Evolutionary Algorithms + Domain Knowledge = Real-World Evolutionary Computation

Using Knowledge and Reasoning to Control Search and Vice-versa

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NFL, Meta-Heuristics & Hybrid SC: Outline

- The NFL
- Tuning or Controlling the Object-Level Problem Solver (PS) with Meta-Heuristics
- Soft Computing Overview
  - SC Components: PR, FL, NN, EA
- Using SC to implement the Meta-Heuristics: Modeling with FL and EA
- Example of Hybrid SC Systems at GE
  - FLC Parameter Tuning by EA
  - FLR and F-CBR Parameter Tuning by EA
  - EA Parameter Setting (by EA) or Control (by FL)
- Conclusions
Off-line Meta-Heuristics

- Meta-Level PS
- Performance of Object-level PS
- Parameters of Object-level PS
- Object-level Problem Solver (PS)
- Suite of Representative Problems
- Off-line Tuning
- Run-time Parameters for Object-level PS
- Object-level Problem Solver (PS)
- Object-level Problem
- Run-time Environment
Examples of Off-line Meta-heuristics

Meta- Level PS

Object- Level PS

EA
NN
EA
EA
EA
EA

FLC
FLC
Controller
NN
EA
BBN
CBR

Control Problem
Control Problem
Control Problem
Optimiz. Problem
Optimiz. Problem
Classif. Problem
Classif. Problem

Tuning FLC Parameters
Tuning FLC Parameters
Tuning Gain Schedule Parameters
Tuning NN Parameters
Tuning EA Parameters
Evolving Tuning Bayesian Classifiers
Evolving & Tuning CBR Classifiers
Hybrid Soft Computing: FLC Tuned by EAs

Approximate Reasoning
- Probabilistic Models
- Multivalued & Fuzzy Logics
- Fuzzy Systems
- Fuzzy Logic Controllers

Functional Approximation/Randomized Search
- Neural Networks
- Evolutionary Algorithms
- Multivalued Algebras
- Evolution Strategies
- Evolutionary Programs
- Genetic Algorithms

HYBRID FLC/EA SYSTEMS
FLC Generated and Tuned by EA
FLC Tuned by EA - Outline

- Components & Historical Approaches
- Application to Automatic Train Handling (ATH)
- Solution Architecture
- Analysis of Results
- Remarks
FL Controllers Tuned by EAs

• FLC
  - FLC = KB + Inference Engine (with Defuzz.)
  - KB parameters:
    » Scaling factors (SF)
    » Membership Functions (MF)
    » Rule set (RS)

• EA
  - Encoding: binary or real-valued
  - Chromosome: string or table
  - Fitness function: Sum quadratic errors, entropy
  - Operators: one-point crossover, max-min arithmetical crossover, point-radius crossover.
FL Controllers tuned by EAs (cont.)

• Historical Approaches:
  - **Karr 91-93:**
    - Chromosome = concatenation of all termsets.
    - Each value in a termset was represented by 3 binary-encoded parameters.
  - **Lee & Takagi 93:**
    - Chromosome = 1 TSK rule (LHS: memb. fnct. RHS pol.)
    - Binary encoding of 3-parameter repr. of each term
  - **Surman et al: 93:**
    - Fitness function with added entropy term describing number of activated rules
FL Controllers tuned by EAs (cont.)

- **Historical Approaches (cont.):**

  - **Kinzel et al. 94:**
    
    » Chromosome = Rule Table
    
    » Point-radius crossover changing 3x3 rule window (similar to a two-point crossover for string representation)
    
    » Order of tuning:
      
      – Initialize rulebase according to heuristics
      
      – Apply GAs to find best rule table
      
      – Tune membership function of best rule set

  - **Herrera et al. 95:**
    
    » Chromosome = concatenation of all rules
    
    » Real-valued encoding, Max-min arithmetical crossover
SC in Train Handling: An Example

- Problem Description: *Automated Train Handling*
  - Control a massive, distributed system with little sensor information
  - Freight trains consist of several hundred heavy railcars connected by couplers (train length up to two miles)
  - Couplers have a dead zone and a hydraulically damped spring, causing railcars to move relative to each other and train length to change by 50 – 100 ft.
  - The position of the cars and couplers cannot be electronically sensed
SC in Train Handling: An Example

• Solution Requirements
  • An automated system has to satisfy multiple goals:
    - Tracking a velocity reference (defined over distance) to enforce speed limits and respect the train schedule
    - Providing a degree of train-handling uniformity across all crews
    - Operating the train in fuel-efficient regimes
    - Maintaining a smooth ride by avoiding sudden accelerations or brake applications (slack control)

Multi-body regulation problem, subject to proper slack management, without sensors for most of the state
SC in Train Handling: An Example

• Description of Our Approach
  - Use a Velocity Profile externally generated (using classical optimization or Evolutionary Algorithms)
  - Use a Fuzzy Logic Control (FLC) to track the velocity reference (Fuzzy PI Control)
  - Use an Evolutionary Algorithms to tune the FLC parameters to minimize velocity tracking error and number of throttle changes
  - Implement control actions with fuzzy rule set to maintain slack control
FLC tuned by EAs: Our Approach

• Chromosome (real-valued encoding)
  - Chr. 1 = Scaling factors;
  - Chr. 2 = Termsets;
  - Chr. 3 = Rules (not used)

• Order of tuning (as in Zheng '92):
  - Initialize rulebase with standard PI structure and termsets with uniformly distributed terms
  - Apply EAs to find best scaling factors
  - Apply EAs to find best termsets
  - Apply EAs to find best rule set (not used)

• Transition from large to small granularity
# FLC Sensitivity to Parameter Changes

## Changing a Scaling Factor

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<th>Low</th>
<th>Medium</th>
<th>High</th>
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## Changing a Term in X1

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## Changing a Rule

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Architecture: Modules, Fitness Funct.

- **Architecture**
  - EA: pop.size=50; P(cross)=.6; P(mut)=.001
  - Three Types of fitness functions
  - Train Simulator: NSTD (STD+TEM)
  - Fuzzy PI (Ke, Kedot, KΔu)

- **Fitness functions** \((f_1, f_2, f_3)\)

\[
\begin{align*}
  f_1 &= \min \left( \sum_{i} |notch_i - notch_{(i-1)}| + |dynbrake_i - dynbrake_{(i-1)}| \right) \\
  f_2 &= \min \left( \sum_{i} |v_i - v_i^d| \right) \\
  f_3 &= \min \left( \sum_{i} \frac{|notch_i - notch_{(i-1)}|}{K_1} + w_2 \frac{|v_i - v_i^d|}{K_2} \right)
\end{align*}
\]
FLC tuned by GAs

GA (GENESIS) → SF or MF

Fitness Function → Meta-Level PS

Train Simulator → FLC (PI)

Object-Level PS
Experiment Design

• 12 test (4 for each fitness function)
  - Initial SF with initial MF;
  - EA tuned SF with Initial MF
  - Initial SF with EA tuned MF;
  - EA tuned SF with EA tuned MF

• Train Simulation:
  - 14 miles long flat track
  - 1 uniformly heavy train with 100 cars and 4 locomotives
  - Analytically computed velocity profile
Experiment Design

• Representation:
  - SF: 3 floating point values for Ke, Kedot, KΔu
  - MF (21-9) = 12 values
    » 21 parameters: [(Left\(i\), Center\(i\), Right\(i\)) for \(i=1, \ldots, 7\)]
    » 9 dependent values: [(Left\(i\) = Right\((i+1)\)) for \(i=1, \ldots, 6\)]
    + [Center\(1\) = Center\(7\)] + [Right\(1\) = Left\(7\) = 0]
  - Constraints to maintain 0.5 terms overlap, for best interpolation
## Experiments Results

### Experiment Results with $f_1$

<table>
<thead>
<tr>
<th>Description</th>
<th>Time</th>
<th>Journey</th>
<th>Fuel</th>
<th>Fitness</th>
<th>Gen.</th>
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<tbody>
<tr>
<td>Initial SF; Initial MF</td>
<td>26.5</td>
<td>14.26</td>
<td>878</td>
<td>73.2</td>
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<tr>
<td>EA tuned SF; Initial MF</td>
<td>27.8</td>
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<td>14.64</td>
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### Experiment Results with $f_3$

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Tuning of FLC with EA: Remarks

• Verified tuning order proposed by Zheng (92)
  » SF tuning: major impact
  » MF tuning: minor impact
  » RS tuning: almost no impact

• For both f1 and f3, fuel minimization is implicitly derived from throttle jockeying minimization

• Complex fitness function (requiring simulation run - 23 sec for each chromosome evaluation)
  limited trials number - with no apparent impact

• Successfully tested on simulated 43 mile long track with altitude excursions
  » (Selkirk, NY->Framingham, MA)
Results of EA Tuned PI on 43 mile Track
Results of EA Tuned PI on 43 mile Track

- Manually tuned controller
- GA tuned controller

- NOTCH POSITION
  - 8

- reference

- Notch
- Brake

- mile

- Results of EA Tuned PI on 43 mile Track
Results of EA Tuned PI on 43 mile Track
Results of EA Tuned PI on 43 mile Track