Soft Computing Approaches to Constitutive Modeling in Geotechnical Engineering

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Contents

- Introductory Remarks on Soft Computing
- SelfSim: Constitutive Modeling from System Response
- Several Applications of SelfSim
- Field Calibration of constitutive Models in Deep Excavations
Soft Computing

- Soft computing methods are inspired by the computing and problem solving strategies in nature.

- They are fundamentally different than the mathematically based problem solving methods.

- Soft computing tools are neural networks, genetic algorithm and fuzzy logic.
Problem Solving in Nature

- Nature solves very difficult inverse problems.
- Nature does not use mathematics.
- Two main components of nature’s problem solving strategies are:
  - Learning
  - Reduction in disorder
- Nature utilizes random search and gradual improvement.
Forward Problems

Input → System Model → Output
Inverse Problems

Type 1. Input is unknown

Type 2. System is unknown
Inverse Problem of Constitutive Modeling

Material Test

Stresses → Plasticity → Strains

?
Inverse Problem of Constitutive Modeling from Field Measurements

- In many geotechnical problems it is too difficult to sample or perform realistic material tests.
- Often field measurements are available.

Forces $\rightarrow$ System $\rightarrow$ Displacements
Autoprogressive Algorithm

Loads → Finite Element Model → Field Measurements

Conductive Model?
Autoprogressive Algorithm

Structure is modeled by FE and constitutive model is represented by a NN.

Pre-train NN material model to learn linearly elastic constitutive behavior

Apply boundary forces: apply $\Delta P_n$, compute $\Delta U_n$

$$P_n = P_{n-1} + \Delta P_n$$
$$K_n \delta U^{j}_{n} = P_n - I^{j-1}_{n}$$
$$\Delta U^{j}_{n} = \Delta U^{j-1}_{n} + \delta U^{j}_{n}$$
$$\sigma_n = \sigma_{n \text{NN}}(\varepsilon_n, \ldots : \ldots)$$

Enforce boundary displacements

$$\delta U_n = \overline{U}_n + U_n$$

$$(\sigma_n + \delta \sigma_n) = \text{NN}((\varepsilon_n + \delta \varepsilon_n), \ldots : \ldots)$$

Train Neural Networks

$$\sigma_n = \sigma_{n \text{NN}}((\varepsilon_n + \delta \varepsilon_n), \ldots : \ldots)$$
Learning Material Behavior from Response of a Simple Structure

FE Analysis A, Force BC

NN Training

FE Analysis B, Displacement BC

Simulated Experiment, Von-Mises Plasticity with hardening

Train a NN to learn the material behavior from the response of this structure
Evolution of Load-Displacement

![Graph showing load-displacement relationship with data points for different passes.](image)
NN Learning of Material Behavior
NN Learning of Material Behavior
Time dependent behavior of reinforced concrete
Creep of Concrete Beam

Experiment by Bakoss et al. (1982)

- Top surface
- Bottom surface
- Instant
- 12 days
- 60 days
- 130 days
- 513 days

- Deflection vs. Time (days)
- Strain
- Pass20
Field Calibration of Time-Dependent Behavior in Segmental Bridges Using Self-Learning Simulation
Case study: Pipiral Bridge (Colombia)

each span: 125m
The Challenge: Deflection Control

Jan 10, 2002: 73 days (12 segments)
Feb 14, 2002: 108 days (all 18 segments)
Jul 11, 2002: 255 days (all 18 segments)

- design camber at the completion
Field Calibration of the Pipiral Bridge
Improvement of Camber by Using SelfSim

- Jan 10, 2002: 73 days (12 segments)
- Feb 14, 2002: 108 days (all 18 segments)
- Jul 11, 2002: 255 days (all 18 segments)
Learning the hysteretic behavior of soil from the seismic site response
Application of SelfSim to synthetically generated downhole array data - case1

Layer 1

- Sinusoidal motion
- Single layer
Application of SelfSim to synthetically generated downhole array data- case1

Layer1

- cyclic motion
- single layer

![Graphs showing Stress vs Strain for different passes of SelfSim and comparison with Hyperbolic model + Masing rule.](image-url)
Application of SelfSim to synthetically generated downhole array data - case2

- seismic motion
- multiple layers
- same soil properties

Layer 1
Layer 2
Layer 3
Layer 4
Application of SelfSim to synthetically generated downhole array data- case2

- seismic motion
- multiple layers
- same soil properties
Applications in Ophthalmology
- Characterizing the material properties of human cornea for simulating Individualized laser surgery
- Measurement of intra-ocular pressure (IOP)
- Developing a new instrument

Applications in bio-medical imaging
- Characterizing the material properties of soft tissue
- Imaging of the material properties of soft tissue for diagnostics and disease progression
Simulation of Goldman Applanation Tonometer

Before loading steps

First step

Second step

0.02mm

15mmHg

Applanation
Real-time soil model for tool-medium interaction in virtual reality environment
DEM Machine-Medium Interaction
DEM Machine-Medium Interaction
DEM Machine-Medium Interaction
Integration of numerical modeling and field observations for deep excavations
1. Field Measurements

Initializing or Pre-training stress strain data from:
1. Linear elastic
2. Laboratory tests
3. Case histories
4. Approximate constitutive models

\[ \sigma, \varepsilon \]

Stress-Strain Pairs
Training of NANN

2. SelfSim Training FEM, iterated

a) Simulate Construction Sequence
   => extract stresses

b) Apply Measurements
   => extract strains

Neural Network
Constitutive Soil Model

3. Forward FEM analysis with trained NN material model

and/or

Next excavation stage

Similar excavations
Synthetic “Field” Measurements

- B/2 = 20 m
- H = 15 m
- Support Spacing = 2.5 m
- Diaphragm Wall
  - Thickness = 0.9 m
  - E = 2.3 \times 10^4 \text{ MPa}
  - \nu = 0.2

Lateral Wall Deflection (cm)

Distance behind the wall (m)

MIT-E3 "Field" Measurements

Surface Settlement (cm)

Support Spacing = 2.5 m

Diaphragm Wall

Thickness = 0.9 m

E = 2.3 \times 10^4 \text{ MPa}

\nu = 0.2
No SelfSim training
SelfSim training

Lateral Wall Deflection (cm) vs. Distance behind the wall (m)

Training: Pass #1 using Exc. depth = 2.5m data

Surface Settlement (cm) as a function of Depth (m)

Training: Pass #1 using all Exc. depth = 2.5m data
SelfSim training

Lateral Wall Deflection (cm) vs. Distance behind the wall (m)

Training: Pass #1 - using Exc. depth=5m data

Surface Settlement (cm)

Depth (m)
SelfSim training

Lateral Wall Deflection (cm) vs. Distance behind the wall (m)

Surface Settlement (cm) vs. Depth (m)

Training: Pass #1
- using Exc. depth=10m data
SelfSim training

Lateral Wall Deflection (cm)

Distance behind the wall (m)

Surface Settlement (cm)

Training: Pass #1
using Exc.depth=12.5m data

Training: Pass #1
using Exc.depth=12.5m data
SelfSim training

Lateral Wall Deflection (cm) vs. Distance behind the wall (m)

Training: Pass #1 using all Exc. data

Surface Settlement (cm) at various Depths (m): 2.5, 5.0, 7.5, 10, 12.5, 15, 20, 25, 30, 35, 40

Training: Pass #1 using all Exc. data
SelfSim training

Lateral Wall Deflection (cm)

Distance behind the wall (m)

Training: Pass #2
using all Exc. data

Surface Settlement (cm)

Training: Pass #2
using all Exc. data

Depth (m)
SelfSim training

Lateral Wall Deflection (cm) vs. Distance behind the wall (m)

Training: Pass #4 using all Exc. data

Depth (m)

Surface Settlement (cm)
SelfSim training

Lateral Wall Deflection (cm) vs Distance behind the wall (m)

Training: Pass #6 using all Exc. data

Depth (m)

Surface Settlement (cm)

Training: Pass #6 using all Exc. data
SelfSim training

Lateral Wall Deflection (cm)

Distance behind the wall (m)

Training: Pass #8 using all Exc. data

Depth (m)

Surface Settlement (cm)

Training: Pass #8 using all Exc. data
Evaluate a Trained NN model

Distance from Diaphragm Wall, x (m)

Support Spacing
h=2.5m

Diaphragm Wall
Length, L=40m
Thickness, t =0.9m
E = 2.3x10^4 MPa
ν =0.2

SelfSim Analysis

Stress and Strain

Simulate Laboratory Tests

Distance from Diaphragm Wall, x (m)

Support Spacing
h=2.5m

Diaphragm Wall
Length, L=40m
Thickness, t =0.9m
E = 2.3x10^4 MPa
ν =0.2

Distance behind wall (m)

Surface Displacement (mm)

Depth (m)

NN
MIT E-3
Plane Strain Tests (PST)

- SelfSim
  - MITE3 OCR1.0
  - SelfSim Elastic Pre-train

- Secant Modulus, $(\delta \sigma_1 - \delta \sigma_3) / 2 \sigma_0^\gamma$

- Maximum Shear Strain, $\gamma$ (%)
SelfSim Training

Case 1
Distance behind the wall (m)

Case 2
Distance behind the wall (m)

Case 3
Distance behind the wall (m)

Surface Settlement (cm)

Lateral Wall Deflection (cm)

Case 1 after training with all three cases

Case 2 after training with all three cases

Case 3 after training with all three cases

40 m Flexible Wall

30 m Stiff Wall

40 m Flexible Wall

Soil behavior to be learned

Distance behind the wall (m)

Depth (m)

Exc. Depth (m)

Surface Settlement (cm)

Lateral Wall Deflection (cm)

h_s = 2.5 m
B/2 = 20 m

h_s = 5.0 & 2.5 m
B/2 = 30 m

h_s = 2.5 & 5.0 m
B/2 = 40 m
SelfSim Training

**Case 1**

- **Distance behind the wall (m)**
- **Surface Settlement (cm)**
- **Lateral Wall Deflection (cm)**
- **Depth (m)**

- **Soil behavior to be learned**
  - $h_s = 2.5m$
  - $B/2 = 20m$

**Case 2**

- **Distance behind the wall (m)**
- **Surface Settlement (cm)**
- **Lateral Wall Deflection (cm)**
- **Depth (m)**

- **Soil behavior to be learned**
  - $h_s = 5.0 \& 2.5m$
  - $B/2 = 30m$

**Case 3**

- **Distance behind the wall (m)**
- **Surface Settlement (cm)**
- **Lateral Wall Deflection (cm)**
- **Depth (m)**

- **Soil behavior to be learned**
  - $h_s = 2.5 \& 5.0m$
  - $B/2 = 40m$

**Exc. Depth (m)**

Case 1 after training with all three cases

Case 2 after training with all three cases

Case 3 after training with all three cases
SelfSim Training

Case 1
Case 2
Case 3

Distance behind the wall (m)

Surface Settlement (cm)

Lateral Wall Deflection (cm)

Soil behavior to be learned

40m Flexible Wall

h_s=2.5m
B/2=20m

12.5
7.5
10
15

30m Stiff Wall

h_s=5.0 & 2.5m
B/2=30m

12.5
7.5
10
15

40m Flexible Wall

h_s=2.5 & 5.0m
B/2=40m

12.5
7.5
10
15

Surface Settlement (cm)

Depth (m)

Ex. Depth (m)
SelfSim Training

**Case 1**
- Distance behind the wall (m)
- Surface Settlement (cm)
- Lateral Wall Deflection (cm)
- Depth (m)
- Soil behavior to be learned
- hₜ = 2.5m
- B/2 = 20m
- Exc. Depth (m)

**Case 2**
- Distance behind the wall (m)
- Surface Settlement (cm)
- Lateral Wall Deflection (cm)
- Depth (m)
- Soil behavior to be learned
- hₜ = 5.0 & 2.5m
- B/2 = 30m
- Exc. Depth (m)

**Case 3**
- Distance behind the wall (m)
- Surface Settlement (cm)
- Lateral Wall Deflection (cm)
- Depth (m)
- Soil behavior to be learned
- hₜ = 2.5 & 5.0m
- B/2 = 40m
- Exc. Depth (m)
Prediction of New Case

Lateral Wall Deflection (cm)

Distance behind the wall (m)

Depth (m)

Soil behavior to be learned

h = 2.5m
B/2 = 20m
Prediction of New Case after Case 1

Soil behavior to be learned

Prediction of "New" Case after training with Case 1

Depth (m)

Lateral Wall Deflection (cm)

Distance behind the wall (m)

Surface Settlement (cm)
Prediction of New Case after Case 1 & 2

Lateral Wall Deflection (cm)

Depth (m)

Surface Settlement (cm)

Distance behind the wall (m)

Soil behavior to be learned

h_s = 2.5m
B/2 = 20m
Prediction of New Case after Case 1,2&3

Soil behavior to be learned after training with all three cases.
LURIE RESEARCH CENTER
(a) Stage 1:  
Exc. +1.5 m

(g) Stage 7:  
Exc. -7.3 m
Simplified Construction Sequence

Stage 0
Reference Configuration
Stage 1
Undrained Excavation
16 days dewatering
Stage 2
Installation
Tieback 1
Stage 3
Undrained Excavation
86 days dewatering
Stage 4
Installation
Tieback 2
Stage 5
Undrained Excavation
38 days dewatering
Stage 6
Installation
Tieback 3
Stage 7
Undrained Excavation
25 days dewatering
No Training

(a) No Training

(b) No Training

<table>
<thead>
<tr>
<th>Exc Stage</th>
<th>Measured</th>
<th>Pre-trained</th>
</tr>
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<tbody>
<tr>
<td>Exc. 1.5 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tieback 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exc. -2.4 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tieback 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exc. -5.8 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tieback 3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exc. -7.3 m</td>
<td></td>
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</tbody>
</table>
SelfSim Training

(a) 10 Passes of Training

(b) 10 Passes of Training

<table>
<thead>
<tr>
<th>Exc Stage</th>
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<th>SelfSim</th>
</tr>
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<tbody>
<tr>
<td>Exc. 1.5 m</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Tieback 1</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Exc. -2.4 m</td>
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<td>—</td>
</tr>
<tr>
<td>Tieback 2</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Exc. -5.8 m</td>
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<td>—</td>
</tr>
<tr>
<td>Tieback 3</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Exc. -7.3 m</td>
<td>—</td>
<td>—</td>
</tr>
</tbody>
</table>
SelfSim Training

(a) Stage 1: Exc. +1.5 m
(b) Stage 2: Tieback 1
(c) Stage 3: Exc. -2.4 m
(d) Stage 4: Tieback 2
(e) Stage 5: Exc. -5.8 m
(f) Stage 6: Tieback 3
(g) Stage 7: Exc. -7.3 m
SelfSim Training

(a) Stage 1: Exc. +1.5 m
(b) Stage 2: Tieback 1
(c) Stage 3: Exc. -2.4 m
(d) Stage 4: Tieback 2
(e) Stage 5: Exc. -5.8 m
(f) Stage 6: Tieback 3
(g) Stage 7: Exc. -7.3 m
Assessment of extracted soil model

\[(\sigma'_v - \sigma'_h)/2\sigma'_v\]

Extracted Clay Model (SelfSim)
Triaxial tests (Holman, 2005)
Elastic Pre-training
Assessment of extracted soil model

\[ \frac{(\sigma'_v - \sigma'_h)}{2\sigma'_v_0} \]

\(\varepsilon_{axial}\) (%)

| Extracted Clay Model (SelfSim) | \--- | \--- |
| Triaxial tests (Holman, 2005) | + | + |
| Elastic Pre-training | \--- | \--- |
Concluding Remarks

- Most of the difficult engineering problems are inverse problems.

- Very effective methods can be developed for solving these inverse problems by learning from nature’s problem solving strategies.

- Neural networks, genetic algorithm and fuzzy logic enable development of these methods.

- Soft computing methods use nature’s strategies of reduction in disorder and learning.
Concluding Remarks

- Soft computing methods are fundamentally different from the conventional mathematically based methods.

- Soft computing methods operate with
  - Imprecision tolerance
  - Non-universality
  - Functional non-uniqueness.