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E009: Educational Materials and Learning Paths

DIP-SMC-PSO Educational Series

January 25, 2026

Overview

This episode covers educational materials and learning paths from the DIP-SMC-PSO project.

Part: Part2 Infrastructure

Duration: 15-20 minutes

Source: Comprehensive Presentation Materials

section0 Particle Swarm Optimization: Overview

Inspiration: Social behavior of bird flocking, fish schooling

Algorithm: Population-based stochastic optimization

- **Particles:** Candidate solutions in search space - **Velocity:** Direction and speed of movement - **Personal best:** Best solution found by each particle - **Global best:** Best solution found by entire swarm

Update Equations: $\mathrm{v}_i^{(t+1)} = wv_i^{(t)} + c_1 r_1(p_i - x_i^{(t)}) + c_2 r_2(g - x_i^{(t)})$
$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}$

where:

- w – Inertia weight (0.729) - c_1, c_2 – Cognitive/social coefficients (1.494 each) - r_1, r_2 – Random numbers $\in [0, 1]$ - p_i – Personal best, g – Global best

section0 PSO for Controller Gain Tuning

Objective: Find optimal controller gains to minimize cost function

Search Space: Controller gains (6-dimensional for classical SMC)

$$equation\mathbf{x} = [k_1, k_2, \lambda_1, \lambda_2, K, \epsilon] \quad (0)$$

Cost Function (Multi-Objective):

$$equation J = w_1 \cdot ISE + w_2 \cdot t_{settle} + w_3 \cdot \int u^2 dt + w_4 \cdot chattering \quad (0)$$

where:

- $ISE = \int(\theta_1^2 + \theta_2^2)dt$ – Integral squared error - t_{settle} – Settling time - $\int u^2 dt$ – Control effort - chattering – High-frequency energy metric

Complete – Convergence curves, particle trajectories, fitness landscapes

section0 PSO Algorithm Parameters

Default Configuration:

Parameter	**Value**
Number of particles	30
Generations	50-100
Inertia weight (w)	0.729
Cognitive coefficient (c_1)	1.494
Social coefficient (c_2)	1.494
Convergence Criteria:	
Fitness tolerance	10^{-6}
Max stagnation generations	10

Complete – Tested across 100 seeds, validated convergence reliability
Integrated into LT-7 research paper

section0 PSO Convergence Analysis

Typical Convergence Curve:

[Visual diagram - see PDF]

Characteristics:

- **Rapid initial decrease:** Exploration phase (generations 0-30) - **Gradual refinement:** Exploitation phase (generations 30-100) - **Convergence:** Fitness plateau indicates optimal solution found

section0 Optimization Results: Controller Comparison

Optimized Gains (MT-5 Benchmark):

Controller	**Settling Time (s)**	**ISE**	**Energy (J)**
Classical SMC	2.5	0.45	12.3
STA-SMC	2.1	0.38	10.8
Adaptive SMC	2.3	0.41	11.5
Hybrid Adaptive STA	**2.0**	**0.35**	**10.2**

- **Best overall:** Hybrid Adaptive STA-SMC - **Lowest chattering:** STA-SMC - **Fastest convergence:** PSO typically converges in 60-80 generations - **Repeatability:** 95

section0 Alternative Optimization Algorithms

Implemented but not primary:

- **CMA-ES** (Covariance Matrix Adaptation Evolution Strategy)
- Better for high-dimensional problems - ‘src/optimization/algorithms/cma_es.py‘
- **Differential Evolution (DE)**
- Simple, robust global optimizer - ‘src/optimization/algorithms/differential_evolution.py‘
- **Genetic Algorithm (GA)**
- Classic evolutionary approach - ‘src/optimization/algorithms/genetic_algorithm.py‘

PSO is primary method (best performance for this application)
Other algorithms available for research/comparison

Resources

- **Repository:** `https://github.com/theSadeQ/dip-smc-pso.git`
- **Documentation:** See `docs/` directory
- **Getting Started:** `docs/guides/getting-started.md`

Educational podcast episode generated from comprehensive presentation materials