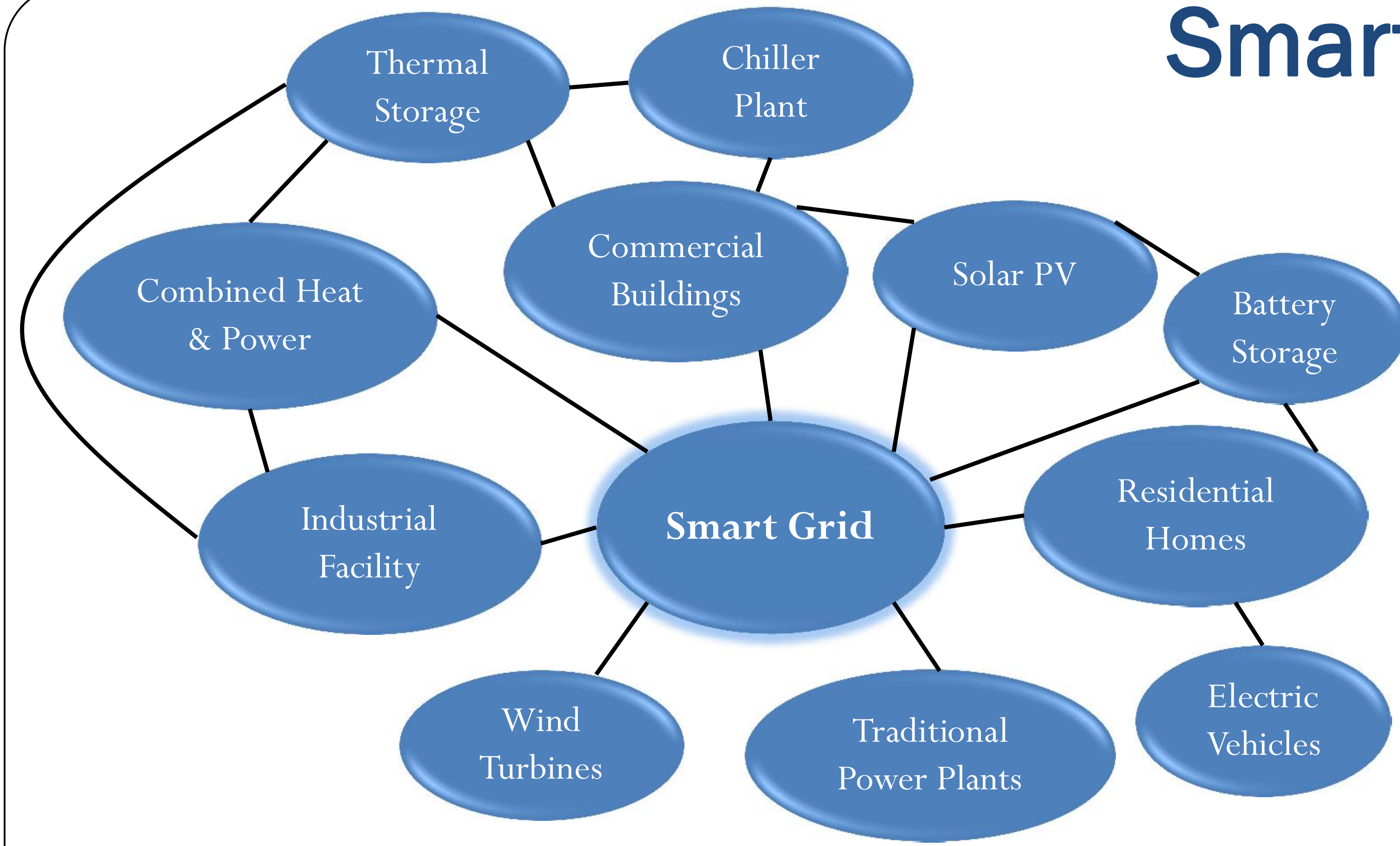


Smart Energy Matrix

Wesley Cole

- Interconnected, dynamic empirical and first-principles models
  - Includes multiple time scales and varying sizes (10-1000s of variables)
- Multi-period, predictive optimization to determine operational strategy
- Incorporate actual data such as ERCOT electricity prices, Mueller home consumption data, Austin Energy turbine performance, & Austin weather

Multistate PCA and Multistate PLS for Continuous Processes

Ricardo Dunia(Emerson-UT Austin)

Achievements:

• Novel methodology to define operating regions and transition trajectories between states of operation.

• These techniques enhance the procedure to normalize process variables for process monitoring and fault detection.

Future Work:

-Online implementation for real-time applications

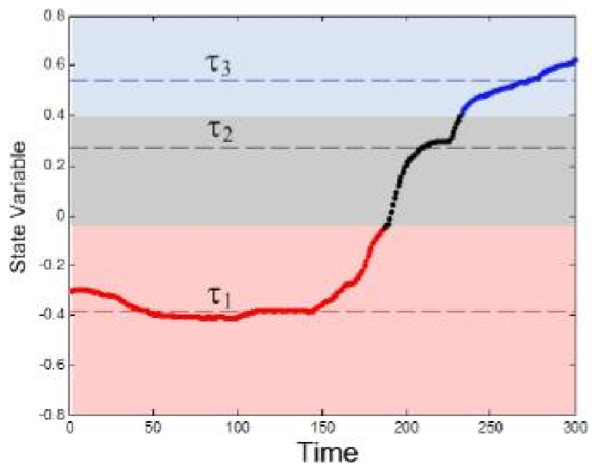


Figure 1- State Variable used for CO_2 Capture process

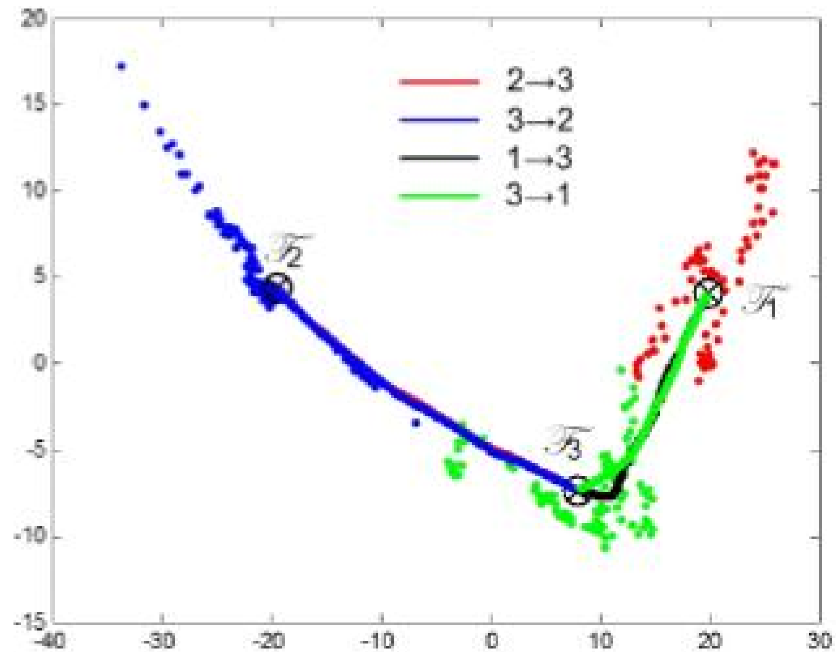
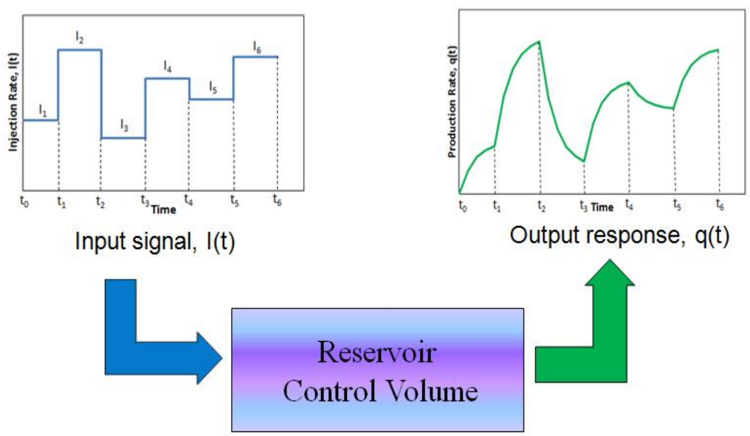


Figure 2- Transition trajectories between operating points

Oil Reservoir Modeling and Optimization using the Capacitance Resistive Model (CRM)

Victor C. Duribe

As the total oil reserves deplete, the optimization of oil reservoirs, as well as accurate prediction of future production rates have become of immense importance. This research would focus on addressing this issue using the CRM.



Schematic representation of the dynamic impact of an injection rate signal on the total fluid production rate.

<u>Research Objectives:</u>

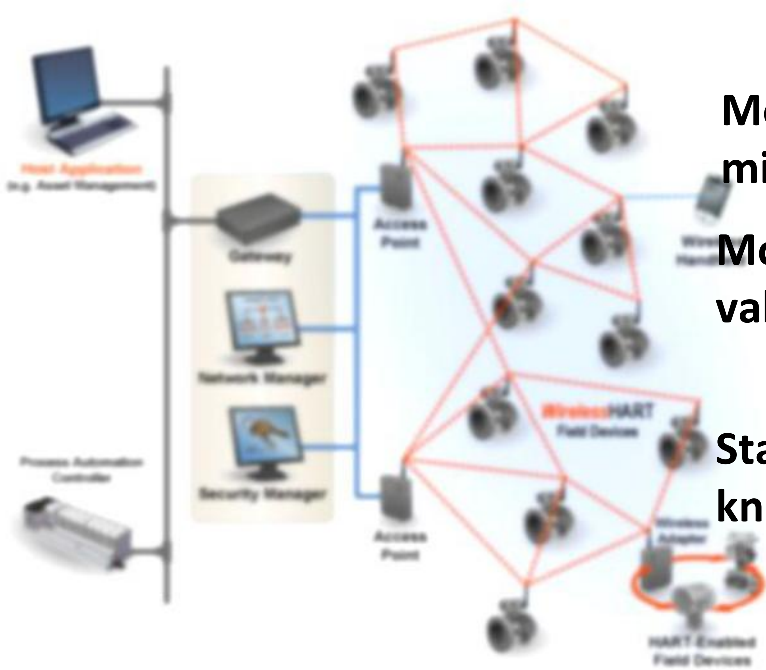
- Determination of the impact of injection rate profile on model performance
- Validation of the Integrated CRM (ICRM) using real field data
- Extension of the CRM (and ICRM) to non-vertical wells

Feedback Control using a Wireless Network

Doug French | dhfrench@hotmail.com

Estimated ~80% reduction in engineered and installed cost, but there is no free lunch….

Current open topics in wireless networked control:



Meaningful performance metrics that balance control performance with battery life and network bandwidth

Modifying controller structure for more frequently missing data

Monitoring and transmission criteria that maximize the value of information sent

State estimation where non-transmission gives the knowledge of range of value, but not the value itself

Control Performance Assessment (CPA)
Xiaojing Jiang, Ph.D. Dec 2012
Sponsored by NSF/GOALI

- **Achievements:**

➢ Developed a new method to determine potential improved performance and improved controller tuning factors;

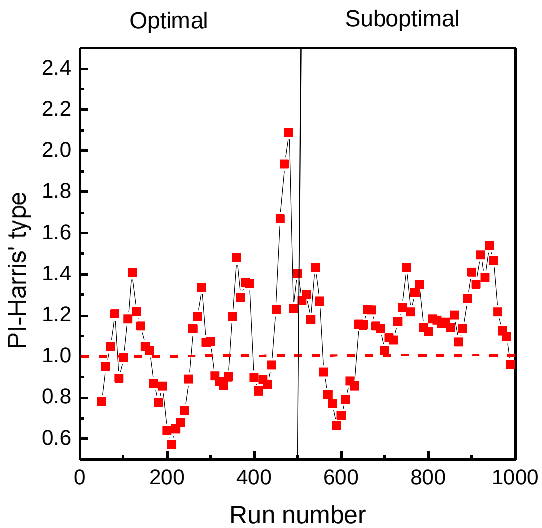
➢ Developed a new CPA method to determine whether the control is optimal or not (treatment of time delay and high-mix parameters). See Figure below for control chart range.

- **Future plans:**

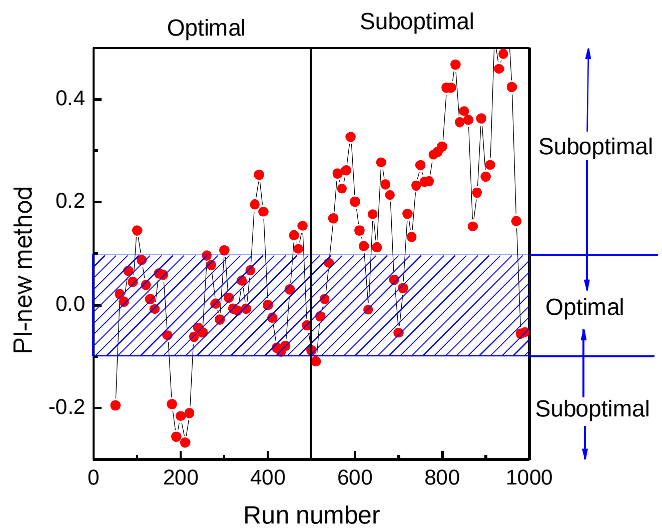
➢ Apply the new method to DMOS6

➢ Extend the new method to other R2R controllers

➢ TI Sponsor: John Stuber



Traditional



New

Facility energy management in semiconductor manufacturing

Kriti Kapoor, Prof. T. F. Edgar

UT Austin main campus has CHP generation using natural gas; satisfying all electric, heating and cooling demands.

Campus cooling load optimization includes

- Forecasting of total cooling and electric load
- Modeling of chillers, cooling towers, pumps, turbines, boilers, TES tanks
- Shifting cooling loads across various chillers and across different times of a day; and estimation of energy savings

UT Austin and TI Dallas north campus have similar

- Electricity loads
- Cooling loads
- Thermal storage (TES) tanks

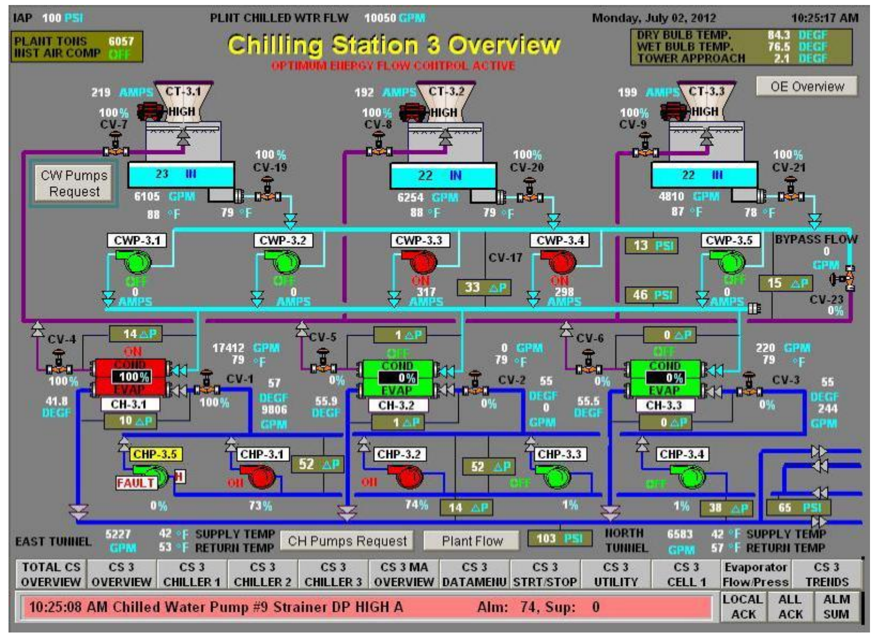


Figure: Layout of Chilling Station 3 at UT Austin

Future work

- Apply UT findings to TI CHP opportunity
- Use adaptive modeling strategies to track changes in operating conditions

Dynamic simulation and advanced control of Combined Heat and Power (CHP) plants

Jongsuk Kim, Ph.D. Dec 2013 (Sponsored by CHEMSTATIONS)

- **Achievements:**

  1) Applied a nonlinear Model Predictive Control (MPC) to a Heavy-Duty Gas Turbine (HDGT) power plant for frequency and temperature control
  2) Formulated model predictive controller as a nonlinear programming problem by applying orthogonal collocation on finite elements to provide fast solution times
  3) Demonstrated that the MPC controller provided superior output responses to disturbances in electric load compared to the PID/logic based control scheme
  4) Developed dynamic model of a Heat Recovery Steam Generator (HRSG)

- **Future plans:**

  1) Apply thermal Energy Storage (TES) in conjunction with CHP system to improve energy efficiency in industrial plants
  2) Optimize UT campus cooling system to reduce energy usage
  3) Supervisory control to monitor and control the entire CHP system

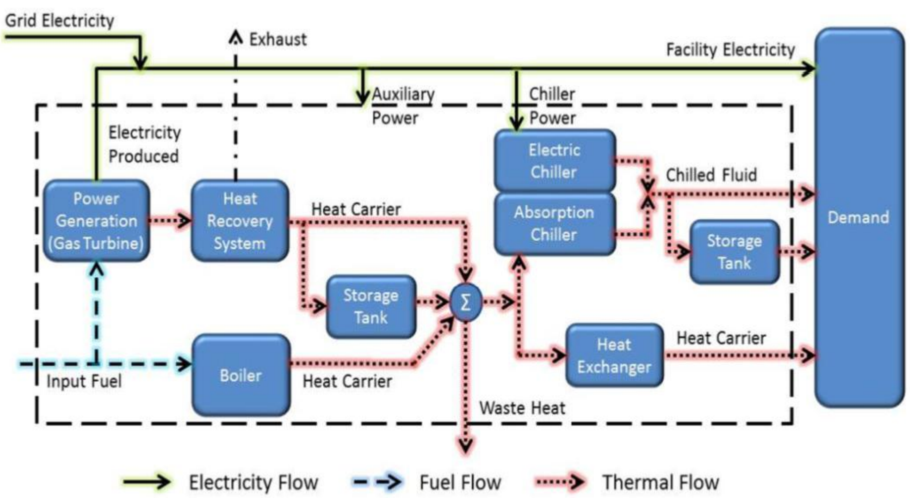


Figure 1. Schematic of Combined Heat and Power (CHP) – Thermal Energy Storage (TES) system.

Virtual Metrology Project Summary

UT ChE: Bo Lu, Professors Tom Edgar. TI: John Stuber

Virtual Metrology

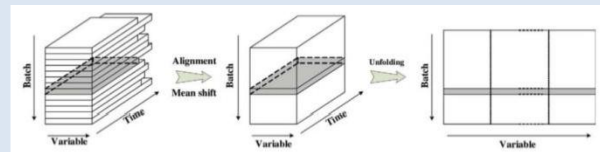
- A data driven model that decomposes the equipment trace data into hidden components that correlates to product quality (PLS)
- Using this model, product quality predictions can be made from tool trace data
- A successful VM model can be integrated in fault diagnostics systems, controllers and be used for process monitoring

Data

- FDC detection trace data, 100 samples per batch, 3D unfolded
- VM measurements – Critical dimension, trim time average etch rate

Goal

- Predicting C035.A trim etch rate from trace data

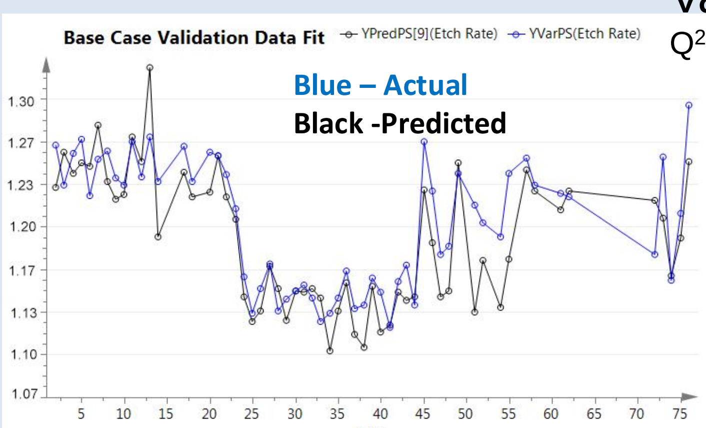


Method

M-PLS (Projection to Latent Structure) – multivariate method, suited for rank-deficient data

- Training data – 300 wafers
- Validation data – 3 lots ~ 75 wafers

Results - Validation Data

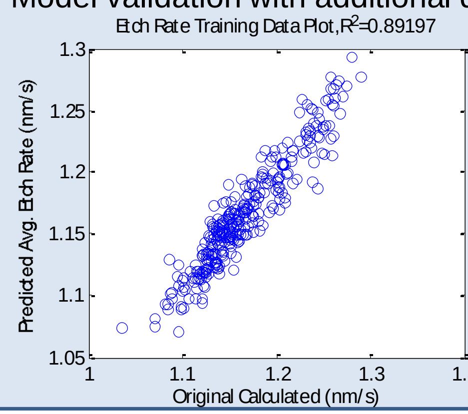


Validation

Q^2 = 0.771

Current Effort

- Reproducing SIMCA results in MATLAB and TIMS instead of proprietary SIMCA + ARTIST package
- Improving SIMCA results in MATLAB
- Model validation with additional data



MATLAB Training R^2 0.89

Validation score: Q^2 ~0.40

Enhancement of Capacitance Resistive Model (CRM) for Primary, Secondary and Tertiary Recovery

Anh Nguyen

CRM uses tank model concept to infer reservoir characteristics. This research is to develop CRM to apply the model on real oil fields.

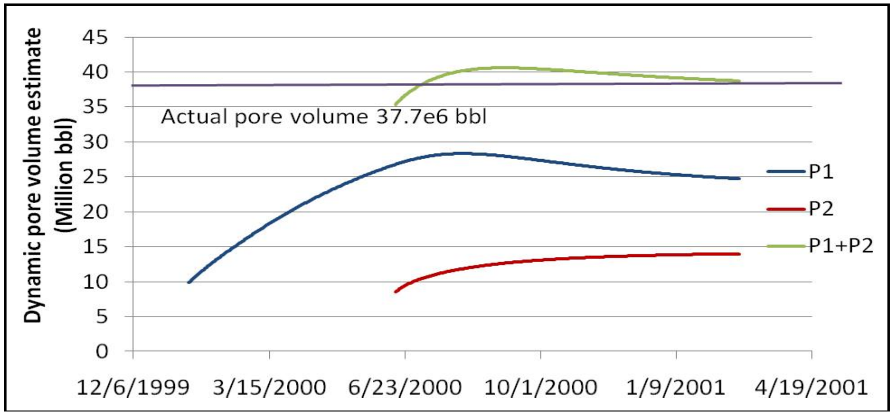
• Achievements:

1. For secondary recovery application: Evaluate consistency of CRM results, calculate sensitivity of CRM results on radial limit, analyze fitting window selection, study CRM forecast capability, apply CRM optimization on part of the field and analyze the results
2. Propose new model: integrated capacitance-resistive (ICR) to determine producer productivity index and dynamic pore volume and average reservoir pressure for oil primary production, validate ICR on various synthetic fields and actual field. data
3. Develop ICR model for primary gas reservoir, validate on synthetic fields and actual field data
4. Study CRM applicability on water alternating gas (WAG) injection field data with different weight on water injection rate
5. Develop and validate the method to infer transmissibility from CRM results
6. Compare CRM results to tracer test data and synthetic field streamline results

• Future plans:

1. Study data noise and co-linearity effects on CRM results
2. Develop CRM model for WAG field and validate on synthetic data

Fig. 1: Estimated dynamic pore volumes of wells P1 and P2 in synthetic primary recovery field vs. field actual pore volume

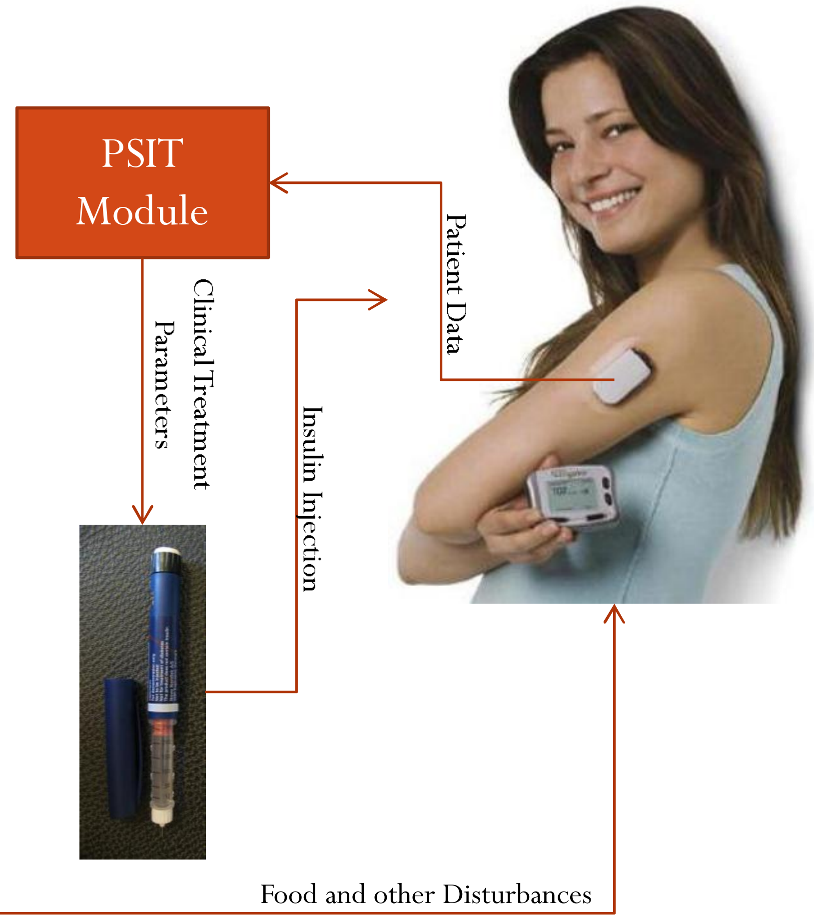


Clinical Decision Support Systems

Ramiro Palma (UT Austin)

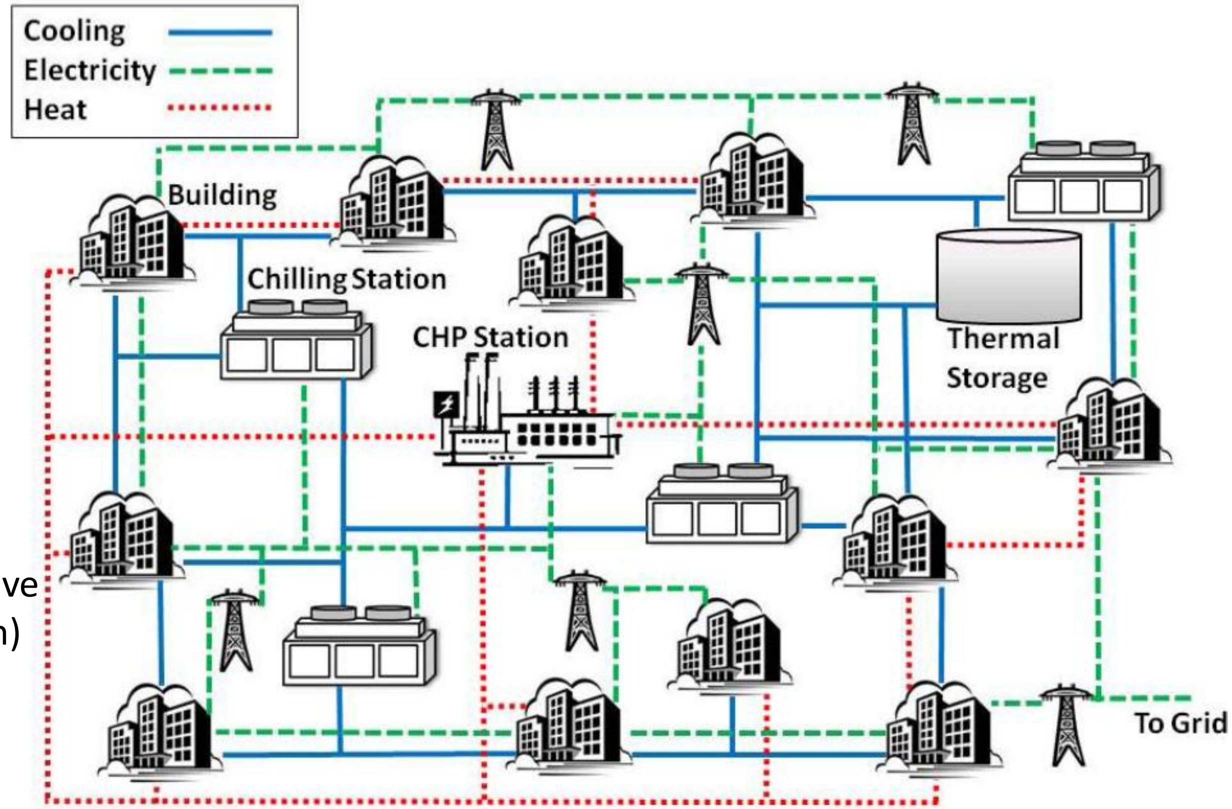
Achievements:

1) Developed connection between existing mathematical models of diabetes and clinically important treatment parameters
2) Developed patient specific insulin therapy system
3) Developed model of physical sensor environment to improve sensor placement
4) Developed Markov model of disease progression to compare insulin treatment strategies



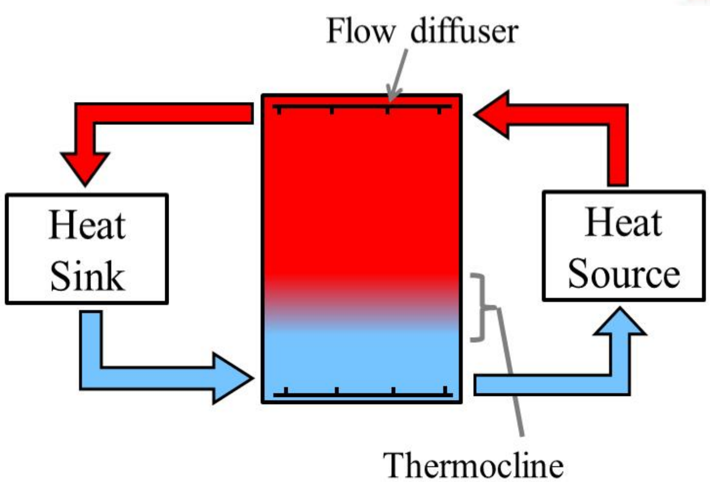
Dynamic Optimization of Complex Energy Systems with Energy Storage

-Kody Powell



Research Objectives

- Develop novel methodologies to forecast energy supply and demand
- Use cutting edge modeling and optimization techniques (e.g., heirchical optimization to separate dynamic and static problems, adaptive grid modeling, dynamic optimization) to improve system performance
- Determine optimal use of energy storage technology



A thermocline thermal energy storage system with hot and cold fluids separated by a density gradient

Highly-Integrated Energy Systems

- Combined heat and power with district heating and cooling
- Multiple energy networks in a single system
- Thermal energy storage
- Solar thermal systems
- Smart electric and energy grid

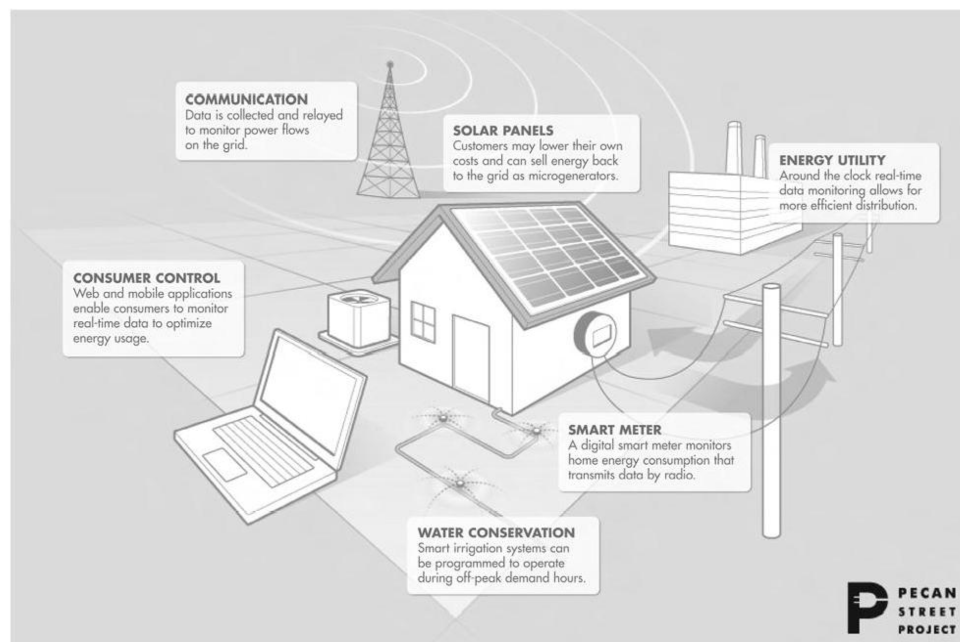
Demand Response & Forecasting: Keys to a Smarter Grid

Akshay Sriprasad

Research Interests

- Investigating the effects of new residential energy phenomena such as community energy storage (CES), plug-in hybrid electric vehicles (PHEV), and solar photovoltaic (solar PV) devices on the Austin electricity grid and residential peak load. We collaborate closely with the Pecan Street Inc. smart grid research consortium for our smart-grid research work.
- Developing empirical forecasting models and other tools that can help formulate demand response strategies at the residential and community level and enable battery storage optimization.

Pecan Street Inc.



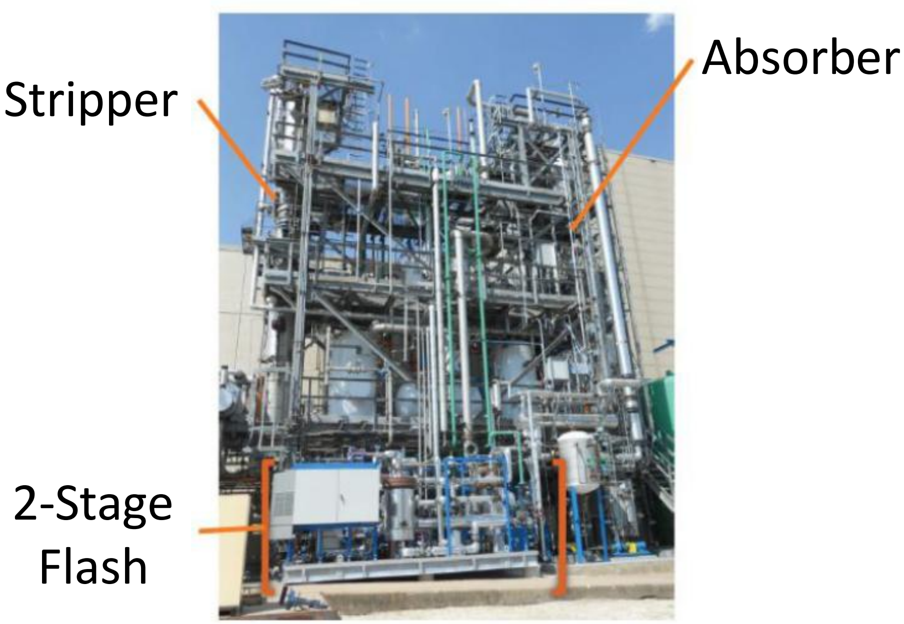
For more information please visit www.pecanstreet.org

Dynamic Modeling and Control of Amine Scrubbing for CO_2 Capture

Matt Walters (Co-Advised by Dr. Gary Rochelle)

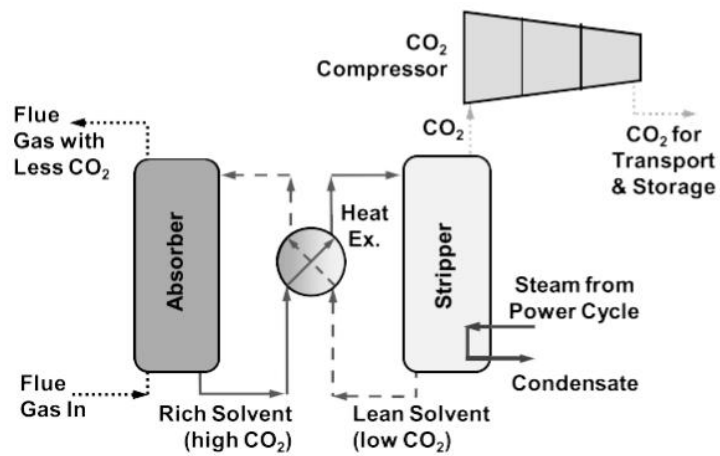
Achievements

- Two-stage flash alternative stripper configuration
  - Dynamic model developed
  - Validated with SRP pilot plant data



Future work

- Model other configurations
  - Interheated Stripper
  - Intercooled Absorber
- Synthesize process control and monitoring strategies (e.g. MPC)
- Explore flexible capture scenarios in response to peak demand



Work supported by Luminant Carbon Management Program

$\mathcal{L}_1$ Adaptive Control Theory and Application

Shu Xu

➢ **Advantages of $\mathcal{L}_1$ Adaptive Controller**

- Fast adaptation rate without affecting robustness
- Withstand variable time-delays
- Increasing the time-delay does not affect the number of parameters that needed to be adapted

➢ **Achievements:**

- Built $\mathcal{L}_1$ adaptive control architecture for Distillation Process
- Time Delay analysis for the system
- Compared the results obtained from $\mathcal{L}_1$ adaptive controller with those from PI, Vogel-Edgar Controller.

➢ **Future Work**

- Build $\mathcal{L}_1$ Control system for MIMO Distillation Process

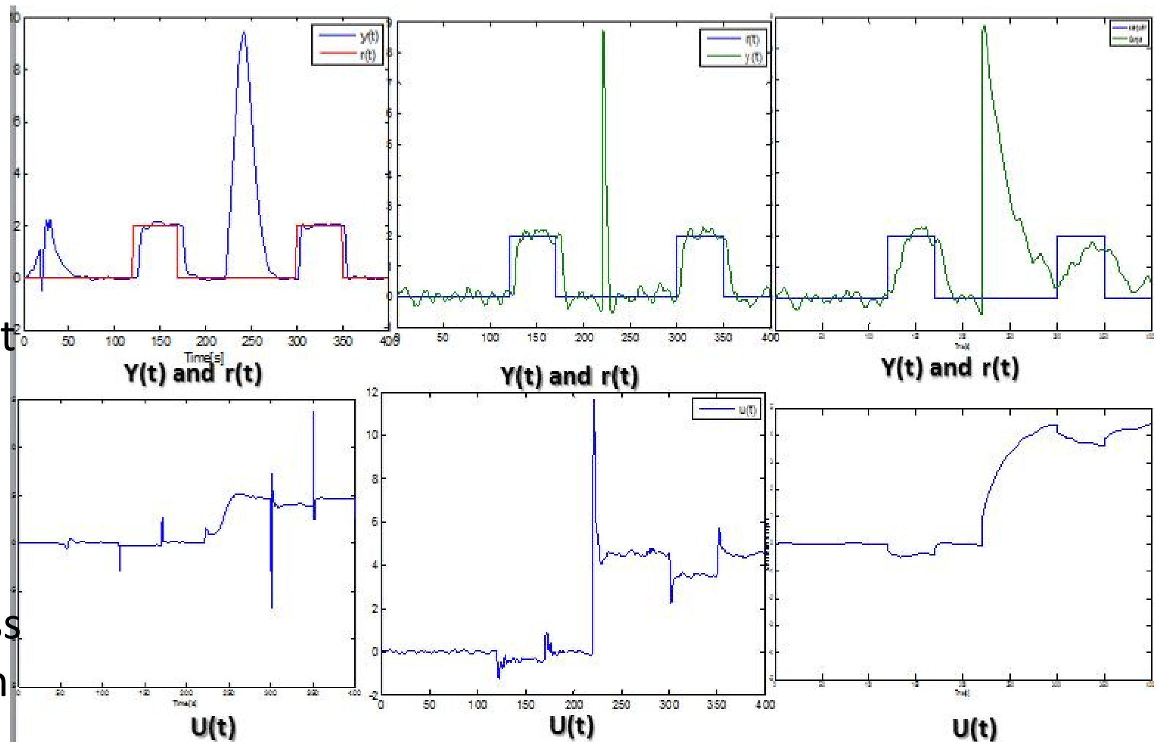


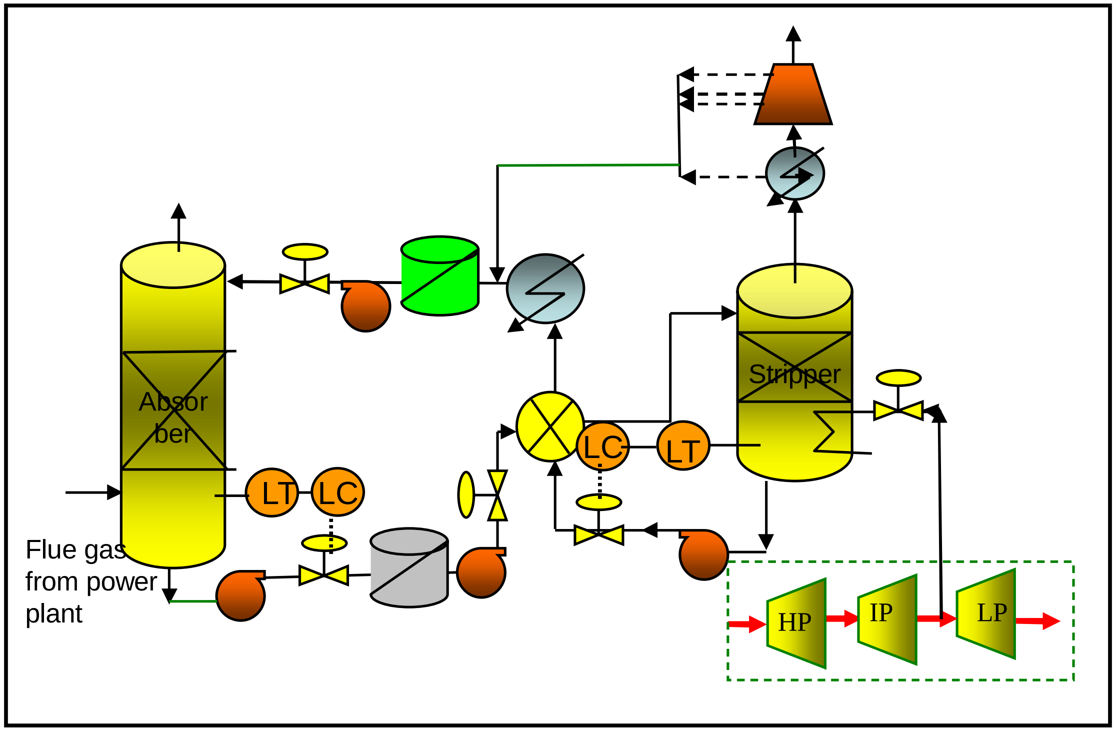
Figure (a). Vogel-Edgar Controller Figure (b). $\mathcal{L}_1$ Adaptive Controller Figure (c). PI Controller

Figure1.1 Comparisons of Three Controllers(Sampling Time=1s.)
(Row 1) System output Y(t)and Set point Signal r(t)
(Row 2) Controller Output U(t)

Dynamic Modeling, Optimization and Control of Amine Plant to Remove CO2 from Coal Fired Power Plants

Sepideh Ziaii , Dr. Gary Rochelle , Dr. Thomas Edgar

Luminant Carbon Management Program Industrial Associates Program for CO_2 Capture by Aqueous Absorption



Modeling in Aspen Custom Modeler®:

•Dynamic rate-based model of packed columns (absorber & stripper) and reboiler
• Simplified steady state model of heat exchangers
•General performance curve for compressor and pumps
•Ellipse law for steam turbines

Optimization and control :

• Multi-variable optimization : Optimize manipulating variables to minimize energy in response to partial load operational scenarios
• Explore optimum control strategies for dynamic operations
•Investigate the effects of hold up in the storage tanks
•Application of variable speed compressor in operation