Control System Research Activities

@ Chulalongkorn University
จุฬาลงกรณ์มหาวิทยาลัย
Pillar of the Kingdom

Outline

- Profiles
- Facilities
- Research Activities

Control System Research Lab (CSRL)

Established since 1985

Objective

To conduct research and development in areas of control systems, analysis, design and applications

Strategic Research Area

Advanced control & optimization, embedded systems & robotics

Faculty Members

Watcharapong Khovidhungij

Manop Wongsaisuwan

Suchin Arunsawatwong

David Banjerdpongchai

Jitkomut Songsiri

Students as of Mar 2016

1 PhD
7 Master
14 Undergrad
1 Postdoc

Offerred courses

Linear Control Systems I & II

Computational Techniques for Engineers

Digital Control Systems

Introduction to Mathematical Analysis

Control System Theory

Convex Optimization

Multivariable Control

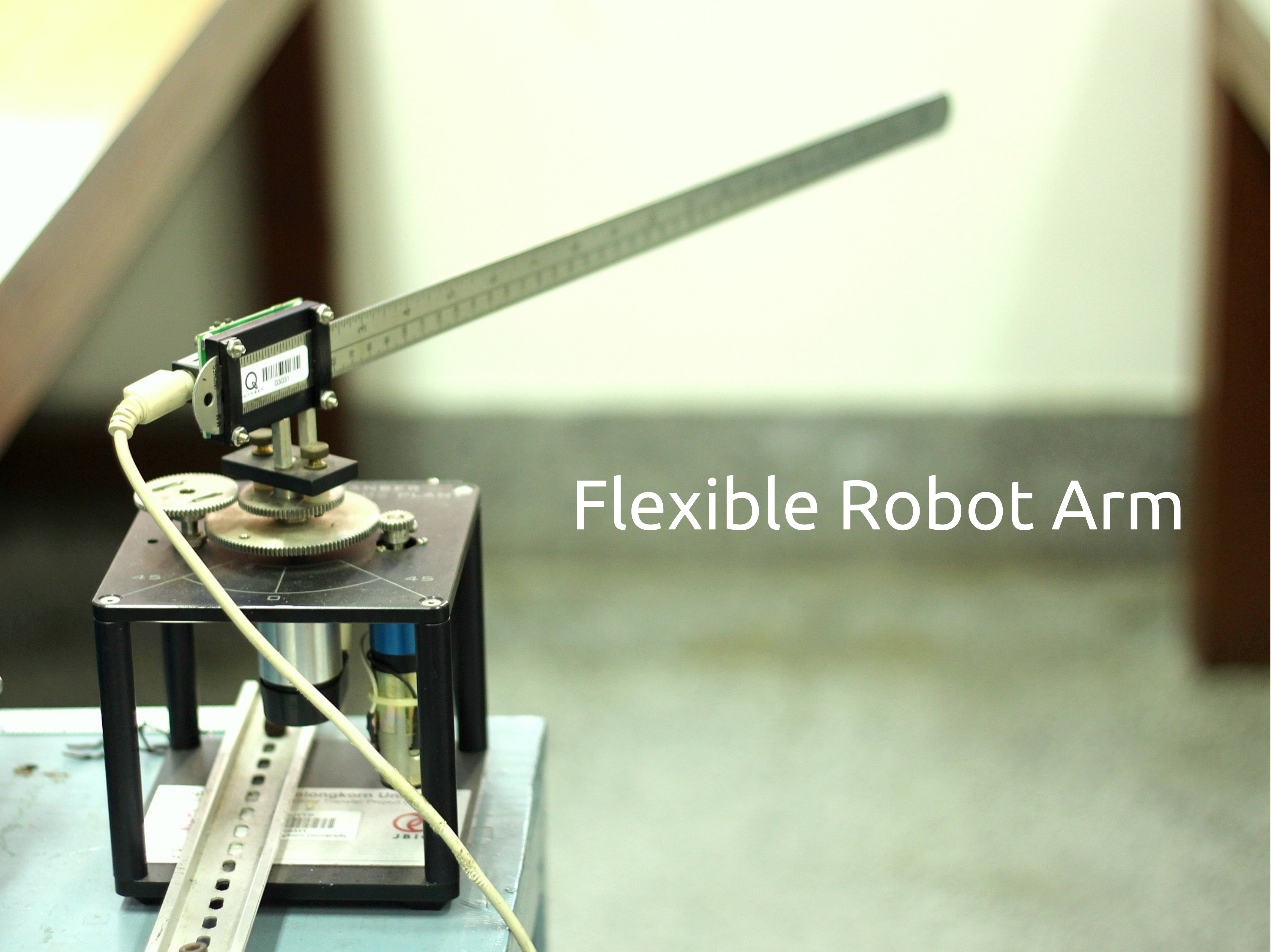
Nonlinear Control Systems

Introduction to Optimization Techniques

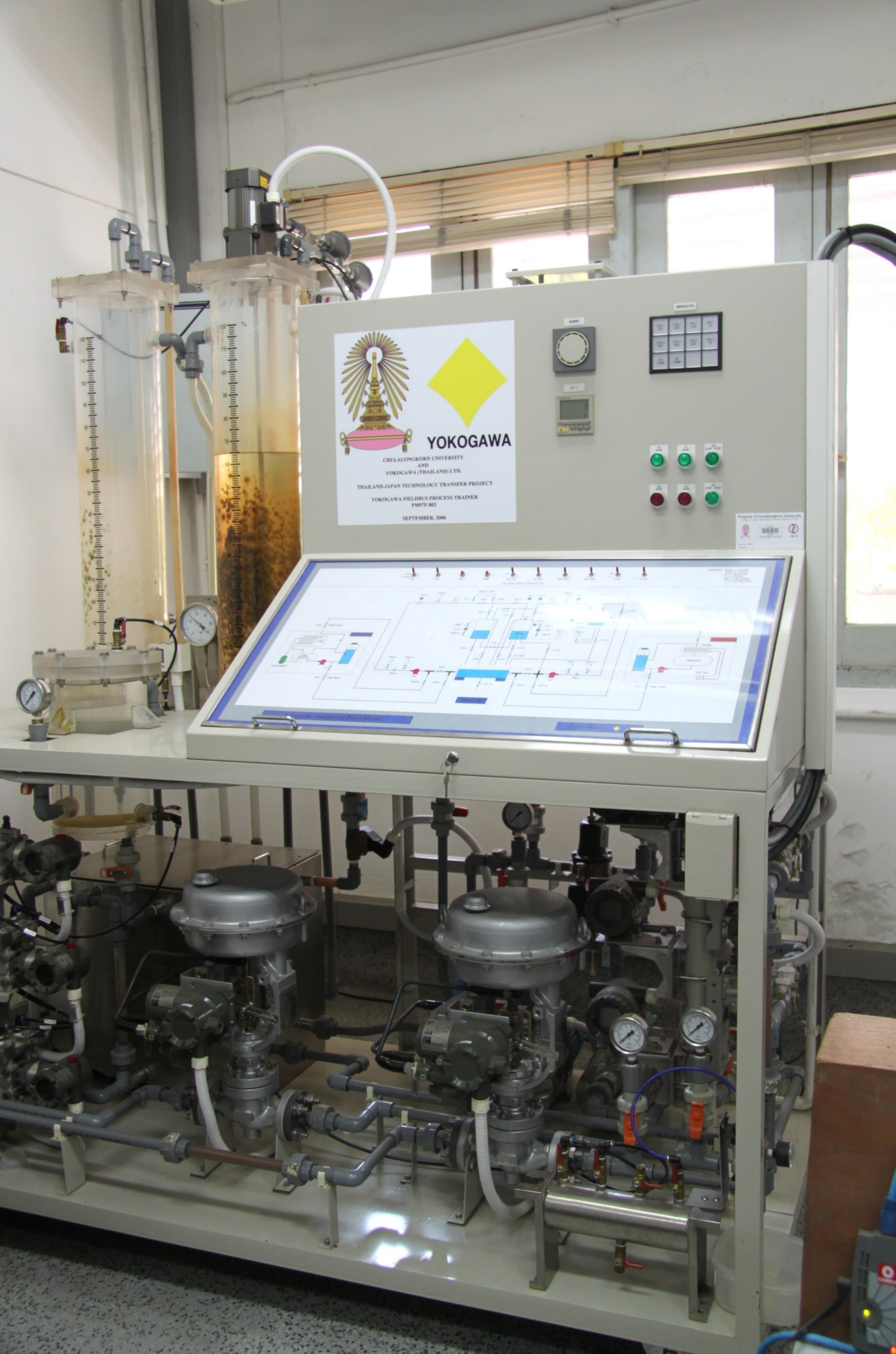
System Identification

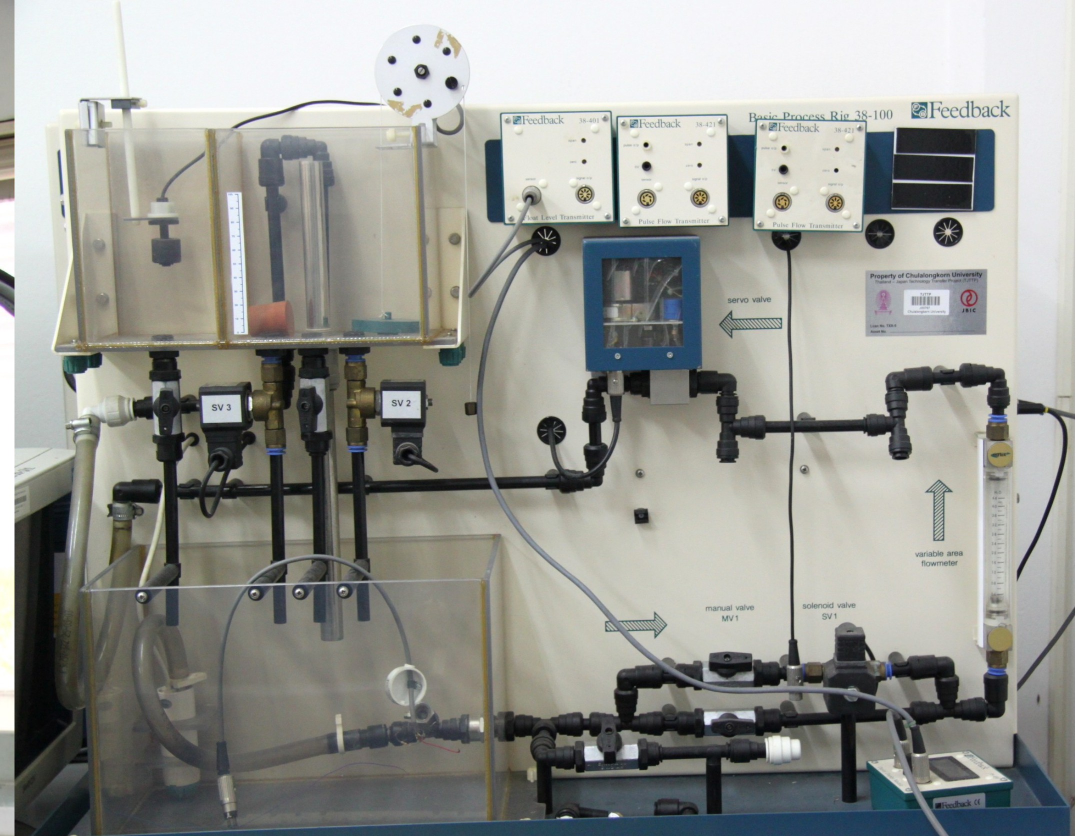
Industrial Control and Instrumentation


Research & Lab equipment
YOKOGAWA
PROCESS
CONTROLLER
deviation
monitor
set value


Flexible Robot Arm

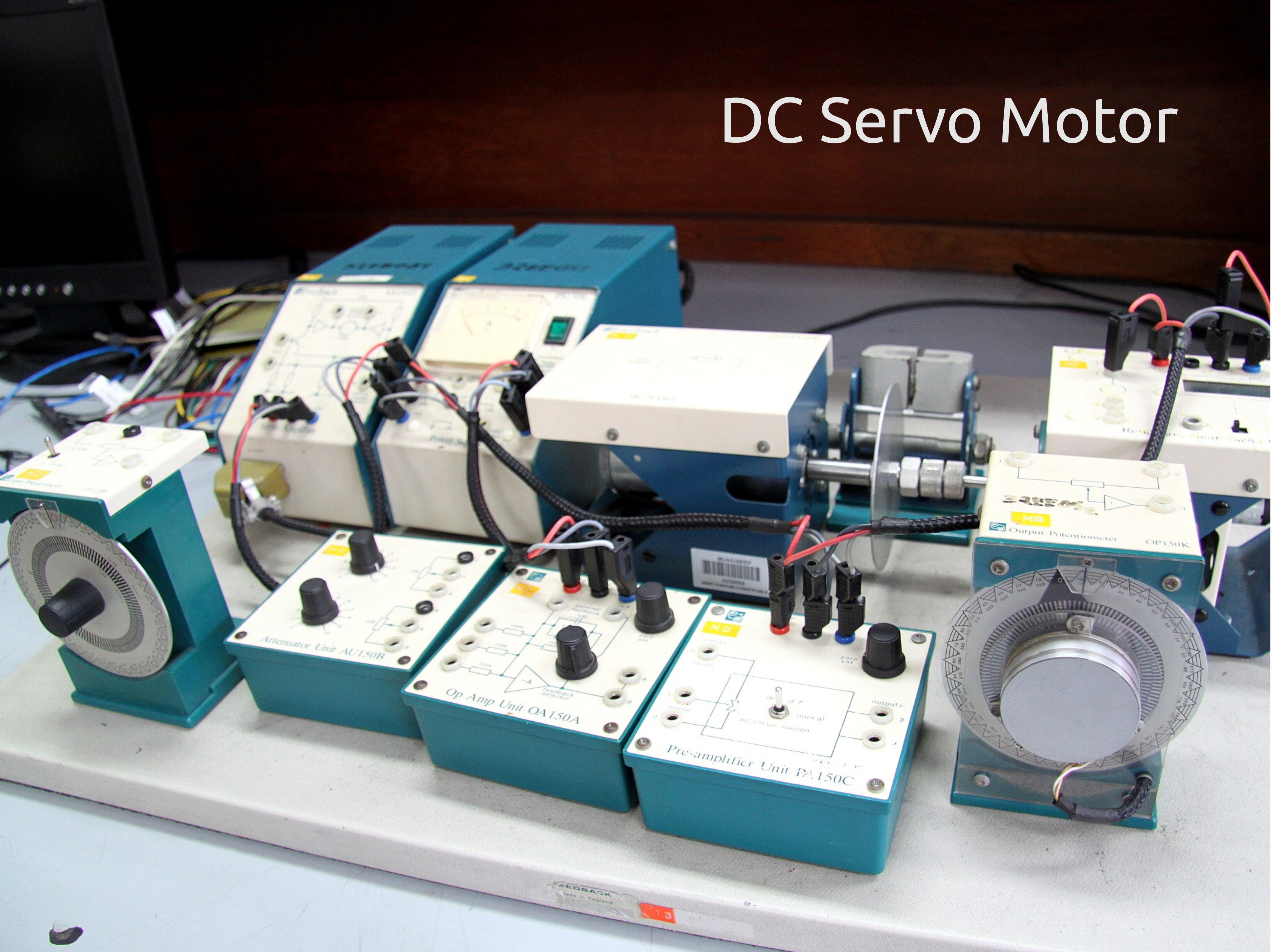
Multi-DOF Torsion



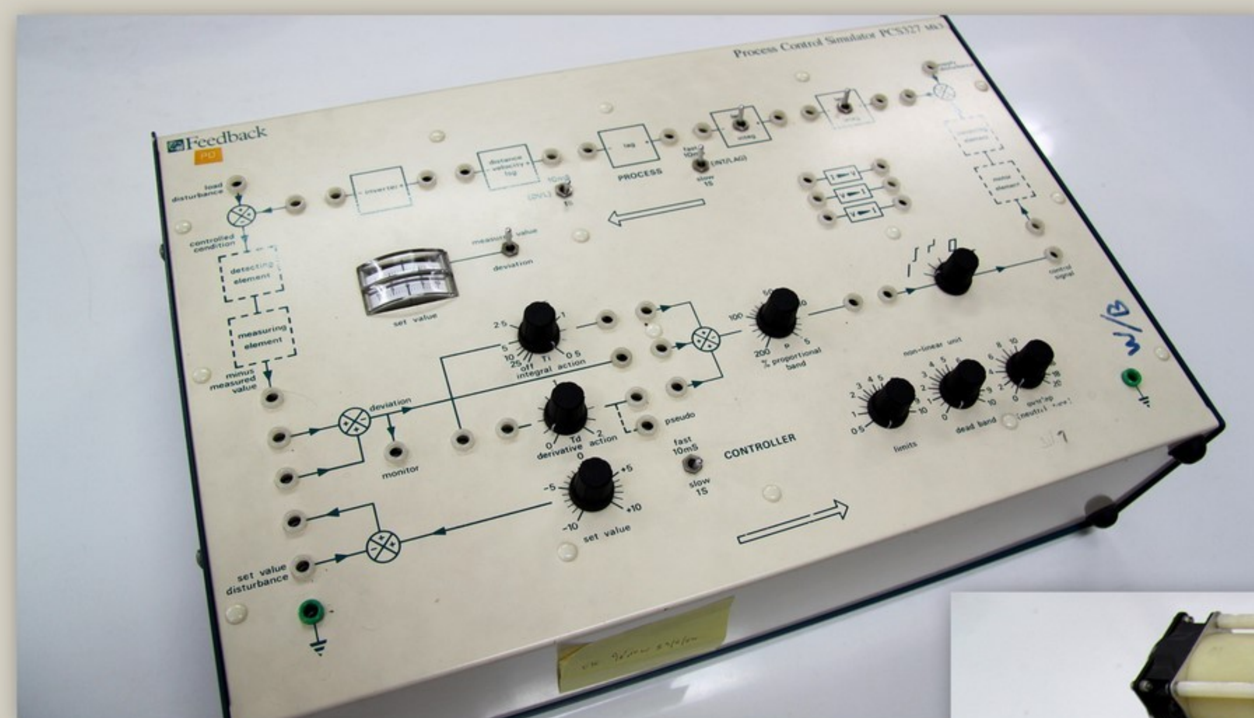


Process control

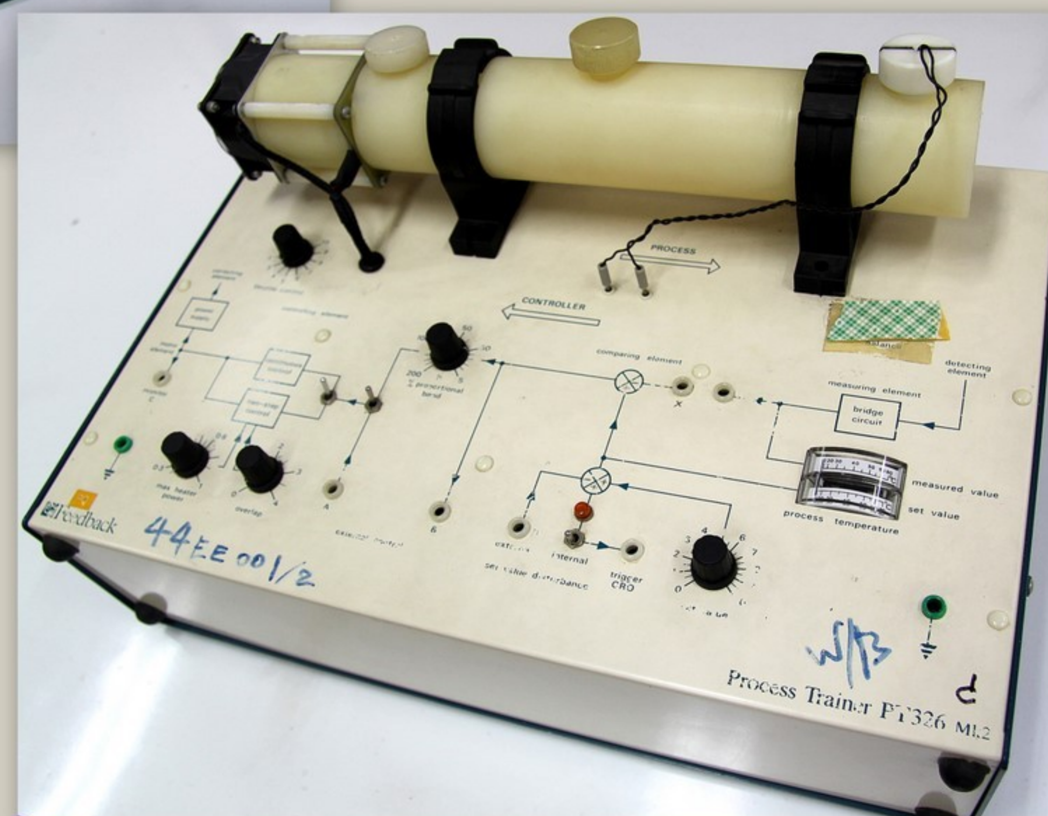
DC Servo Motor

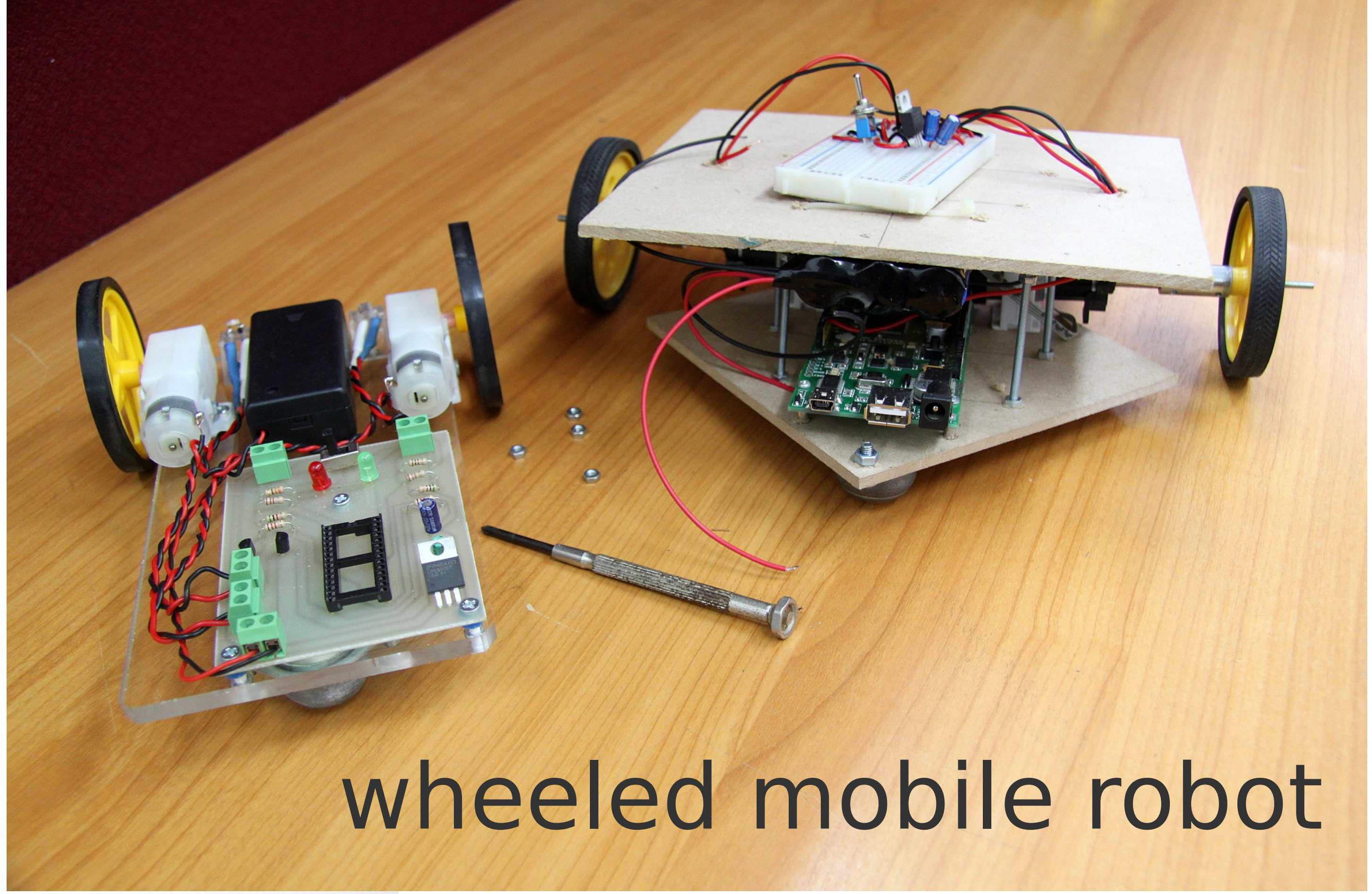


Process Simulator



Heat Exchanger





wheeled mobile robot

CNC machine

Work environment

Research Activities

Control design and optimization in power systems

Advanced process control

Stability analysis for nonlinear systems

Control design for non-rational MIMO plants

Robotics and SLAM

Sparse optimization in system identification

Economic Optimal Operation of Cogeneration with Heat Storage for Building Energy Management System

Kebsiri Manusilp and David Banjerdpongchai

Design dispatch strategy of cogeneration with heat storage tank for Building Energy Management System (BEMS).

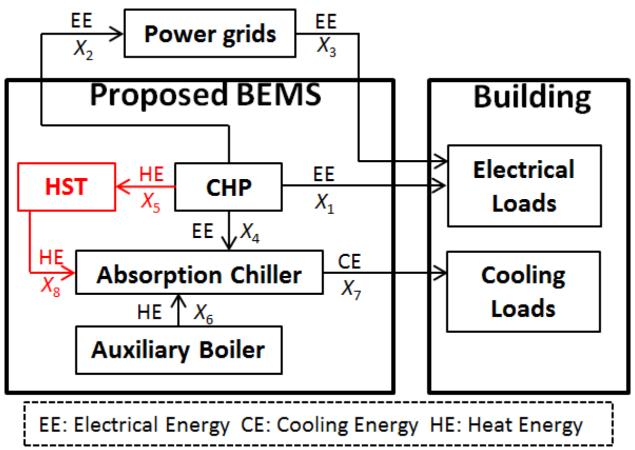


Diagram of Heat storage for BEMS.

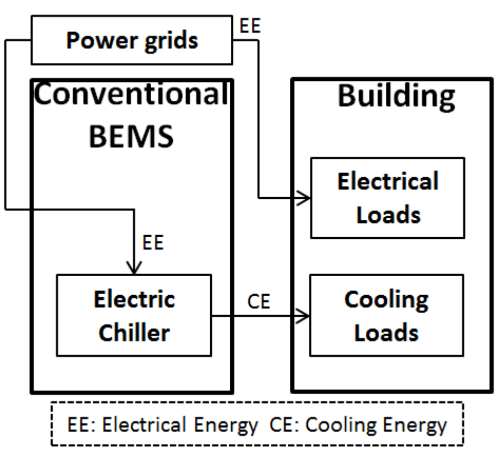


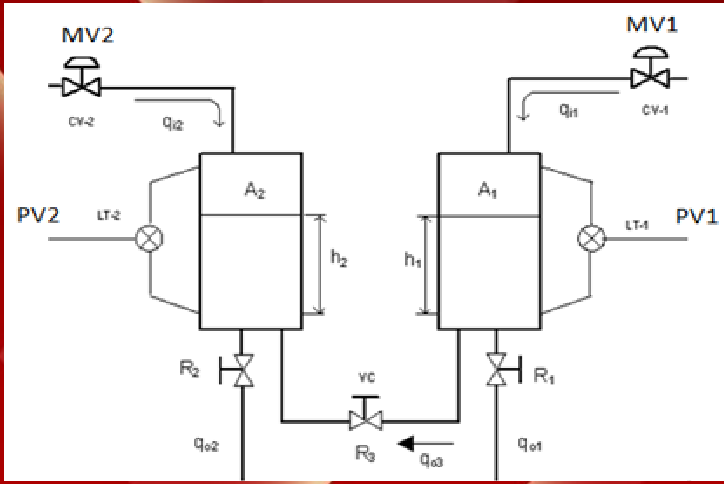
Diagram of conventional BEMS.

The energy supply of BEMS consists of combined heat and power (CHP), an auxiliary boiler, an absorption chiller and power grids. Normally, CHP operation will release waste heat so a heat storage tank (HST) is installed to utilize the waste heat. Heat storage constraint is taken into account of dispatch strategy.

Cogeneration with and without heat storage working under economic optimal operation are compared to show energy efficiency improvement.

Cascade MPC and PI control for two-tank level control process

Paramat Chonbodeechalermroong and David Banjerdpongchai



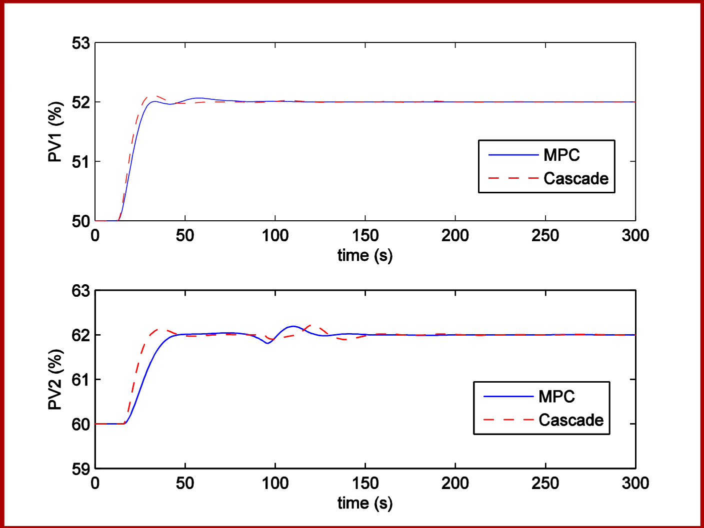
$$\begin{bmatrix}\Delta PV_1\\ \Delta PV_2\end{bmatrix} = \begin{bmatrix}G_{11}(s) & G_{12}(s)\\ G_{21}(s) & G_{22}(s)\end{bmatrix}\begin{bmatrix}\Delta MV_1\\ \Delta MV_2\end{bmatrix}$$

$$G_{11}(s) \cong \frac{3e^{-13s}}{280s+1}, G_{12}(s) \cong \frac{0.1e^{-83s}}{300s+1}$$

$$G_{21}(s) \cong \frac{1.8e^{-95s}}{350s+1}, G_{22}(s) \cong \frac{0.93e^{-16s}}{185s+1}$$

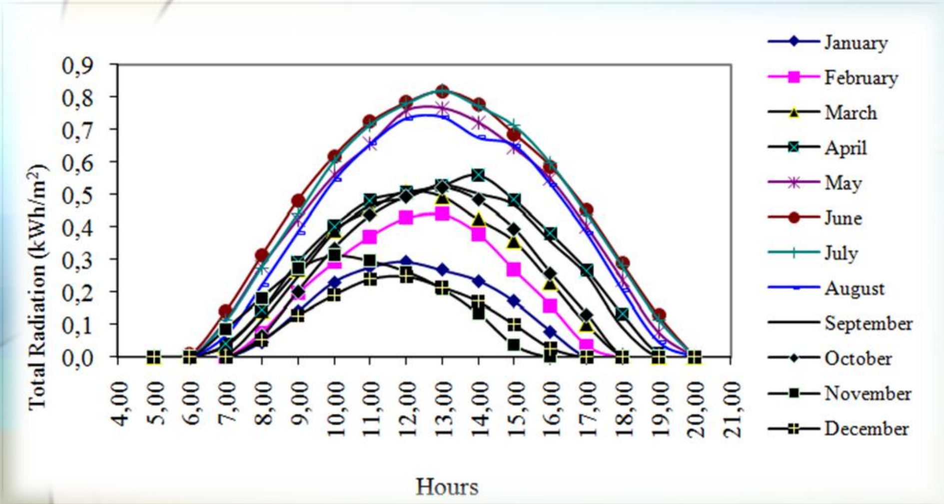
This process is a 2-input and 2-output system with time-delay.

Objective:
Compare the performance of output signals (PV) from MPC controller and cascade controller.



Solar Irradiance and PV Power Generation Forecasting

Rujipart Kruakaew and David Banjerdpongchai



Inherent factor

1. Global horizontal irradiance
2. Temperature
3. Humidity
4. Wind speed
5. Cloud cover

PV output

$$I_{cell} = I_{sc} - I_o\left\{exp\left[\frac{q(V_d)}{aKT}\right] - 1\right\} - \left(\frac{V_d}{R_p}\right)$$

$$V_{module} = N_s.\left(V_d - I_{cell}.R_p\right)$$

Solar Irradiance effect

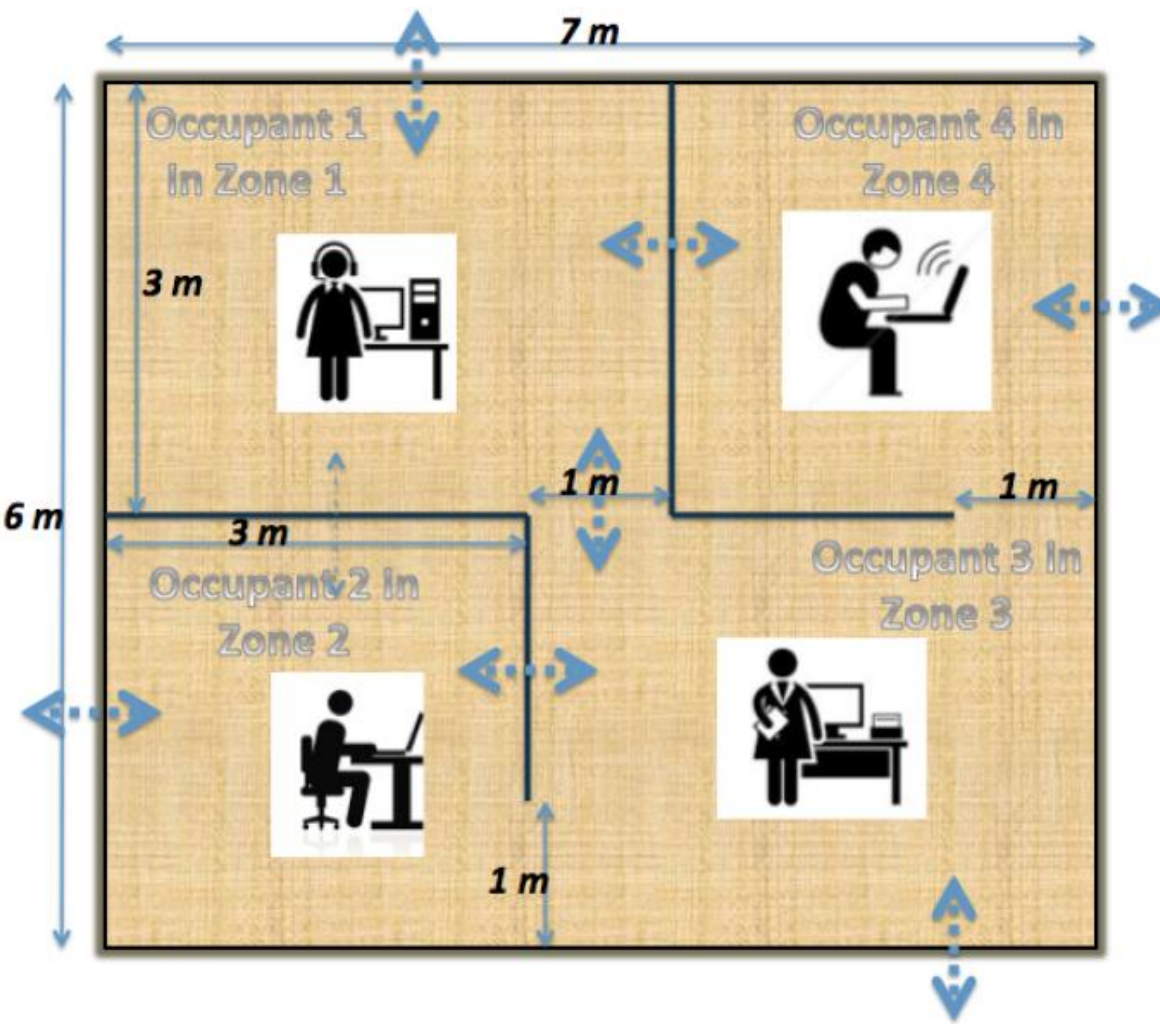
$$I_{sc,G} = I_{sc,Gref}\cdot\left(\frac{G}{G_{ref}}\right)$$

$$R_{p,G} = R_{p,Gref}\cdot\left(\frac{G_{ref}}{G}\right)$$

We aim to forecast solar irradiance by using physical data that is collected from satellite images and ground-based stations. Then, we can forecast PV power generation precisely.

Iterative Learning Control for Multi-Agent Systems with Applications to Building Energy Management Systems

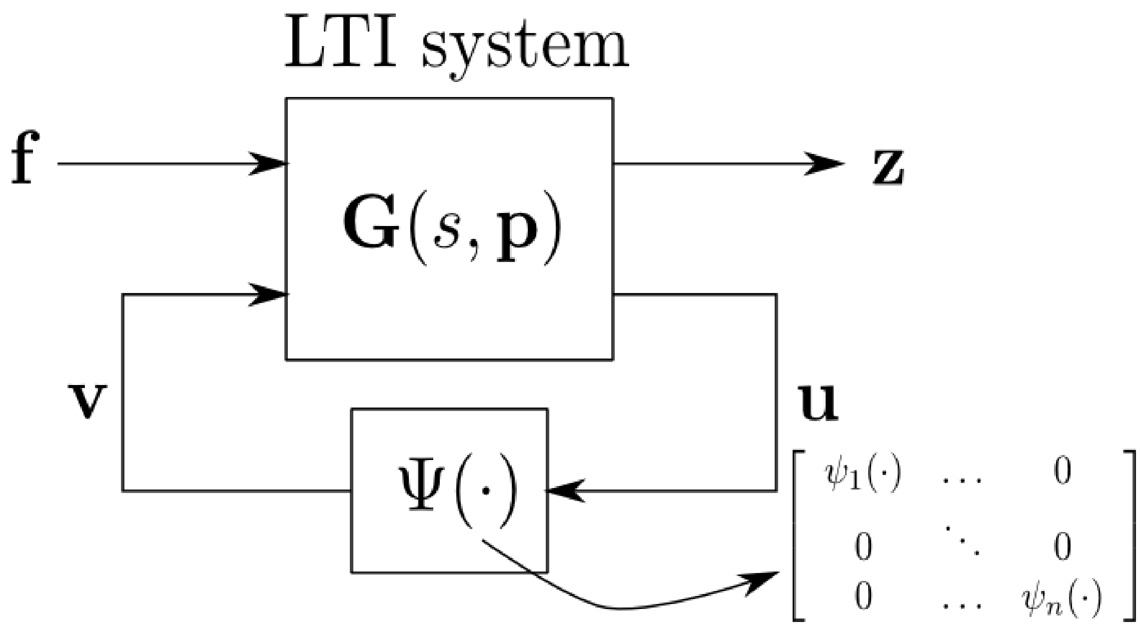
Pham Van Tuynh and David Banjerdpongchai



- Formulate BEMS as Multi Agent System (MAS) using Distributed Controller.
- Objective to save energy by minimizing thermal losses and control efforts of tracking temperature profile.
- Proposed methodology is Iterative Learning Control of MAS

Design of Control Systems with Nonlinear Elements using Zakian's Principle of Matching

Tadchanon Chuman and Suchin Arunsawatwong



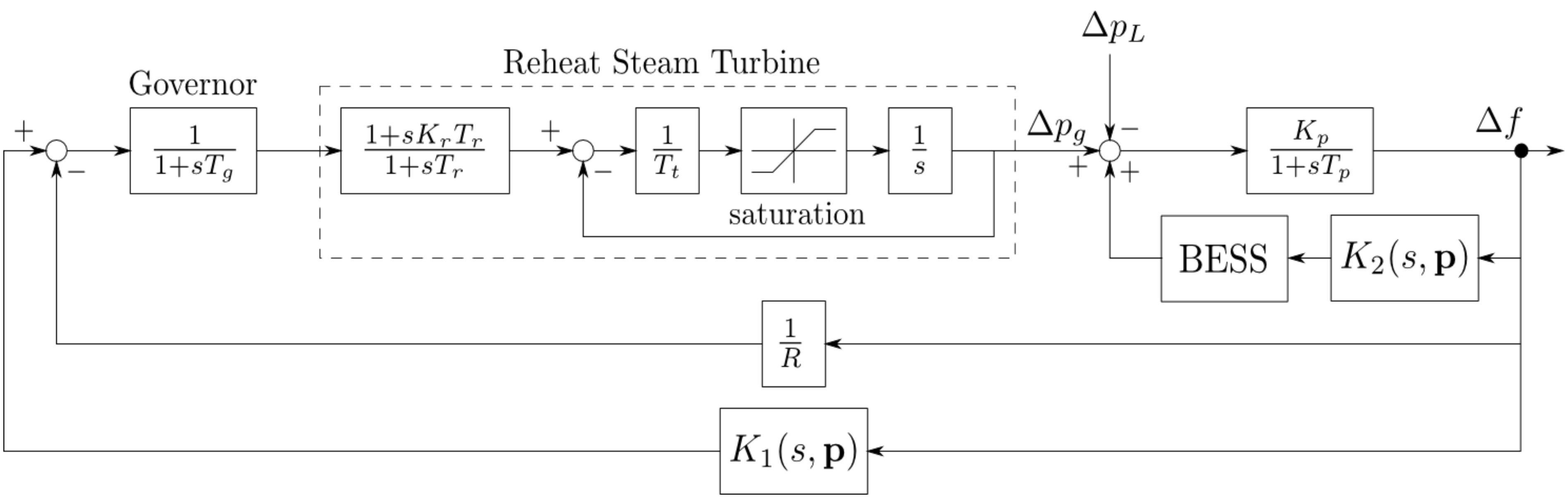
Develop the method for designing a systems in which the plant consists of a sector-bounded nonlinearity and linear time-invariant convolution plants.

Design Problem

ensure that all the outputs always stay within their prescribed bounds for any possible input

Design of Load Frequency Controller for Power Systems Subject to Bounded Persistent Disturbances

Patipan Kalvibool and Suchin Arunsawatwong

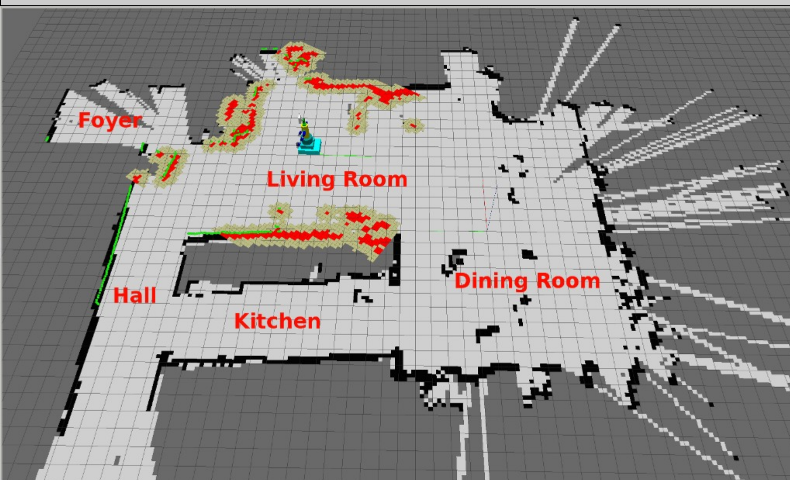


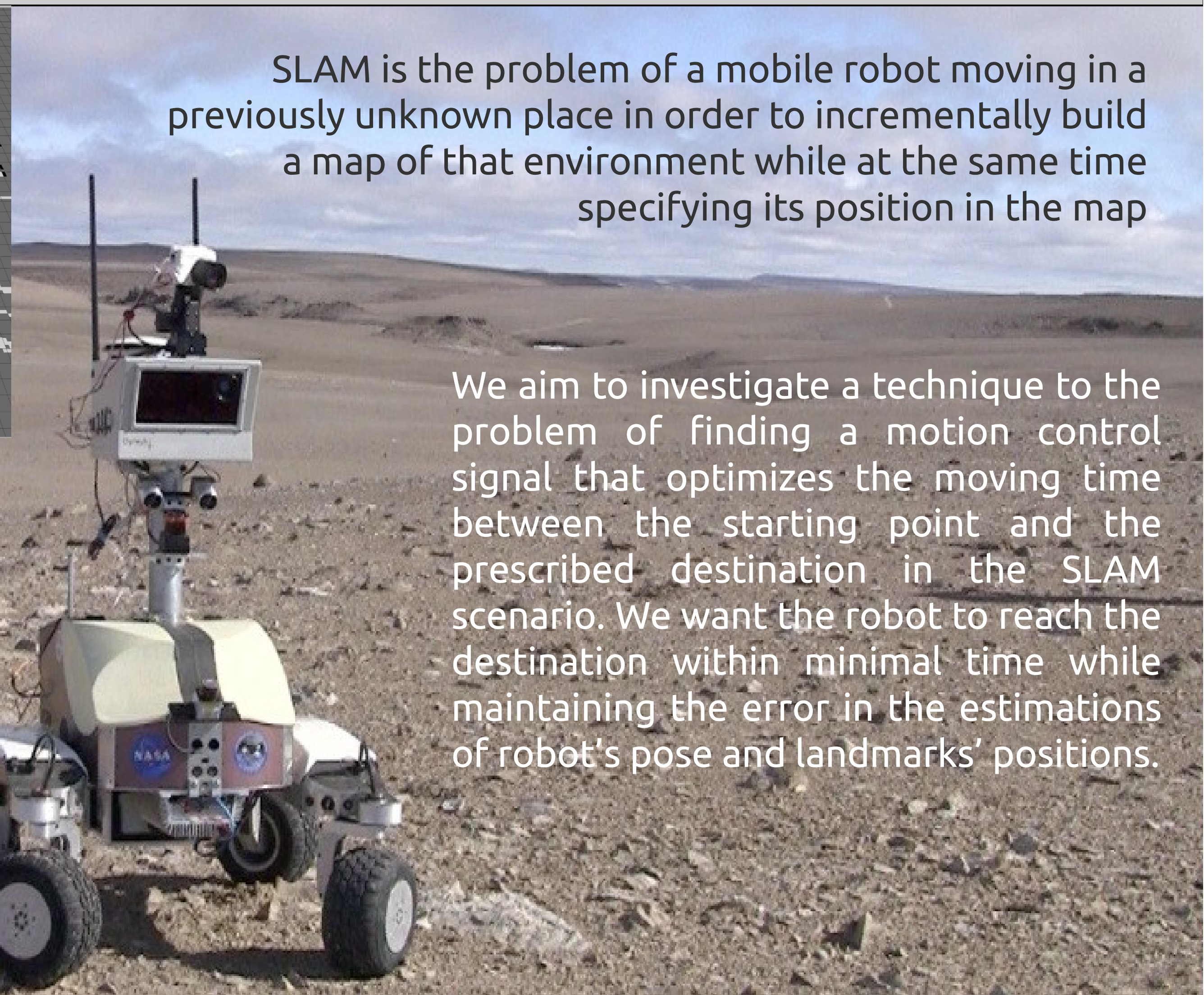
Develop the method for designing controllers for LFC of power systems operating under persistent disturbances

Design Problem	ensure that the system frequency, the generation rate and the power output from BESS always lie within the the prescribed bounds

Simultaneous Localization and Mapping (SLAM)

Hong Khac Nguyen and Manop Wongsaisuwan





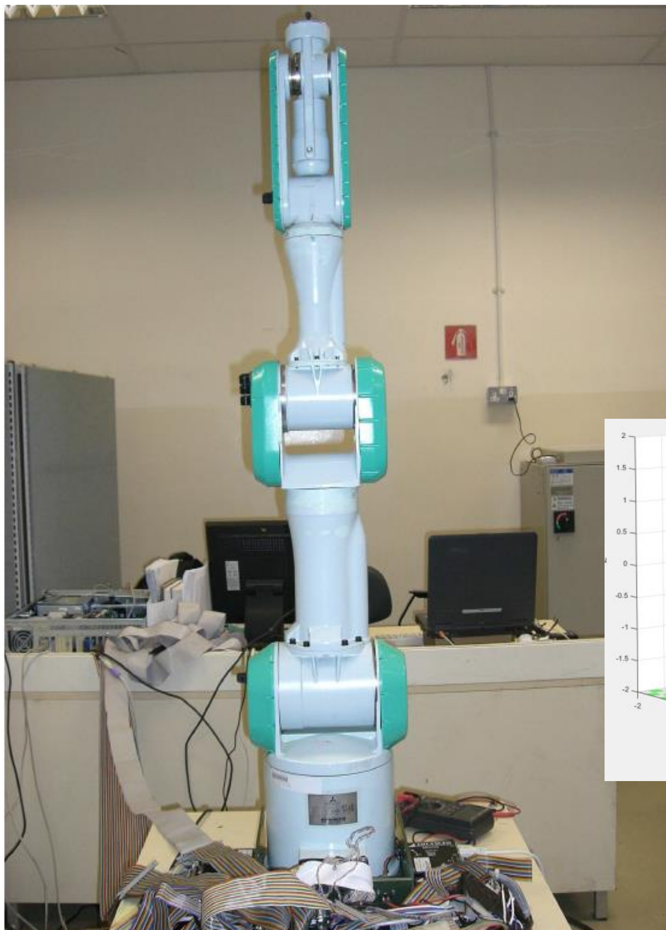
SLAM is the problem of a mobile robot moving in a previously unknown place in order to incrementally build a map of that environment while at the same time specifying its position in the map

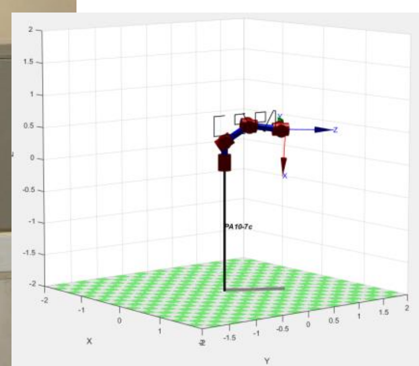
We aim to investigate a technique to the problem of finding a motion control signal that optimizes the moving time between the starting point and the prescribed destination in the SLAM scenario. We want the robot to reach the destination within minimal time while maintaining the error in the estimations of robot's pose and landmarks' positions.

This work focuses on UKF-SLAM (Unscented Kalman Filter) which is a derivative-free filter and produces equal or better results than Extended Kalman filter

Low Cost Controller Design for Mitsubishi PA10 robot arm

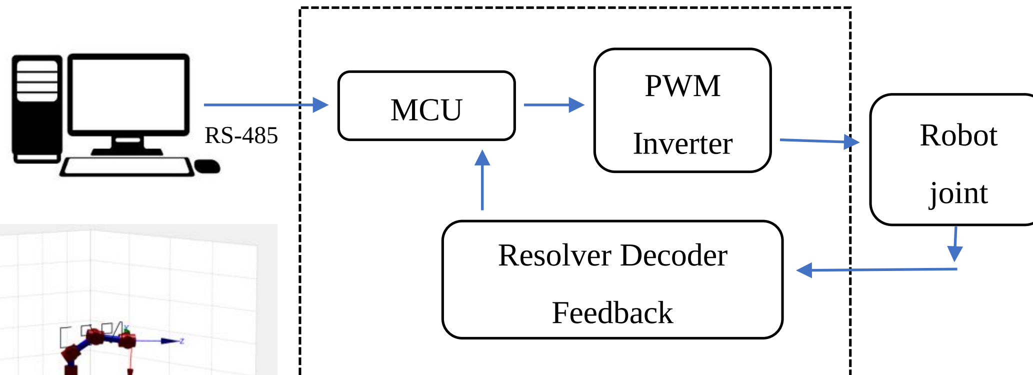
Sereiratha Phal and Manop Wongsaisuwan



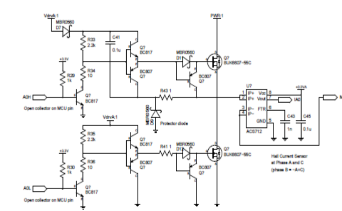


Mitsubishi PA-10

The Mitsubishi PA-10 is a robotic manipulator which possesses 7 degrees of freedom, thus a so-called shoulder, elbow and wrist.



Controller design structure



We aim to construct low cost robot controller prototype based on PID controller for the robot arm which can drive the joint of the robot according to commend from the PC to the specific ordered position.

Backstepping Controller Design for PDEs

Kananart Kuwaranancharoen and Watcharapong Khovidhungij

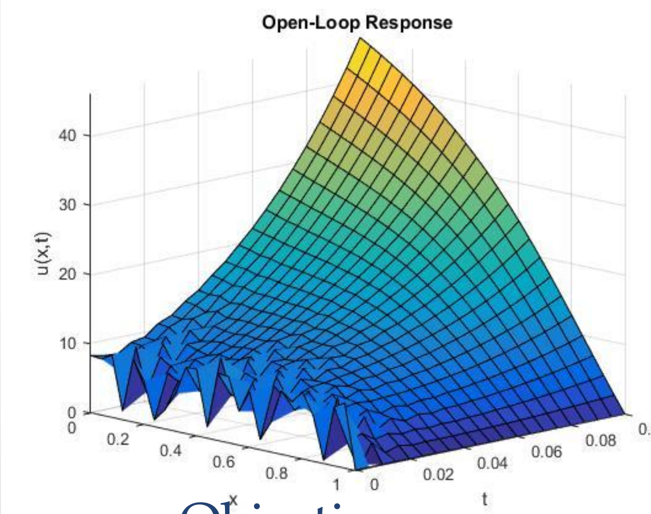
Equation: $u_t = u_{xx} + bu_x + \lambda u$

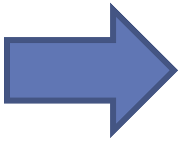
Boundary Condition: $u_x(0) = -\frac{b}{2}u(0), \quad u(1,t) = 0$

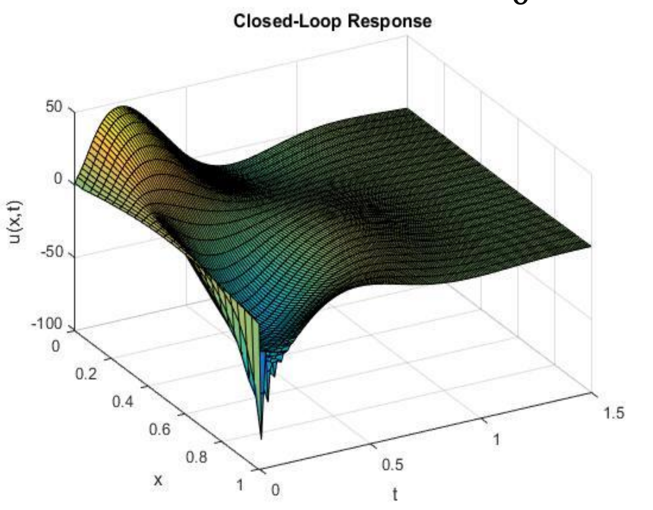
Controller:

$$u_x(1) = -\frac{1}{2}(\lambda_0 + b)u(1) - \int_0^1 \lambda_0 e^{-\frac{b}{2}(1-y)} \left[\frac{I_1\left(\sqrt{\lambda_0(1-y^2)}\right)}{\sqrt{\lambda_0(1-y^2)}} + \frac{I_2\left(\sqrt{\lambda_0(1-y^2)}\right)}{1-y^2}\right] u(y)\, dy$$

where $\lambda_0 = \lambda - \frac{b^2}{4}$





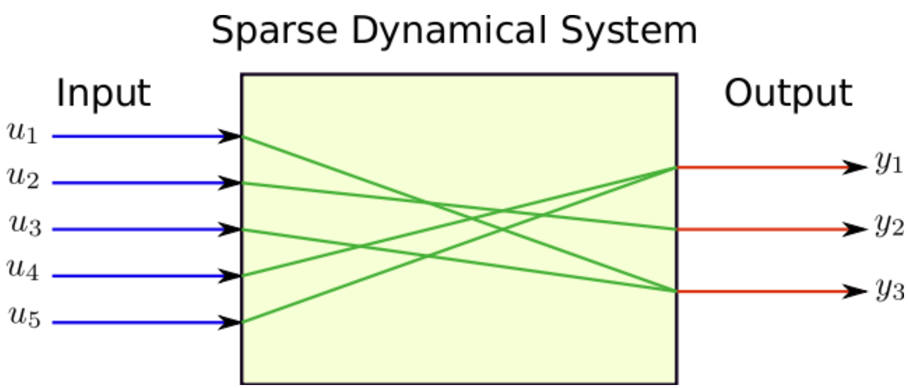


Objective:

Design the Backstepping Controller to stabilize Linear and Non-linear Parabolic PDE and Simulate the results

Sparse Optimization in System Identification

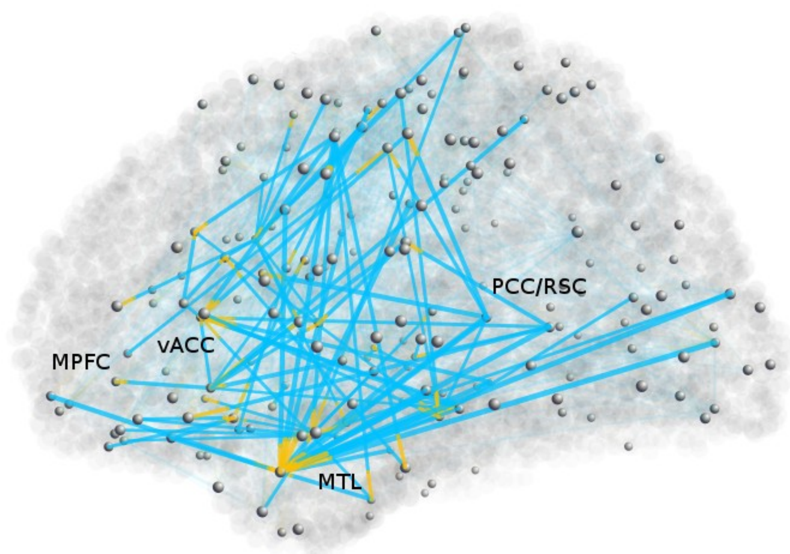
Jitkomut Songsiri



Benefits of having sparse representation or parsimonious models

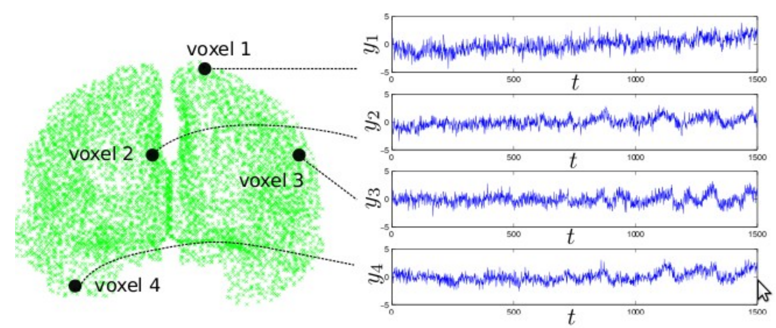
avoid over fitting in estimation

provide a meaningful relationship between variables in the system



Sparse structure in brain signals

(fMRI time series)



$\dot{x} = Ax + Bu$ sparse dynamic matrix

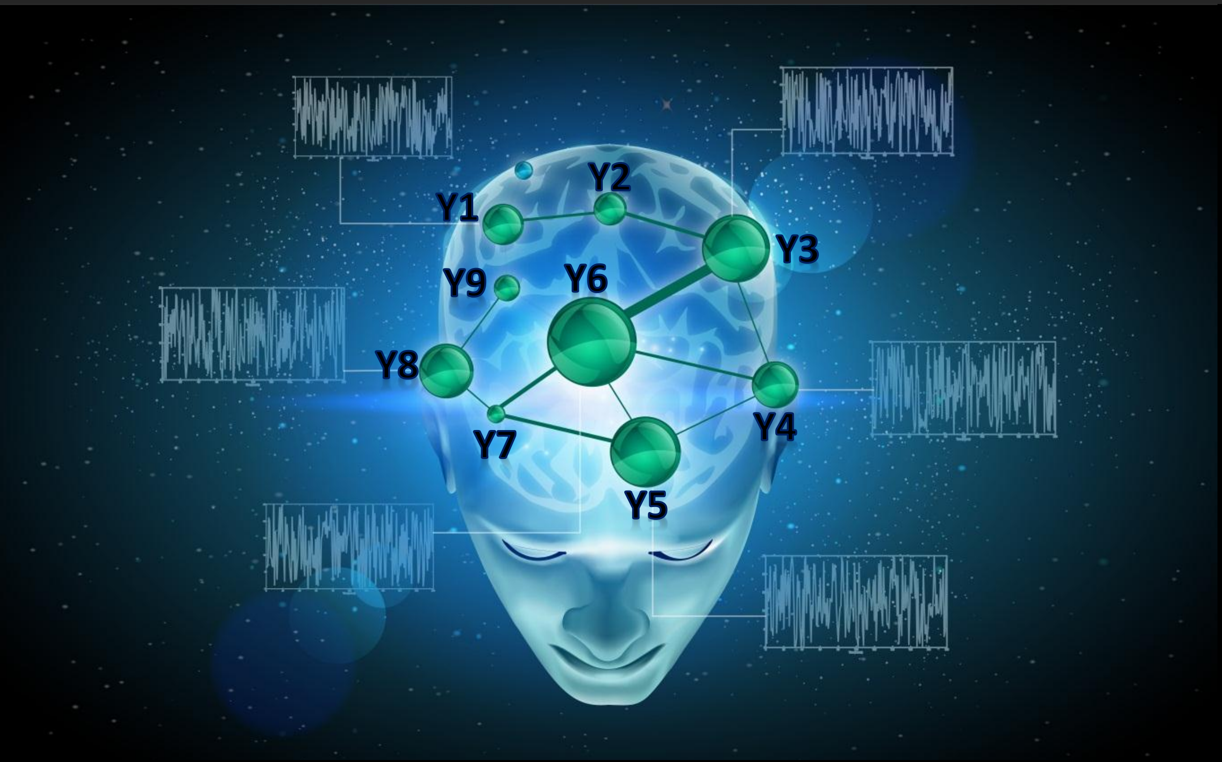
$y(t) = \int_0^t h(t-\tau)u(\tau)d\tau$ sparse impulse matrix

$S(\omega) = \sum_{k=-\infty}^{\infty} R_k e^{-j\omega k}$ sparse spectrum

sparse inverse spectrum

A Convex Formulation of Structural Equation Modeling in fMRI Study

Anupon Pruttiakaravanich and Jitkomut Songsiri



- Using a convex optimization framework to seek a sparse matrix A and noise covariance ψ such that an estimated covariance Σ is close to its sample covariance matrix S in the sense that the Kullback-Leiber divergence function is minimized.

$$A = \begin{bmatrix} 0 & a_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 0 & a_{23} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & a_{32} & 0 & a_{34} & 0 & a_{36} & 0 & 0 & 0 \\ 0 & 0 & a_{43} & 0 & a_{45} & a_{46} & 0 & 0 & 0 \\ 0 & 0 & 0 & a_{54} & 0 & a_{56} & a_{57} & 0 & 0 \\ 0 & 0 & a_{63} & a_{64} & a_{65} & 0 & a_{67} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{76} & 0 & a_{78} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & a_{87} & 0 & a_{89} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & a_{98} & 0 \end{bmatrix}$$

Nonzero entries in the path matrix (A) represent a causal relationship between two regions.

$\boxed{A_{ij} = 0 : \text{No path or relationship from } Y_j \text{ to } Y_i}$

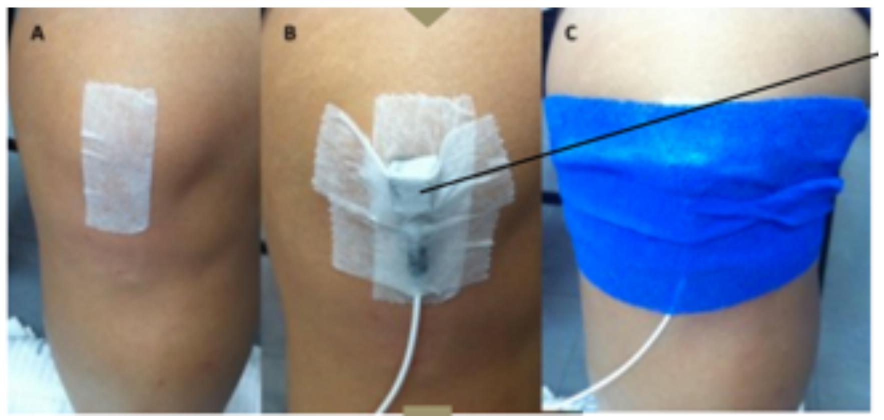
$$\min_{\Sigma, \psi} \ \operatorname{logdet}(\Sigma) + \mathbf{tr}(S\Sigma^{-1}) - \operatorname{logdet}(S) \text{-n}$$

subject to

$$\begin{bmatrix} \Sigma^{-1} & (I-A)^T \\ I-A & \psi \end{bmatrix} \succcurlyeq 0$$
$$0 \preccurlyeq \psi \preccurlyeq \alpha I$$
$$P(A) = 0$$

with variable $A \in \mathbb{R}^{\text{nxn}}, \psi \in \mathbb{S}_+^{\text{n}}, \Sigma \in \mathbb{S}_+^{\text{n}}$ and $P(A)$ explains the zero constraint on the entries of A.

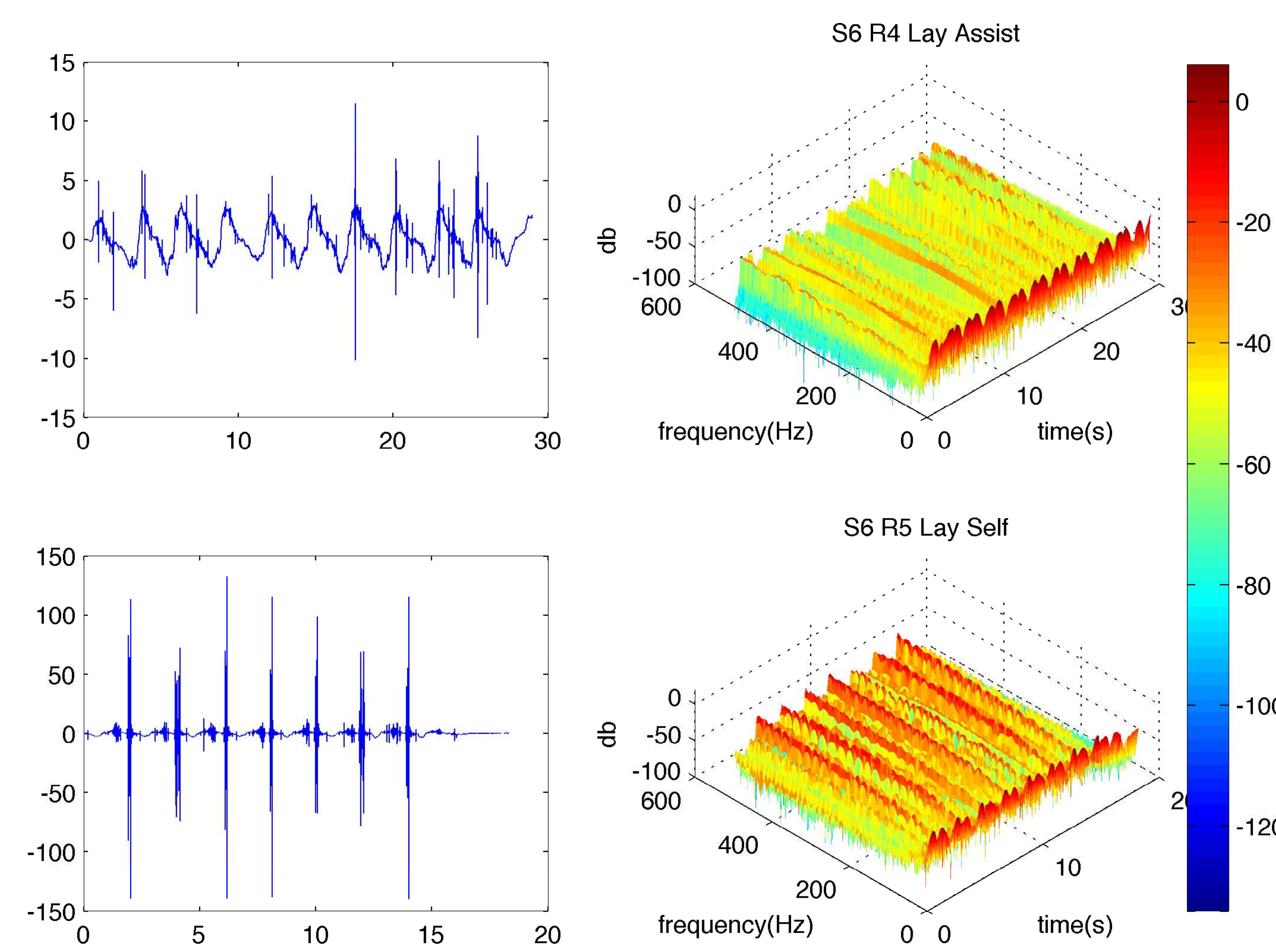
Classification of normal and abnormal knee by knee vibration signal



An accelerometer attached to patients knee.

The signals and their time-frequency plot.

The high magnitude indicates the more possibilities on abnormality.



Collaborative Network

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Pillar of the Kingdom

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