Material Modelling
for the Simulation of Microforming Processes
at Elevated Temperature

D. D’Addona, R. Teti
Dept. of Materials and Production Engineering
University of Naples Federico II, Italy
Introduction (1)

• The investigation on the applicability of artificial neural networks for the modelling of the mild steel and nickel base superalloys behaviour at elevated temperature in the case of microforming processes is presented.

• Intelligent computation tools with the goal of performing production engineering tasks must incorporate knowledge of the dynamics of the physical systems involved.

• Such knowledge is properly represented by behavioural models which may be built from experimental data: the process of modelling from data may be performed either by using structural models or by learning input-output relationships directly from the data.

• The knowledge available in the field of metal forming processes is often of a non deterministic type: in many cases, the ”optimal” selection of process parameters in metal forming operations is largely based on human experience.
Introduction (2)

• The **rheological behaviour** of hot formed metals is represented through **constitutive equations**, where the **material response** is correlated only to the **istantaneous values** of process parameters (strain, strain rate, temperature)

• The introduction of **neural networks** (NNs) has led to **alternative models** being proposed to **predict the flow stress** of various metal materials

• The **evaluation of the NN models** for flow stress prediction was carried out on the basis of **laboratory data** of the stress-strain behaviour of **different materials**:
  – **mild steel**
  – **nickel base superalloy** (Nimonic 115)

subjected to **compression tests** with different temperature and strain rate conditions
Material and Experimental Tests: Mild Steel

• The performance of the NN models is evaluated with reference to laboratory data of the stress-strain behavior of mild steel under compression.

• The mild steel composition was:
  C 0.16, Mn 0.63, Si 0.33, Ni 0.24, Cr 0.16, Mo 0.04, Cu 0.17, Al 0.05, S 0.047, P 0.011

• Hot compression tests were carried out at different constant values of temperature and strain-rate to evaluate the material sensitivity to process parameters variations.

  • Selected values of strain rate were: 
    \( \varepsilon' = 0.02 \text{ s}^{-1}, 0.5 \text{ s}^{-1}, 5.0 \text{ s}^{-1} \)
  
  • Selected temperatures were: 
    \( T = 950 \degree \text{C}, 1050 \degree \text{C}, 1150 \degree \text{C} \)
Summary of Experimental Results: Mild Steel

- **7 valid compression tests** were carried out; during each compression test, experimental data were sampled from the stress-strain curve.

<table>
<thead>
<tr>
<th>Test id.</th>
<th>Temperature (°C)</th>
<th>Strain rate (s(^{-1}))</th>
<th># of curve data points</th>
</tr>
</thead>
<tbody>
<tr>
<td>125A</td>
<td>950</td>
<td>0.02</td>
<td>2328</td>
</tr>
<tr>
<td>135A</td>
<td>1150</td>
<td>0.02</td>
<td>2323</td>
</tr>
<tr>
<td>315A</td>
<td>950</td>
<td>0.50</td>
<td>494</td>
</tr>
<tr>
<td>325B</td>
<td>1050</td>
<td>0.50</td>
<td>493</td>
</tr>
<tr>
<td>515B</td>
<td>950</td>
<td>5.00</td>
<td>497</td>
</tr>
<tr>
<td>525A</td>
<td>1050</td>
<td>5.00</td>
<td>499</td>
</tr>
<tr>
<td>535A</td>
<td>1150</td>
<td>5.00</td>
<td>299</td>
</tr>
</tbody>
</table>

Summary of hot compression tests of mild steel.
Flow Stress-Strain Curves: Mild Steel

For each compression test, a curve vector consisting in a sequence of data points, identified by a stress value $\sigma$ and a strain value $\varepsilon$ was generated.

![Graph of stress-strain curves]

Experimental stress-strain curves at T = 950 °C and various strain rate values
Material and Experimental Tests: Nimonic 115

- Nickel base superalloy, **Nimonic 115**: nickel-chromium-cobalt base alloy, strengthened with additions of
  
  Mo: 3.0 – 5.0 %, Al: 4.5 – 5.5 %, Ti: 3.5 – 4.5%

- The sample was mounted on the testing machine, heated up to the testing temperature at a rate of 5 °C/s, held at temperature for 30 s max, and then compressed at constant strain-rate up to a maximum strain of 0.8%

- The selected values of **strain rate** were:
  
  $e' = 0.1 \text{ s}^{-1}, 1 \text{ s}^{-1}, 15 \text{ s}^{-1}$

- The selected **temperatures** were:
  
  $T = 1100 \degree \text{C}, 1140 \degree \text{C}, 1180 \degree \text{C}$
Summary of Experimental Results: Nimonic 115

- 9 valid compression tests were carried out; during each compression test, experimental data were sampled from the stress-strain curve.

<table>
<thead>
<tr>
<th>Test id.</th>
<th>Temperature (°C)</th>
<th>Strain rate (s⁻¹)</th>
<th># of curve data points</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1100</td>
<td>0.1</td>
<td>80</td>
</tr>
<tr>
<td>2</td>
<td>1100</td>
<td>1.0</td>
<td>79</td>
</tr>
<tr>
<td>3</td>
<td>1100</td>
<td>15.0</td>
<td>79</td>
</tr>
<tr>
<td>4</td>
<td>1140</td>
<td>0.1</td>
<td>73</td>
</tr>
<tr>
<td>5</td>
<td>1140</td>
<td>1.0</td>
<td>74</td>
</tr>
<tr>
<td>6</td>
<td>1140</td>
<td>15.0</td>
<td>81</td>
</tr>
<tr>
<td>7</td>
<td>1180</td>
<td>0.1</td>
<td>150</td>
</tr>
<tr>
<td>8</td>
<td>1180</td>
<td>1.0</td>
<td>74</td>
</tr>
<tr>
<td>9</td>
<td>1180</td>
<td>15.0</td>
<td>74</td>
</tr>
</tbody>
</table>
Flow Stress-Strain Curves: Nimonic 115

- For each compression test, a curve vector consisting in a sequence of data points, identified by a stress value, $\sigma$, and a strain value, $\varepsilon$, was generated.

Experimental stress-strain curves of Nimonic 115 for $\varepsilon' = 0.1$ s⁻¹ and different temperatures.
Neural Network Data Processing

- To **model the material response** to hot forging process conditions, different **3-layered cascade-forward back-propagation NNs** were trained and tested to produce a mapping from input vectors to output values.

- The **inputs** to the NNs were: strain, strain-rate, temperature and experimental curve features combined to form input vectors with a number of components variable between 3 and 7.

- The **NN output** value was in all cases the **flow stress**, $\sigma$.

- The **strain** $\varepsilon$ of each data point plus the other **input parameters** were sequentially **presented** to the **NN input layer** and the corresponding **flow stress** $\sigma$ was fed to the **output layer** for NN training.

- **NN training** was performed by the “**leave-k-out**” method: one pattern vector given by one experimental curve ($k = 1$) was held back in turn for the recall phase, and the other pattern vectors were used for learning.

- During **NN testing**, the complete stress-strain curve for a given test condition is reconstructed and the error is evaluated by comparison with the actual experimental curve.

- Desired flow stress $\sigma$, predicted flow stress $\sigma_{\text{pred}}$ and percent error $E\% = (\sigma_{\text{pred}} - \sigma)/\sigma_{\text{pred}}$ were **plotted versus strain**.

D. D'Addona, R. Teti, Material Modelling
Neural Network Configurations

• Different NN configurations were constructed according to the size of the input vectors

<table>
<thead>
<tr>
<th>NN configuration</th>
<th>Input vector</th>
<th>Output vector</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-3-1</td>
<td>{ \varepsilon, \varepsilon', T }</td>
<td>\sigma</td>
</tr>
<tr>
<td>6-3-1</td>
<td>{ \varepsilon, \varepsilon', T, \ln(\varepsilon), \ln(\varepsilon'), 1/T }</td>
<td>\sigma</td>
</tr>
<tr>
<td>7-3-1</td>
<td>{ \varepsilon, \varepsilon', T, \varepsilon_p, \ln(\varepsilon), \ln(\varepsilon'), 1/T }</td>
<td>\sigma</td>
</tr>
</tbody>
</table>

\varepsilon = strain; \varepsilon' = strain-rate; T = temperature; \varepsilon_p = peak strain*; \sigma = flow stress

* The \( \varepsilon_p \) value utilized was obtained by averaging the \( \varepsilon_p \) values of the curves available for training, i.e. all curves but the one left out for testing
Performance of Neural Network Configurations

<table>
<thead>
<tr>
<th>Test id.</th>
<th>Curve RMS error</th>
<th>3-3-1 NN</th>
<th>6-3-1 NN</th>
<th>7-3-1 NN</th>
</tr>
</thead>
<tbody>
<tr>
<td>125A</td>
<td></td>
<td>15.3</td>
<td>12.1</td>
<td>6.5</td>
</tr>
<tr>
<td>135A</td>
<td></td>
<td>51.8</td>
<td>48.3</td>
<td>27.8</td>
</tr>
<tr>
<td>315A</td>
<td></td>
<td>65.2</td>
<td>57.6</td>
<td>12.7</td>
</tr>
<tr>
<td>325B</td>
<td></td>
<td>83.6</td>
<td>48.9</td>
<td>29.0</td>
</tr>
<tr>
<td>515B</td>
<td></td>
<td>83.6</td>
<td>76.9</td>
<td>31.7</td>
</tr>
<tr>
<td>525A</td>
<td></td>
<td>27.1</td>
<td>23.2</td>
<td>9.7</td>
</tr>
<tr>
<td>535A</td>
<td></td>
<td>28.3</td>
<td>20.1</td>
<td>15.9</td>
</tr>
</tbody>
</table>

![Performance of the NN configurations in terms of curve RMS error](Image)

(a) mild steel; (b) Nimonic 115
Neural Network Processing Results: NN 7-3-1
Test 315A: Mild Steel (T = 950 °C, ε = 0.50)

Desired and predicted flow stress vs. strain

Flow stress percent error vs. strain
Neural Network Processing Results: NN 7-3-1
Test n. 5: Nimonic 115 (T = 1140 °C, \( \varepsilon = 1.0 \))

Desired and predicted flow stress vs. strain

Flow stress percent error vs. strain
Conclusions

• The **modelling** of the **rheological behaviour** of a **mild steel** and **nickel based superalloy** under **hot deformation conditions** was carried out through **flow stress prediction** using different **feed-forward BP NN** configurations.

• The results obtained by using only strain, strain-rate and temperature as NN input features did not allow for stress-strain curve reconstruction.

• For input vectors containing features accounting for both:
  - the analytical relationships among the process parameters
  - the influence of peak strain on the material behaviour modelling

  the NN model could accurately describe both metals flow stress under hot forging conditions.

• The implementation of **NN based approach** for the **modelling of the material behaviour** in **forming** at high temperature can **provide**
  - the **required enhancement** of process knowledge
  - the **improved capability for material properties evaluation** necessary for developing simulation methods applicable at **microscale level**.
Material Modelling
for the Simulation of Microforming Processes
at Elevated Temperature

D. D’Addona, R. Teti
Dept. of Materials and Production Engineering
University of Naples Federico II, Italy