Nonlinear Black-Box Modeling of Electric Arc Furnaces
An Application of Adaptive Fuzzy Rule-Based Systems

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STEEL-MAKING

• A multi-billion dollars industry

• Expanding & upgrading steadily

• Increasing power level & furnace capacity

• Resulting in significant electrical disturbances

• To Model the nonlinear characteristics of EAF accurately.

• To investigate the application of fast learning modeling networks.
ELECTRIC ARC FURNACES
A Typical Electric Arc Furnace Power Profile
OBJECTIVES

- Application of fuzzy logic systems to model electric arc furnaces

- To provide the rationale and to justify the use of fuzzy modeling for electric furnaces

- To investigate the application of fuzzy logic systems to electric arc furnace modeling

- To compare performance between models based on fuzzy logic systems and those of artificial neural networks
METHOD

➢ Conventional modeling:
  □ Based on a group of mathematically derived and explicit equations

➢ Nonlinear black-box modeling:
  □ Based on the data obtained from the operational EAFs and structures suitable for nonlinear modeling
    • Radial Basis Function Networks
    • Multi-Layer Perceptron Networks
    • Fuzzy Logic Systems
    • Adaptive Fuzzy Logic Systems
NONLINEAR BLACK-BOX MODELING

Finding a non-linear relationship, \( g \), between the past observations \([u_t, y_t]\) and the next output \( y_{t+1} \):

\[
y_{t+1}^* = g(u^t, y^t)
\]  \hspace{1cm} (1)

\[
u^t = [u_1 \ u_2 \ ... \ u_t]
\]  \hspace{1cm} (2)

\[
y^t = [y_1 \ y_2 \ ... \ y_t]
\]  \hspace{1cm} (3)

\[
y_{t+1} = g(u^t, y^t) + \epsilon_{t+1}
\]  \hspace{1cm} (4)

The goal is to minimize \( \epsilon_{t+1} \).
NONLINEAR BLACK-BOX MODELING

Approximation:
- Considering a family of functions
- Parameterizing with $\theta$:

$$g(u^t, y^t, \theta)$$  \hspace{1cm} (5)

The parameterized function family:

$$g(u^t, y^t, \theta) = \sum \alpha_k g_k(u^t, y^t)$$  \hspace{1cm} (6)

The quality of approximation:
\[
\sum_{t=1}^{N} \left\| y(t) - g(u^t, y^t, \theta) \right\|^2
\]

(7)

**NEURAL NETWORKS**
General architecture of the MLP network

\[ f(x_1, \ldots, x_n) = \sum_{i=1}^{m} \omega_i \cdot g \left( \sum_{j=1}^{n} w_{ij} x_j - \theta_i \right) \]

- \( w_{ij}, b_{ij} \): weights & biases - hidden layer
- \( i \): number of inputs; 1, \ldots, \( n \)
- \( j \): number of neurons; 1, \ldots, \( m \)
- \( \omega_{jk} \): weights - output layer
- \( k \): number of outputs

Sigmoid function
\[ g(x) = \frac{1}{1 + e^{-x}} \]
\[ f(x_1, \ldots, x_n) = \sum_{i=1}^{m} w_i \Phi(||x - c_i||) \]

where:
- \( w_j \): weights - output layer
- \( r_j, c_j \): RBF center & width
- \( j \): RBF neurons; 1,...,m

\[ \Phi(x) = e^{-\frac{(x-c)^2}{\sigma^2}} \]

General architecture of RBF network
RESULTS

MLP-Network response to training data & its error

MLP-based model for EAF
RESULTS

RBF NETWORK RESPONSE TO TRAINING DATA & ITS ERROR

RBF NETWORK RESPONSE TO VALIDATION DATA & ITS ERROR

RBF-based model for EAF
FUZZY LOGIC SYSTEMS

• A rigorous mathematical discipline
• Successfully applied to engineering applications

- Ability to generalize
- Ability to express nonlinear input/output relationships by a set of qualitative if-then rules
- Ability to handle numerical data & linguistic knowledge
- Ability to provide model when the mathematical model does not exist or is ill-defined
- Ability to acceptably respond to the unforeseen situations
- Ability to predict behavior of the system, under some conditions
ADAPTIVE FUZZY LOGIC SYSTEMS

(a) Sugeno fuzzy inference engine;

\[ Z = \frac{\sum_{i=1}^{m} z_i w_i}{\sum_{i=1}^{m} w_i} \]
(b) Fuzzy inference using neural network type structure
APPLICATION JUSTIFICATION

1. Nonlinear black-box modeling capability

2. Universal approximation ability

3. Functional equivalence between fuzzy logic system with radial basis function networks
IMPLEMENTATION

(a) Straightforward fuzzy partitioning
(b) Clustering & parameter optimization
## RESULTS

### FUZZY LOGIC SYSTEM

<table>
<thead>
<tr>
<th>Network</th>
<th>Rules</th>
<th>Train Test Cases</th>
<th>Error %</th>
<th>Train Time [p.u.]</th>
</tr>
</thead>
<tbody>
<tr>
<td>FLS</td>
<td>94</td>
<td>300/600</td>
<td>17.50</td>
<td>37.86</td>
</tr>
<tr>
<td>FLS</td>
<td>130</td>
<td>1000/1500</td>
<td>17.51</td>
<td>31.55</td>
</tr>
<tr>
<td>FLS</td>
<td>139</td>
<td>1500/3000</td>
<td>17.32</td>
<td>30.30</td>
</tr>
<tr>
<td>AFLS</td>
<td>6</td>
<td>300/600</td>
<td>1.34e-2</td>
<td>1.37e-2</td>
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<td>1000/1500</td>
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<td>4</td>
<td>1500/3000</td>
<td>1.57e-2</td>
<td>1.64e-2</td>
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</tbody>
</table>
## RESULTS

### RADIAL BASIS FUNCTION

<table>
<thead>
<tr>
<th>NEURONS HIDDEN LAYER</th>
<th>TRAINING VALIDATION CASES</th>
<th>TRAINING ERROR%</th>
<th>VALIDATION ERROR%</th>
<th>TRAINING TIME [P.U.]</th>
</tr>
</thead>
<tbody>
<tr>
<td>146</td>
<td>300/600</td>
<td>2.90</td>
<td>7.17</td>
<td>4.90</td>
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<td>169</td>
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<td>3.77</td>
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<td>0.46</td>
<td>5.95</td>
<td>24.42</td>
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<tr>
<td>304</td>
<td>600/1000</td>
<td>0.14</td>
<td>5.82</td>
<td>57.11</td>
</tr>
<tr>
<td>327</td>
<td>1000/1500</td>
<td>0.38</td>
<td>6.40</td>
<td>128.67</td>
</tr>
</tbody>
</table>
RESULTS

EAF models based on FLS, Adaptive FLS and RBF networks
RESULTS - FUZZY LOGIC SYSTEMS

- Using a large set of training data:
  - Does increase the training time
  - Increase in the quality of the model is not proportional to the increase in the size of the data set.

- Comparison with the Radial Basis Networks:
  - Significant improvement in terms of implementation time.

- Computational results:
  - Promising.
RESULTS - ADAPTIVE FLS

- Using a large set of training data:
  - Does increase the training time.
  - Does not necessarily decrease the training error.
  - Does not improve the quality of the training.

- Comparison with the fuzzy logic systems:
  - Reduced number of the rules.
  - Improved performance error.

- Computational results:
  - Compare well with the existing measurements and that of the RFB.
NEW ASPECTS OF WORK

• Application of nonlinear black-box modeling to Electric Arc Furnaces

• Application of Fuzzy Logic Systems to model EAF

• Practical justification for application of FLSs as means of nonlinear black-box modeling to EAFs

• Implementation of a frame of reference suitable for evaluating other nonlinear black-box modeling techniques
CONCLUSIONS

• Successful implementation of AFLS-based models for EAF

• Successful qualitative comparison between the AFLS-based models and the recorded data

• Building the modeling benchmark comparing MLP, RBF, FLS & AFLS networks

• FLS approximates the dynamic of EAF despite the inherent nonlinear characteristics and time-variant parameters of EAF

• Accurately

• Fast
CONCLUSIONS

- The fuzzy modeling method has faster implementation time than other nonlinear methods such as RBF.

- The accuracy of adaptive fuzzy modeling is not only comparable with that of RBF networks but also shows improvement.

- Adaptive fuzzy logic systems are established as model structures suitable for nonlinear black-box modeling for the EAF.

- Fast training speed of fuzzy logic systems.