BEARS | SinBerBEST

Parameter and Optimal Performance Modelling in Smart Buildings

Maojiao Ye[1], Prof. Guoqiang Hu[1], Prof. Costas Spanos[2]
[1]Nanyang Technological University
[2]UC Berkeley

Supported by:

Funded by:
NATIONAL
RESEARCH
FOUNDATION

Motivation

- Smart buildings can effectively reduce CO2 emissions and energy consumption while increasing human comfort through energy management, sensing, control, and information technologies.
- It is **challenging to model the complex physical and cyber processes** (e.g., HVAC, lighting, occupant activities) in smart buildings, especially as an integrated system.
- It is highly demanded to characterize and model the **optimal performance of processes** in smart buildings so as to predict and optimize the energy consumption and human comfort.
- The optimal performance of the processes in smart buildings **may not be invariant** due to uncertainties, faults, occupant activities, and varying environment conditions.

2012 Main Objectives

- Design a scheme to model the parameters and optimal performance for the physical and cyber processes of smart buildings. This scheme will ultimately consider:
  - – Continuous physical processes
  - – Discrete-time events, faults, cyber processes
  - – Occupant behavior
  - – Disturbances and uncertainties
  - – Interdependencies among the processes and events.
- Develop modelling tools for smart buildings by adapting multi-agent theory, games, and machine learning tools.
- Develop a unified framework for identification and optimization of physical processes subject to uncertainties and networked interactions.

The Problem and Approach

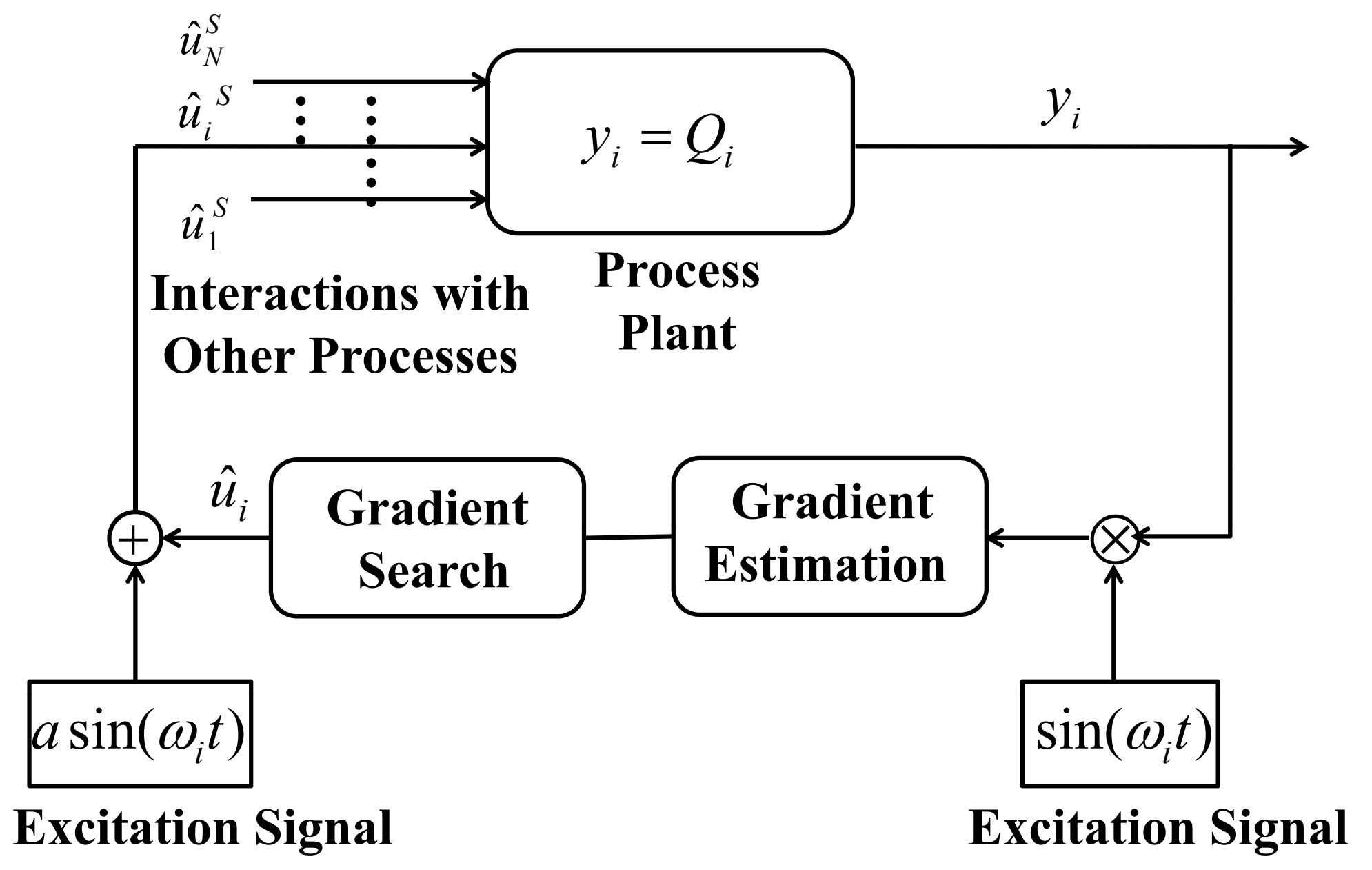
- How to characterize the interactions among networked physical processes in the building?
- How to handle the uncertainties that cannot be modeled?
- How to design a scheme to identify the optimal performance and certain parameters in the model?
- How to balance the trade-off between accuracy and convergence speed?

Proposed approach:

- A multi-agent method is adapted to describe the processes. Each process is modeled as an agent. Games are formulated to handle the interactions among the processes. An extremum learning method is designed to estimate the parameters and optimal performance of the processes.

Identification and Optimization Scheme

The modelling and control co-design framework for identification and optimization of N processes



N-Process Games

Design action strategies for N processes to converge to a small neighborhood of a Nash equilibrium (NE)

$$\begin{aligned} Q_i(u_i^*(t), u_{-i}^*(t), \varsigma_i(t)) &> Q_i(u_i(t), u_{-i}^*(t), \varsigma_i(t)) \\ \forall u_i &\neq u_i^*, i \in \mathbb{N} \end{aligned}$$

$$Q_i^*(t) \triangleq Q_i(u_i^*(t), u_{-i}^*(t), \varsigma_i(t))$$

Time-Varying NE

The convergence can be enabled by designing the gradient estimation and gradient search modules and well selection of the excitation signals.

Gradient Estimation

Real-time gradient estimation: Design an update law to extract the gradient of the utility function under uncertainties and networked interactions.

$$\mu(u_i, \hat{u}_{-i}^S, \varsigma_i) = \frac{1 - e^{-Ts}}{Ts}\left[Q_i(u_i, \hat{u}_{-i}^S, \varsigma_i)\sin(\omega_i t)\right]$$

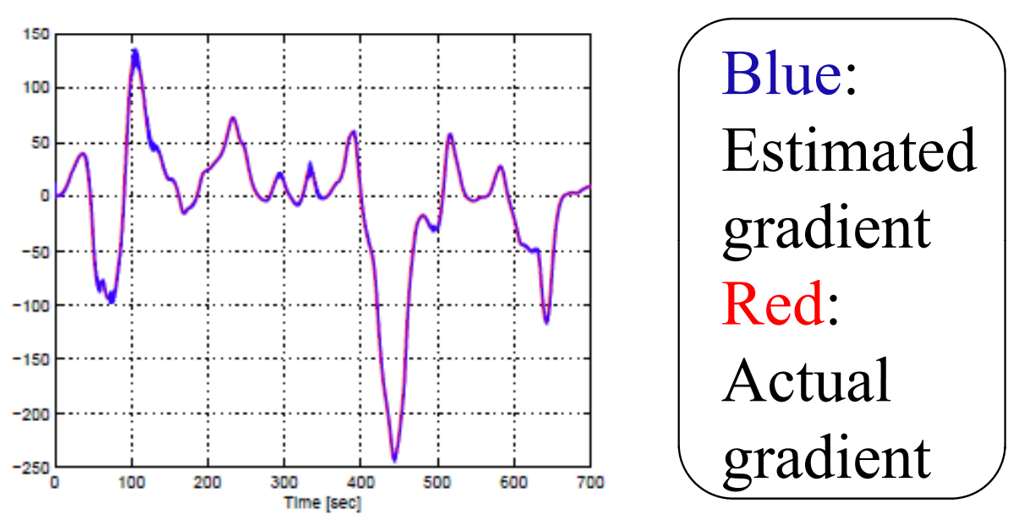
$$\mu(u_i, \hat{u}_{-i}^S, \varsigma_i) = \frac{a}{2} Q_{iu_i}(\hat{u}_i, \hat{u}_{-i}^S, \varsigma_i(t)) + \mathcal{O}(\cdot)$$

Example: For a single process with utility function

$Q(u,\varsigma) = 4\varsigma^3 - \varsigma(u^2 - \varsigma)^2$, ς uncertain parameter

The actual gradient used for comparison:

$$Q_u(u,\varsigma) = -4u\varsigma(u^2 - \varsigma)$$



Gradient Search

Gradient Search for Tracking a Time-Varying Nash equilibrium: Consider an update law for $\hat{u}_i$ of the form $\dot{\hat{u}}_i = \lambda_i$.Design a gradient search law $\lambda_i(t)$ such that $\|\hat{u}_i(t) - u_i^*(t)\| \to 0$ as $t \to \infty, i \in \mathbb{N}$ using the estimated signals $\hat{u}_i(t)$ and $Q_{iu_i}(\hat{u}_i, \hat{u}_{-i}, \varsigma_i)$ where $\hat{u}_i(t)$ is the estimation of $u_i(t)$ and $Q_{iu_i}(\hat{u}_i, \hat{u}_{-i}, \varsigma_i)$ is the estimated gradient of $Q_i(u_i, u_{-i}, \varsigma_i)$ with respect to $u_i(t)$ at $u_i(t) = \hat{u}_i(t)$.

In classic extremum seeking scheme for a constant extremum, steepest descent can be used. For the case of **time-varying** Nash equilibrium, a new method is needed.

Gradient Search Algorithm

$$\begin{aligned} \lambda_i &= k_1 Q_{iu_i} + \Phi - c_1 \hat{u}_i \\ \dot{\Phi} &= c_2 k_1 Q_{iu_i} + k_2 sgn(Q_{iu_i}) \end{aligned}$$

Gradient Search Example

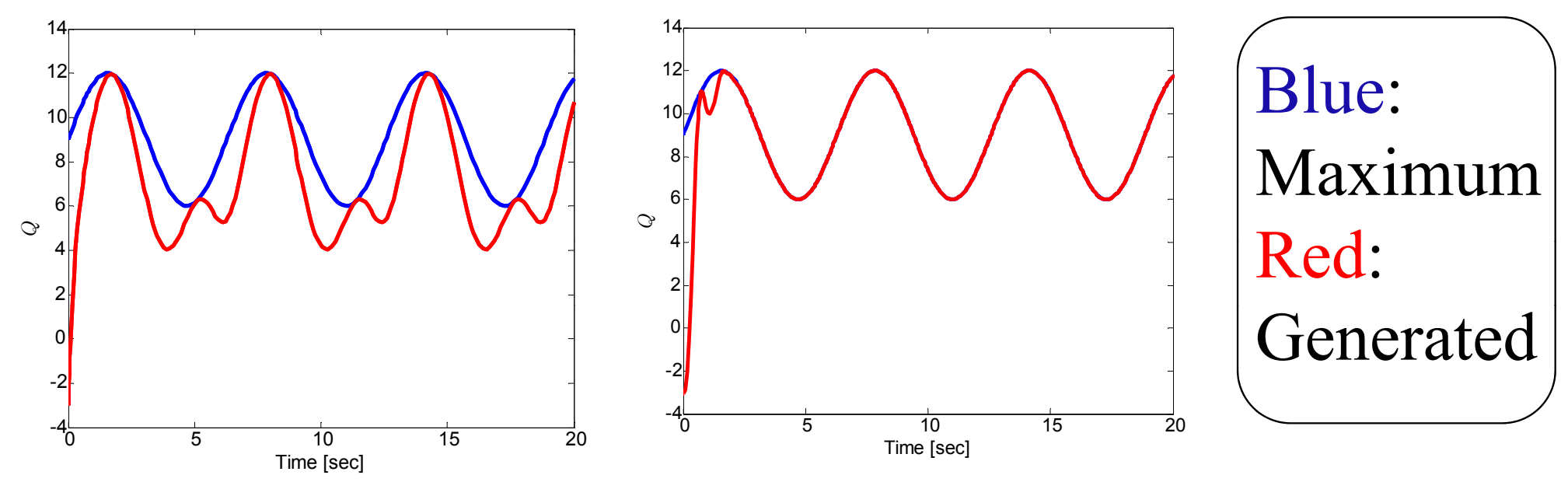
Consider the time-dependent mapping

$$Q = (3 + \sin(t))[3 - (\theta + 1 - 4\sin(t))^2]$$

The extremum point and the optimal value are

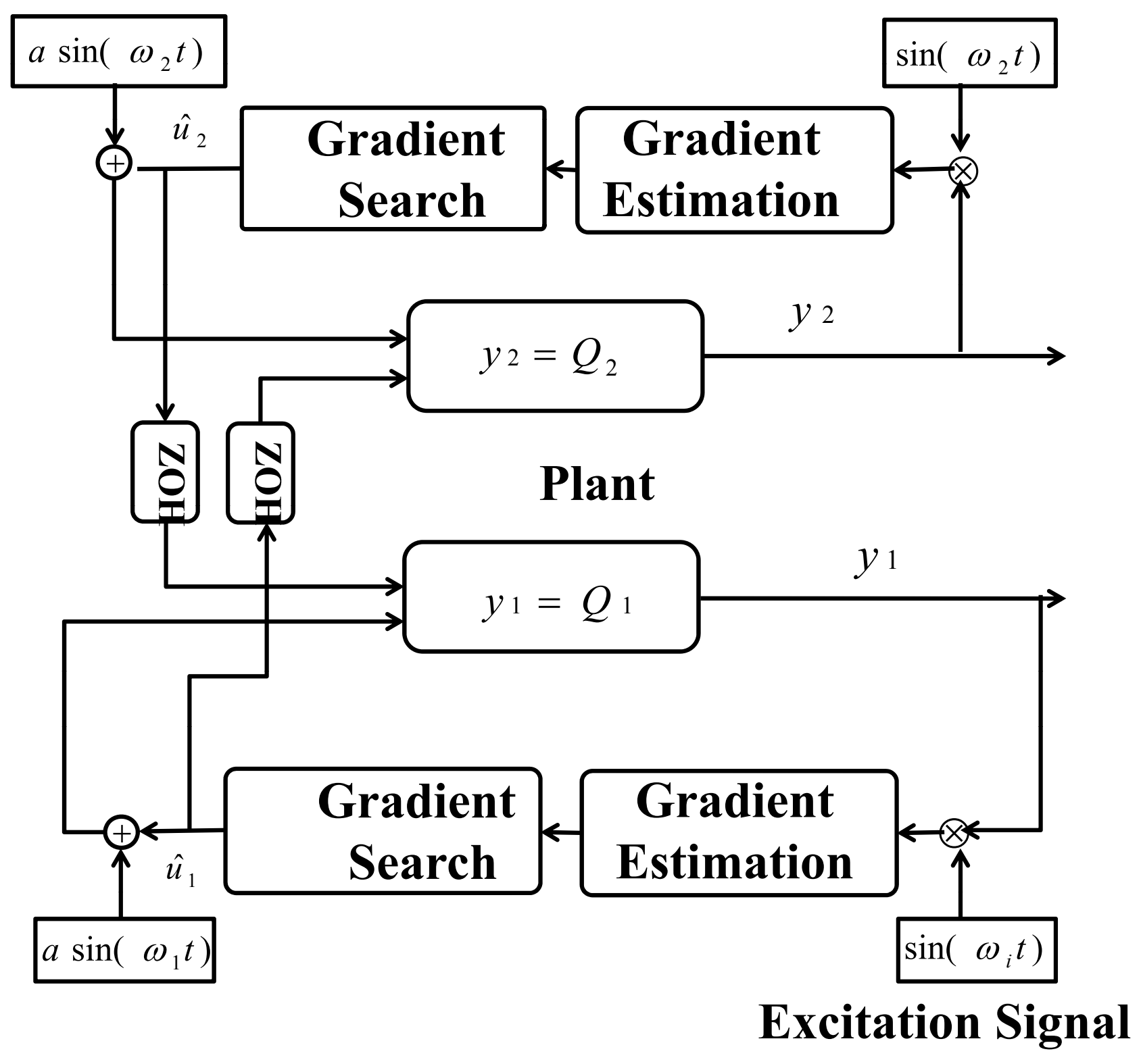
$$\begin{aligned} \theta^*(t) &= 4\sin(t) - 1, \\ Q^*(t) &= 3(3 + \sin(t)). \end{aligned}$$

The gradient is $Q_\theta = -2(3 + 2\sin(t))(\bar{\theta} + 1 - \sin(t))$



Steepest descent **Proposed method**

Block Diagram for An Example with Two Processes



Simulation for Three Processes

Consider a three-process game with the payoff functions

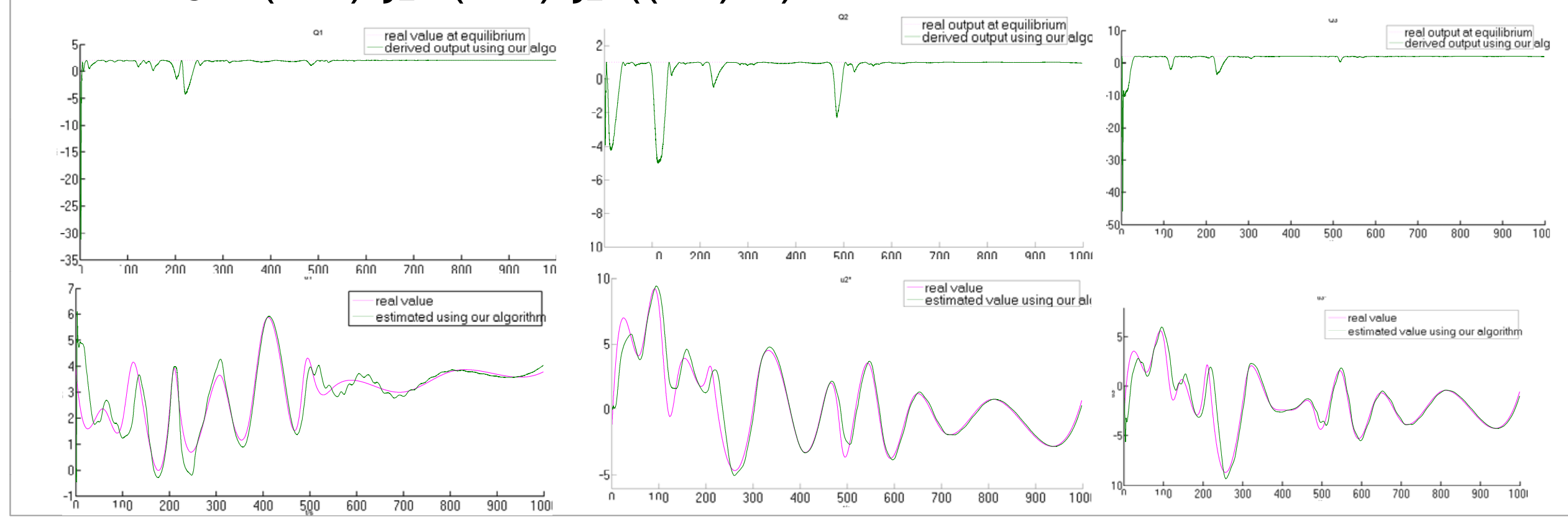
$Q_1 = -(u_1 - (1/3)u_2 + u_3 - \varsigma_1 - 1)^2 + 2$
$Q_2 = -(-(1/4)u_1 + u_2 - (1/2)u_3 - \varsigma_2 + 3)^2 + 1$
$Q_3 = -(-u_1 - u_2 + u_3 + 5)^2 + 2$

ς_1, ς_2 are uncertainties

The Nash equilibrium for the three processes are:

$u_1^* = (1/3)\varsigma_1 - (4/9)\varsigma_2 + ((34)/9)$
$u_2^* = (1/4)\varsigma_1 + (4/3)\varsigma_2 - ((16)/3)$
$u_3^* = (5/6)\varsigma_1 + (8/9)\varsigma_2 - ((59)/9)$

Upper three: optimal payoff
Lower three: time-varying NE



Conclusions

- Proposed a modelling method by leveraging multi-agent theory, games, and learning methods.
- Developed a unified framework for identification and optimization of physical processes subject to uncertainties and networked interactions.
- Designed estimation algorithms to extract measurable information from the processes.
- Designed a distributed seeking method to learn the process parameters and optimal performance.

Future Goals

- Study processes that have different dimensions and dynamic properties
- Consider both discrete-time and continuous-time processes within the same framework
- Explore event-driven mechanisms to integrate occupant behaviors into the identification and optimization scheme
- Conduct experimental test in a building to evaluate the proposed scheme and methods