

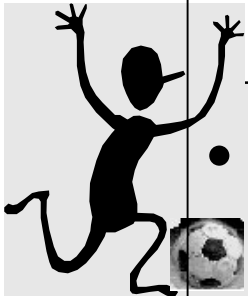
***Evolutionary Algorithms + Domain Knowledge =
Real-World Evolutionary Computation***

***Using Knowledge and Reasoning to Control Search
and Vice-versa***

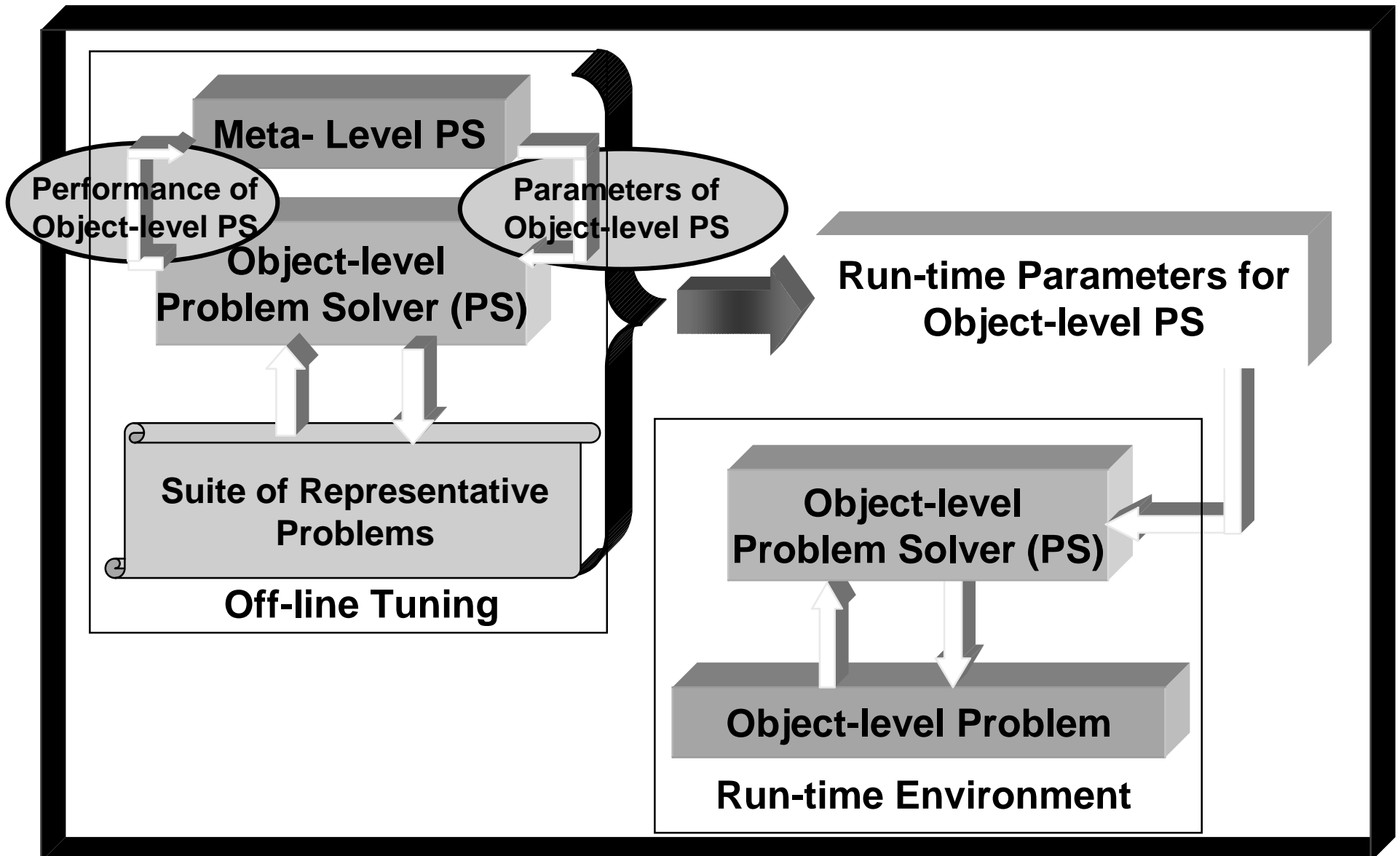
Piero P. Bonissone
GE Global Research Center
bonissone@crd.ge.com

NFL, Meta-Heuristics & Hybrid SC: Outline

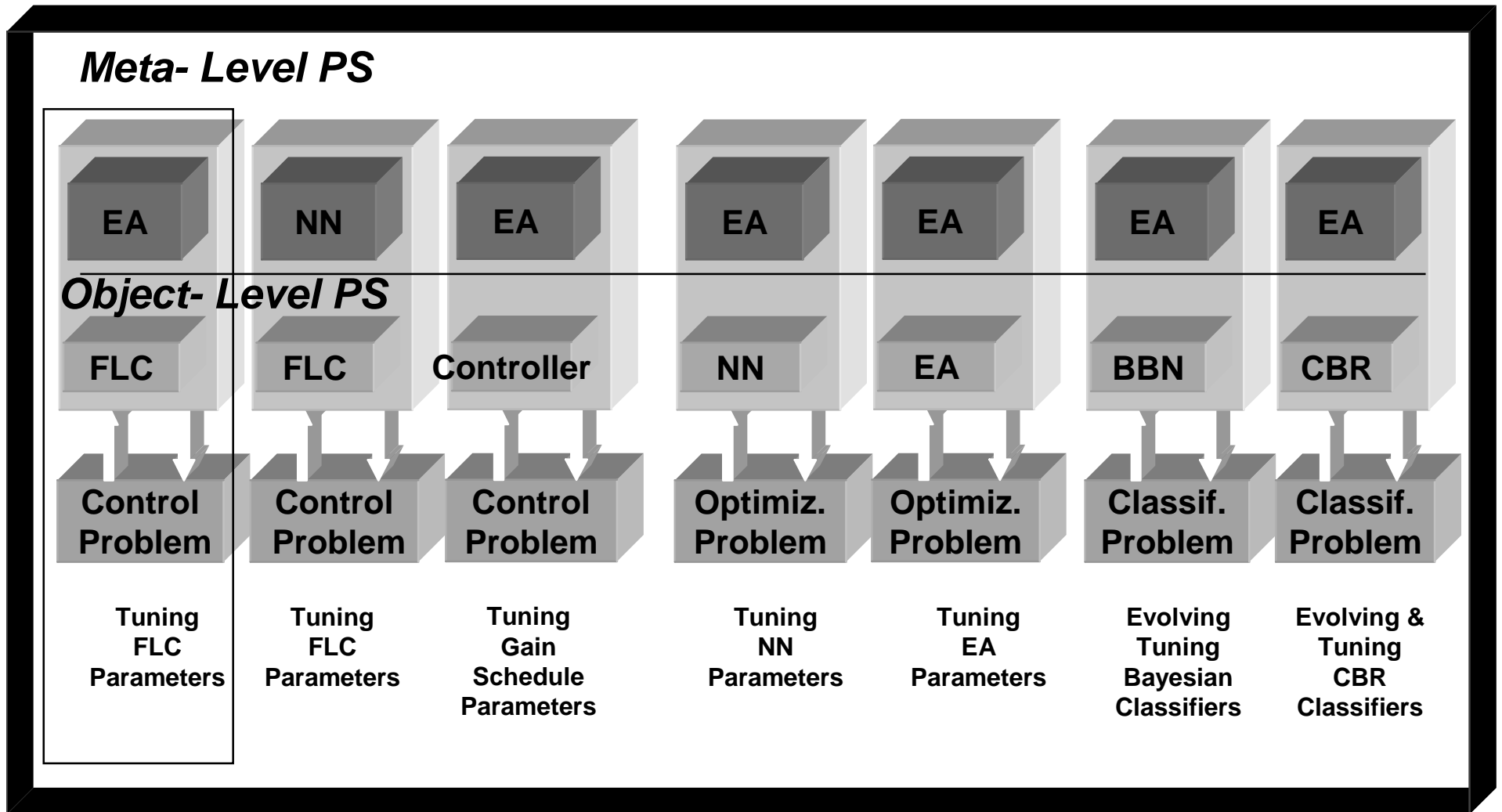
- The NFL
- Tuning or Controlling the Object-Level Problem Solver (PS) with Meta-Heuristics
- Soft Computing Overview
 - SC Components: PR, FL, NN, EA
- Using SC to implement the Meta-Heuristics: Modeling with FL and EA
- **Example of Hybrid SC Systems at GE**
 - **FLC Parameter Tuning by EA**
 - FLR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



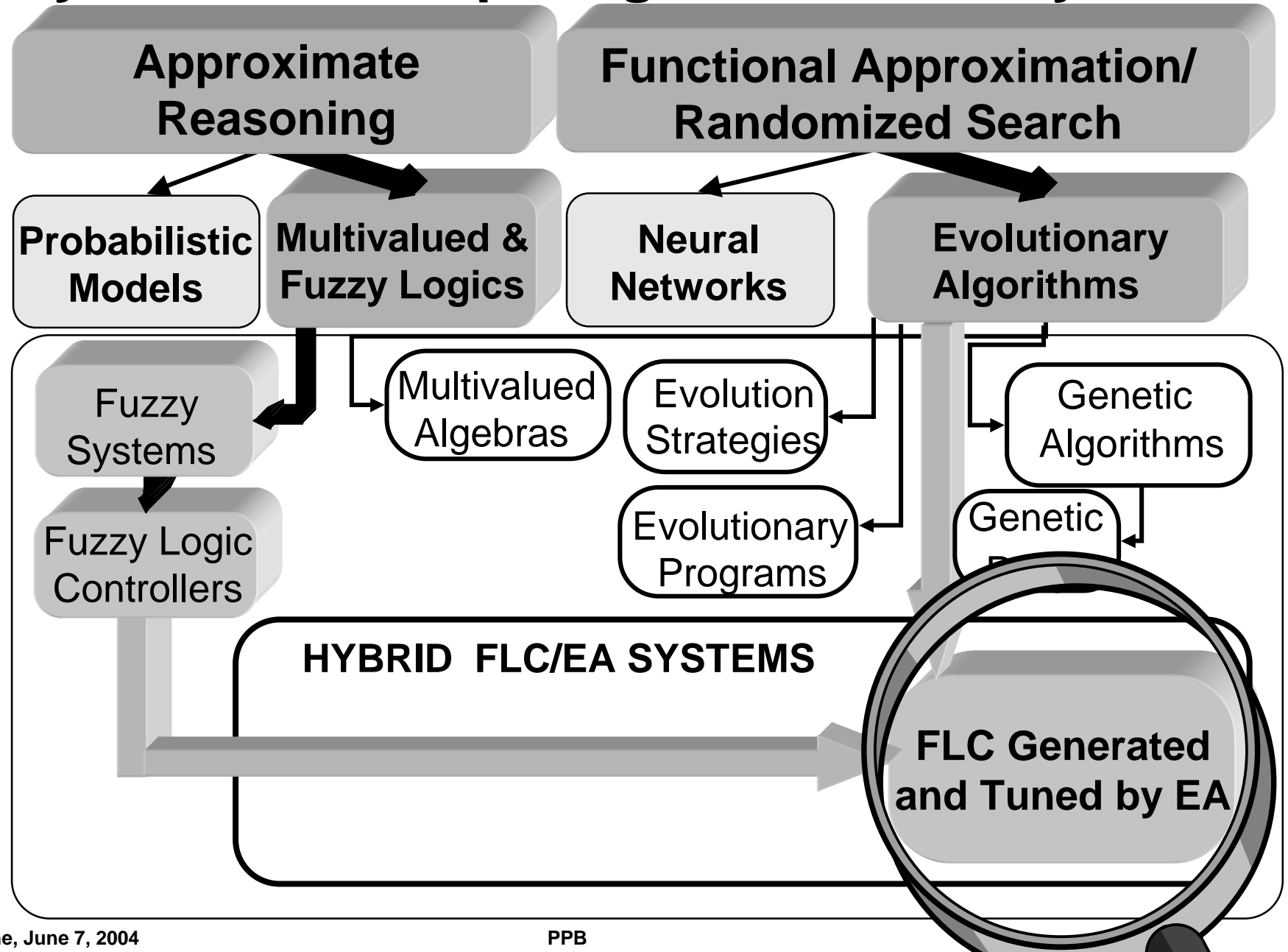
Off-line Meta-Heuristics



Examples of Off-line Meta-heuristics



Hybrid Soft Computing: FLC Tuned by EAs



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. fct. 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

X1	X2				
	<i>Very Low</i>	<i>Low</i>	<i>Medium</i>	<i>High</i>	<i>Very High</i>
<i>Very Low</i>	PH	PH	PM	PL	ZE
<i>Low</i>	PH	PM	PL	ZE	NL
<i>Medium</i>	PM	PL	ZE	NL	NM
<i>High</i>	PL	ZE	NL	NM	NH
<i>Very High</i>	ZE	NL	NM	NH	NH

Changing a Term in X1

X1	X2				
	<i>Very Low</i>	<i>Low</i>	<i>Medium</i>	<i>High</i>	<i>Very High</i>
<i>Very Low</i>	PH	PH	PM	PL	ZE
<i>Low</i>	PH	PM	PL	ZE	NL
<i>Medium</i>	PM	PL	ZE	NL	NM
<i>High</i>	PL	ZE	NL	NM	NH
<i>Very High</i>	ZE	NL	NM	NH	NH

Changing a Rule

X1	X2				
	<i>Very Low</i>	<i>Low</i>	<i>Medium</i>	<i>High</i>	<i>Very High</i>
<i>Very Low</i>	PH	PH	PM	PL	ZE
<i>Low</i>	PH	PM	PL	ZE	NL
<i>Medium</i>	PM	PL	ZE	NL	NM
<i>High</i>	PL	ZE	NL	NM	NH
<i>Very High</i>	ZE	NL	NM	NH	NH

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)

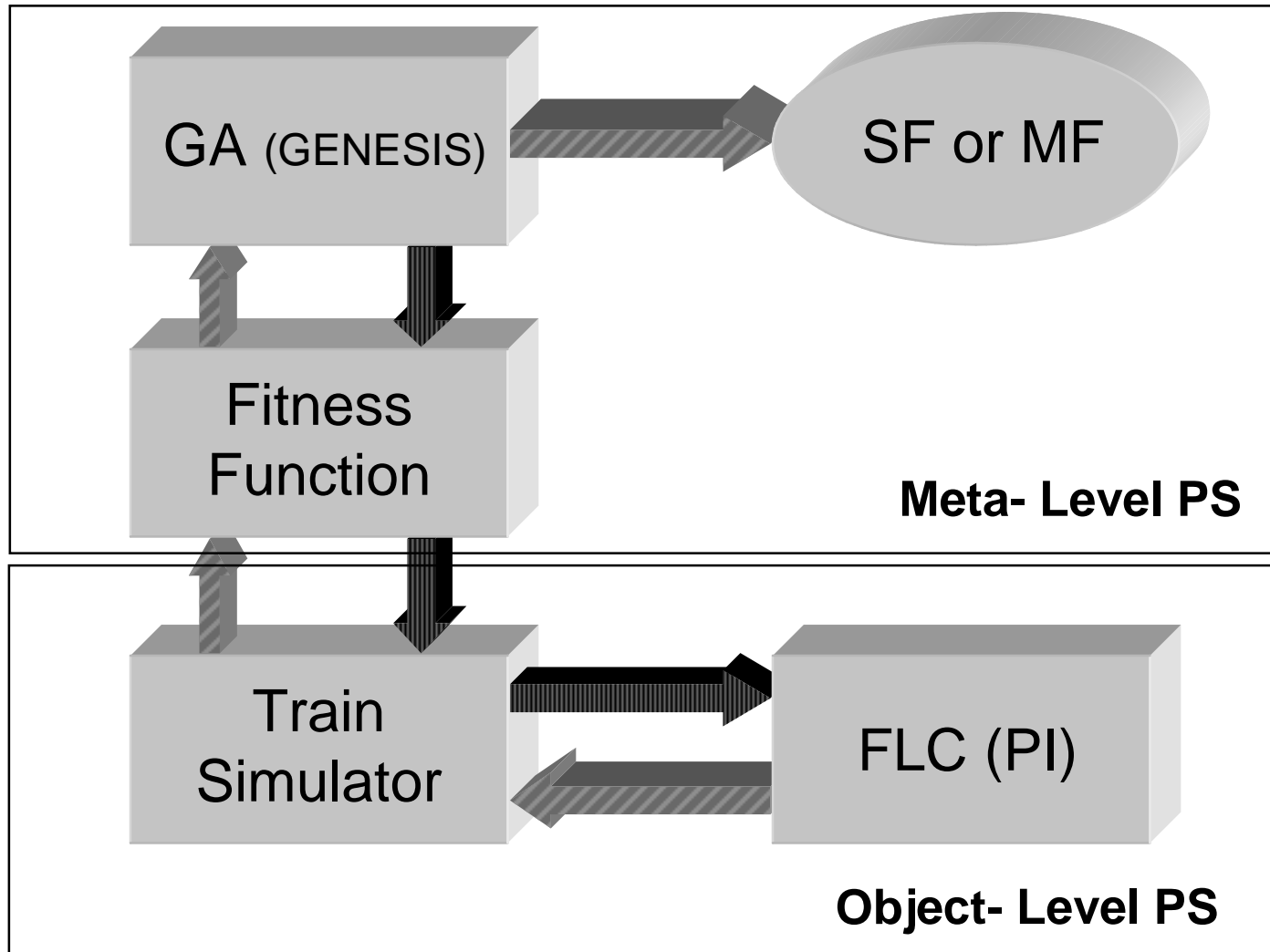
- **Fitness functions (f_1, f_2, f_3)**

$$f_1 = \min\left(\sum_i |notch_i - notch_{(i-1)}| + |dynbrake_i - dynbrake_{(i-1)}|\right)$$

$$f_2 = \min\left(\sum_i |v_i - v_i^d|\right)$$

$$f_3 = \min\left(w_1 \frac{\sum_i |notch_i - notch_{(i-1)}|}{K_1} + w_2 \frac{(\sum_i |v_i - v_i^d|)}{K_2}\right)$$

FLC tuned by GAs



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 K_e , K_{edot} , $K\Delta u$**
- **MF (21-9) = 12 values**

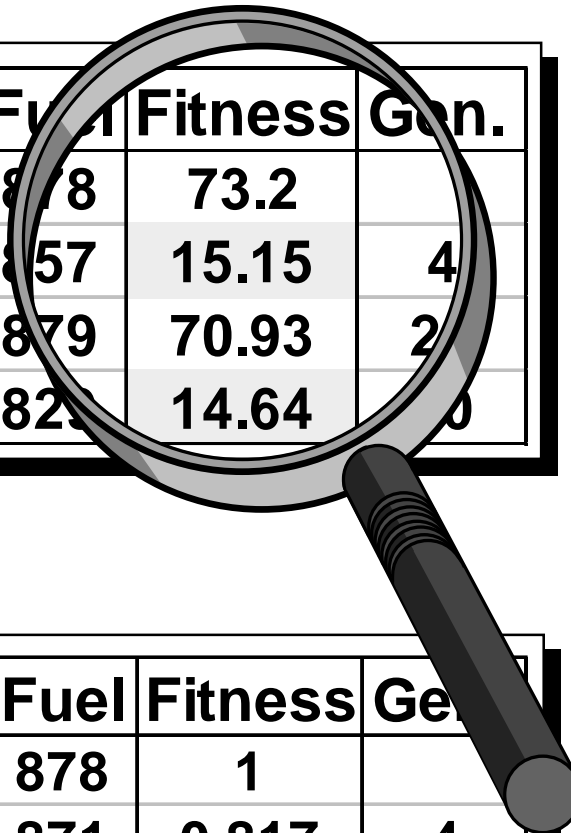
» 21 parameters: $[(Left_i, Center_i, Right_i)]$ for $i=1, \dots, 7]$
» 9 dependent values: $[(Left_i = Right_{(i+1)})]$ for $i=1, \dots, 6]$
+ $[Center_1 = Center_7] + [Right_1 = Left_7 = 0]$

- **Constraints to maintain 0.5 terms overlap, for best interpolation**

Experiments Results

- Experiment Results with f_1

Description	Time	Journey	Fuel	Fitness	Gen.
Initial SF; Initial MF	26.5	14.26	878	73.2	
EA tuned SF; Initial MF	27.8	14.21	857	15.15	4
Initial SF; EA tuned MF	26.00	14.18	879	70.93	20
EA tuned SF; EA tuned MF	28.3	14.12	825	14.64	10



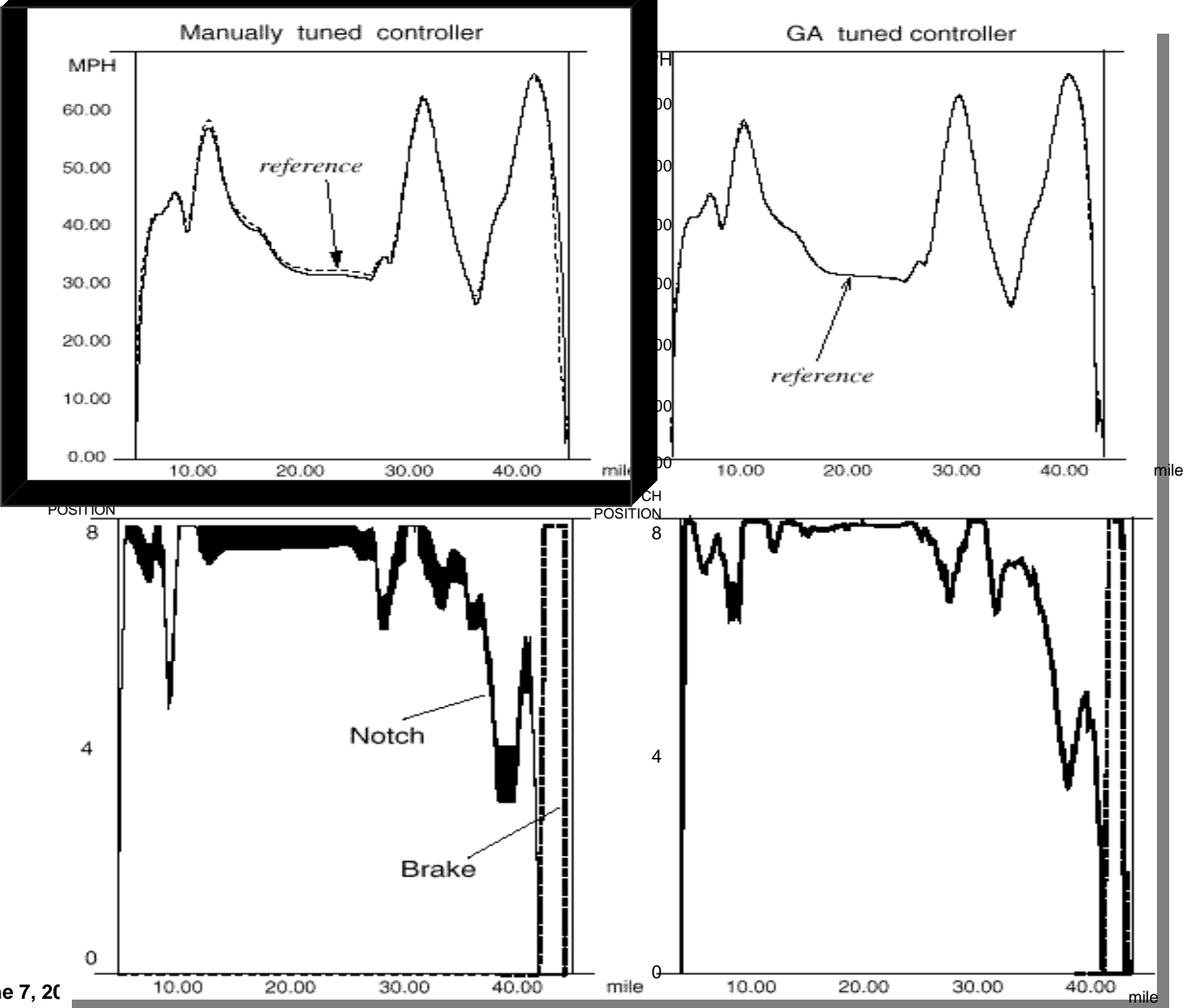
- Experiment Results with f_3

Description	Time	Journey	Fuel	Fitness	Gen.
Initial SF; Initial MF	26.5	14.26	878	1	
EA tuned SF; Initial MF	27.2	14.35	871	0.817	4
Initial SF; EA tuned MF	26.26	14.18	871	0.942	20
EA tuned SF; EA tuned MF	27.3	14.35	872	0.817	10

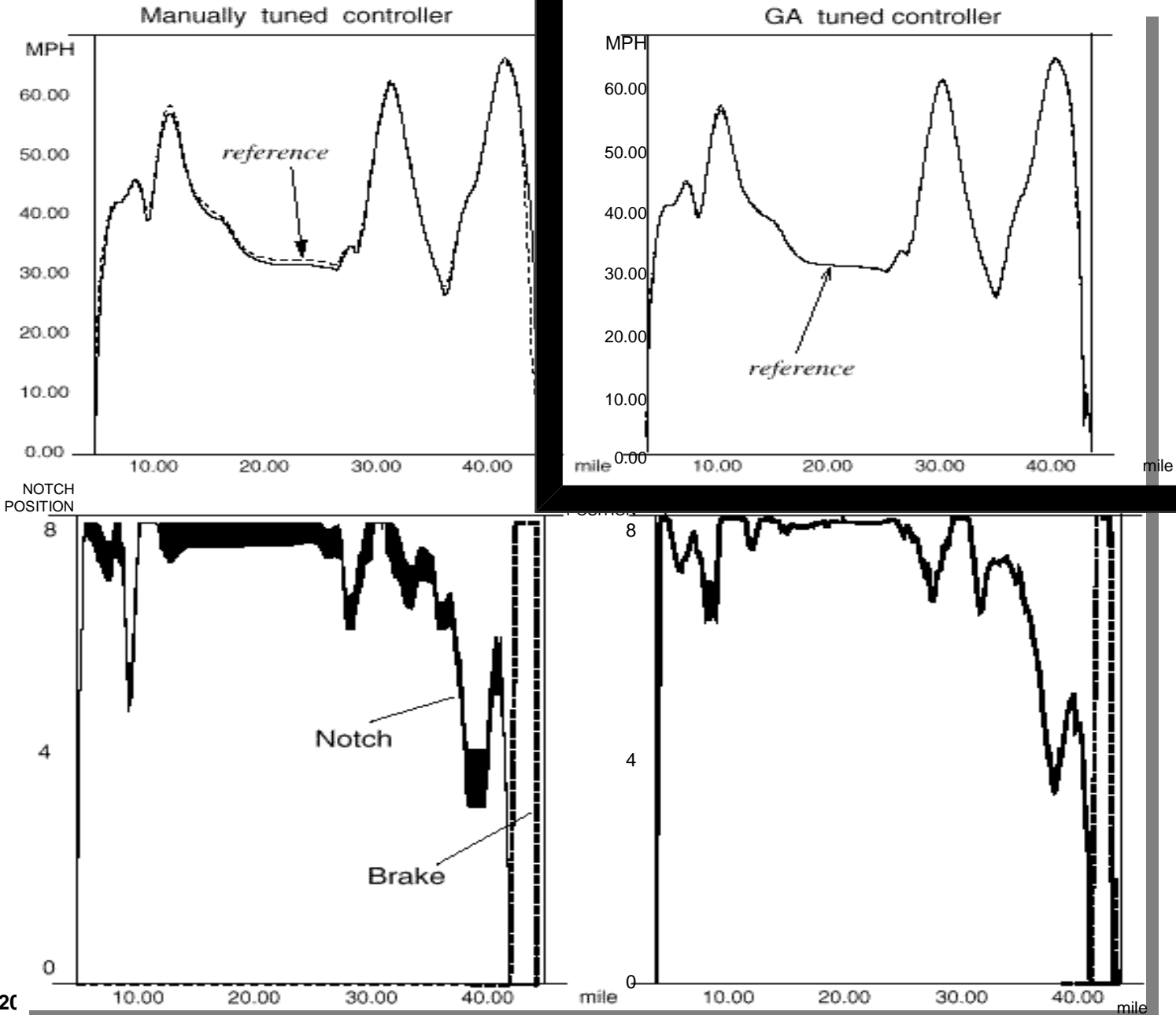
Tuning of FLC with EA: Remarks

- 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)

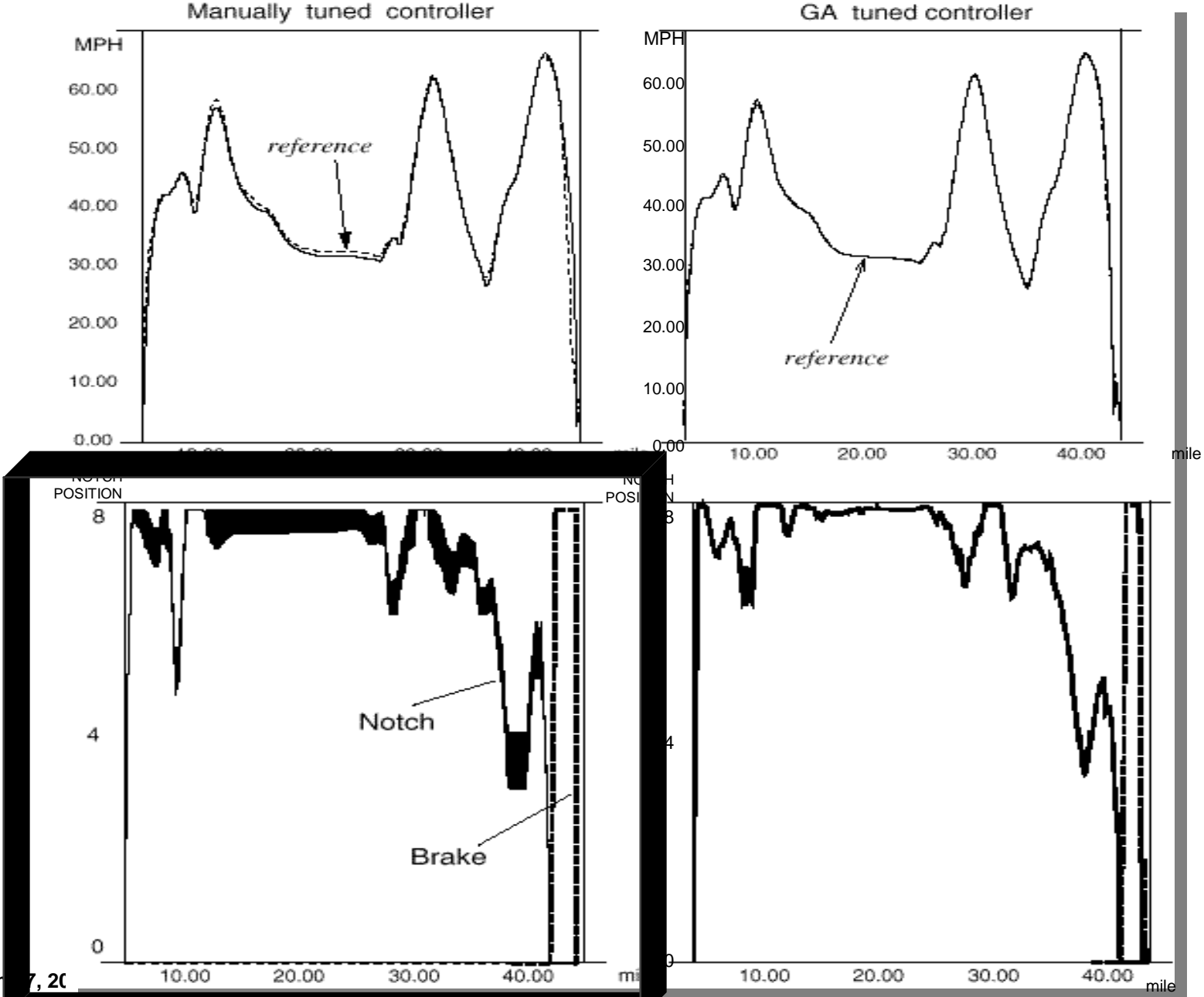
Results of EA Tuned PI on 43 mile Track



Results of EA Tuned PI on 43 mile Track



Results of EA Tuned PI on 43 mile Track



Results of EA Tuned PI on 43 mile Track

