Development of Integrated Biomimetic Framework with Intelligent Monitoring, Cognition, and Decision Capabilities for Control of Advanced Energy Plants

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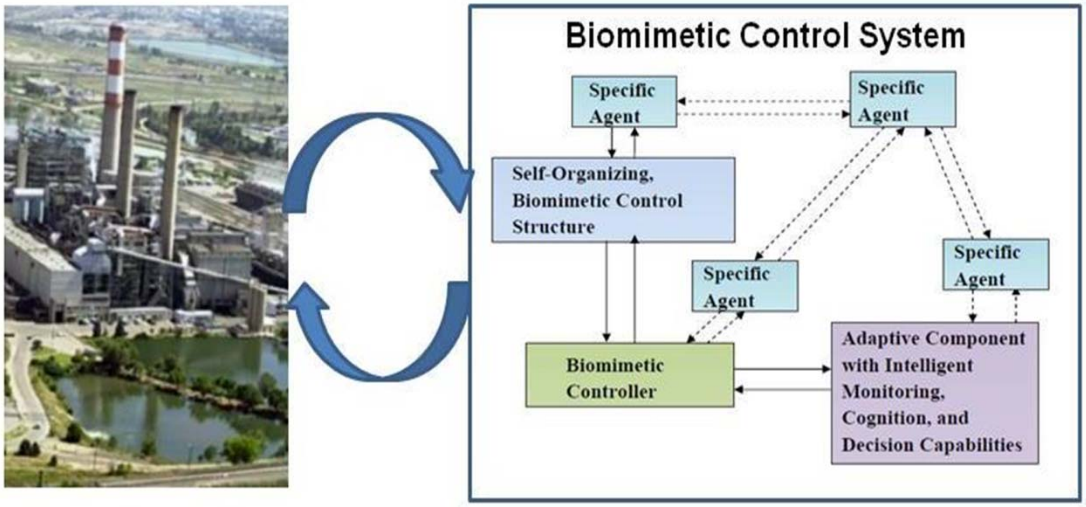
Challenges in Modern Control

- Fast changing and highly interacting process dynamics
- Operation under large number of constraints with evolving boundary
- Agile plant operation quickly adapting to changing requirements
- Short-term vs long term operational objectives
- Highly conflicting control objectives –profit vs environmental performance vs equipment life vs plant availability

Our Approach



- Self-organization of the control structure that mimics the function of the cortical areas of human brain
- Distributed and adaptive controllers that mimic the rule of pursuit present in ants
- Intelligent monitoring, cognition, and decision capabilities that mimic the immune system
- Seamless integration and coordination in the entire framework that includes both the control structures and the controllers by mimicking the central nervous system

Tasks and the Team

Kickoff: 1/15/2014

Tasks:

Task 2.0 Development of Algorithms for Biomimetic, Self-Organizing Control Structure Selection
Team: Profs. Turton, Bhattacharyya, and PhD student Temitayo Bankole

Task 3.0 Development and Implementation of Biomimetic Controller Design Method
Team: Prof. Lima, and PhD student Gaurav Mirlekar

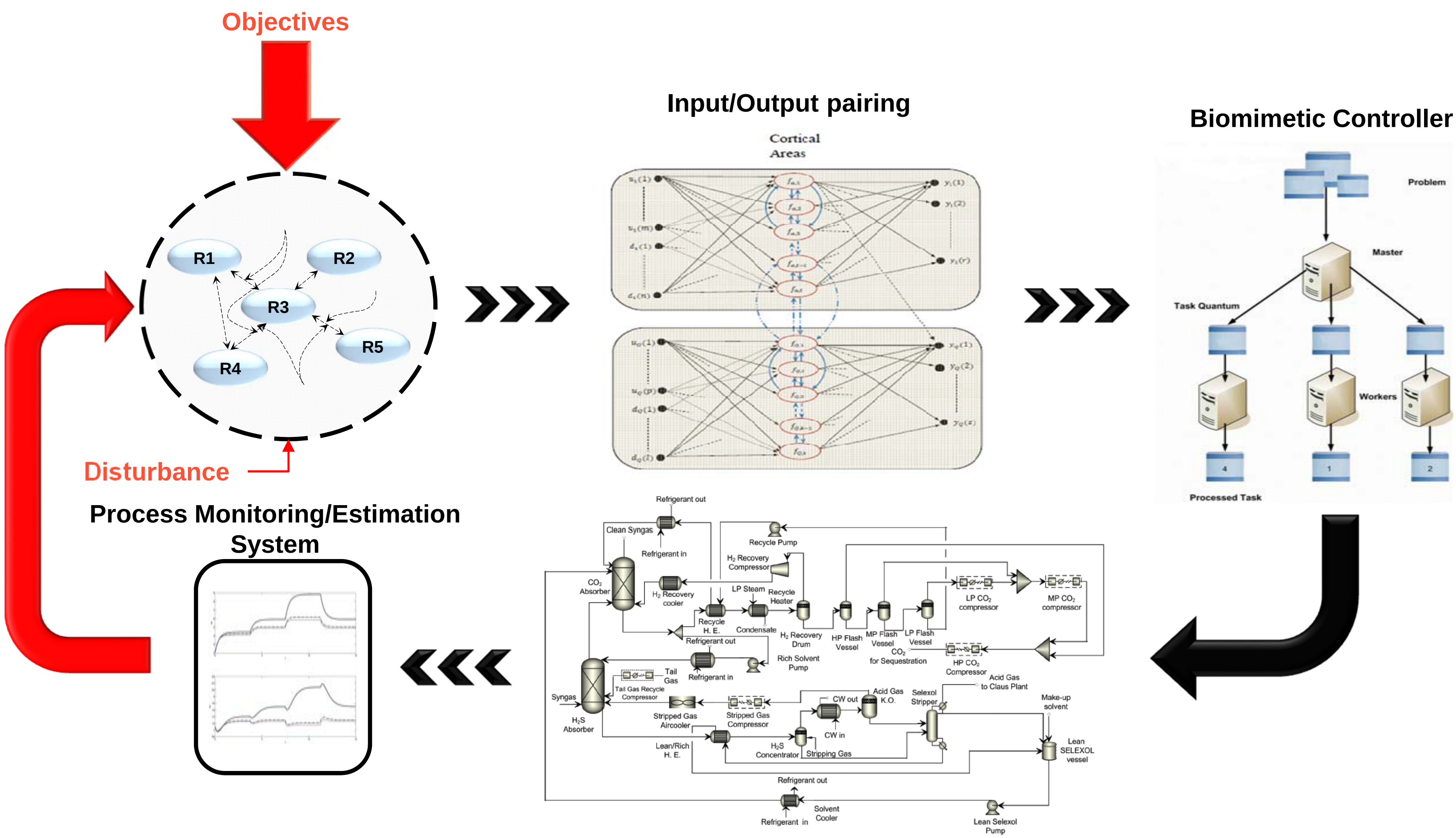
Task 4.0 Development of Biomimetic Adaptive Controllers with Intelligent Monitoring, Cognition, and Decision Capabilities
Team: Prof. Perhinschi, and PhD student Ghassan Al-Sinbol

Task 5.0 Development of a Multi-Agent Optimization Framework for Control Structure Design, and State and Parameter Estimation
Team: Prof. Diwekar, and post-doctoral fellow Berhane Gebreslassie

Task 2.0 Development of Algorithms for Biomimetic, Self-Organizing Control Structure Selection

Task 2.1 Development of Dynamic Causal Model (Q1-Q8)

- Exploits the functional specialization and integration that characterizes the cortical/sub-cortical areas of human brain

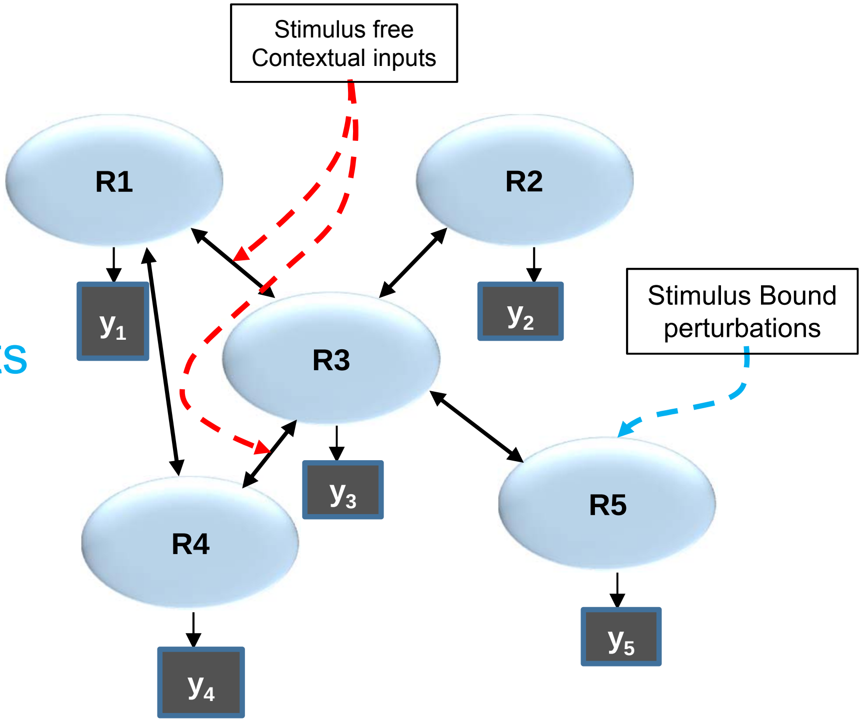


Dynamic Causal Modeling

- Latent connectivity
- Induced Connectivity
- Extrinsic influence of inputs

$$\dot{z} = \left(A + \sum_j u_j B^j\right) z + Cu$$

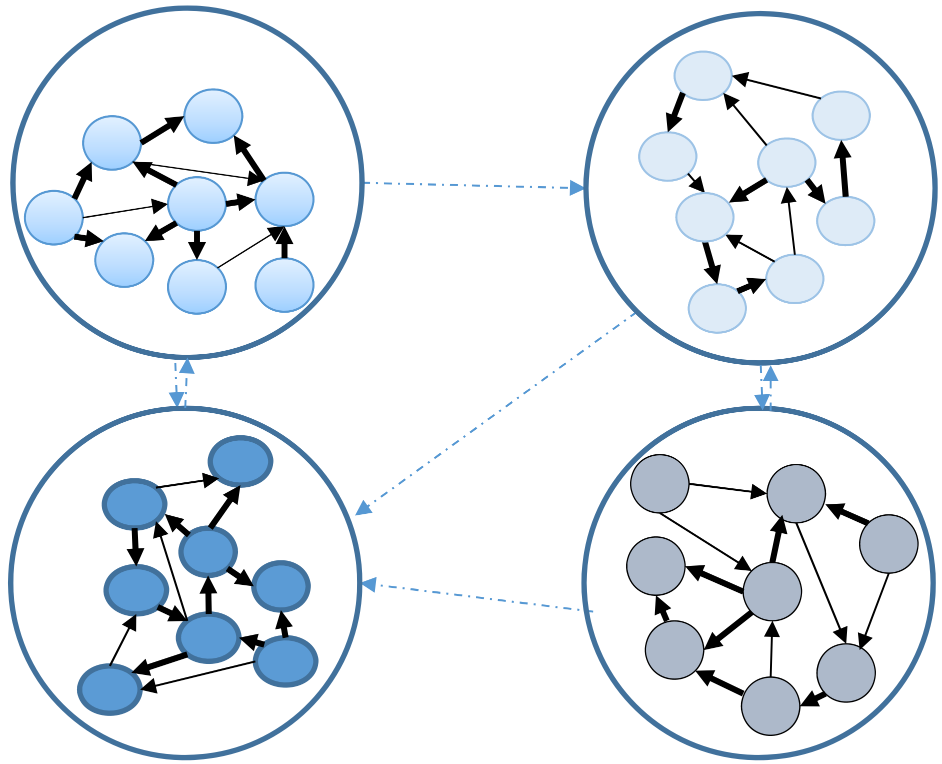
$$\hat{\theta} = \{A, B^j, C\}$$



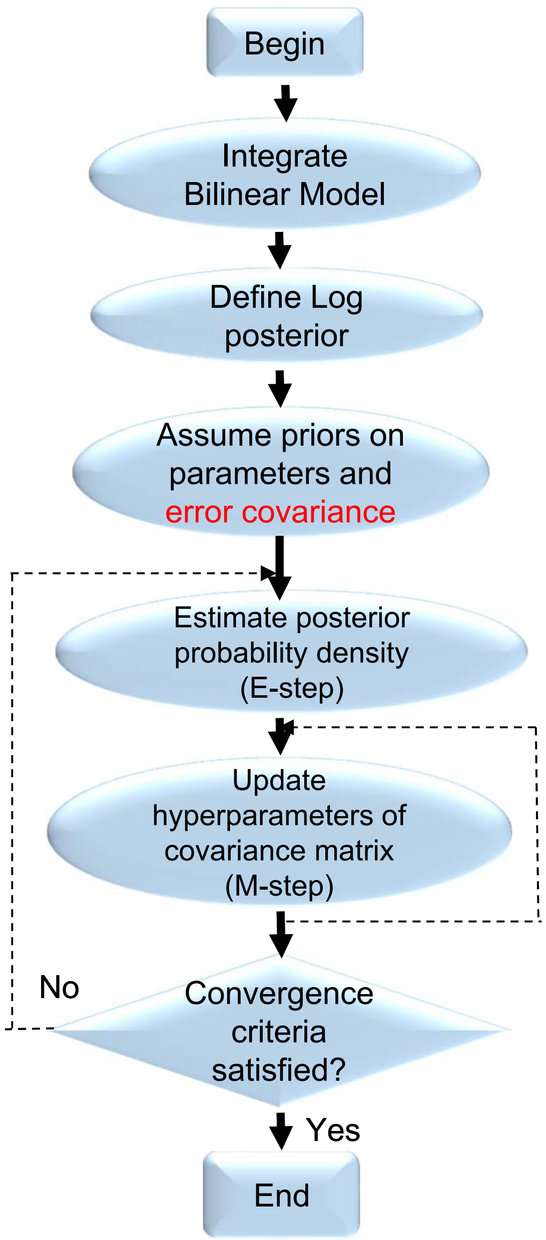
Friston, K J., Lee H., and Will P., "Dynamic causal modelling."Neuroimage 19.4 (2003): 1273-1302.

Dynamic Selection of Controlled Variables

- Establish levels of connectivity between plant sections (islands)
- Separate islands based on connectivity
- Parallelize controlled variable selection
- Reduction of combinatorial problem of controlled variable selection
- Controlled/manipulated variable selection



Methodology



$$Y(t_f) = Y(\mathrm{T}\Delta t) = \prod_{k=0}^{T-1} exp\left(\Delta t\left(A + \sum_{j=1}^{M} B^j u_j(k\Delta t)\right)\right) Y(0)$$

$$l = \ln p(y|\theta, \lambda; u) + \ln p(\theta; u)$$

$$C_\theta = \mathrm{diag}\{\eta_\theta\}, C_\epsilon = \sum \lambda_j Q_j$$

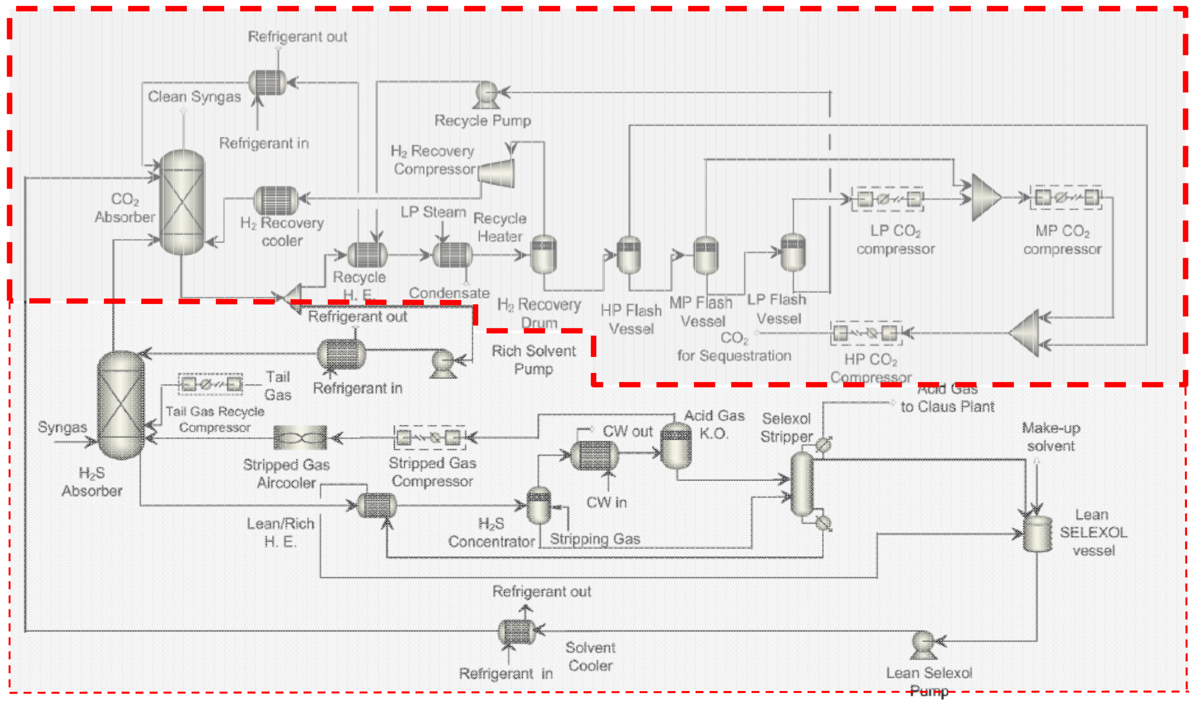
$$\eta_{\theta|y} \leftarrow \eta_{\theta|y} - \langle \frac{\partial^2 l}{\partial \theta^2} \rangle^{-1} \frac{\partial l(\eta_{\theta|y})}{\partial \theta}$$

$$\lambda = \lambda - \langle \frac{\partial^2 F}{\partial \lambda^2} \rangle^{-1} \frac{\partial F(\lambda)}{\partial \lambda}$$

where $F = \int q(\theta) \ln \frac{p(\theta, y|\lambda; u)}{q(\theta)} d\theta$

Acid Gas Removal Unit

- CO_2 Absorber section
  - CO_2 absorption
  - H_2 recovery
  - CO_2 recovery
  - Lean solvent recycle
  - CO_2 sequestration



- H_2S Absorber/Selexol stripper section
  - H_2S absorption
  - H_2S recovery
  - Selexol stripping/recovery

- 32 independent input variables
- 38 independent output variables
- 250 data points collected

Results: CO_2 Absorber section

Strong connectivity from:

- CO_2 absorber to H_2S absorber
- H_2 recovery drum to CO_2 absorber
- LP flash drum to CO_2 absorber

Weak connectivity from:

- CO_2 absorber to HP flash

Strong connectivity from:

- HP flash to MP flash
- MP flash to LP flash
  - Due to *H_2 vapor only*

			CO_2 Absorber	HP flash	MP flash	LP flash	H_2S absorber
CO_2 Absorber	H_2S	Vapor					
		Liquid					
	CO_2	Vapor					
		Liquid					
	T						
H_2 recovery drum	H_2S	Vapor					
		Liquid					
	CO_2	Vapor					
		Liquid					
	T						
HP flash	H_2	Vapor					
		Liquid					
	CO_2	Vapor					
		Liquid					
	T						
MP flash	H_2	Vapor					
		Liquid					
	CO_2	Vapor					
		Liquid					
	T						
LP flash	H_2	Vapor					
		Liquid					
	CO_2	Vapor					
		Liquid					

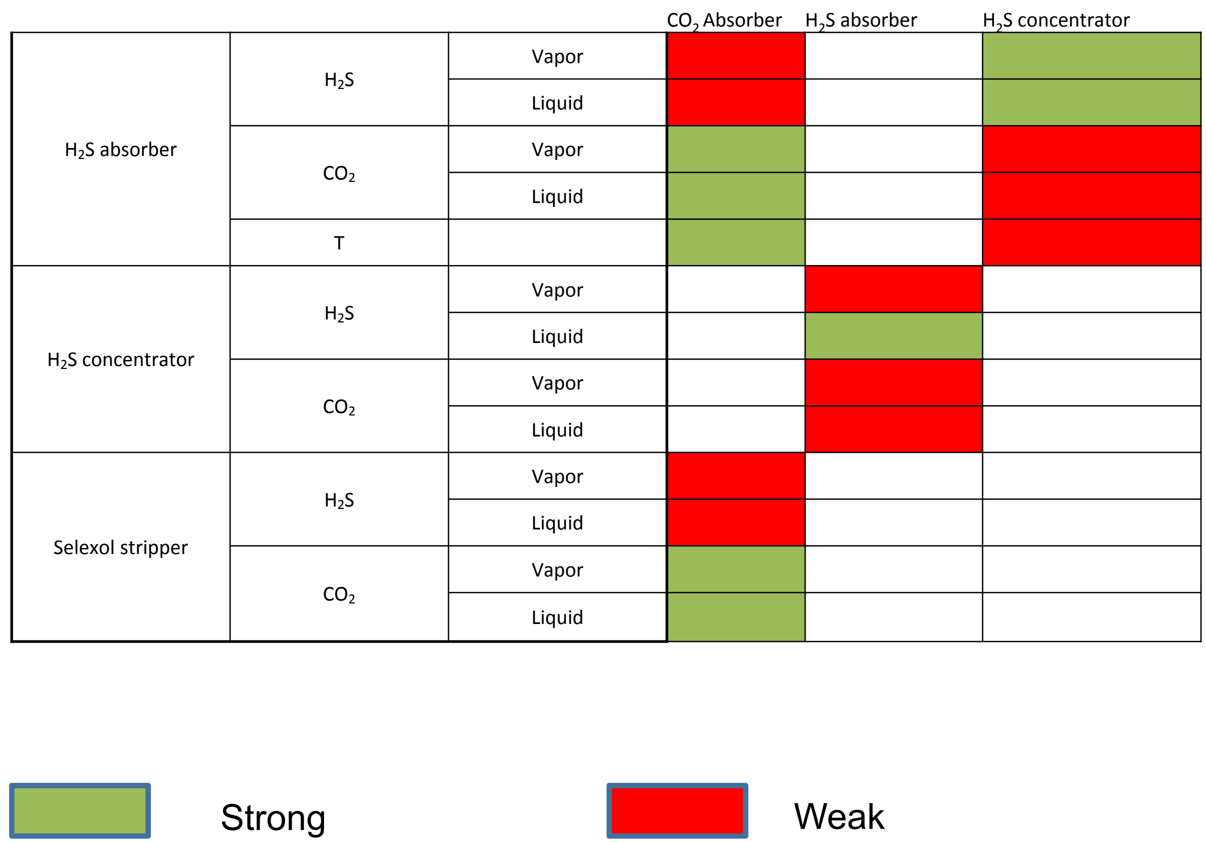
Strong

Weak

Results: H_2S Absorber section

Strong connectivity from:

- H_2S absorber to CO_2 absorber due to *CO_2 and T only*
- H_2S absorber to H_2S concentrator due to *H_2S only*
- H_2S concentrator to H_2S absorber due to *H_2S (liquid) only*
- Selexol Stripper to H_2S absorber due to *CO_2 only*



Year 3 Tasks (Task 2)

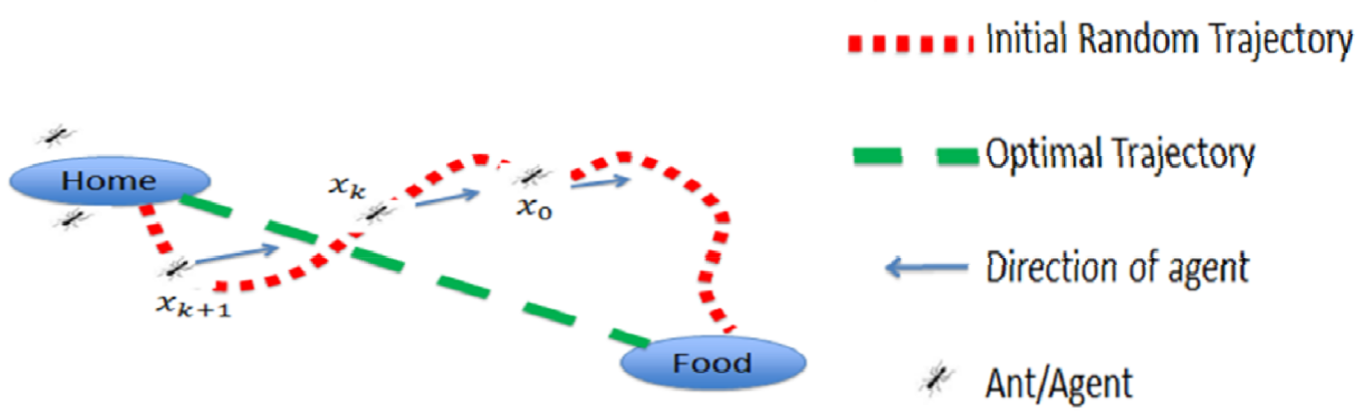
Task 2.2 Development of Multi-Agent Optimization Based Approach for Controlled Variable Selection (Q5-Q11)

Task 2.3 Implementation of the Algorithms in the Plant-Wide Model of an IGCC plant with CO_2 Capture (Q8-Q12)

Task 3.0 Development and Implementation of Biomimetic Controller Design Method

Task 3.1 Development of Deterministic Biomimetic Controller Design (Q1-Q6)

- Modified Generalized Sampled Local Pursuit (GSLP) algorithm*
- Solved intermediate optimal control problems employing *dynopt* # (gradient-based solver) in MATLAB
- Developed Biologically-Inspired Optimal Control Strategy (BIO-CS)
- Apply strategy to chemical and power systems



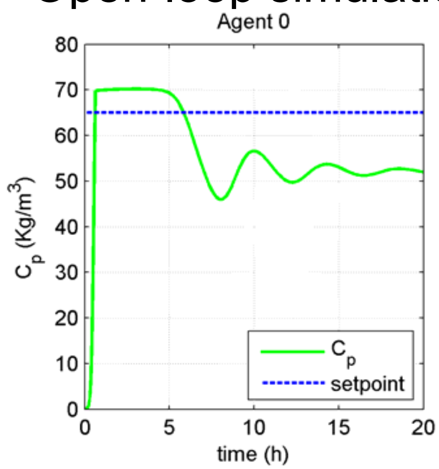
*Hristu-Varsakelis D. and Shao C., "A bio-inspired pursuit strategy for optimal control with partially constrained final state". *Automatica*, **2007**.
#Cizniar M., Fikar M. and Latifi M. A., "MATLAB DYNamic OPTimisation code". User's Guide, Version 4.1, **2010**.

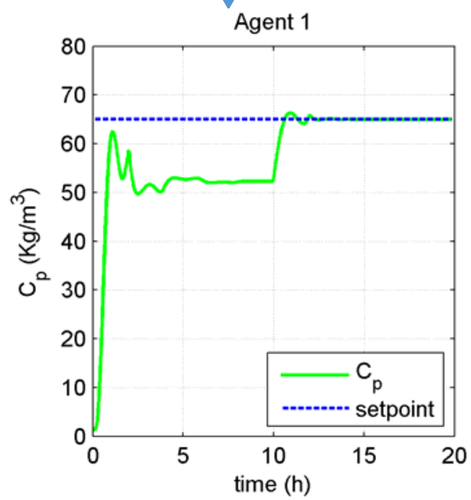
BIO-CS Results: Chemical Process Example (Fermentation Process*: Concentration Profiles)

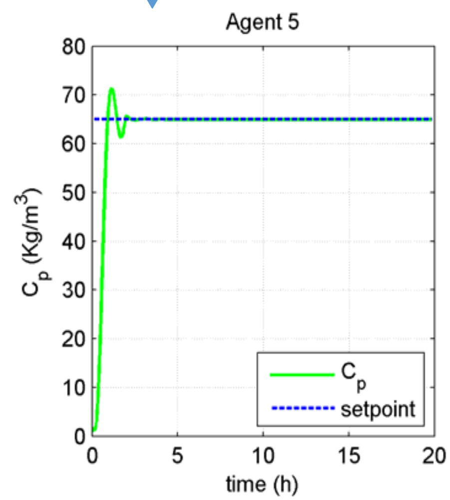
Optimal control solver: *dynopt*

Closed-loop simulation

Open-loop simulation



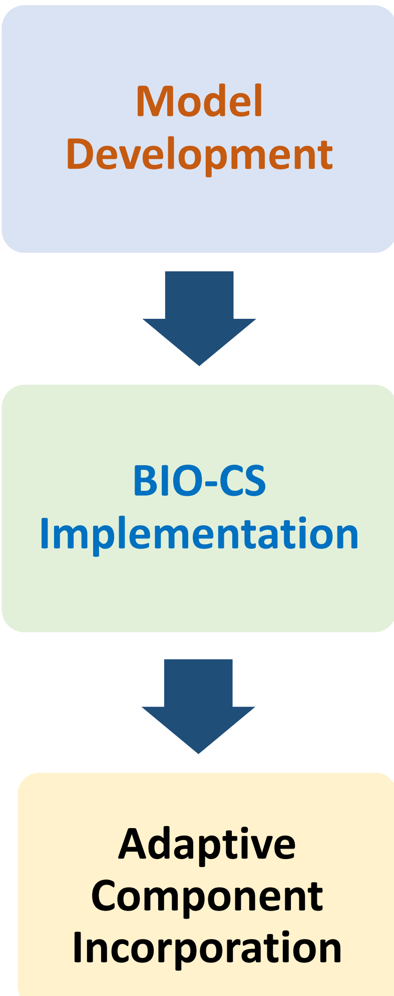




- Oscillations in C_P profile for open-loop simulation
- Improvement in closed-loop response as the number of agents increases
- Computational time: avg. for each agent ≈ 2 min
- Ongoing collaborative work: analyzing the replacement of *dynopt* solver by Efficient Ant Colony Optimization (EACO) techniques (with Dr. Diwekar) for potential enhanced performance

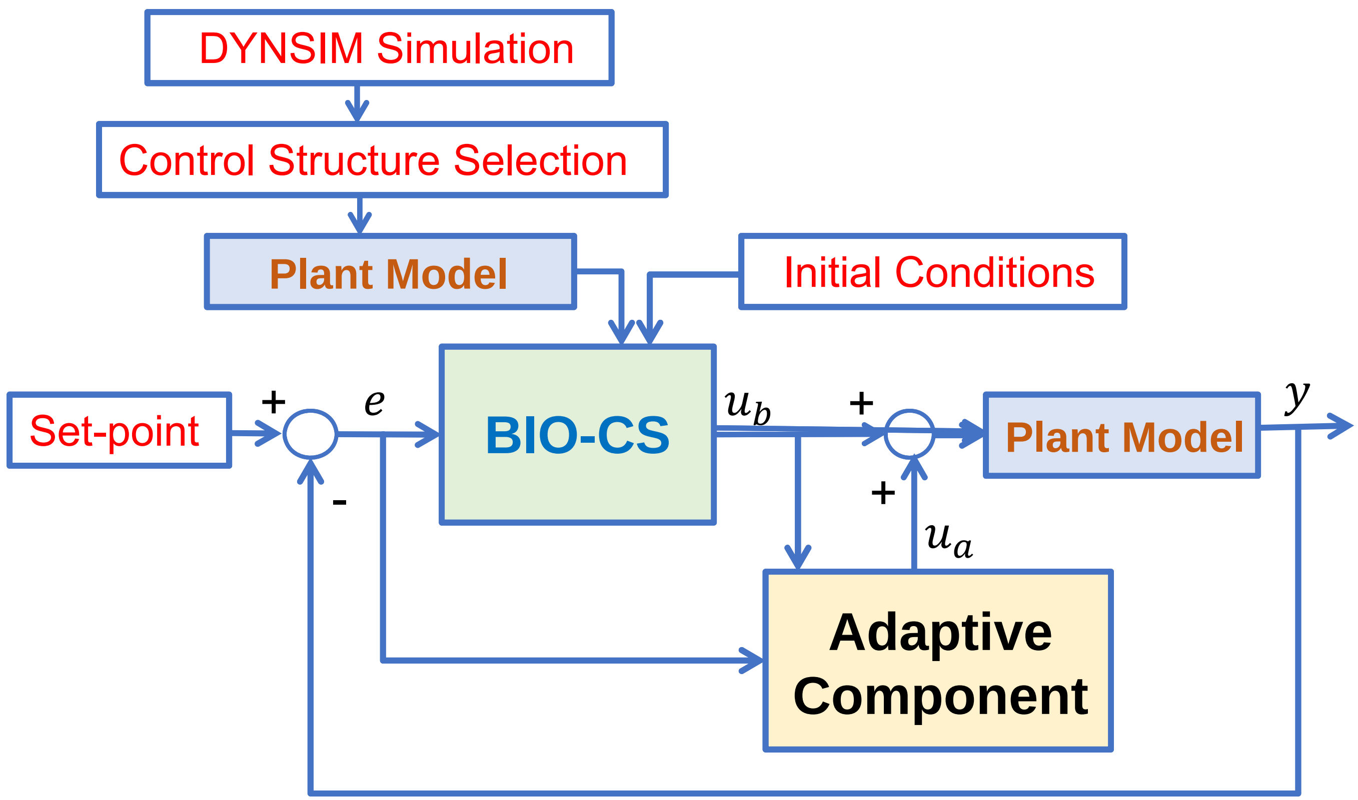
*Lima F. V., Li S., Mirlekar G. V., Sridhar L. N. and Ruiz-Mercado G. J., "Modeling and advanced control for sustainable process systems". Sustainability in the Analysis, Synthesis and Design of Chemical Engineering Processes, G. Ruiz-Mercado and H. Cabezas (eds.), Elsevier, **2016**.
*Mirlekar G. V., Li S. and Lima F. V., "Design and implementation of a Biologically-Inspired Optimal Control Strategy (BIO-CS) for chemical process control". In preparation (available upon request).

Task 3.2 Incorporation of Adaptive Component into Biomimetic Controller Design (Q5-Q9)



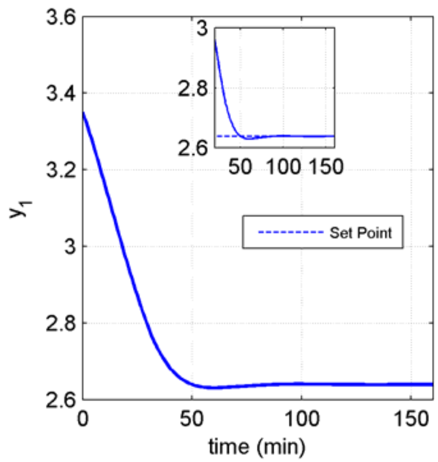
DYNSIM simulation of IGCC-AGR (CO_2 absorber unit):

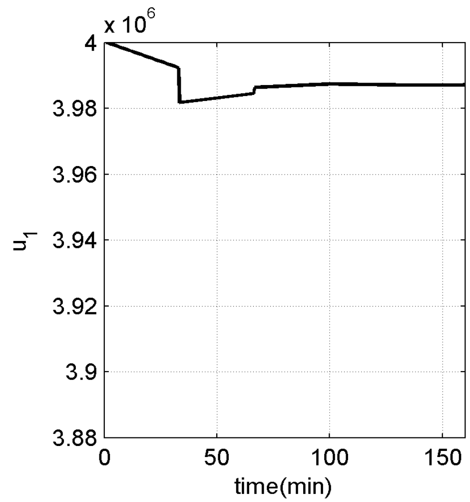
- 2×2 system selected for model development using system identification techniques



BIO-CS with Adaptive Component Results

- Selected SISO (Single-Input-Single-Output) system for BIO-CS implementation in MATLAB
- Goal: setpoint tracking of y_1(% CO_2 in outgoing stream) by manipulating u_1 (flow rate of recycled solvent stream)

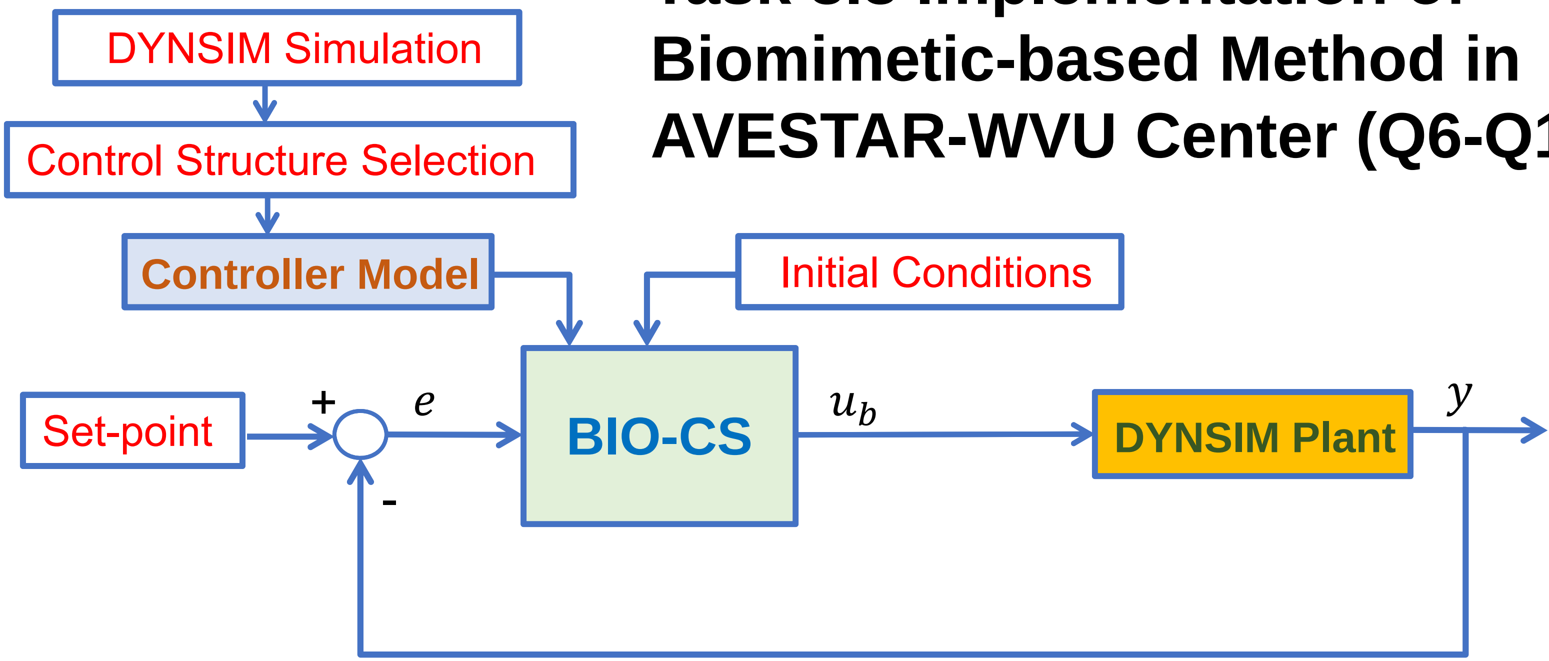




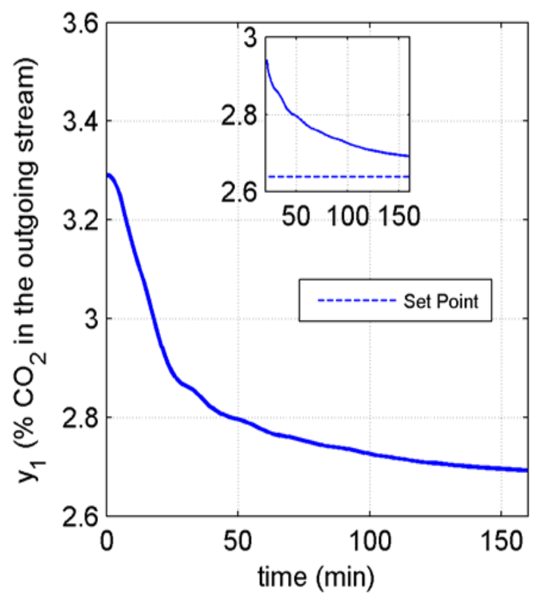
- Simulation of abnormal conditions by altering plant model matrices (A and B)
- Tracking errors for BIO-CS with adaptive component implementations (in collaboration with Dr. Perhinschi)

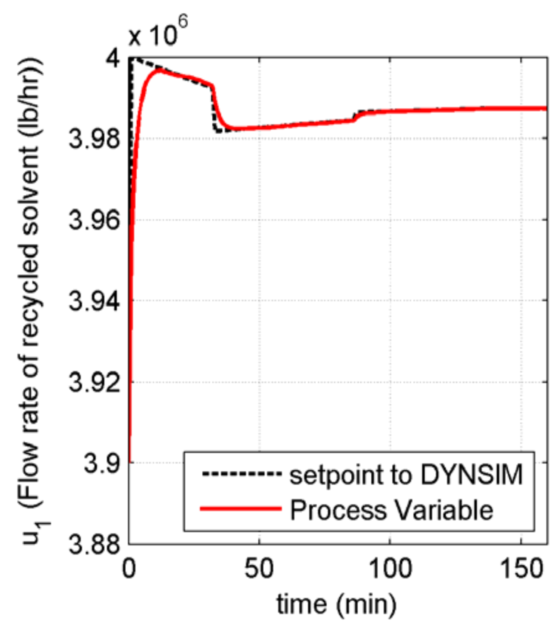
Control Implementation Scenarios			BIO-CS + AIS	PID + AIS
Nominal Condition (with model round off errors)			10.39	15.80
Abnormal Conditions	Actuator Failure	B*[1 0 0 2]	10.40	15.81
		B*[1 0 0 0.5]	10.36	15.80
	Plant Failure	A(3,3)/1.5	10.39	15.81
		A(4,4)/1.5	10.36	15.76

Task 3.3 Implementation of Biomimetic-based Method in AVESTAR-WVU Center (Q6-Q12)

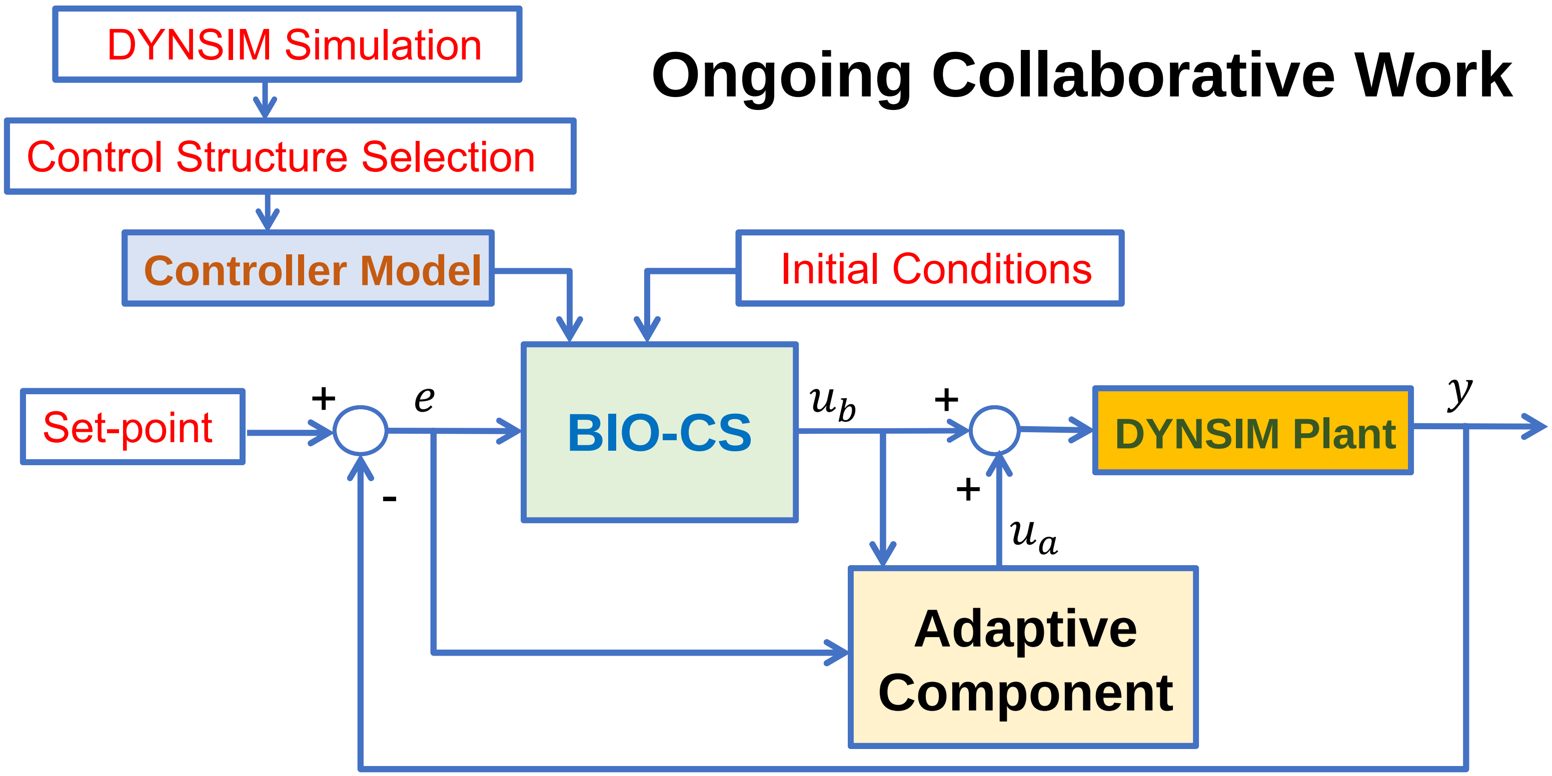


- Deviations from the setpoint are due to plant-model mismatch
- Average computational time to obtain one control trajectory (all agents) ≈ 3 min
- Potential implementation as a supervisory controller





Ongoing Collaborative Work



Challenges:

- Online incorporation of adaptive component into BIO-CS (in collaboration with Dr. Perhinschi)
- Reduce computational time for BIO-CS online implementation

Future Proposed Solutions:

- Adaptive component is expected to compensate for plant-model mismatch
- Analyzing approaches for computational time improvement of algorithm (parallelization, termination at suboptimal solution)

Year 3 Tasks (Task 3)

3.3 Implementation of Biomimetic-based Method in AVESTAR-WVU Center (Q6-Q12)

3.4 Integration of Controller Design Method with Multi-agent Optimization Framework (Q9-Q12)

Task 4. Development of Biomimetic Adaptive Controllers with Intelligent Monitoring, Cognition, and Decision Capabilities

- **Objective:** Development of an intelligent, comprehensive, and integrated framework for advanced power plant monitoring and control. Development and testing of specific methodologies, techniques, and algorithms.

- **Motivation:** Modern power plants must operate at their maximum efficiency in the presence of disturbances and/or abnormal conditions without violating environmental emission standards and causing safety hazards. Handling this challenging task requires intelligent monitoring, decision making, and control.

- **Approach:** The artificial immune system paradigm is inspired by mechanisms of the biological immune system, which exhibit all the valuable characteristics needed to solve the problem of monitoring and controlling complex multi-dimensional technical systems in comprehensive and integrated manner.

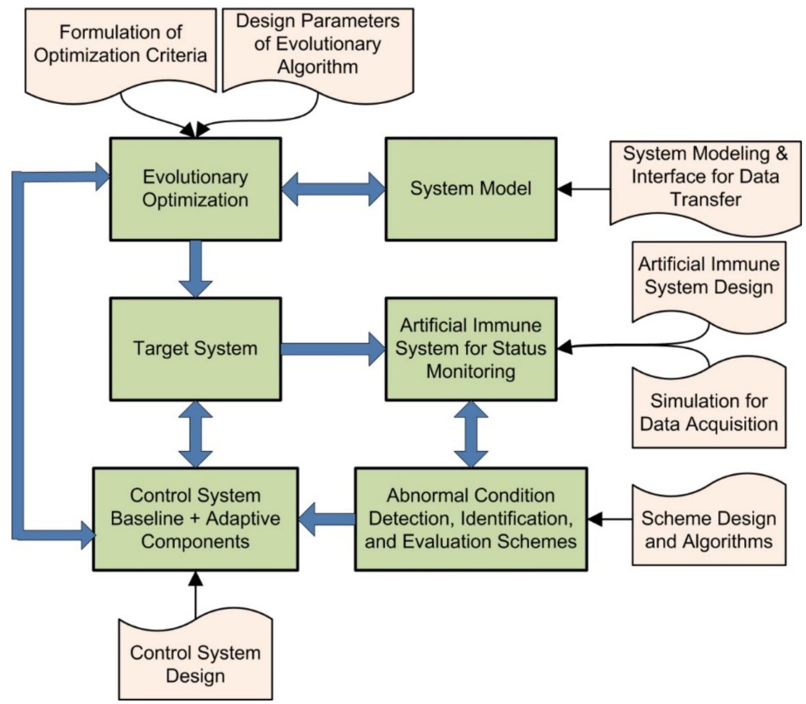
Artificial Immune System (AIS) Paradigm *

Artificial Immune Systems (AIS) is a diverse area of research that attempts to take inspiration from immunology for solving engineering problems.

The AIS paradigm for abnormal condition detection, identification, evaluation, and accommodation (ACDIEA) relies on mechanisms that distinguish between elements of the "self" and "non-self".

The immunity based AC accommodation is approached based on the biological feedback that establishes a balance between the activation and suppression of the antibodies generation.

The immunity evolutionary optimization relies on the general concept of genetic optimization augmented with mechanisms inspired by the generation of highly specific and effective antibodies.,



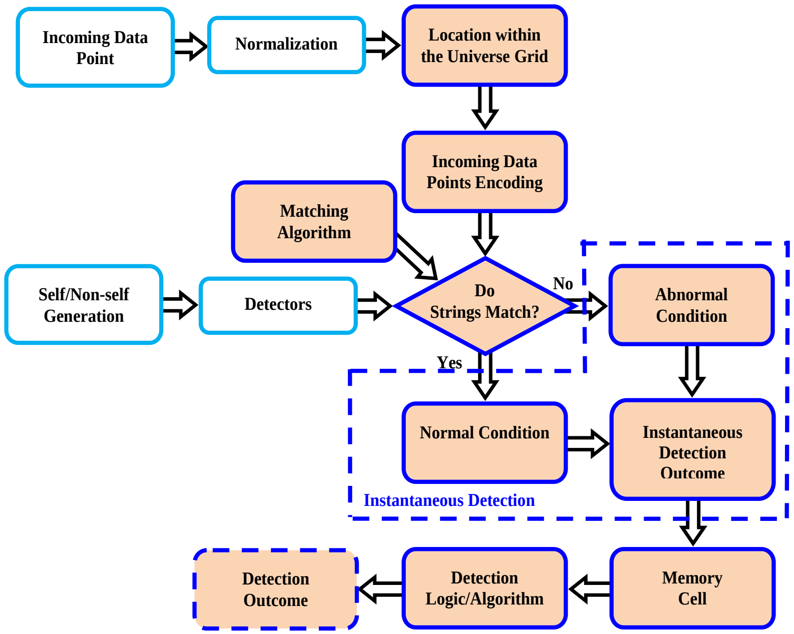
Artificial Immune System for ACDIEA

The AIS for ACDIE paradigm may be regarded as a data-driven modeling methodology that relies on exhaustive collections of system feature measurements and derived variables.

A novel approach to generate the technical system self called the partition of the universe approach (PUA) was developed to facilitate the use of full-dimensional self for system abnormal condition detection *.

AC Detection represents the process through which the existence of an AC is acknowledged within at least one of the targeted system components.

It is based on direct self/non-discrimination and can be performed using negative selection-type or positive selection-type of algorithms.



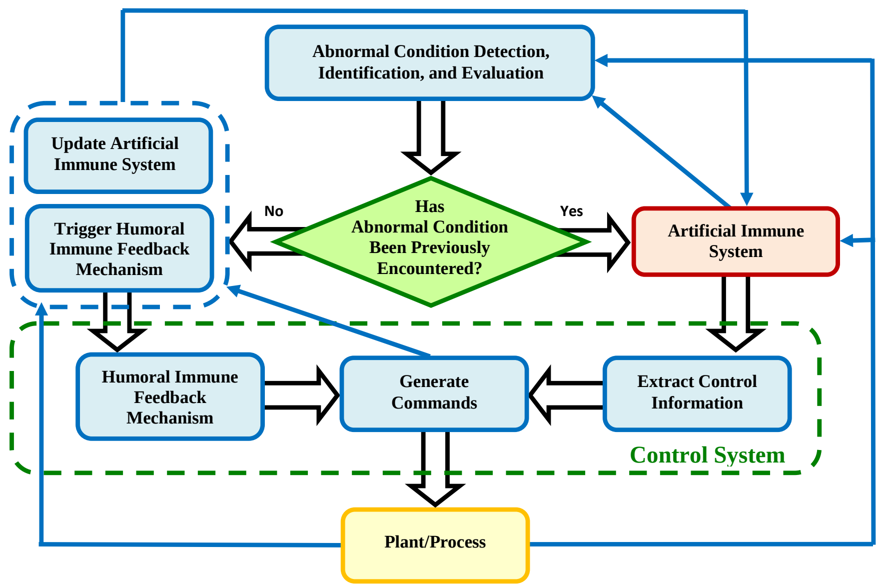
Artificial Immune System for ACDIEA

AC Passive Accommodation process generates warnings and other information and provided to the supervising personnel.

AC Active Accommodation consist of re-evaluation of system parameter and/or triggering of pre-existing compensating modules within the control laws and/or actual computation of commands at post-failure conditions.

The artificial neural network (ANN)-based adaptive mechanism relies on the capability of the ANNs to model/approximate functions.

The artificial immune based (AIS)-based adaptive controller mimics the humoral immune system feedback response.

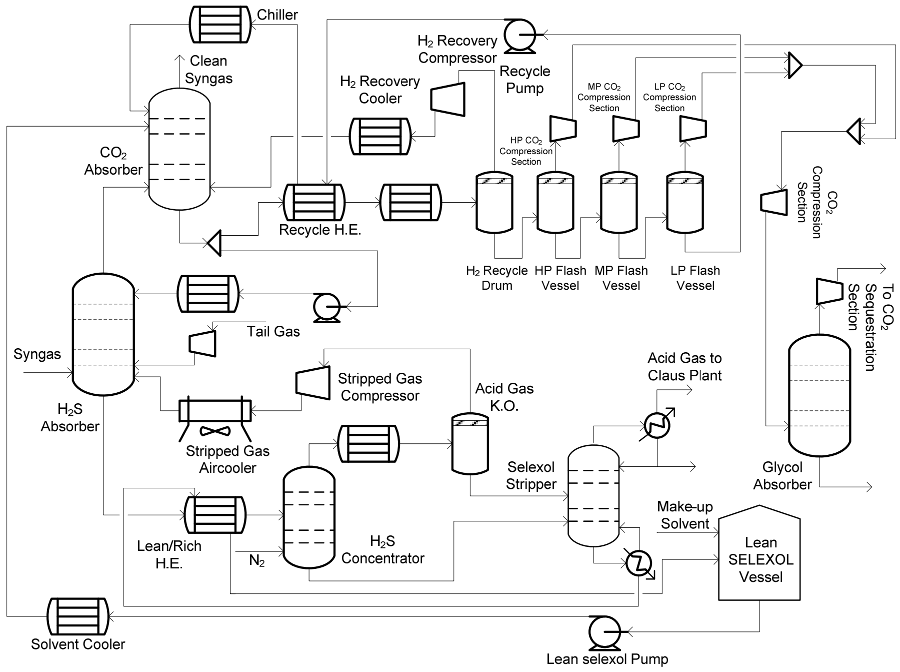


Example Results

The acid gas removal (AGR) unit is part of an integrated gasification combined cycle power plant. The unit selectively removes H_2S and CO_2 using SELEXOL solvent. A Dynsim® model of the AGR unit was used.

A total of 163 features were selected to build the self of the AGR unit, including pressure, temperature, flow rate, and composition measurements across the unit.

Over 700 tests each lasted 270 minutes by varying 6 most significant inputs were used. Normal versus abnormal operation is determined based on system constraints.



Example Results

For the purpose of demonstrating the operation of the proposed AC detection scheme, a limited number of 8 AC that include deposit of solids, such as flyash, and leakages in the pipes or equipment items are presented. No false alarms are recorded.

AC Description

AC	Description
AC1	Solids deposit on the 13th tray of the CO_2 absorber
AC2	Solids deposit on the sump tray of the CO_2 absorber
AC3	Solids deposit on the 23th tray of the H_2S absorber
AC4	Solids deposit on the sump tray of the H_2S absorber
AC5	Solids deposit on the 4th tray of the H_2S concentrator
AC6	Solids deposit on the sump tray of the H_2S concentrator
AC7	Leakage in the H_2 recovery compressor suction line
AC8	Leakage in the H_2 recovery flash drum vapor line

Detection PI

AC	Detection Time [s]	Detection Rate [%]
AC1	2.5	99.3
AC2	2.6	98. 6
AC3	5.6	96.1
AC4	5.3	97.4
AC5	3.3	98.5
AC6	3.4	97.9
AC7	10.2	94.6
AC8	10.5	93.9

Example Results

The two proposed adaptive control mechanisms were implemented and tested using a simple linearized 2-input/2-output/4-state model from Dynsim® for the CO_2 absorption process unit of the IGCC-AGR process.

Actuator failure and other plant abnormal conditions were simulated by altering the elements of the B and A matrices, respectively.

Accommodation PI

Subsystem Condition		PID	PID + ANN States	PID + ANN Outputs	PID + AIS
Nominal		143.68	33.08	84.45	15.80
Actuator Failure	B*[2 0 0 1]	79.45	25.04	47.65	9.78
	B*[0.5 0 0 1]	143.68	33.08	84.45	15.80
	B*[1 0 0 2]	144.06	33.18	84.90	15.81
	B*[1 0 0 0.5]	143.68	33.08	84.45	15.80
Plant Failure	A(1,1)*1.5	Unstable	33.76	650.84	674.79
	A(1,1)/1.5	Unstable	29.53	188.15	563.30
	A(1,2)*2	Unstable	20.64	186.23	560.66
	A(1,2)/1.25	Unstable	32.36	353.07	463.63
	A(2,1)*1.5	Unstable	20.32	187.33	563.80
	A(2,1)/1.5	Unstable	36.30	875.67	674.70
	A(2,2)*2	Unstable	38.90	1.32e+3	664.55
	A(2,2)/3	Unstable	15.18	157.79	473.10
	A(3,3)*1.5	143.66	33.07	84.45	15.81
	A(3,3)/1.5	143.71	33.08	84.46	15.81
	A(3,4)*3	143.76	33.08	84.52	15.73
	A(3,4)/1.1	Unstable	33.15	85.95	17.38
	A(4,3)*1.5	143.70	33.08	84.45	15.81
	A(4,3)/1.5	143.67	33.08	84.45	15.80
	A(4,4)*1.1	Unstable	33.48	90.58	27.62
	A(4,4)/1.5	143.71	33.07	84.46	15.76

Year 2 Tasks (Task 4)

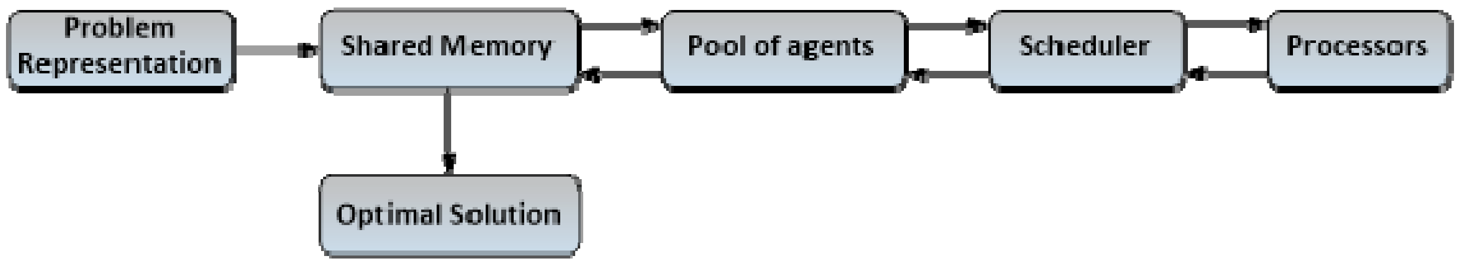
Task 4.3 Development of Artificial Immune System for Intelligent Monitoring, Cognition, and Decision Capabilities (Q1-Q11)

Task 4.4 Development of Biomimetic Adaptive Control Laws (Q3-Q9)

Task 4.5 System Integration and Demonstration (Q7-Q12)

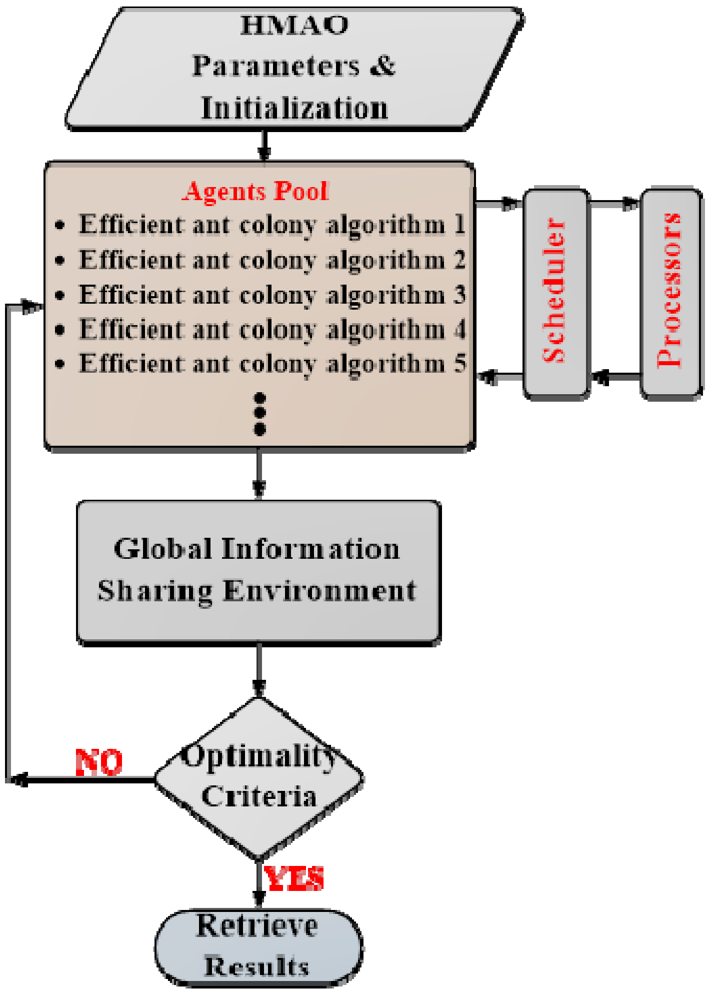
Task 5: Development of Multi-Agent Optimization Framework

Major parts of MAOP framework

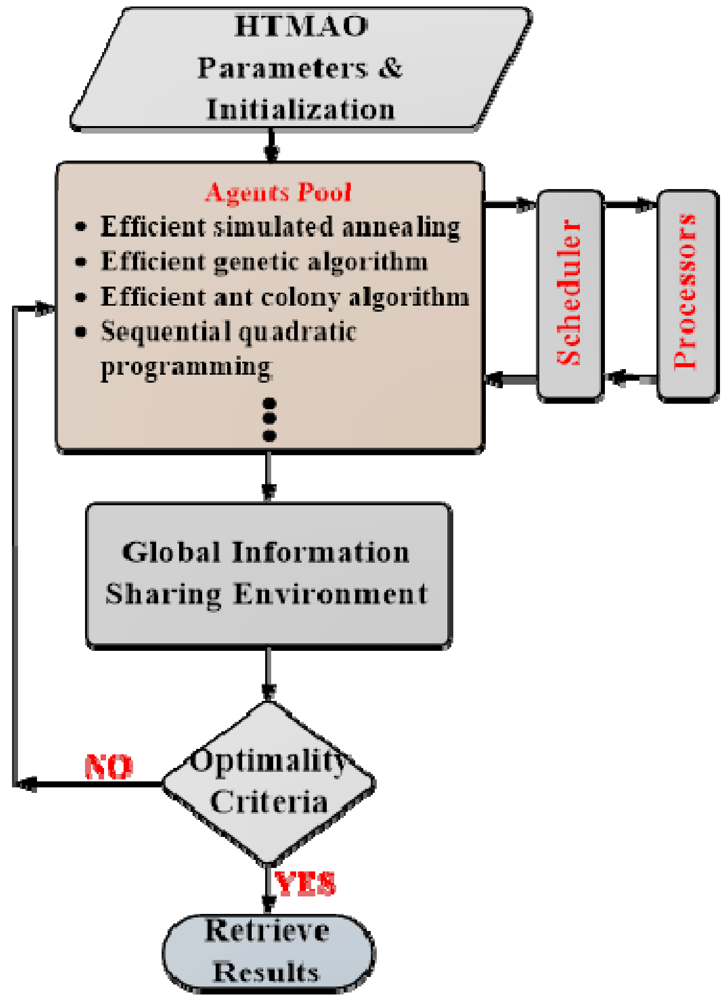


- The emphasis of MAOP framework is enhancing the accommodation of different classes of optimization problems and improving the computational efficiency.
- Focus of MAOP
  - ✓ Diversity of agents involved in the framework,
  - ✓ Coordination between local and global sharing memory
  - ✓ Parallelization of agents.

Diversity



Homogeneous MAOP



Heterogeneous MAOP

A New Efficient Ant Colony Algorithm

- Efficiency of ACO algorithm depends on
  - ✓ Initialization of solution archives
  - ✓ Random number generation for the transition probability test
  - ✓ Adding local search algorithms
- Conventional ACO algorithms
  - ✓ Inefficient initialization of the solution archive
  - ✓ Inefficient random number generation: transition probability test
- Efficient ant colony optimization (EACO) algorithm
  - ✓ n-dimensional uniformity property of Hammersley Sequence Sampling (HSS) to initialize the solution archive
  - ✓ HSS for the transition probability operation test

Results: State Variable Trajectory

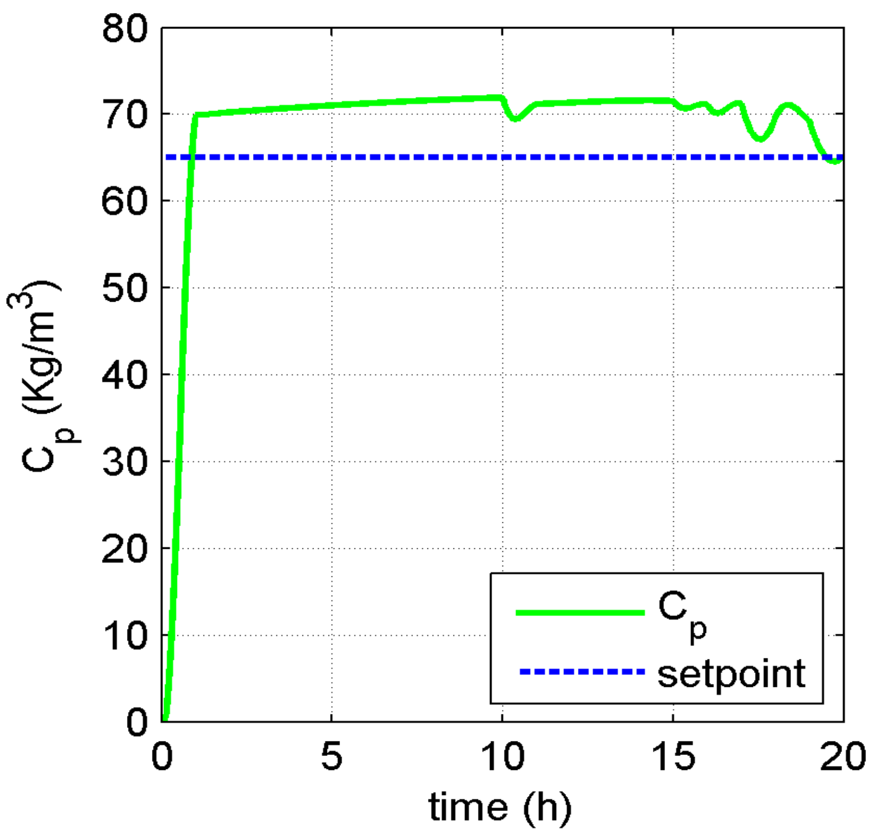


Figure 2. Dynopt: Trajectory of state variables

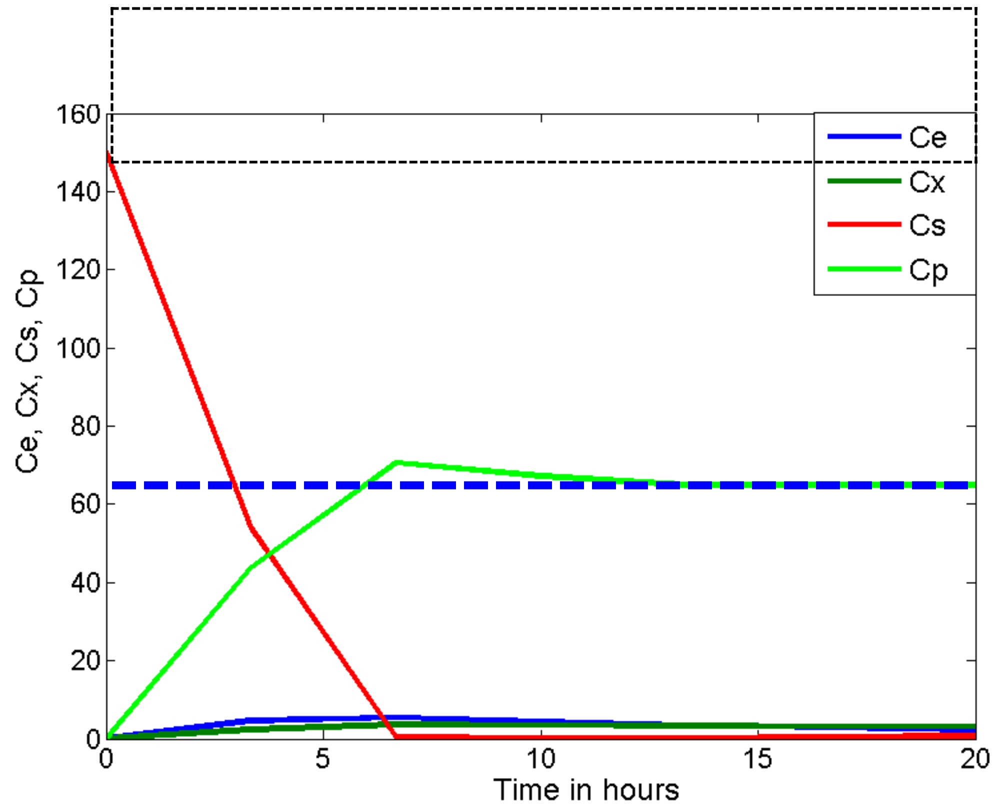


Figure 3. EACO: Trajectory of state variables

- Oscillations in C_P profile

Results: Control Variable Trajectory

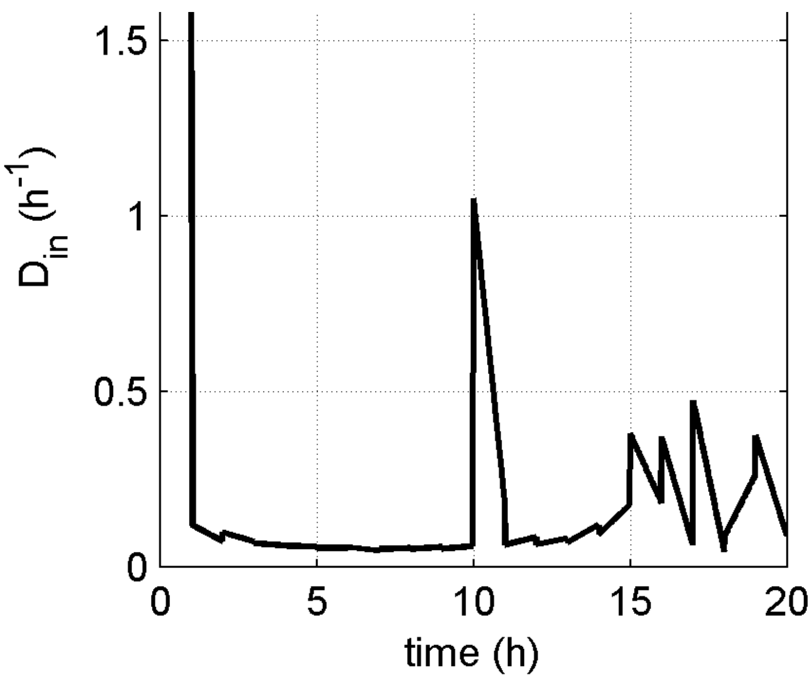


Figure 4. Dynopt: Control variables trajectory.

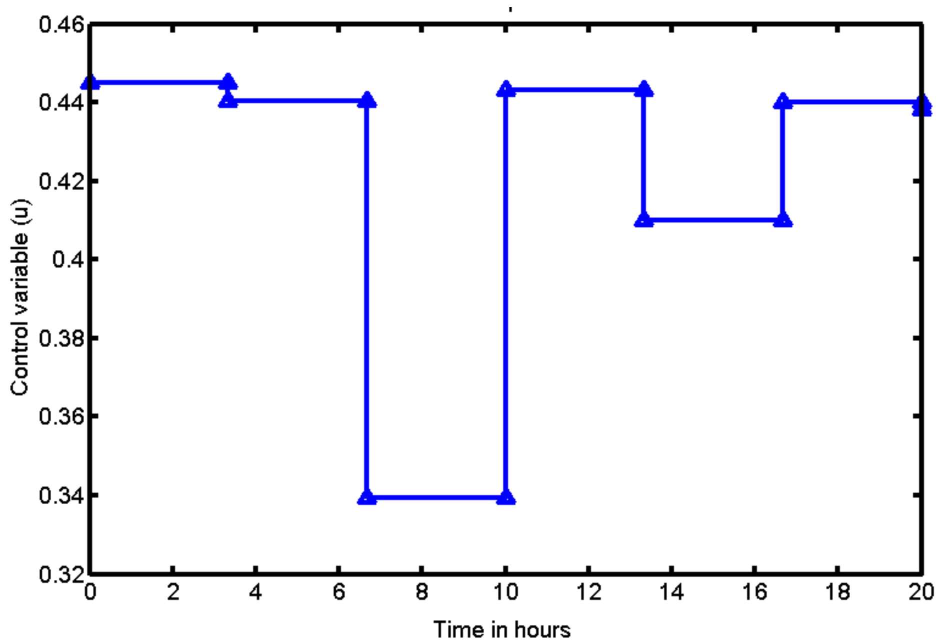


Figure 5. EACO: Control variables trajectory.

Conclusions- Optimal Control with EACO

- The proposed optimal control algorithm handles nonlinearities in the chemical process
- Setpoint tracking of the product concentration for the fermentation process was addressed
- The deterministic and probabilistic approaches were considered in controller implementation and the probabilistic method handles it better.

Benchmark Problems: Convex and nonconvex

Function	***Formula***
Parabolic (convex)	$f_{PR}(x) = \sum_{i-1}^{NDIM} x_i^2$
Ackley (nonconvex)	$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{NDIM}\sum_{i=1}^{NDIM} x_i^2}\right) - \exp\left(\frac{1}{NDIM}\sum_{i=1}^{NDIM}\cos(2\pi x_i)\right) + 20 + \exp(1)$
Rosenbrock (nonconvex)	$f(x) = \sum_{i=1}^{NDIM} (1-x_i)^2 + 100(x_{2i+1} - x_i^2)^2$
Egg Holder (nonconvex)	$f(x) = -(x_2 + 47)\sin\left(\sqrt{\left\lvert x_2 + \frac{x_1}{2} + 47\right\rvert}\right) - x_1 \sin\left(\sqrt{\lvert x_1 - (x_2 + 47)\rvert}\right)$

Parameter Settings of Agents

MAOP Algorithm Parameters	
Number of agents	4
MAXITER	100
CONTITER	5
EPS	1E-5
Oracle (Ω)	0

ESA Algorithm Parameters	
InitTemp	1
MaxRej	30
MaxSuc	10
StopTemp	1E-6
MAXITER	100
CoolSch	0.93T

EGA Algorithm Parameters	
Population size (popsize)	12*NDIM
Selection	0.55
Mutation rate (mutrate)	0.075
MAXGEN	1000
CONITER	10
EPS	1E-4

EACO Algorithm Parameters	
Solution Archive (K)	50*NDIM
Number of ants (nAnts)	NDIM
Evaporation factor (ρ)	0.7
Algorithm parameter (q)	1E-03
MAXITER	2000
CONITER	10
EPS	1E-5

Results: Objective Function comparison

Table 1. Objective Function for NDIM=50

Function	GOPT	EACO OF	EGA OF	ESA OF	FMINCON OF	HMAO OF	HTMAO OF
Parabolic	0	0.00	0.01	0.04	0.00	0.00	0.00
Ackley	0	0.00	0.03	0.19	0.00	0.00	0.00
Rosenbrock	0	0.00	0.79	7.42	0.00	0.00	0.00
Eggholder	-	-36902.25	-37355.03	-36584.67	-935.34	-36902.26	-37403.35

Table 2. Objective Function for NDIM=100

Function	GOPT	EACO OF	EGA OF	ESA OF	FMINCON OF	HMAO OF	HTMAO OF
Parabolic	0	0.00	0.00	5.71	0.00	0.00	0.00
Ackley	0	0.00	0.02	4.47	0.00	0.00	0.00
Rosenbrock	0	0.00	0.75	2.31	0.00	0.00	0.00
Eggholder	-	-73625.72	-86024.42	-72733.24	-73635.23	-73635.23	-78522.01

Key

Optimal or close to optimal solution

Local or suboptimal optimal solution

Results: CPU time comparison

Table 3. Ratio of CPU (Agent/HTMAO) for NDIM=50

Function	EACO / HTMAO	EGA / HTMAO	ESA / HTMAO	FMINCON / HTMAO	HMAO / HTMAO
Parabolic	1.03	0.65	3.68	0.41	1.96
Ackley	1.30	0.60	0.47	0.65	1.30
Rosenbrock	2.24	1.07	0.72	0.66	2.87
Eggholder	4.55	0.68	4.75	0.60	0.74

Table 4. Ratio of CPU (Agent/HTMAO) for NDIM=100

Function	EACO / HTMAO	EGA / HTMAO	ESA / HTMAO	FMINCON / HTMAO	HMAO / HTMAO
Parabolic	1.31	1.79	0.65	0.54	1.39
Ackley	1.43	2.00	6.46	0.59	1.36
Rosenbrock	1.46	1.08	0.46	0.52	2.31
Eggholder	6.81	2.48	0.57	0.55	2.45

Key

Optimal or close to optimal solution

Local or suboptimal optimal solution

Results: Elapsed time Comparison

Table 5. ***Ratio of Elapsed time (Agent/HTMAO)*** **for NDIM=100**

Function	*EACO / HTMAO*	*EGA / HTMAO*	*ESA / HTMAO*	*FMINCON / HTMAO*	*HMAO / HTMAO*
Parabolic	0.99	0.78	2.82	0.62	1.55
Ackley	1.15	0.73	0.63	0.72	1.18
Rosenbrock	1.64	1.04	0.79	0.75	2.06
Eggholder	4.08	0.76	3.71	0.67	0.94

Table 6. ***Ratio of Elapsed time (Agent/HTMAO)*** **for NDIM=100**

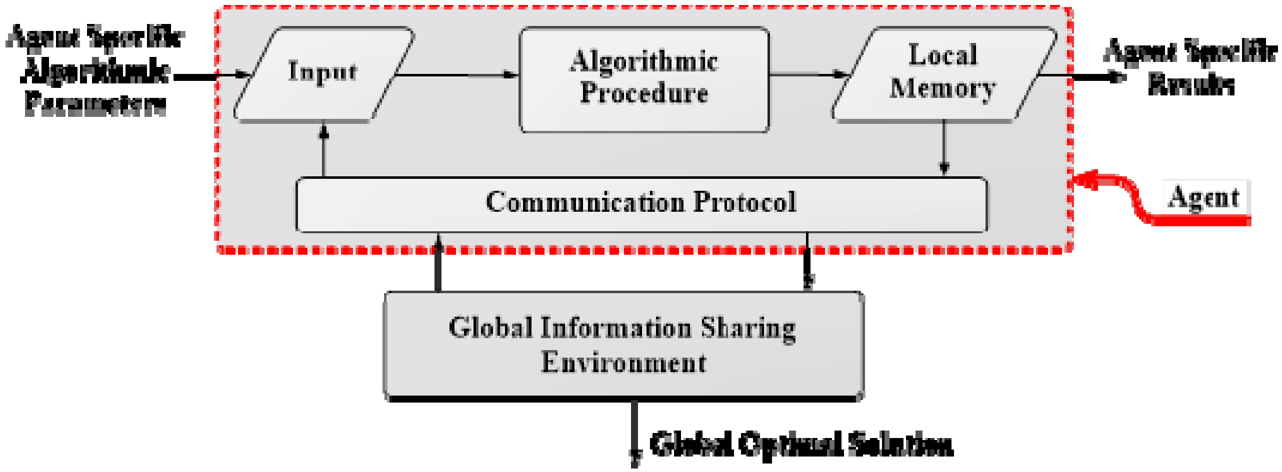
Function	*EACO / HTMAO*	*EGA / HTMAO*	*ESA / HTMAO*	*FMINCON / HTMAO*	*HMAO / HTMAO*
Parabolic	1.31	1.54	0.73	0.64	1.30
Ackley	1.43	1.69	4.40	0.62	1.37
Rosenbrock	1.46	1.08	0.57	0.64	2.45
Eggholder	6.81	2.05	0.53	0.53	3.00

Key

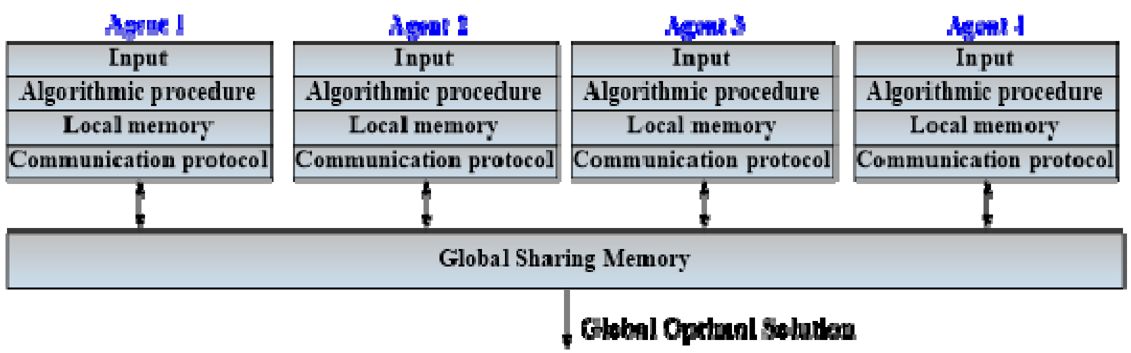
Optimal or close to optimal solution

Local or suboptimal optimal solution

Coordination

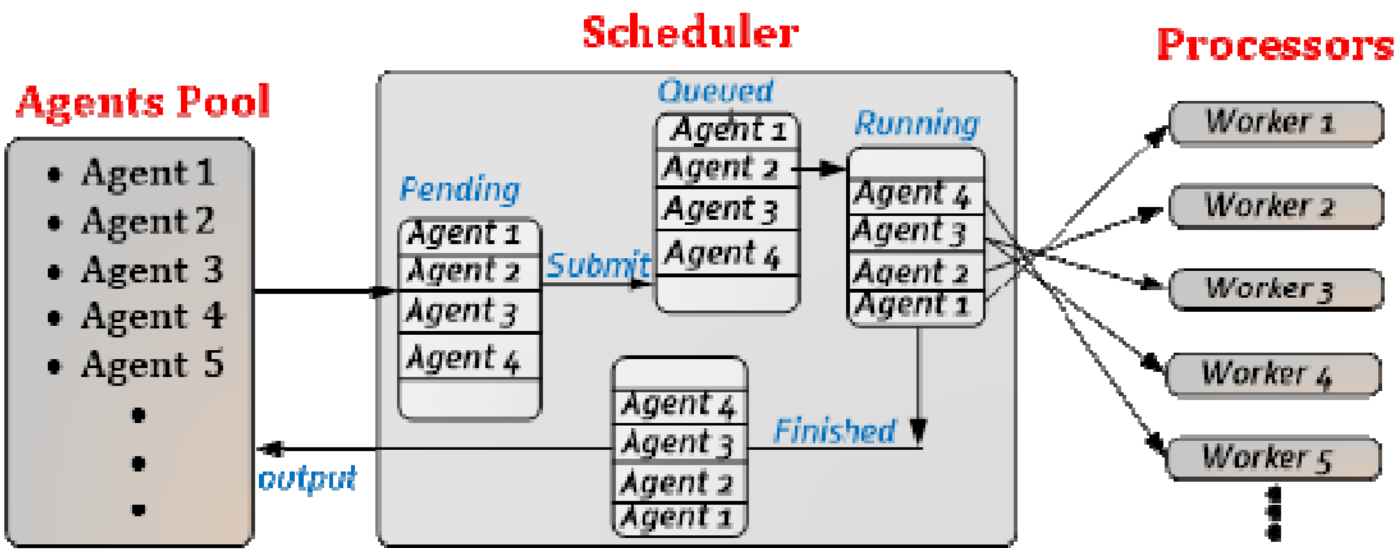


Agent coordination



MAOP with 4 agents

Parallel algorithm



Matlab job scheduler (MathWorks)

Year 3 Tasks (Task 5)

Task 5.3 Development of optimal control agents (Q5-Q9)

Task 5.5 Revisiting control structure design and controller design for the whole plant problems with complete multi-agent framework (Q7-Q12)

Presentations & Publications

Presentations

1. Gebrelassie B. H., Diwekar U., “Efficient Ant Colony Optimization for Deterministic Optimization”, AIChE Annual Meeting, Atlanta, GA, November, 2014
2. Gebrelassie B. H., Diwekar U., “Efficient Ant Colony Optimization for Solvent Selection Using CAMD”, PSE/ESCAPE, Denamark, 2015
3. Mirlekar G. V., Gebreslassie B., Diwekar U., Lima, F. V. “Design and Implementation of a Biomimetic Control Strategy for Chemical Processes Based on Efficient Ant Colony Optimization”, AIChE Annual Meeting, Salt Lake City, UT, November 8-13, 2015
4. Gebreslassie B., Diwekar U. “Multi-Agent Optimization Framework (MAOP) for Large Scale Process System Engineering Optimization Problem”, AIChE Annual Meeting, Salt Lake City, UT, November 8-13, 2015
5. Gebreslassie B., Mirlekar G. V., Lima, F. V., Diwekar U. "Optimal Control based on Efficient Ant Colony (EACO) Algorithm. Case Study: Chemical Process Control", AIChE Midwest Regional Conference, Chicago, IL, March 3-4, 2016
6. Bankole T. S., Bhattacharyya D., “Algorithmic Development of Dynamic Causal Model for Process Plants”, To be presented at the American Control Conference, Boston, MA, July 6-8, 2016

Publications

1. Perhinschi M. G., Al-Sinbol G., Bhattacharyya D., Lima F., Mirlekar G., Turton R., “Development of an Immunity-based Framework for Power Plant Monitoring and Control”, *Advanced Chemical Engineering Research*, Vol. 4, Issue 1, pp. 15-28, September 2015
2. Gebrelassie B. H., Diwekar U., “Efficient Ant Colony Optimization for Computer-Aided Molecular Design: Case Study Solvent Selection Problem”, *Computers & Chemical Engineering*, Vol. 78, pp. 1-9, 2015
3. Gebrelassie B. H., Diwekar U., “Efficient Ant Colony Optimization for Solvent Selection Using CAMD”, Proceeding of PSE/ESCAPE, Denamark, 2015
4. Gebreslassie B., Diwekar U., “Homogenous Multi-Agent Optimization for Process Systems Engineering with Application to Computer Aided Molecular Design”, accepted, Chemical Engineering Science, 2016.
5. Gebreslassie B., Diwekar U., “Efficient Ant Colony Optimization (EACO) Algorithm for Deterministic Optimization”, International Journal of Swarm Intelligence and Evolutionary Computation, Vol. 5, pp. 1-10, 2016
6. Bankole T. S., Bhattacharyya D., “Algorithmic Development of Dynamic Causal Model for Process Plants”, Proceedings of the American Control Conference, Boston, MA, July 6-8, 2016
7. Al-Sinbol, G., Perhinschi,M. Generation of power plant artificial immune system using the partition of the universe approach. International Review of Automatic Control (IREACO) 9(1), 2016.

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Thank you