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

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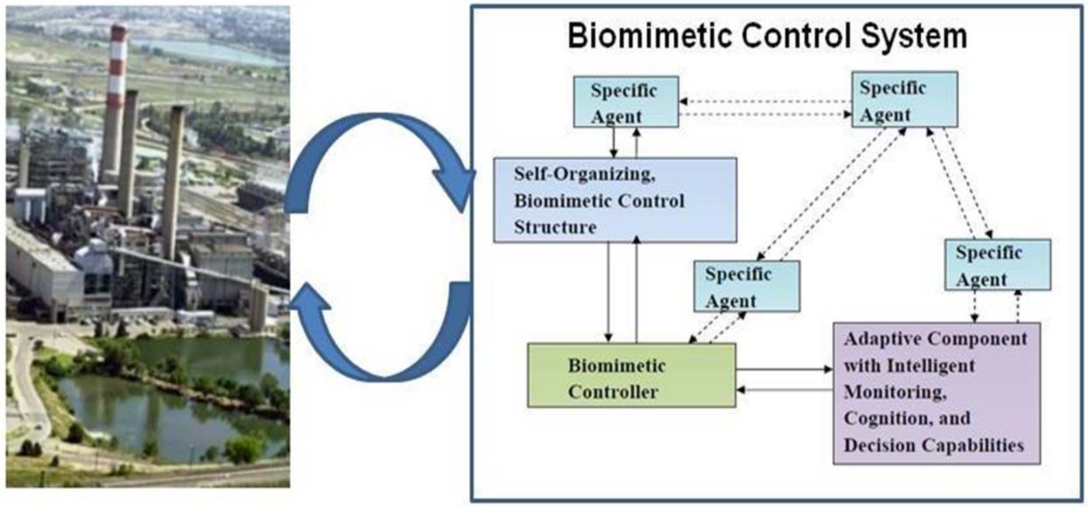
Challenges in Modern Control

- 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

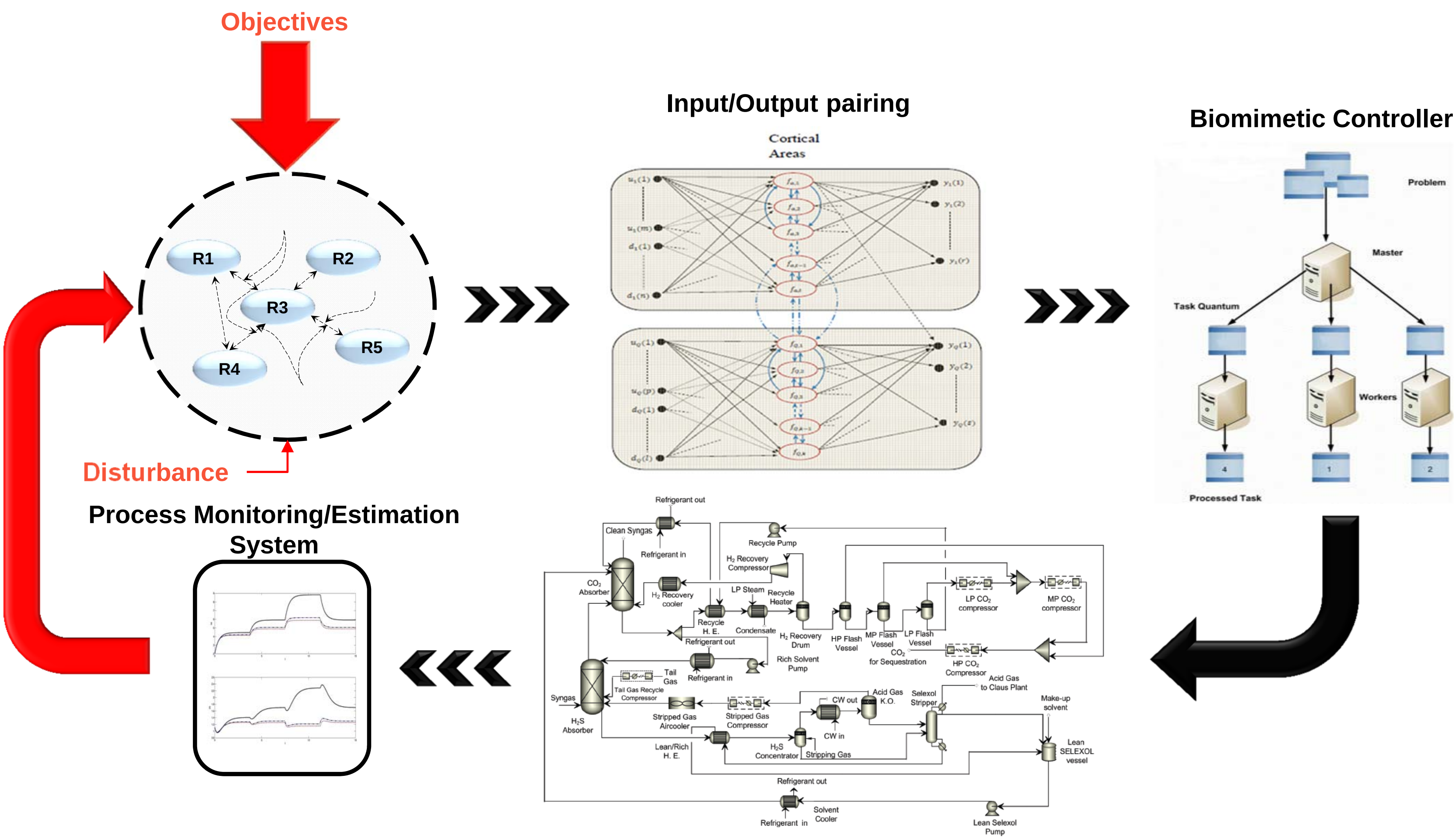
Task 4.0 Development of Biomimetic Adaptive Controllers with Intelligent Monitoring, Cognition, and Decision Capabilities
Team: Prof. Perhinschi, and PhD student Ghassan Al-Sinbol

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

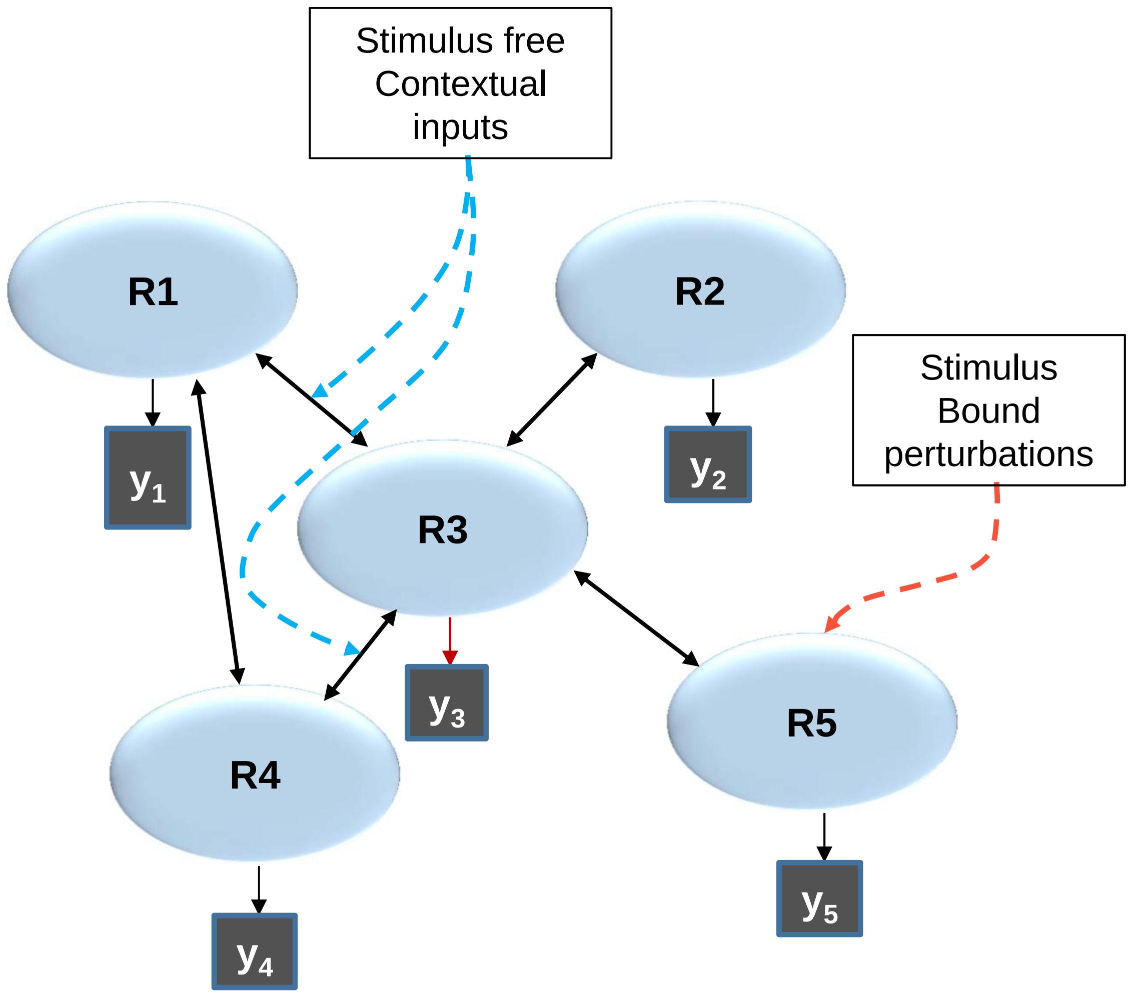


Dynamic Causal Modeling

- Latent connectivity
- Induced Connectivity
- Extrinsic influence of inputs

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

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

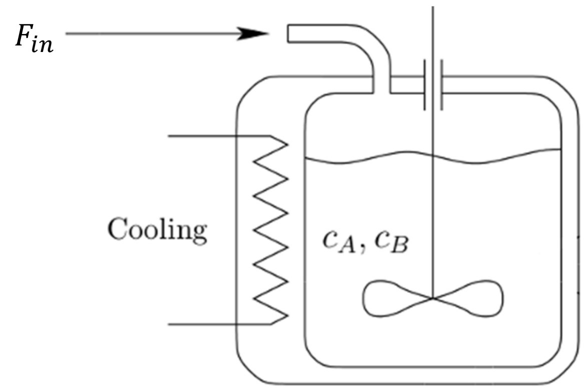


Friston, K J., Lee H., and Will P., "Dynamic causal modelling."*Neuroimage* 19.4 (2003): 1273-1302.

Example Problem

Van de Vusse Reactor

$A \longrightarrow B \longrightarrow$C
$2A \longrightarrow D$



Non Linear Model

$$\dot{C}_A = F_V(C_{AF} - C_A) - k_1 C_A - k_3 C_A^2$$

$$\dot{C}_B = (-F_V - k_2)C_B + k_1 C_A$$

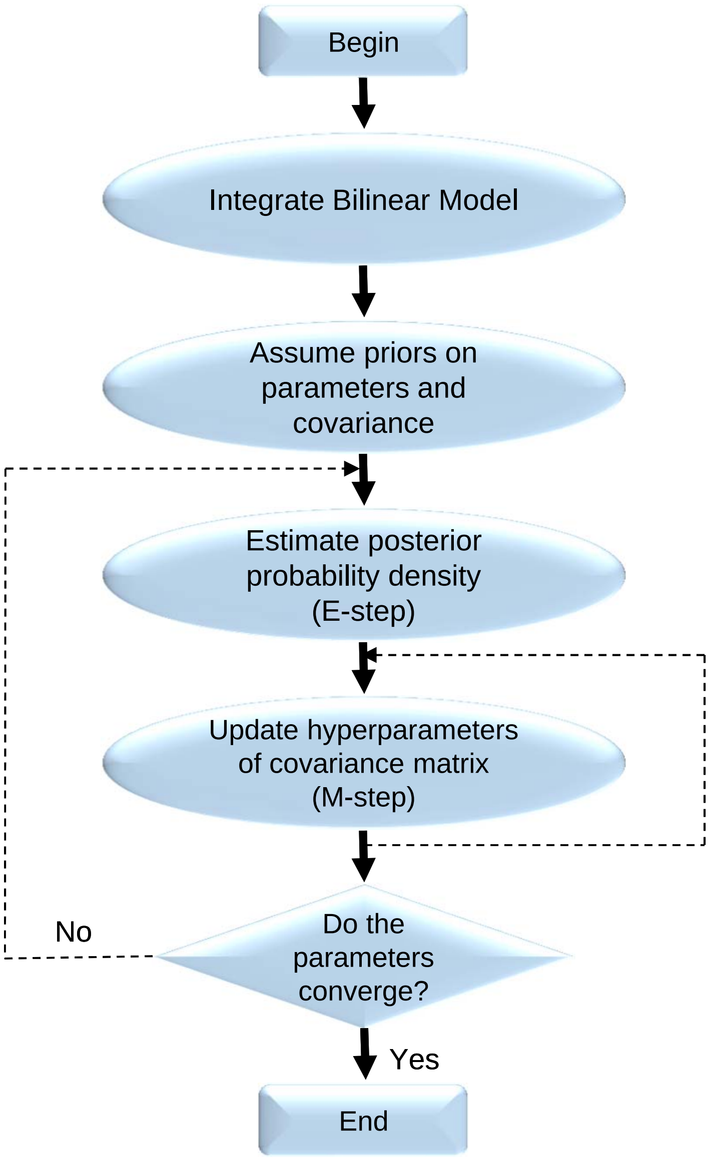
Linear Model

$$\begin{pmatrix} \dot{\overline{C}}_A \\ \dot{\overline{C}}_B \end{pmatrix} = \begin{pmatrix} -F_{Vss} - k_1 - 2k_3 C_{Ass} & 0 \\ k_1 & -F_{Vss} - k_2 \end{pmatrix} \begin{pmatrix} \overline{C_A} \\ \overline{C_B} \end{pmatrix} + \begin{pmatrix} C_{AFss} - C_{Ass} & F_{Vss} \\ -C_{Bss} & 0 \end{pmatrix} \begin{pmatrix} \overline{F_V} \\ \overline{C_{AF}} \end{pmatrix}$$

Bi-Linear Model

$$\begin{pmatrix} \dot{\overline{C}}_A \\ \dot{\overline{C}}_B \end{pmatrix} = \begin{pmatrix} -F_{Vss} - k_1 - 2k_3 C_{Ass} & 0 \\ k_1 & -F_{Vss} - k_2 \end{pmatrix} \begin{pmatrix} \overline{C_A} \\ \overline{C_B} \end{pmatrix} + \overbrace{\overline{F_V} \begin{pmatrix} -1 & 0 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} \overline{C_A} \\ \overline{C_B} \end{pmatrix}}^{\text{Bilinear contribution}} + \begin{pmatrix} C_{AFss} - C_{Ass} & F_{Vss} \\ -C_{Bss} & 0 \end{pmatrix} \begin{pmatrix} \overline{F_V} \\ \overline{C_{AF}} \end{pmatrix}$$

Expectation Maximization Algorithm

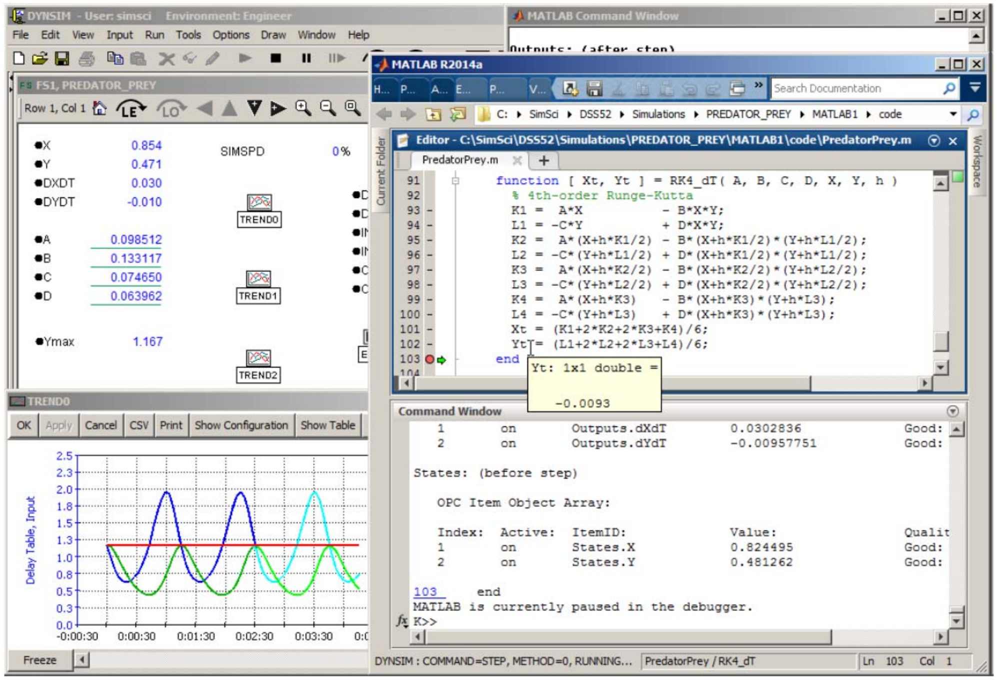


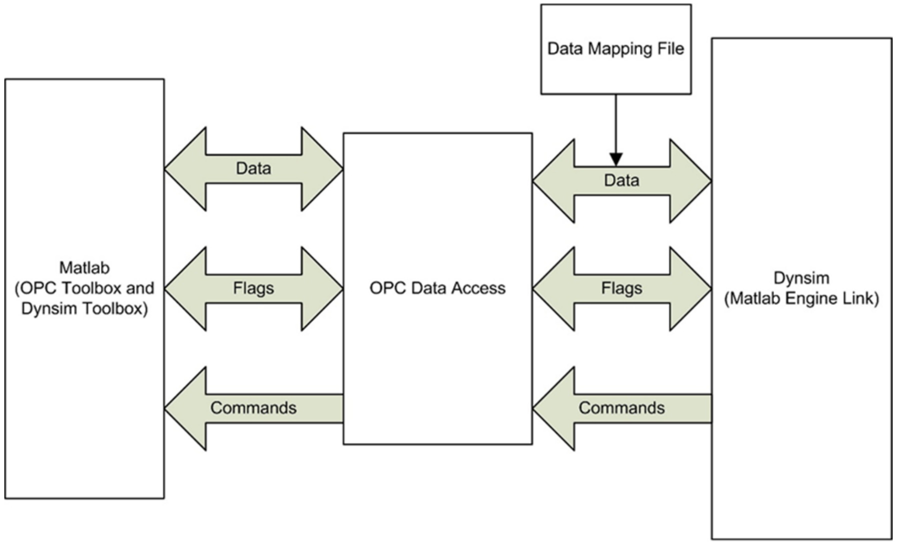
	TRUE	Estimate	%Error
a_{11}	-2.4048	-2.4047	4.0 E -03
a_{12}	0.00	-2.16E-04	-
a_{21}	0.8333	0.835	0.20
a_{22}	-2.2381	-2.2124	1.15
b_{11}	-1.00	-1.00	0.00
b_{12}	0.00	0.00	0.00
b_{21}	-1.00	-1.00	0.00
b_{22}	0.00	0.00	0.00
c_{11}	7.00	7.00	0.00
c_{21}	-1.117	-1.123	0.54

Multi-Software Platform

Dynsim - Matlab Engine Link

- Process model of the integrated gasification combined cycle (IGCC) plant is in Dynsim; Control structure selection and controller algorithms are being developed in MATLAB
- The team worked with the personnel from Schneider Electric to develop the link with financial support from WVU's NRCCE.
- Previous IGCC model upgraded to Dynsim 5.2 version
- Achieved M1: Complete the input-state-output data collection for the DCM





Year 2 Tasks (Task 2)

Task 2.1 Development of Dynamic Causal Model (Q1-Q8)
M5: Successful Development of the DCM
Due: 10/14/15
Success Criteria: A- Development of Dynamic Causal Model (Q6)

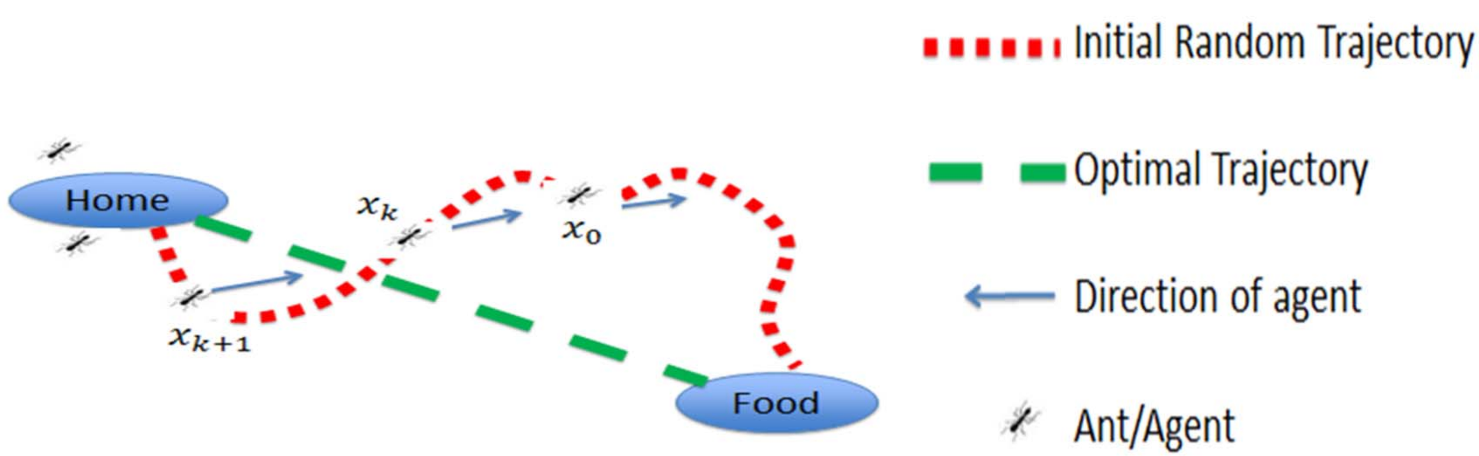
Task 2.2 Development of Multi-agent Optimization Based Approach for Controlled Variable Selection (Q5-Q11)

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

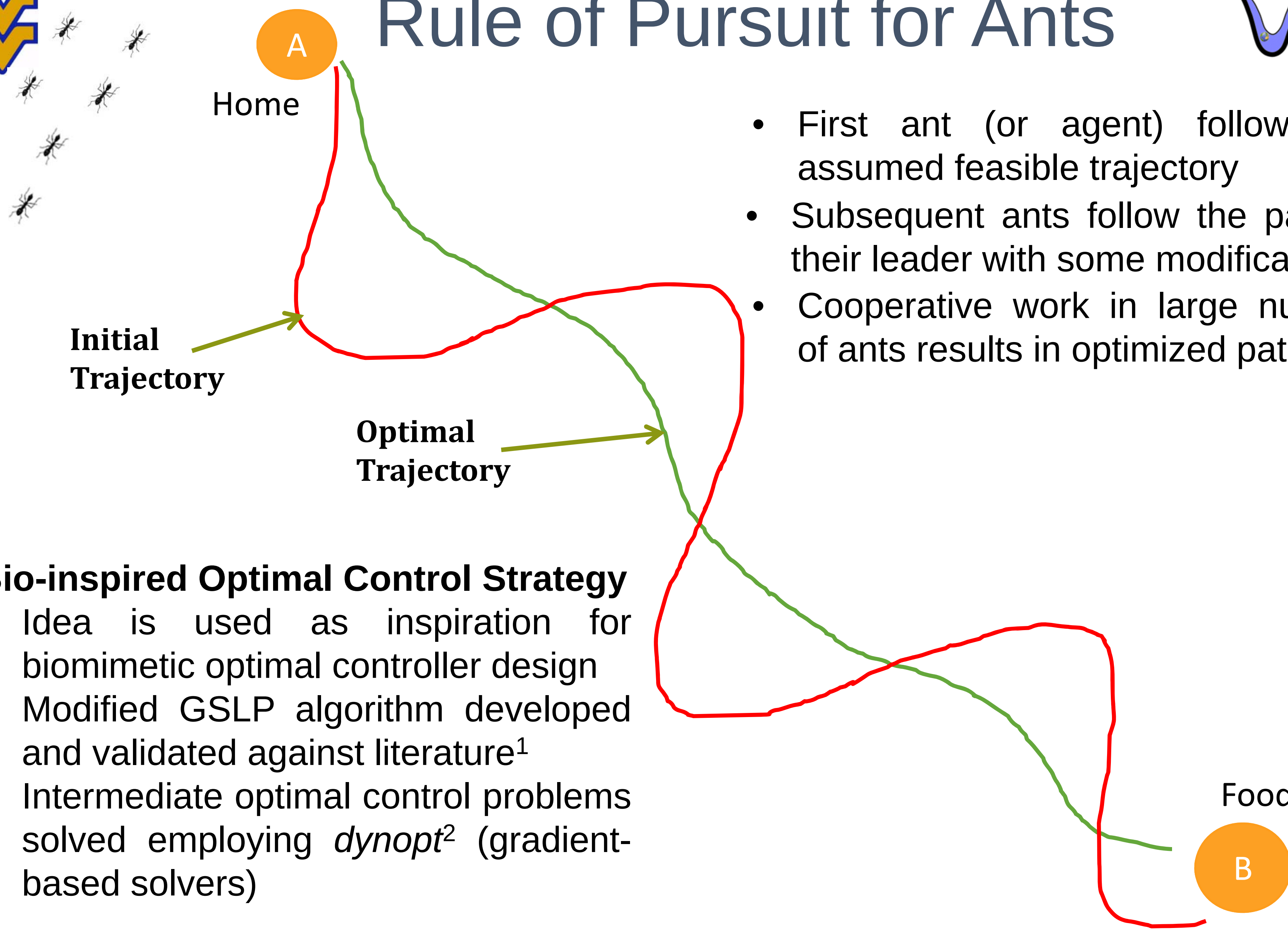
Task 3.0 Development and Implementation of Biomimetic Controller Design Method

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

- Modify Generalized Sampled Local Pursuit (GSLP) algorithm
- Employ optimal control solvers in *dynopt* MATLAB toolbox
- Apply developed approach to chemical process



Rule of Pursuit for Ants



- First ant (or agent) follows an assumed feasible trajectory
- Subsequent ants follow the path of their leader with some modification
- Cooperative work in large number of ants results in optimized path

Bio-inspired Optimal Control Strategy

- Idea is used as inspiration for biomimetic optimal controller design
- Modified GSLP algorithm developed and validated against literature[1]
- Intermediate optimal control problems solved employing *dynopt*[2] (gradient-based solvers)

1. Hristu-Varsakelis D. and Shao C. "A bio-inspired pursuit strategy for optimal control with partially constrained final state". *Automatica*, 43:1265-1273, 2007
2. Cizniar M., Fikar M. and Latifi M. A. "MATLAB DYNamic OPTimisation code". User's Guide, Version 4.1, 2010

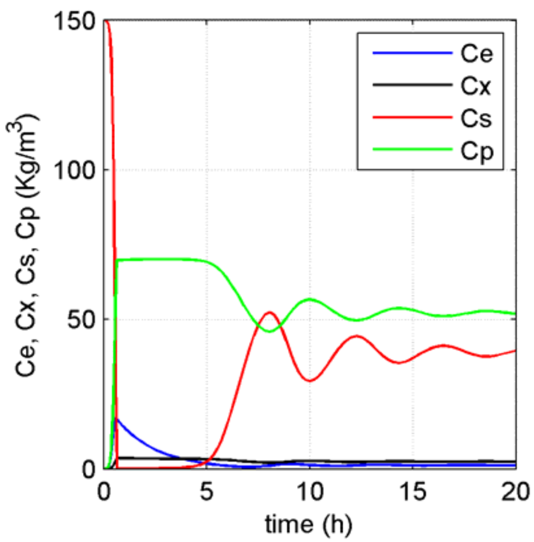
Chemical Process Example (Fermentation Process*)

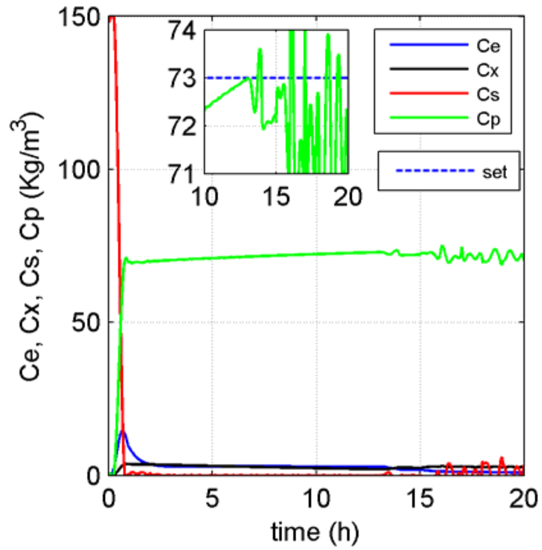
Closed-loop simulation

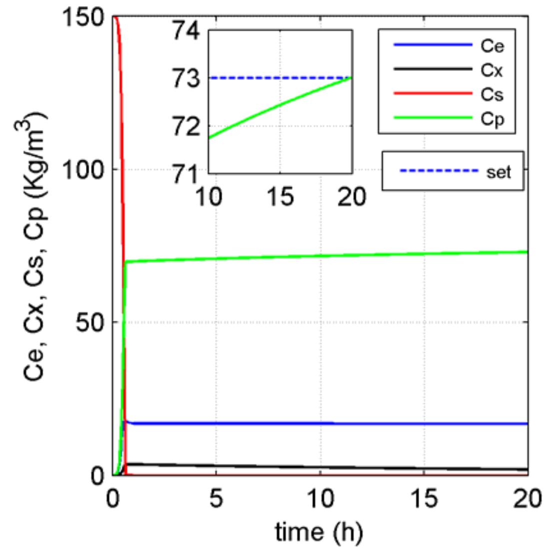
Open-loop simulation

Single *dynopt* implementation

PI controller







- Lower C_P at steady state
- Oscillations in C_P profile

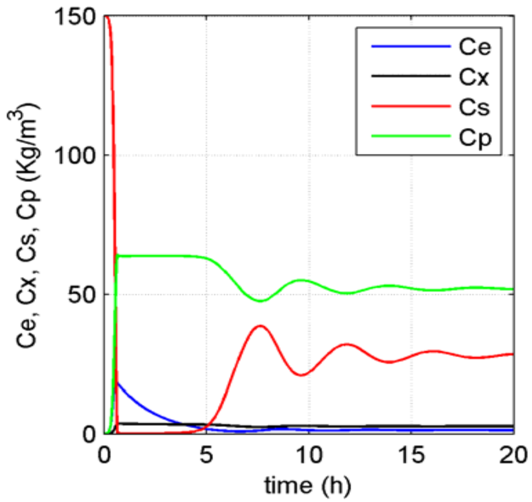
- Higher C_P at steady state
- Fast response
- C_P profile not steady as approaches setpoint

- Higher C_P at steady state
- Slower response

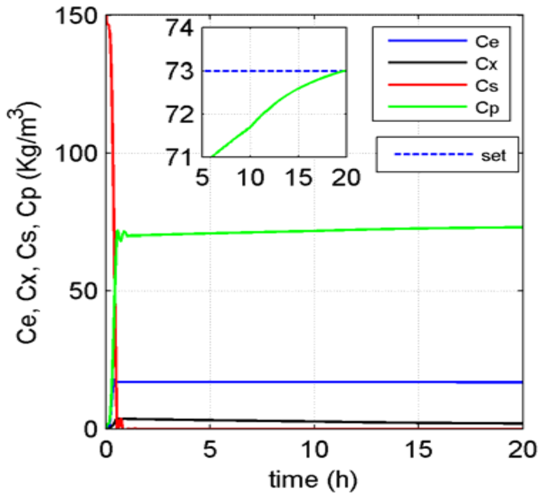
* Sridhar L. N. “Elimination of oscillations in fermentation processes”. *AIChE Journal* , 57(9):2397-2405, 2011

Biomimetic Controller Implementation

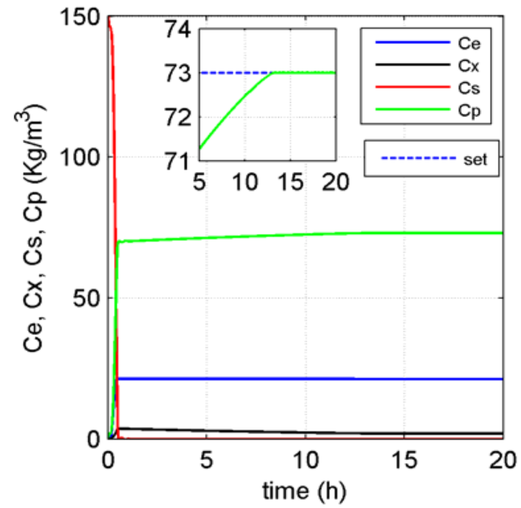
Agent0

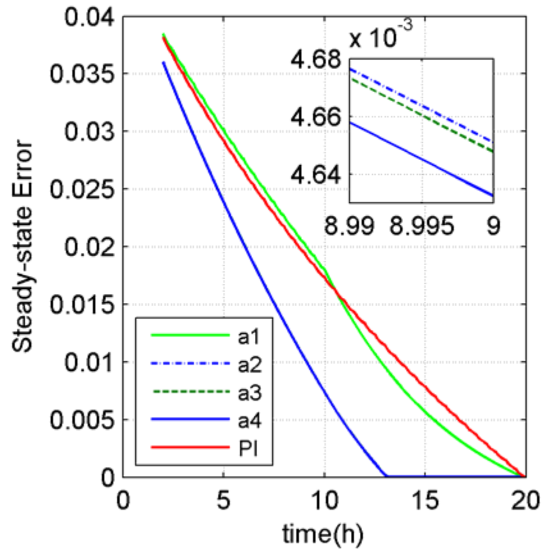


Agent1



Agent4



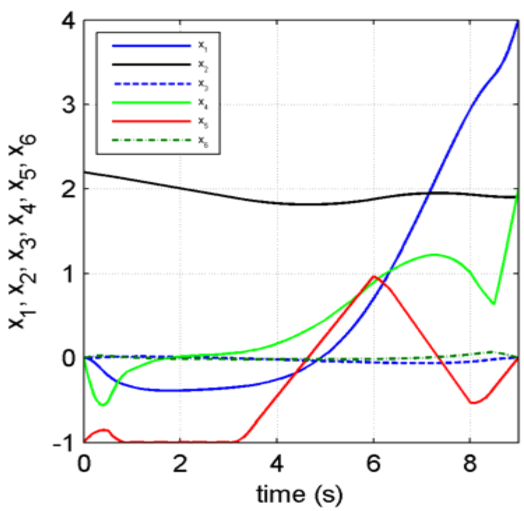


- Higher C_P at steady state
- Fast response and C_P profile steady at setpoint
- Improved performance as number of agents increases

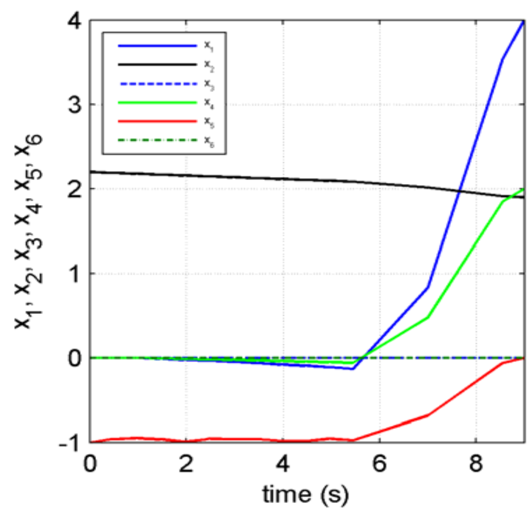
Challenge: potentially large computational time for online application (avg. for each agent $\approx 15\ min$)

Ongoing Collaborative Work

- Analyzing the replacement of *dynopt* solver by Efficient Ant Colony Optimization (EACO) techniques
  - Inspired by the ants' foraging behavior
  - Employ probabilistic and stochastic concepts
  - Developed by Dr. Diwekar's group and implemented for continuous optimization
  - Potential for computational time reduction and improved performance
- EACO preliminary results – optimal control of container crane[1]



dynopt implementation



EACO implementation

1. Hristu-Varsakelis D. and Shao C. "A bio-inspired pursuit strategy for optimal control with partially constrained final state". *Automatica*, 43:1265-1273, 2007

Year 2 Tasks (Task 3)

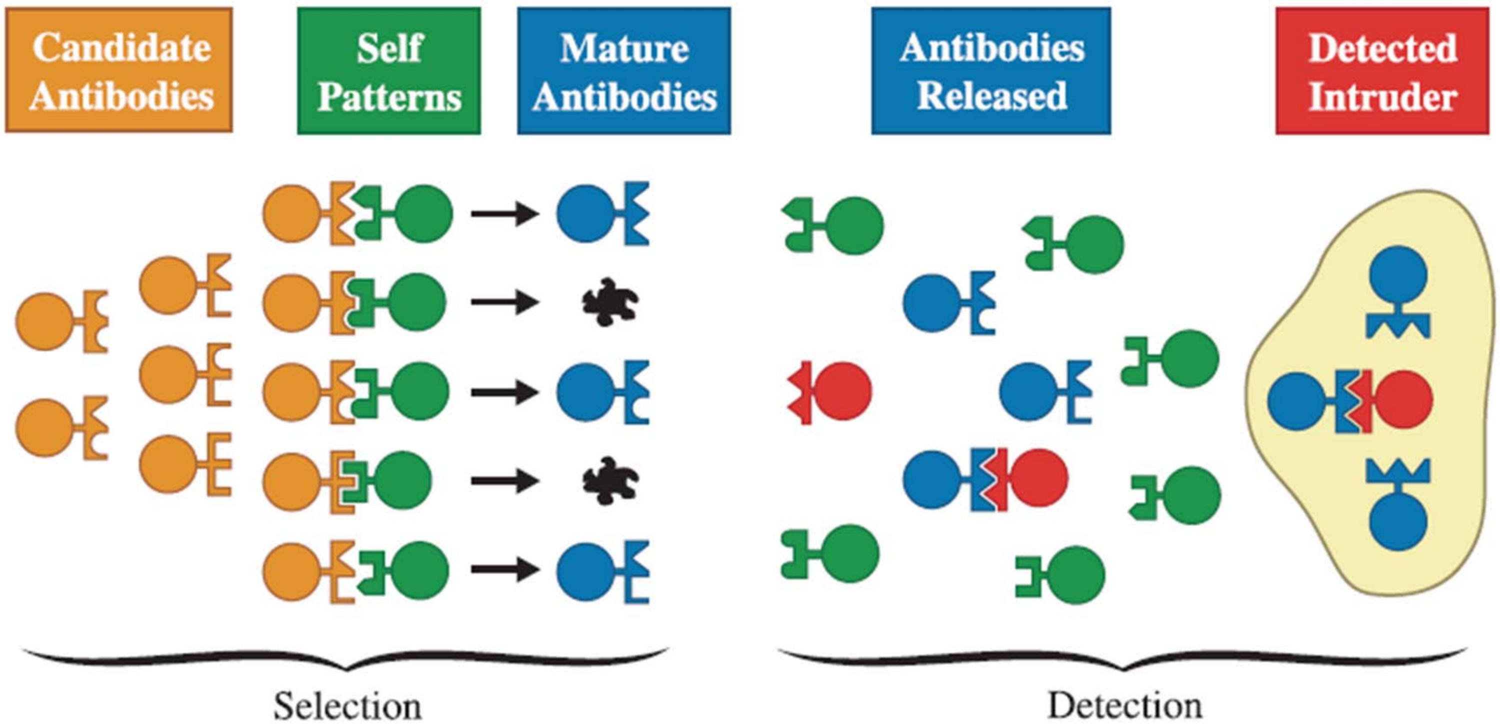
3.1 Development of Deterministic Biomimetic Controller Design (Q1-Q6)
M6: Complete the Development of Deterministic Biomimetic Controller Design
Due: 7/14/15
Success Criteria: B - Successful demonstration of deterministic biomimetic controller (Q6)

3.2 Incorporation of Adaptive Component into Biomimetic Controller Design (Q5-Q9)
M8: Incorporate Adaptive Component into Biomimetic Controller
Due: 1/14/16

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

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

Artificial Immune System (AIS) Paradigm

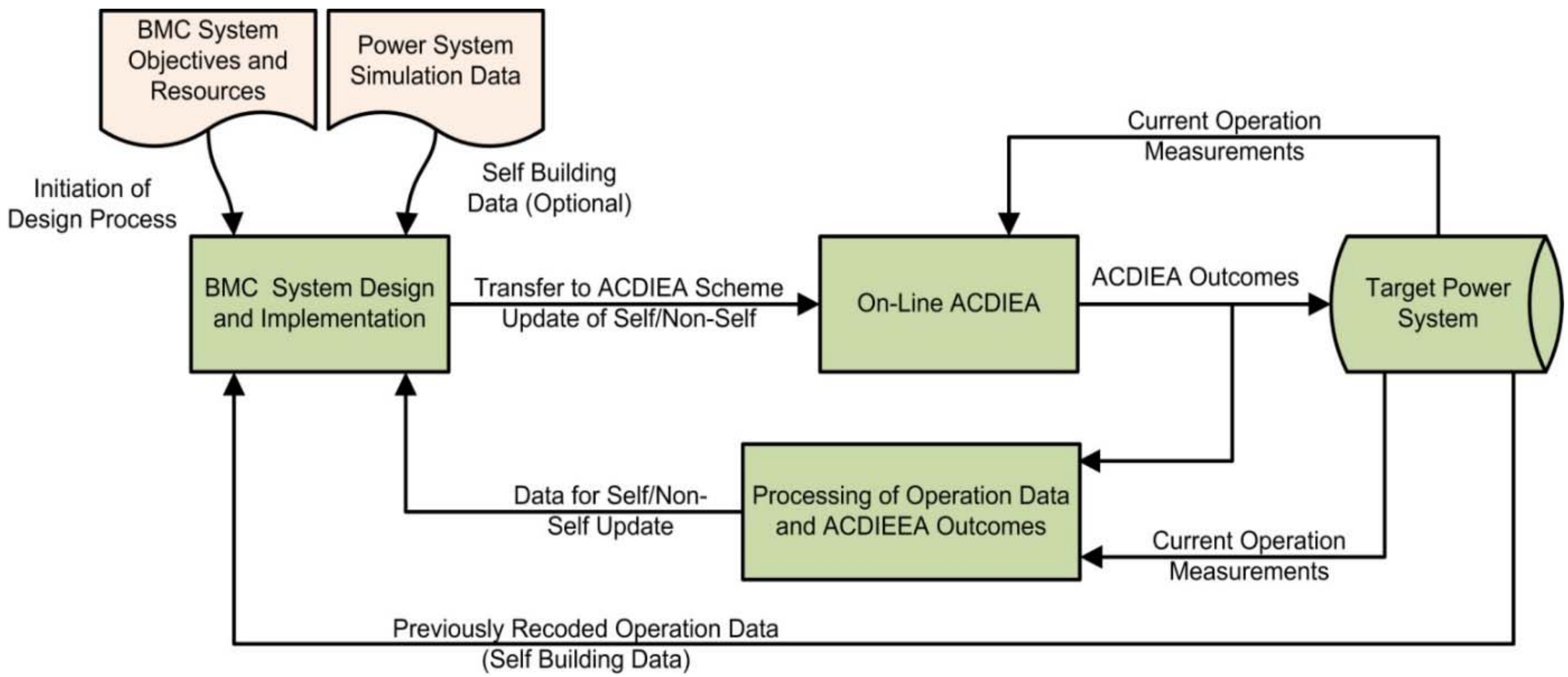


The AIS paradigm relies on mechanisms that distinguish between elements of the "self" (normal conditions) and "non-self" (abnormal conditions).

AIS can be used for a complete system monitoring process, including abnormal condition detection, identification, evaluation, and accommodation (ACDIEA).

General Conceptual Framework for AIS-based Monitoring and Control

- The monitored system is defined by a structured collection of data at normal and abnormal conditions
- (self/non-self) can be continuously updated during operation.
- The HMS strategy consists of using lower order projections instead of the complete high-dimensional self/non-self
- Algorithms based on dendritic cell mechanisms are used for this processing.

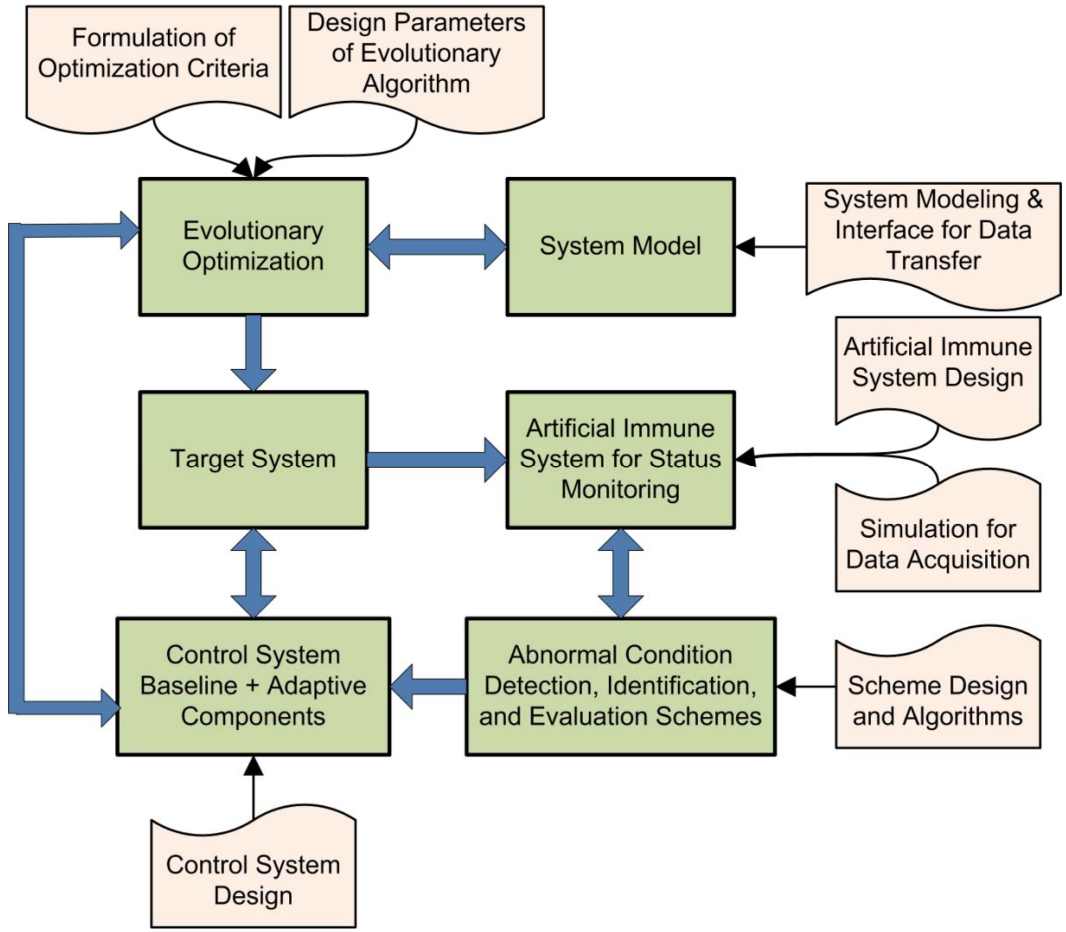


General Conceptual Framework for AIS-based Monitoring and Control

- The AIS paradigm is expected to provide an integrated and comprehensive solution to the problem of system state and health monitoring for ACDIEA.

- The immunity based AC accommodation will be 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 antibodies.



General Framework Architecture for AIS-based System Monitoring and Control

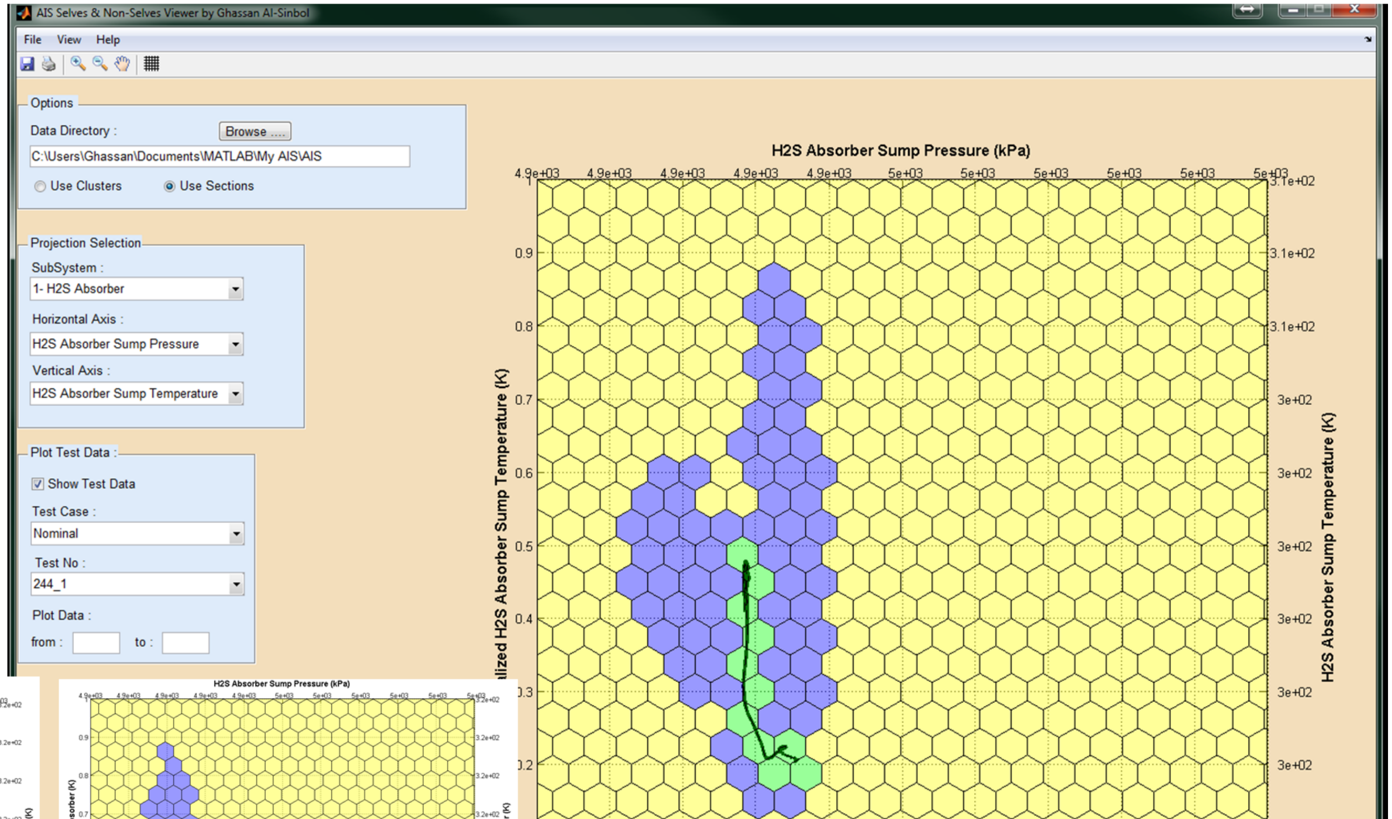
Design of the Artificial Immune System (M2)

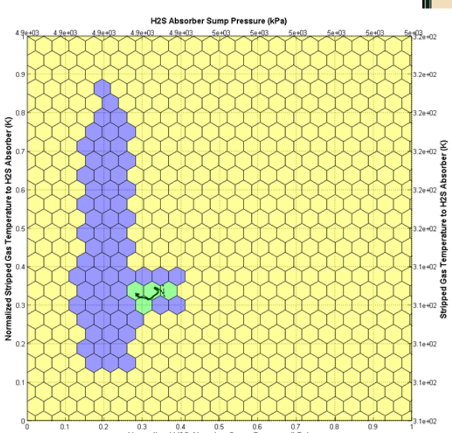
The design of the AIS has been performed by addressing the following issues:

- ***AIS general framework.*** The *targeted system* is composed of a number of subsystems, possibly nested. Specific features are identified such that all phases of the monitoring and control process can be addressed (ACDIEA).
- ***Identification of macro-system structure.*** The acid gas removal (AGR) system, which is part of the integrated gasification combined cycle power plant, has been selected as the targeted system for demonstration purposes within this project.
- ***Definition of features.*** The *feature variables* are the variables that completely define the targeted system and are expected to capture the fingerprints of all AC considered, in terms of occurrence, presence, and severity.
- ***Experimental design for self data acquisition.*** The DYNSIM model of the AGR unit is used to collect data through simulation for building the self/non-self. Operational ranges have been heuristically established for main manipulated variables.
- ***Self/non-self generation.*** A combination of negative selection-type and positive selection-type of algorithms is used for self/non-self generation and structuring. A novel approach relying on hexagonal tessellation of the feature space was developed that simplifies the self/non-self generation process and improves computational efficiency.

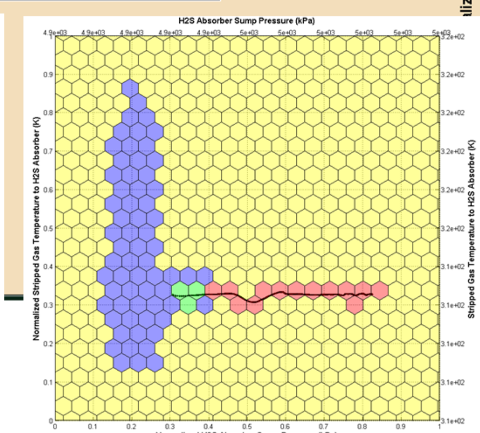
Interactive Visualization Tool for AIS Development and Analysis

AGR system model in DYNSIM
26 subsystems
171 features
Over 700 tests by varying 6 most significant inputs
Normal versus abnormal operation determined based on system constraints





Test Data at Normal Conditions



Test Data at Abnormal Conditions

Year 2 Tasks (Task 4)

Task 4.1 AVESTAR Assessment and Development of Interface Tools for Data Processing (Q1-Q5)

Task 4.2 Development of Immunity Evolutionary Algorithms for Baseline Control Laws Parametric Optimization (Q3-Q9)
M7: Successful implementation and testing of the evolutionary optimization
Due: 1/14/16

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)
M9: Successful implementation and testing of the adaptive control laws
Due: 1/14/16

Task 4.5 System Integration and Demonstration (Q7-Q12)

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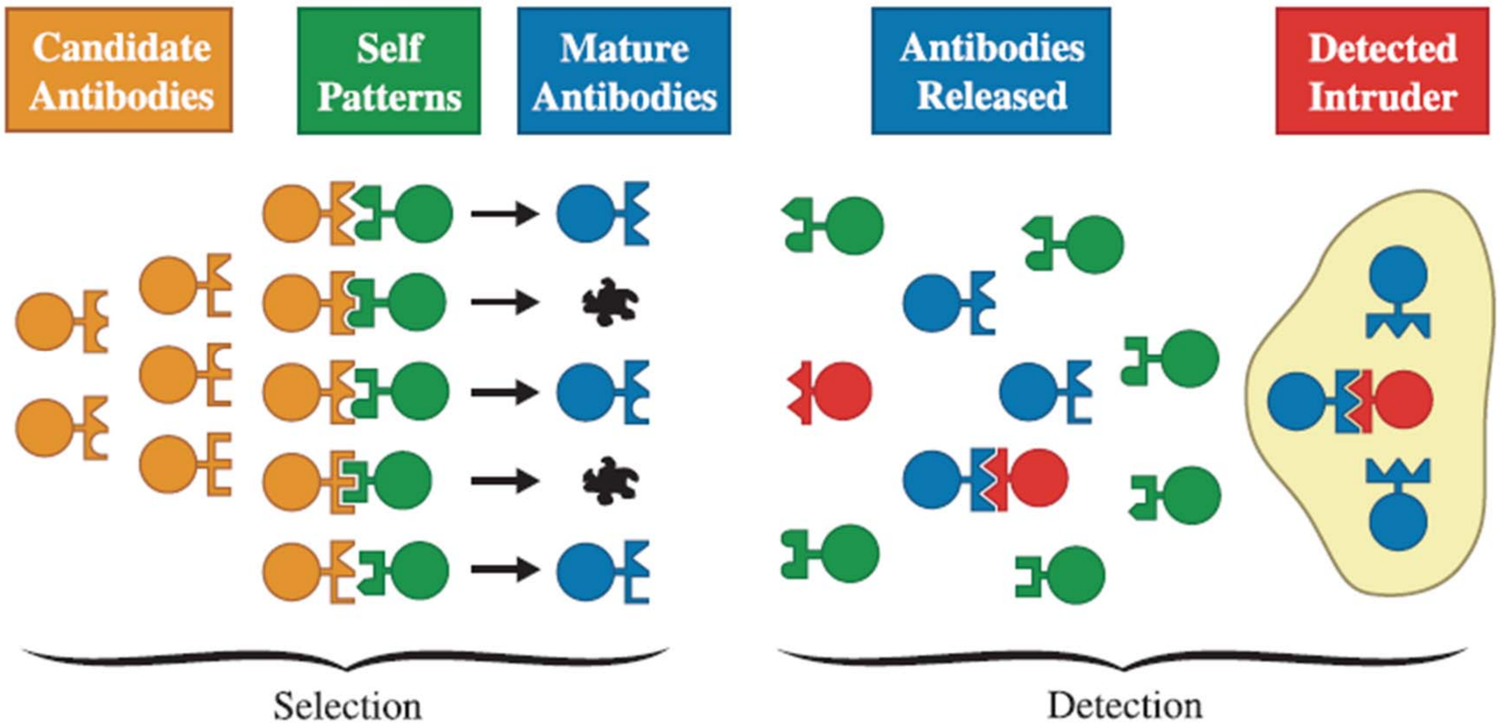

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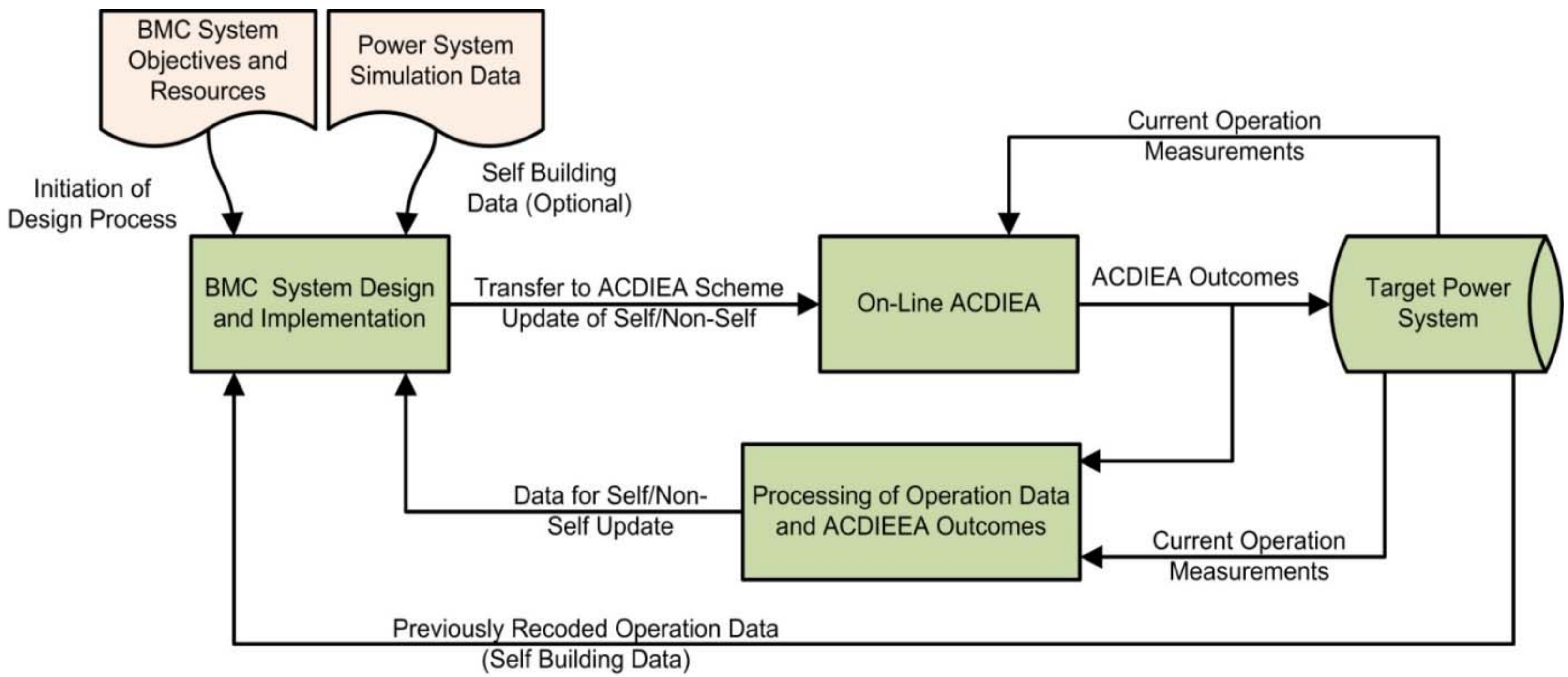

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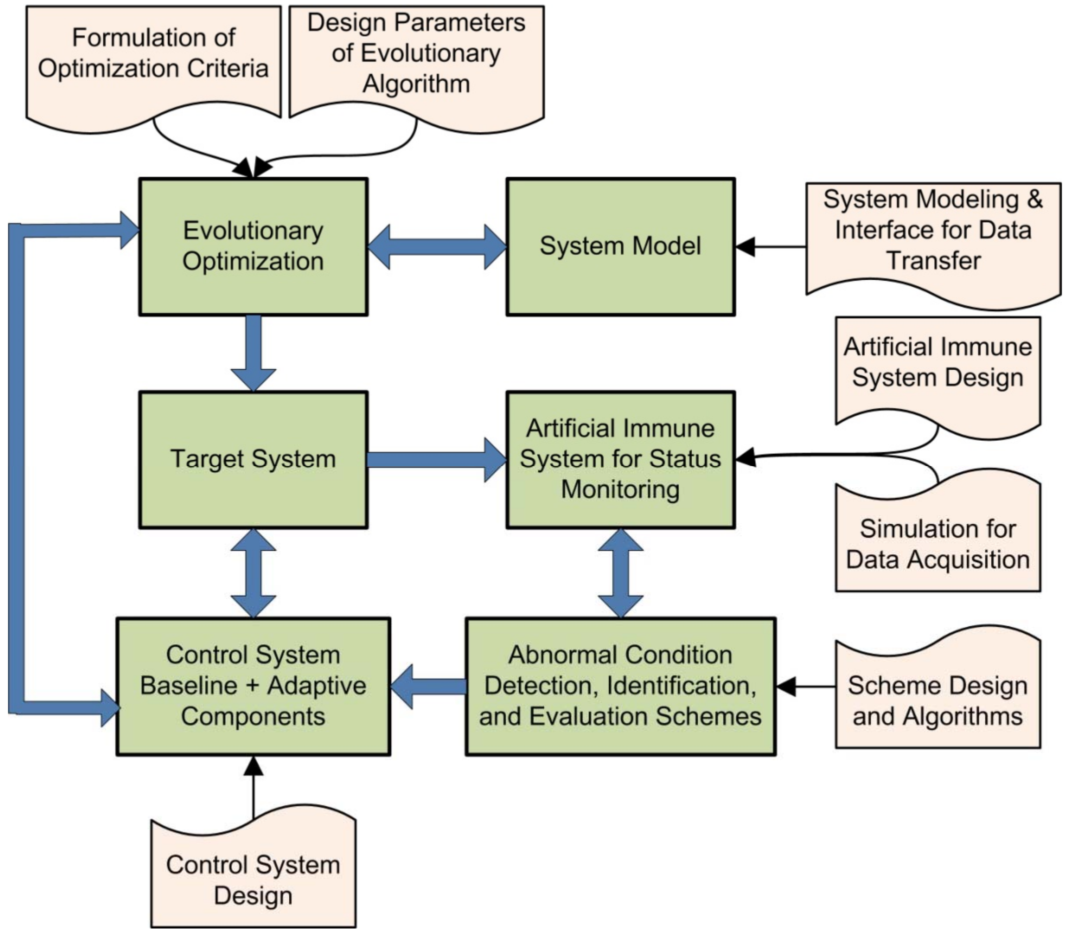

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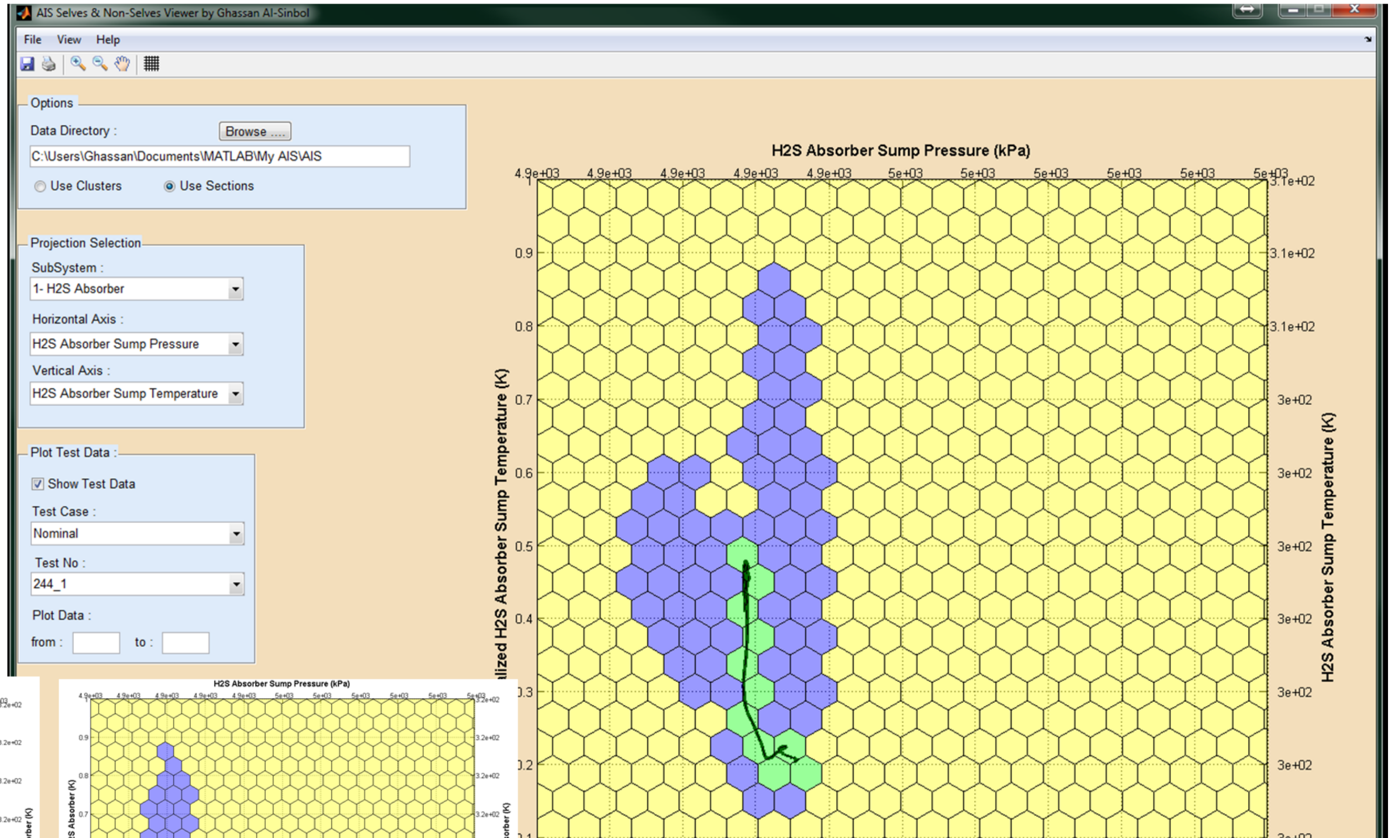

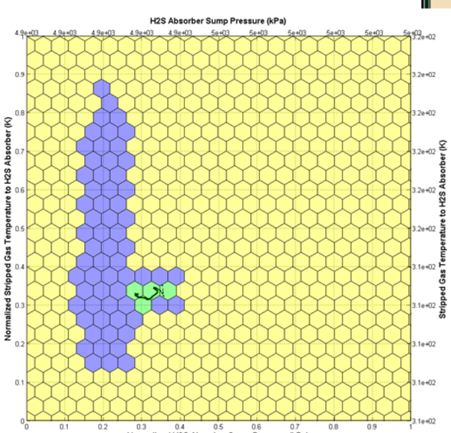

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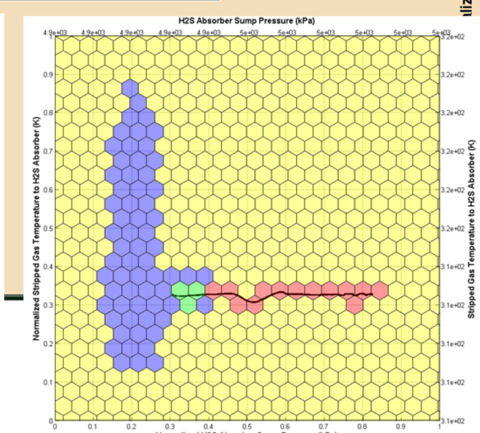

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Due: 1/14/16

Task 4.5 System Integration and Demonstration (Q7-Q12)

Task 5.0 Development of a Multi-Agent Optimization Framework for Control Structure Design, and State and Parameter Estimation

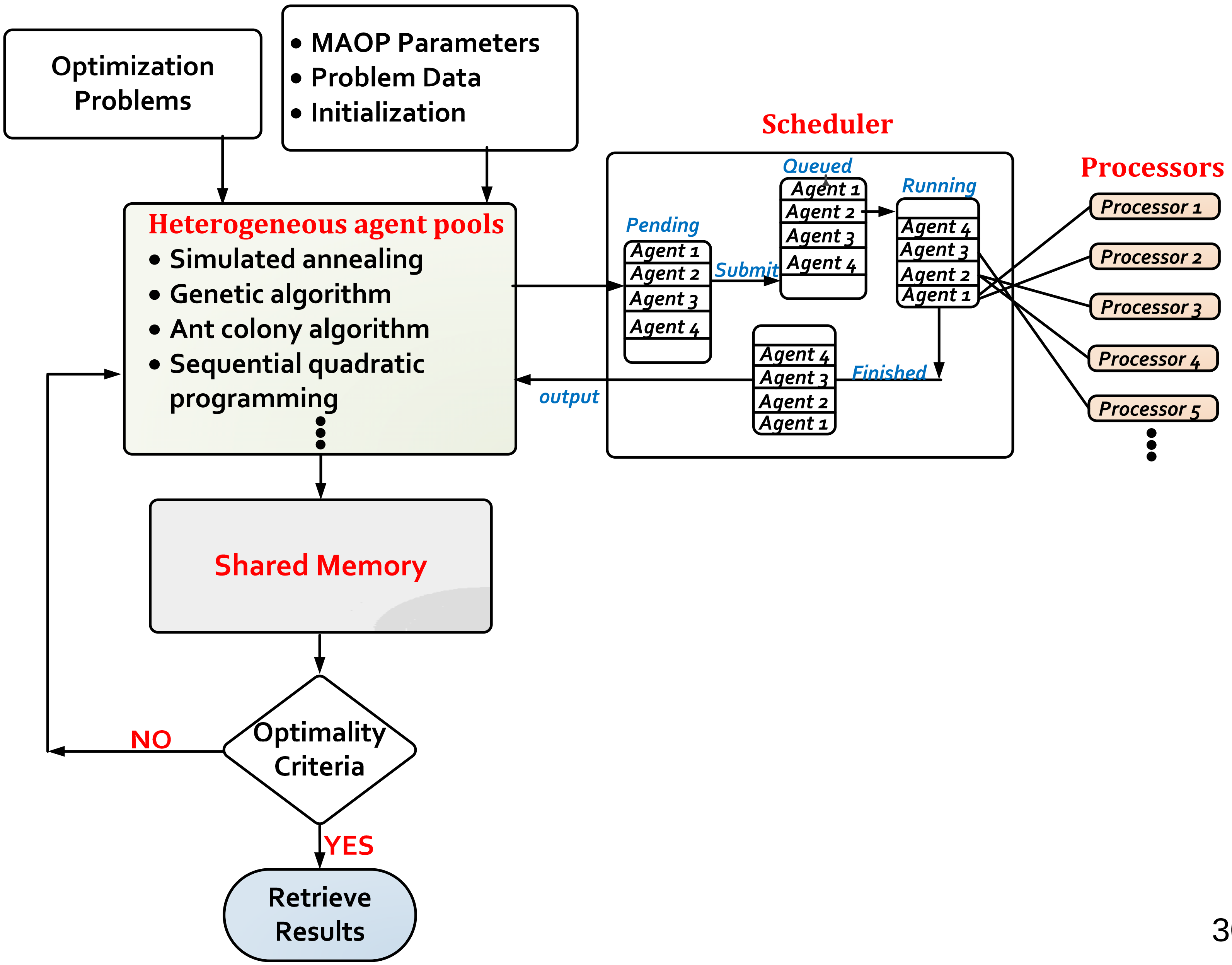
Multi-Agent Optimization (MAOP)

- MAOP is a nature-inspired optimization method, which supports cooperative search by group of algorithmic agents situated in an environment with certain predefined sharing protocol.

- Agent is an autonomous entity with personal declarative memory and behavioral components.

- Agents explore the search space of an optimization problem in parallel based on individual learning and indirectly interacting with other agents through sharing public information organized in sharing memory.

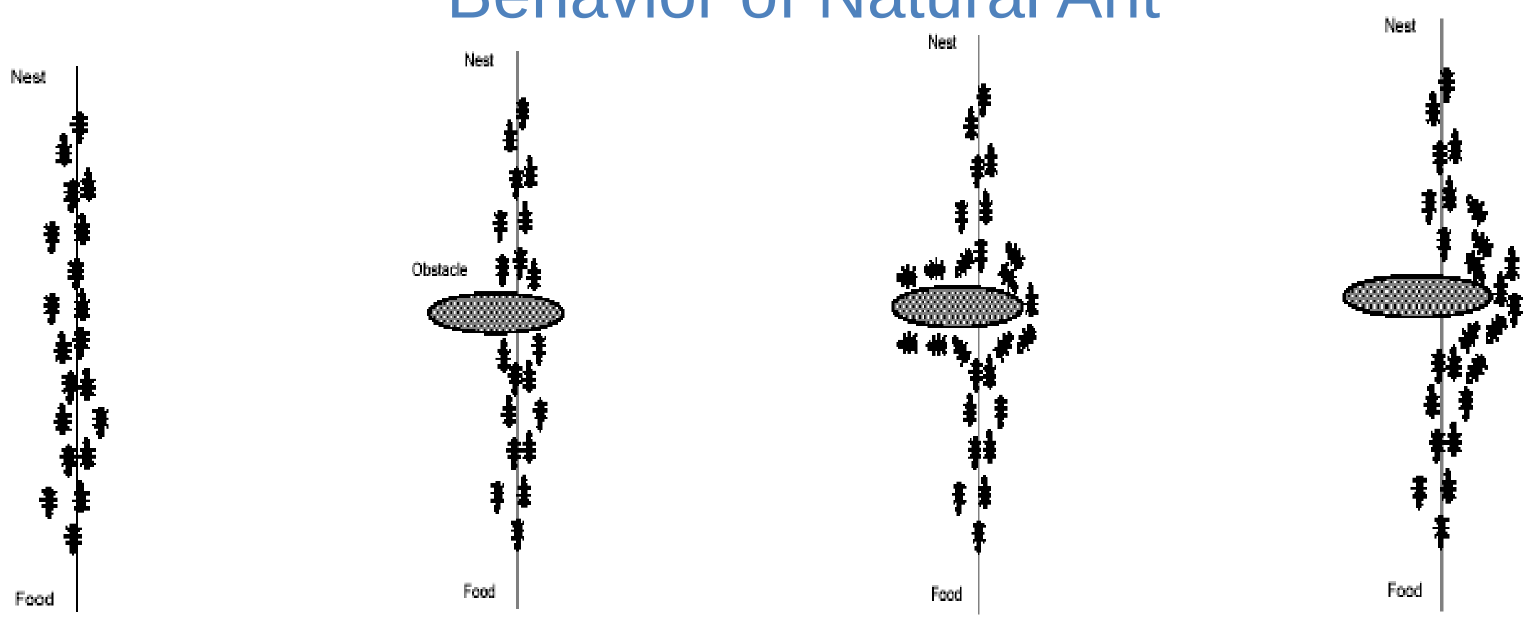
Heterogeneous MAOP Algorithm



Ant Colony Optimization (ACO)

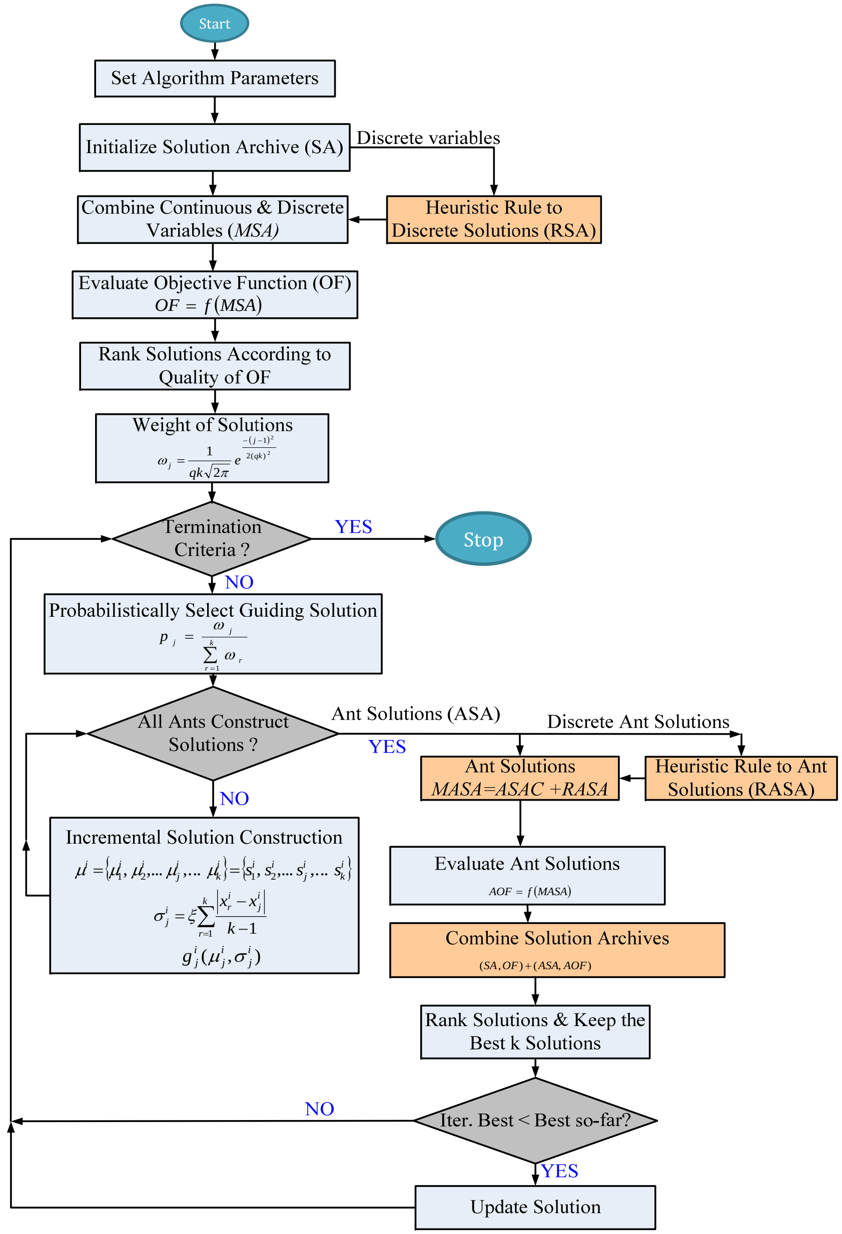
- ✓ ACO is a new metaheuristic approach for solving hard combinatorial, continuous and mixed variable optimization problems.
- ✓ Artificial ants construct solutions depending on probabilistic decisions.
- ✓ The cumulated search experience is according to pheromone trail.

Behavior of Natural Ant



Efficient Ant Colony (EACO) algorithm for MINLP

- Uses probabilistic information more efficiently
- Uses k-dimensional uniformity property of Hammersley Sequence Sampling (HSS)
- HSS is based on a quasi-random number generator



Results: Benchmark Problems & Real World Case Study

Combinatorial: Traveling salesman problem (1)

NCITY	*EACO*		*ACO*		*Improve [%]*	
	Iter	Length	Iter	Length	Iter	Length
10	6	122.8	9	123.4	33	0
20	14	164.2	21	165.3	33	0.7
40	31	208.0	45	207.5	31	-0.2

Mixed-variable: Ellipsoid function (7)

CV/DV		*EACO*	*ACO*	*Improve*
	Glb.Opt	Iter	Iter	[%]
3/2	0	15	43	65
5/5	0	95	117	19
8/7	0	156	177	12
10/10	0	188	266	29

Industrial Case Study: CAMD for Solvent Selection

High boiling point temperature solvents

K	EACO		ACO		Improvement [%]
	m	Iter	m	Iter	
500	0.75	29	0.75	38	23.7
1000	0.71	62	0.71	87	28.7

Low boiling point temperature solvents

K	EACO		ACO		Improvement [%]
	m	Iter	m	Iter	
500	0.61	108	0.62	153	29.4
1000	0.61	64	0.62	136	52.9

Results: Homogenous MAOP

Termination Criteria

DIM	*Max_Iter*
10	10
25	20
50	40
75	60

Table: Comparison of the objective function at fixed number of iterations

Function	DIM	GOPT	OF: MAOP	OF: Standalone	Iter
Parabolic	10	0	0		10
	25	0	0	0.11	20
	50	0	0	0.18	40
	75	0	0	0.36	60
Ellipsoid	10	0	0	0.24	10
	25	0	0	1.03	20
	50	0	0	1.07	40
	75	0	0	1.89	60
Cigar	10	0	0	80.92	10
	25	0	0	252.95	20
	50	0	0.001	450.25	40
	75	0	0.043	847.19	60
Rosenbrock	10	0	0.001	2.16	10
	25	0	0.002	7.88	20
	50	0	0.003	17.37	40
	75	0	0.014	24.31	60

Major Findings

- Developed Efficient Ant Colony Optimization (EACO) algorithm
  - Based on k-dimensional uniformity of HSS.
  - EACO is at least 3-71% more efficient than ACO.
  - Extended EACO to solve optimal control problems.
- Designed a homogenous MAOP framework
  - Developed based on an efficient ant colony algorithm.
  - Different initialization are used for each algorithm.
- The results from the MAOP are always close to the global optimal solutions. However, the results from the standalone stuck on the local suboptimal solutions.

Year 2 Tasks (Task 5)

Task 5.2 Designing MP, EGA and ESA agents and the clustering agent (Q4-Q8)
M8: Successful Development of the MP, EGA and ESA agents
Due: 1/14/16

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)

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Thank you