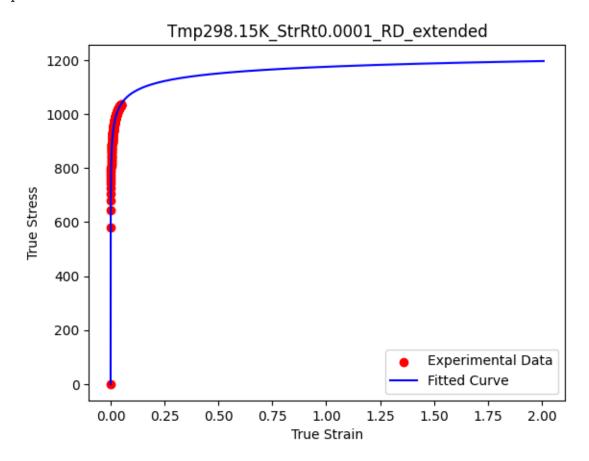


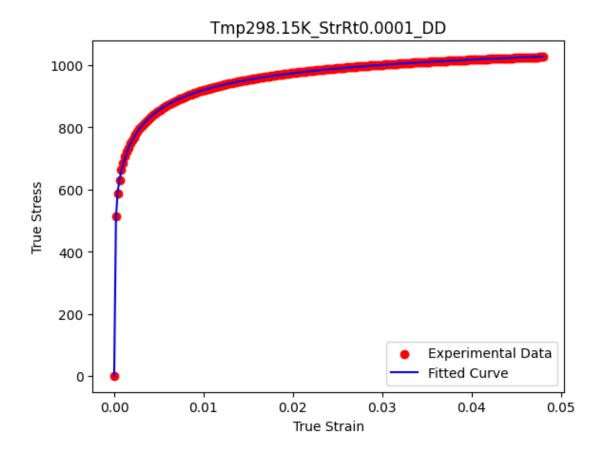
Alpha: -0.0843 A: 1855.4915 Epsilon_0: 0.0005

n: -0.2100 KO: 699.9021 Q: 528.6419 Beta: 12990.0817

Error Metrics: MSE: 1.8040 RMSE: 1.3431 MAE: 1.0403

R-squared: 0.9998

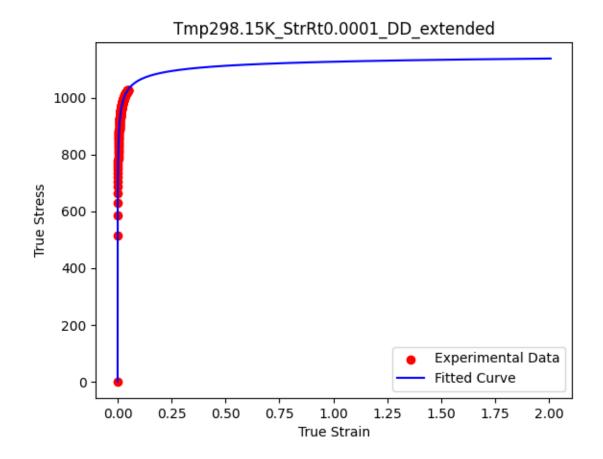


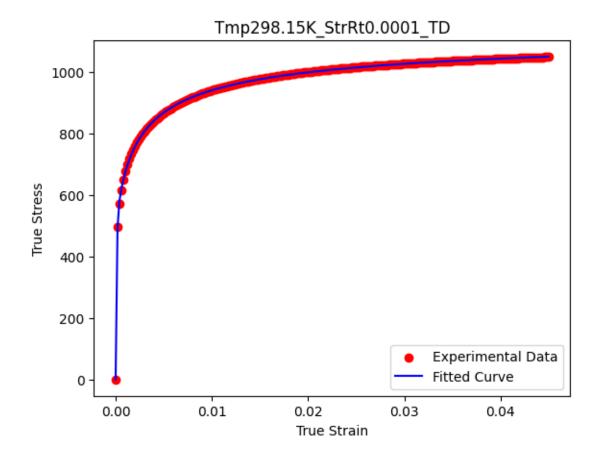


Alpha: -0.0351 A: 1449.0665 Epsilon_0: 0.0007 n: -0.3575

K0: 654.2613
Q: 482.9348
Beta: 11932.3490

Error Metrics: MSE: 1.3216 RMSE: 1.1496 MAE: 0.7950

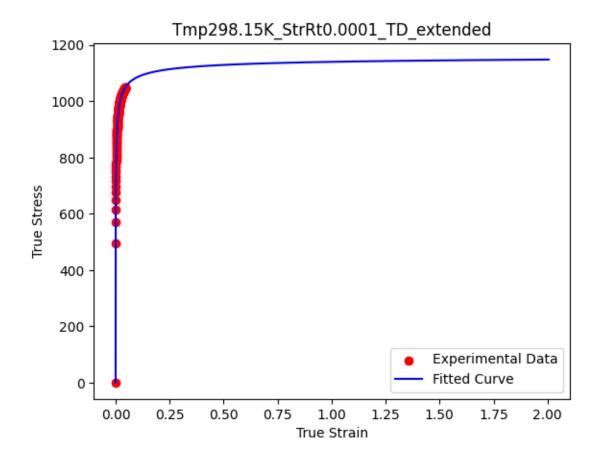


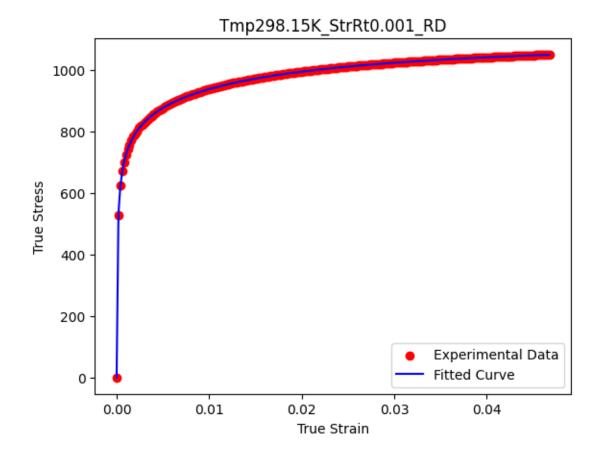


Alpha: -0.0162 A: 1859.3901 Epsilon_0: 0.0010

n: -0.4505 KO: 670.9988 Q: 480.5649 Beta: 11558.5423

Error Metrics: MSE: 1.7418 RMSE: 1.3198 MAE: 0.9458



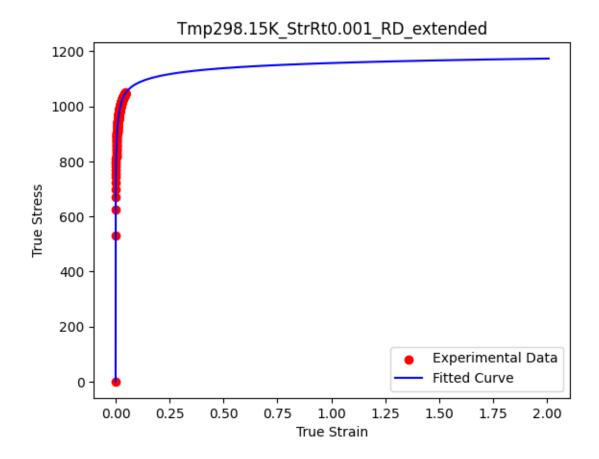


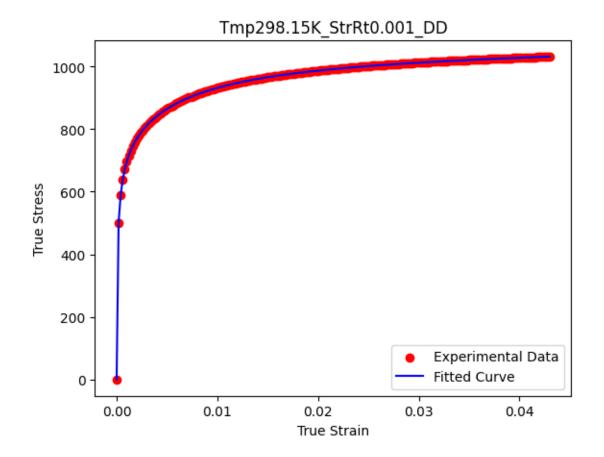
Alpha: -0.1499 A: 829.4386

Epsilon_0: 0.0000

n: -0.2021 K0: 1059.8279 Q: 54.5216 Beta: 76.6431

Error Metrics: MSE: 0.2956 RMSE: 0.5437 MAE: 0.2610



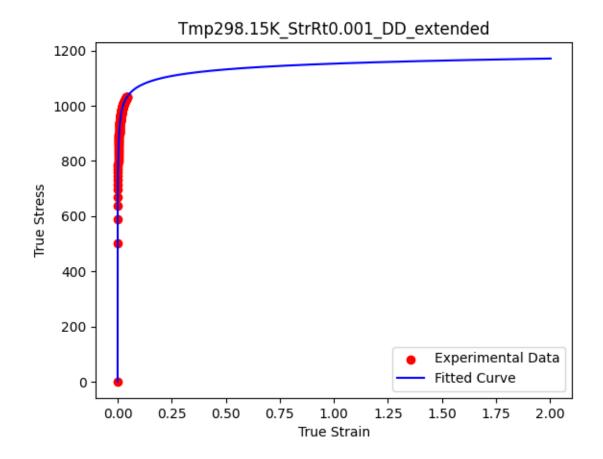


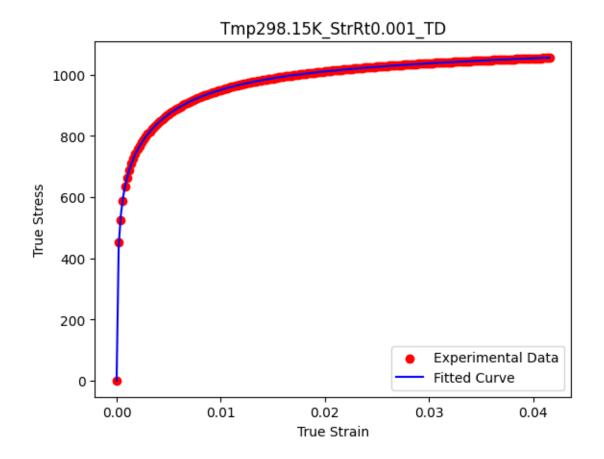
Alpha: -0.1696 A: 896.9352

Epsilon_0: 0.0000

n: -0.1862 KO: 1054.5637 Q: 61.0253 Beta: 156.4644

Error Metrics: MSE: 0.0724 RMSE: 0.2691 MAE: 0.2127



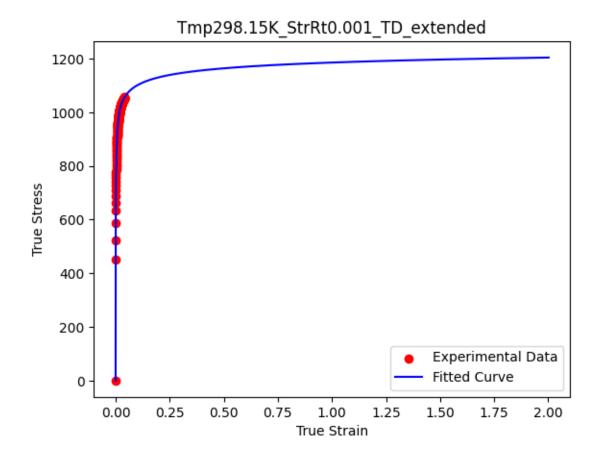


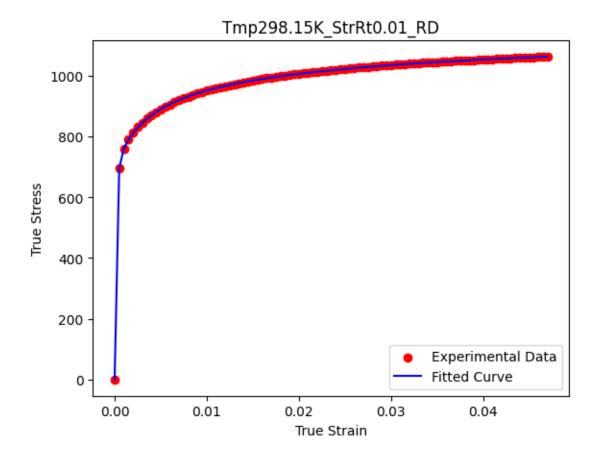
Alpha: -0.1573 A: 898.7127

Epsilon_0: 0.0000

n: -0.2040 KO: 1053.6354 Q: 92.6702 Beta: 201.5890

Error Metrics: MSE: 2.3568 RMSE: 1.5352 MAE: 0.5065

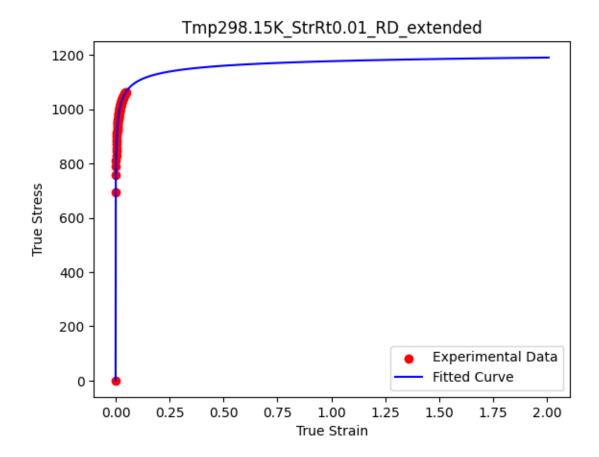


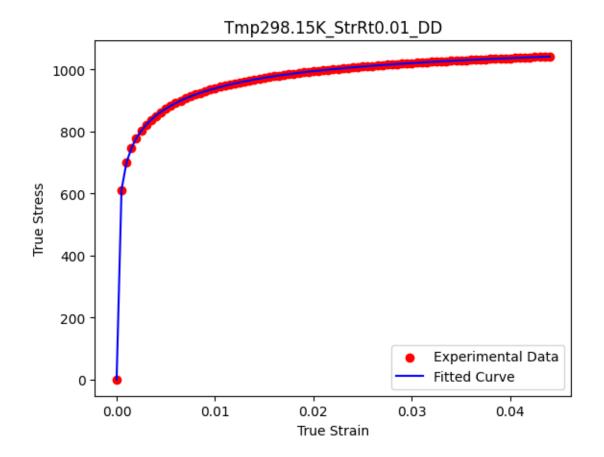


Alpha: -0.0412 A: 1528.7965 Epsilon_0: 0.0017

n: -0.3426 KO: 538.6508 Q: 652.1925 Beta: 6113.3657

Error Metrics: MSE: 0.2257 RMSE: 0.4751 MAE: 0.3518



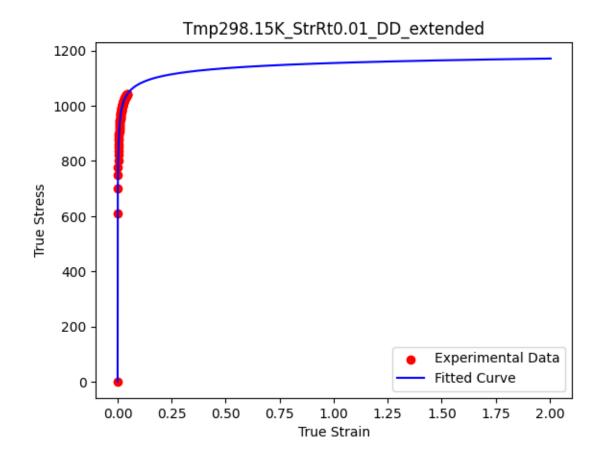


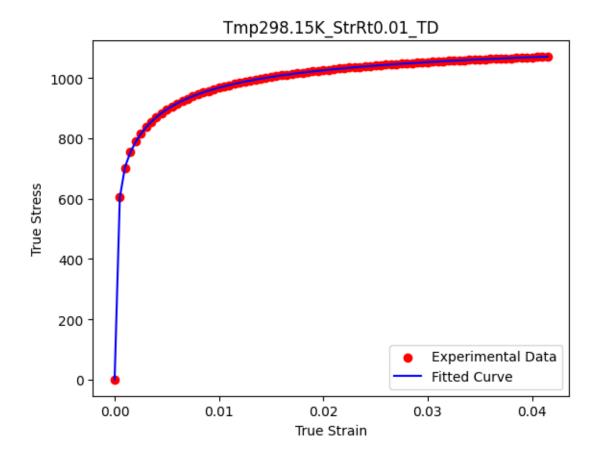
Alpha: -0.1439 A: 786.6893

Epsilon_0: 0.0000

n: -0.2221 K0: 1062.3852 Q: 46.3042 Beta: 130.3721

Error Metrics: MSE: 0.2331 RMSE: 0.4828 MAE: 0.2647

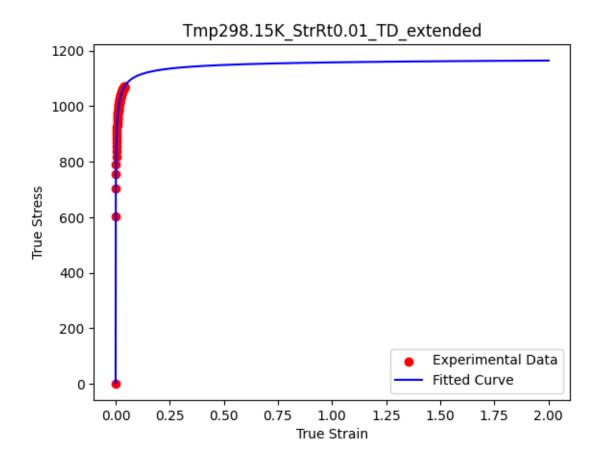


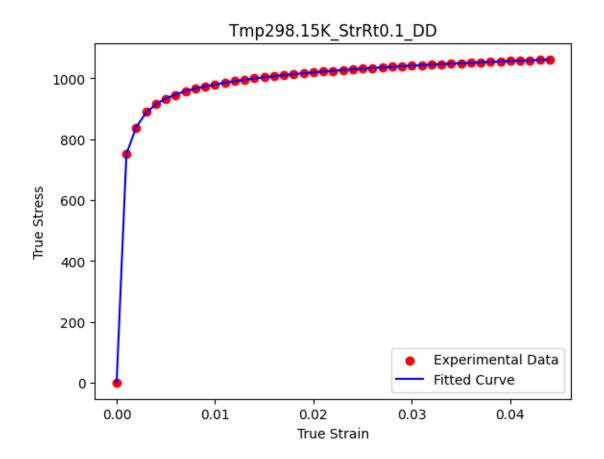


Alpha: -0.0142 A: 1595.8106 Epsilon_0: 0.0013

n: -0.4994 K0: 620.4402 Q: 543.5982 Beta: 5095.2831

Error Metrics: MSE: 0.4123 RMSE: 0.6421 MAE: 0.4282

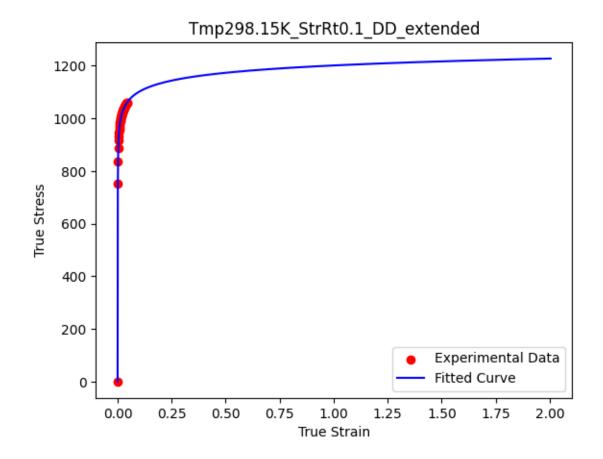


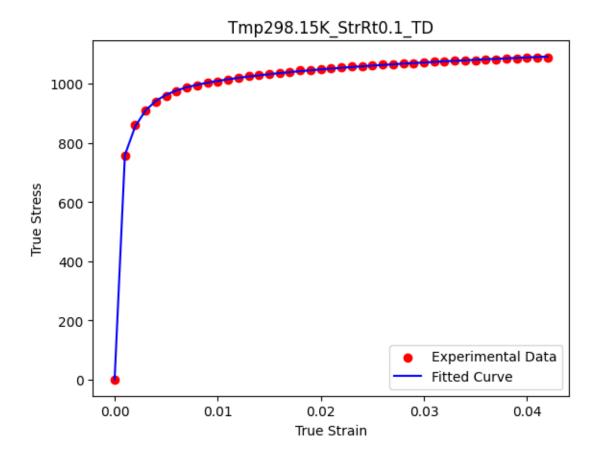


Alpha: -0.2393 A: 1821.1632 Epsilon_0: 0.0000

n: -0.0894 KO: 1192.5889 Q: 128.4945 Beta: 718.7260

Error Metrics: MSE: 0.6722 RMSE: 0.8199 MAE: 0.3893

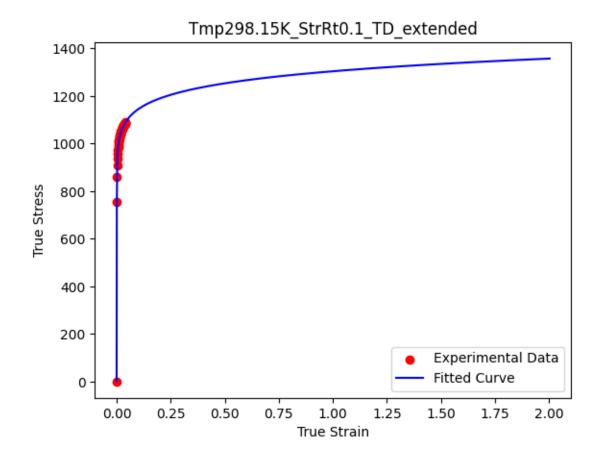


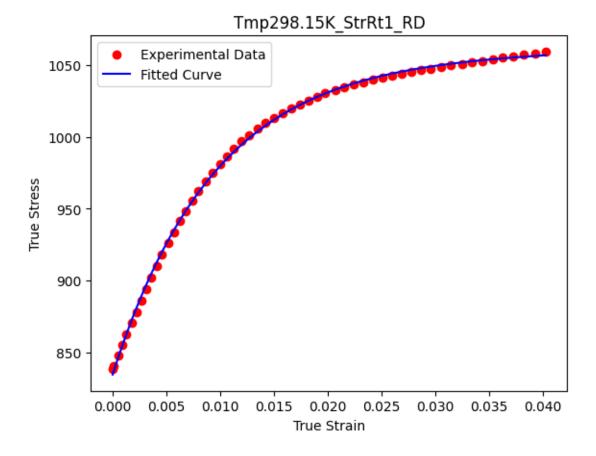


Alpha: 0.8197 A: 1290.7194 Epsilon_0: 0.0000

n: 0.0709 KO: -60.3743 Q: 1426.2732 Beta: 638.7484

Error Metrics: MSE: 3.2585 RMSE: 1.8051 MAE: 1.4837





Alpha: 0.6101 A: 2676.8427

Epsilon_0: 0.0000

n: 2.0233 KO: 2140.0914 Q: 572.5317 Beta: 105.0464

Error Metrics: MSE: 2.8767 RMSE: 1.6961 MAE: 1.4310

