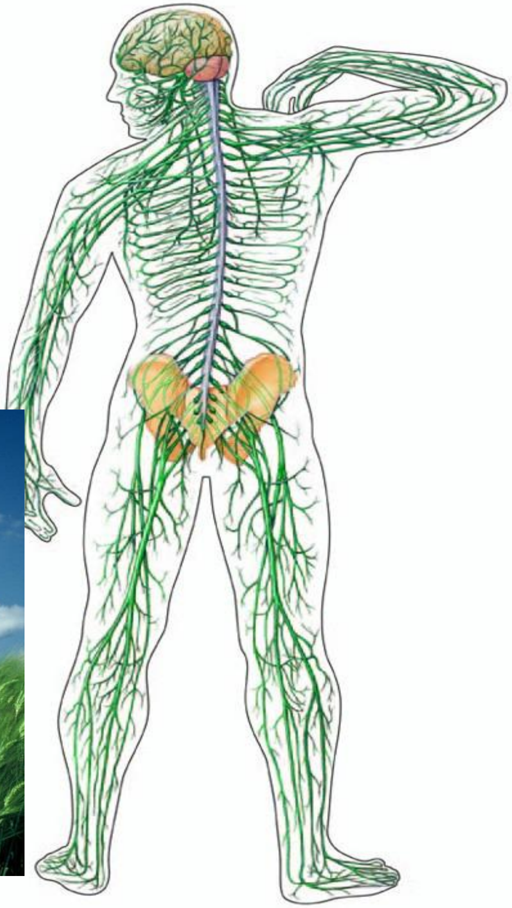
How do we know the world better?

What do we really know?



DATA and CONTEXT

http://www.researchgate.net/post/Estimates_of_quantified_human_sensory_system_throughput10

How do we build context?

- Object and subject—***what and who***
- Time and place—***where and when***
- Correlation and causality—***how and why***

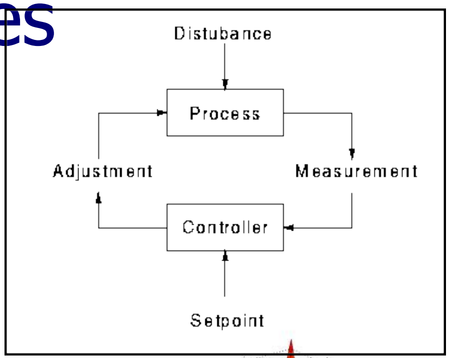
DATA and CONTEXT

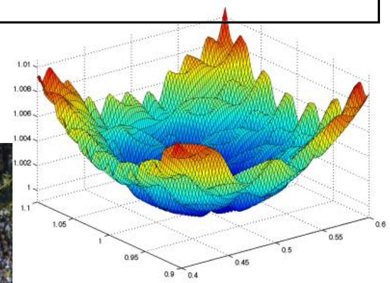
Components of big sensor data

- Sensing or perception of change
  - Uses calibrated static relationships
- Estimation or inference
  - Uses curve fitting in some form
- Feedback control or reacting to changes
  - Uses uncertain, dynamic models
- Optimization for tactical goals
  - Uses precisely calibrated models
- Gaming for strategic goals
  - Uses accumulated experience

DATA and CONTEXT

$$\hat{\boldsymbol{\theta}} = \left(\boldsymbol{\Phi}^T \boldsymbol{\Phi}\right)^{-1} \boldsymbol{\Phi}^T \mathbf{Y}$$





Case: 1 Making and Using Magnetic Maps

Collaborators:

Yan Cui

Magnetic Mapping

- GPS system not accessible in:
  - urban and natural canyons;
  - forests;
  - indoor locations.

indoor locations *

urban canyon

- Current geolocation algorithms:
  - received signal strength (RSS), error 3~5m
  - time difference of arrival (TDOA), error 2~3m
  - radio frequency identification (RFID), error 3~5m
  - <u>our algorithm (Magnetic map), error: 1.5~2m</u>

* Figure available from http://www.gpsbites.com/indoor-location-positioning-krulwich-interview

Building a Magnetic Map

- Magnetic Field Model:

$$\forall m(x, y) \in M,$$
$$m(x, y) = m_{IGRF} + m_{Bias}$$

➢ Measurement:

$$z_m = R_{3\times 3} \cdot (m_{IGRF} + m_{Bias} + m_{Noise})$$

$$\|z_m\| = \sqrt{z_{mx}^{\ 2} + z_{my}^{\ 2} + z_{mz}^{\ 2}} \qquad \|R_{3\times 3}\| = 1$$

M : magnetic map;

$R_{3\times 3}$: rotation matrix;

m_{IGRF} : International Geometric Reference Field;

m_{Bias} : local bias;

m_{Noise} : measurement noise.

- Hardware:

➢ Samsung Galaxy Note II

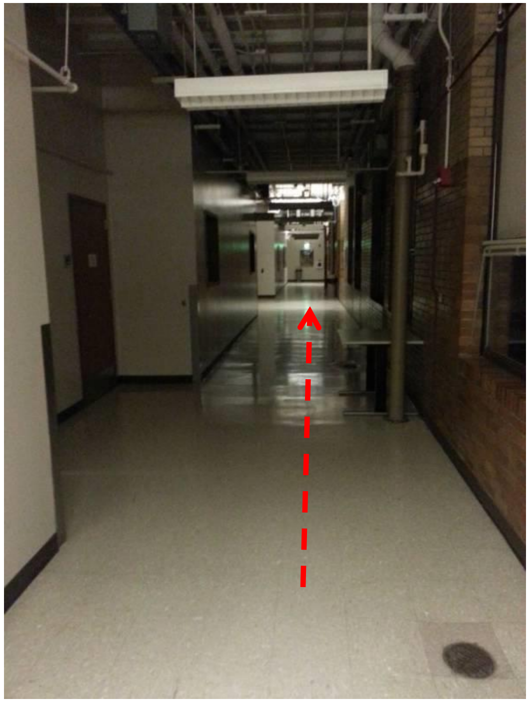
➢ Measurement unit: (μT)

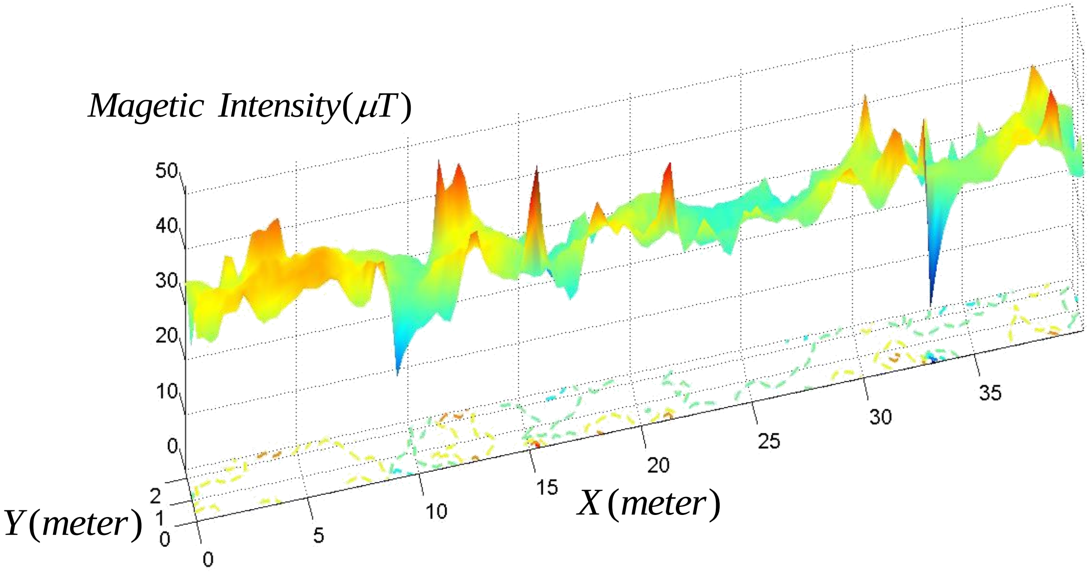
➢ Measurement noise:

$$\sigma_{noise}^2 = 0.0734(Gauss^2)$$

- Floor plan:

➢ Part of Mechanical Engineering Building (2nd floor), Purdue University





Magetic Intensity(μT)
50
40
30
20
10
0
2
1
0
Y(meter)
0
5
10
15
20
25
30
35
X(meter)

Static Estimation

- Measurement:

$$z_m = R_{3\times 3} \cdot (m_{IGRF} + m_{Bias} + m_{Noise})$$

$$\|z_m\| = \sqrt{{z_{mx}}^2 + {z_{my}}^2 + {z_{mz}}^2}$$

- Optimization:
  - Cost Function, $c(p_t)$:

$$c(p_t) = \left| \|z_m\| - m(x, y) \right|$$

$$p = \arg\min_{p \in V} c(p_t)$$

Static Estimation

- Static Estimation Algorithm

  - Definition of Wrapper[6]:

    P: a set;
    IP: subset of **P**;
    IP is a set of *wrappers* for **P**,
    if it satisfies:

    1)P and each singleton of P belong to P;
    2)IP is closed by intersection.

    $\mathbf{P_1}$: a subset of **P**;
    The smallest wrapper $[\mathbf{P_1}]$:

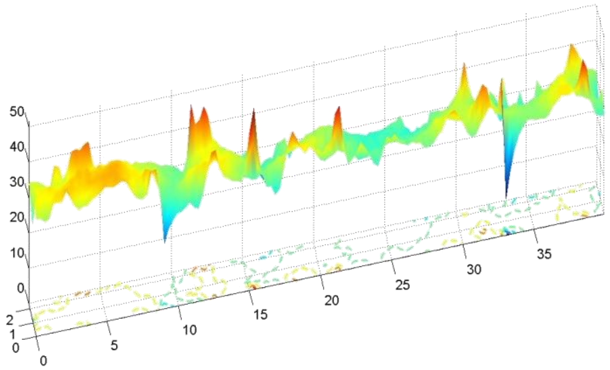
$$[\mathbf{P}_1] = \bigcap \{\mathbf{X} \in \mathbf{IP} \mid \mathbf{P}_1 \subset \mathbf{X}\}$$

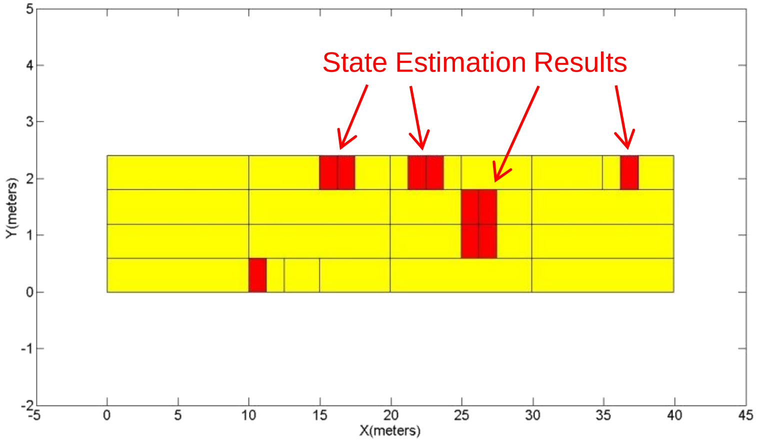
Algorithm:

1. Define the wrapper set $[p]$ for initial guess from $[V]$;
   % wrapper definition can be found in [8].
   Create an relatively big vector set
   $B = \{([p], c(p) = \infty)\}$;
   % to store the entire points and cost values
2. Separate $[p]$ into several smaller sets, denoted as $[p_i]$;
3. Iterations:
   $[p] = [p_i]$
   if ($[p] \neq empty$) then,
   if ($w([p]) < \varepsilon$) then, % width of $[p]$
   $S(:,i) = ([p], \min(c([p])))^T$
   % to store coordinates and minimal
   % cost function values
   else
   bisect $[p]$ into $[p_1]$ and $[p_2]$;
   $\{\mathrm{b}_i \in B \mid \mathrm{b}(:,2i-1) = ([p_1], \min(c(p)))^T$
   $and\ \mathrm{b}(:,2i) = ([p_1], \min(c(p)))^T\}$
   Iterations end until $B = empty$.
4. The estimated interval $[\hat{\mathrm{s}}]$ can be obtained from S
   if $c_i \in S < \overline{c}$
   % if the cost value is lower than upper bound.
   $([p_i], c(p_i)) \in [\hat{\mathrm{s}}]$
   % store this into candidate intervals
   else
   $([p_i], c(p_i)) \notin [\hat{\mathrm{s}}]$ % otherwise, remove it.
   end

Experimental Results

- Candidate locations are well bounded within several small 0.6m×1.25m intervals.

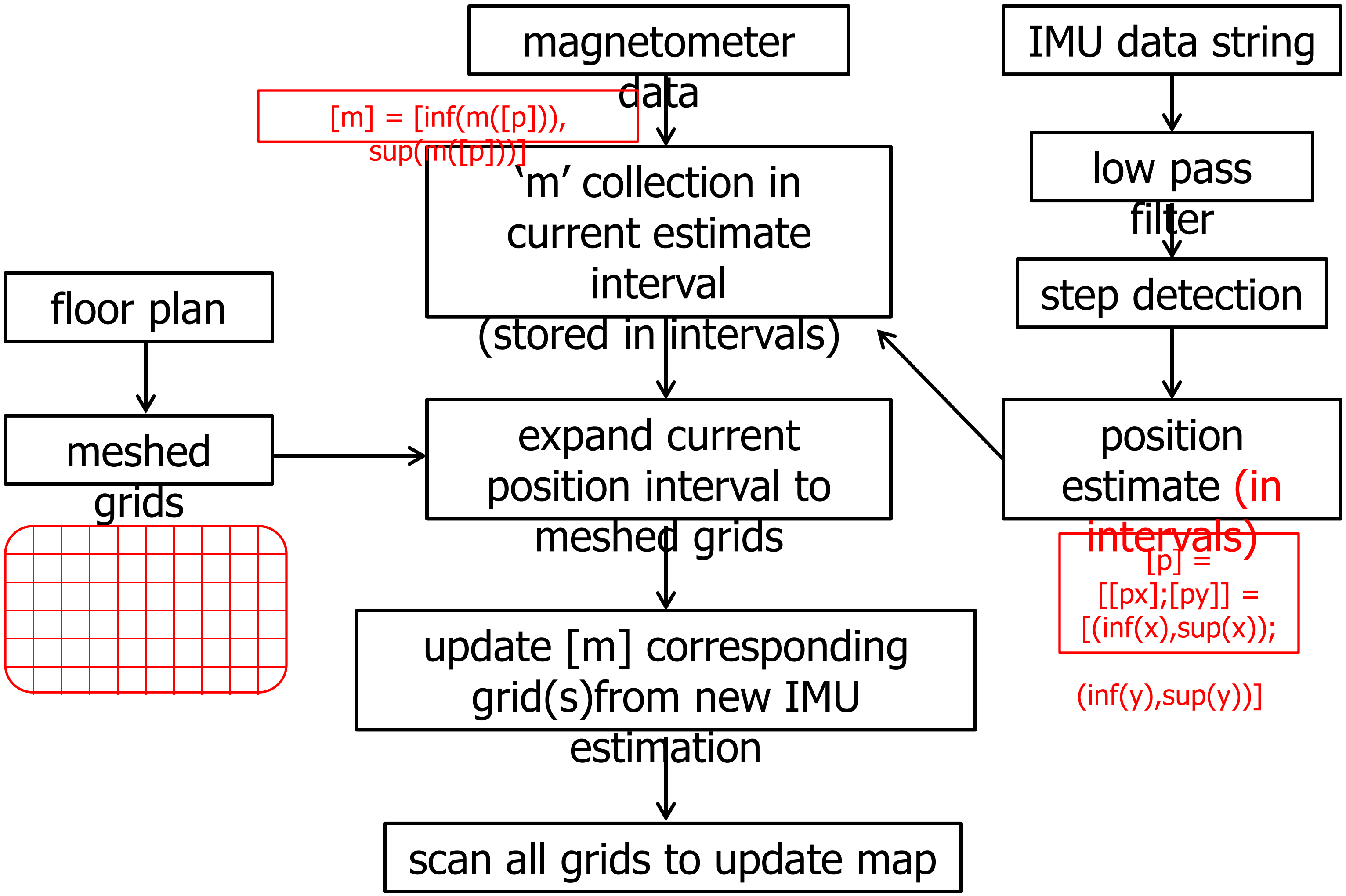




Bounded region from static estimation

Crowdsourcing the Map Construction

For a known floor plan



Crowdsourcing the Map Construction

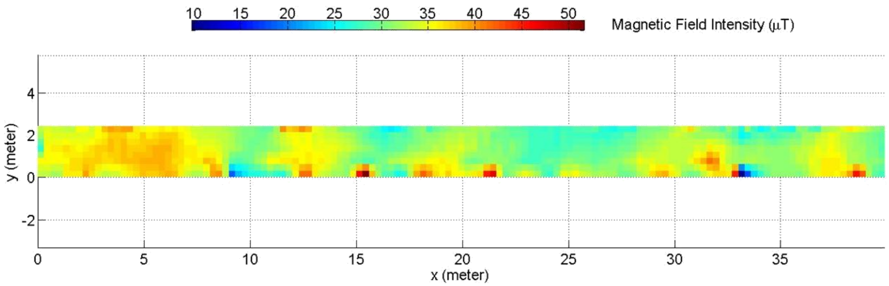


Fig.1. mean value distribution of [m] on a map

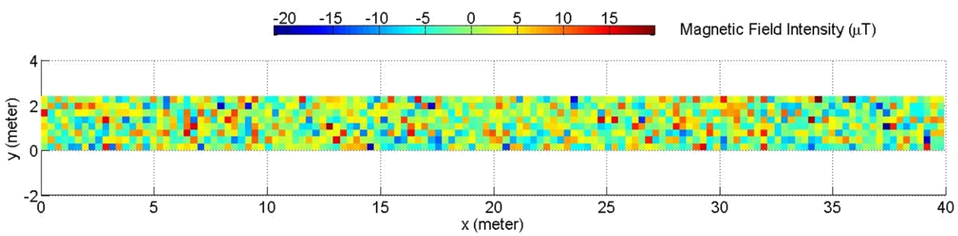


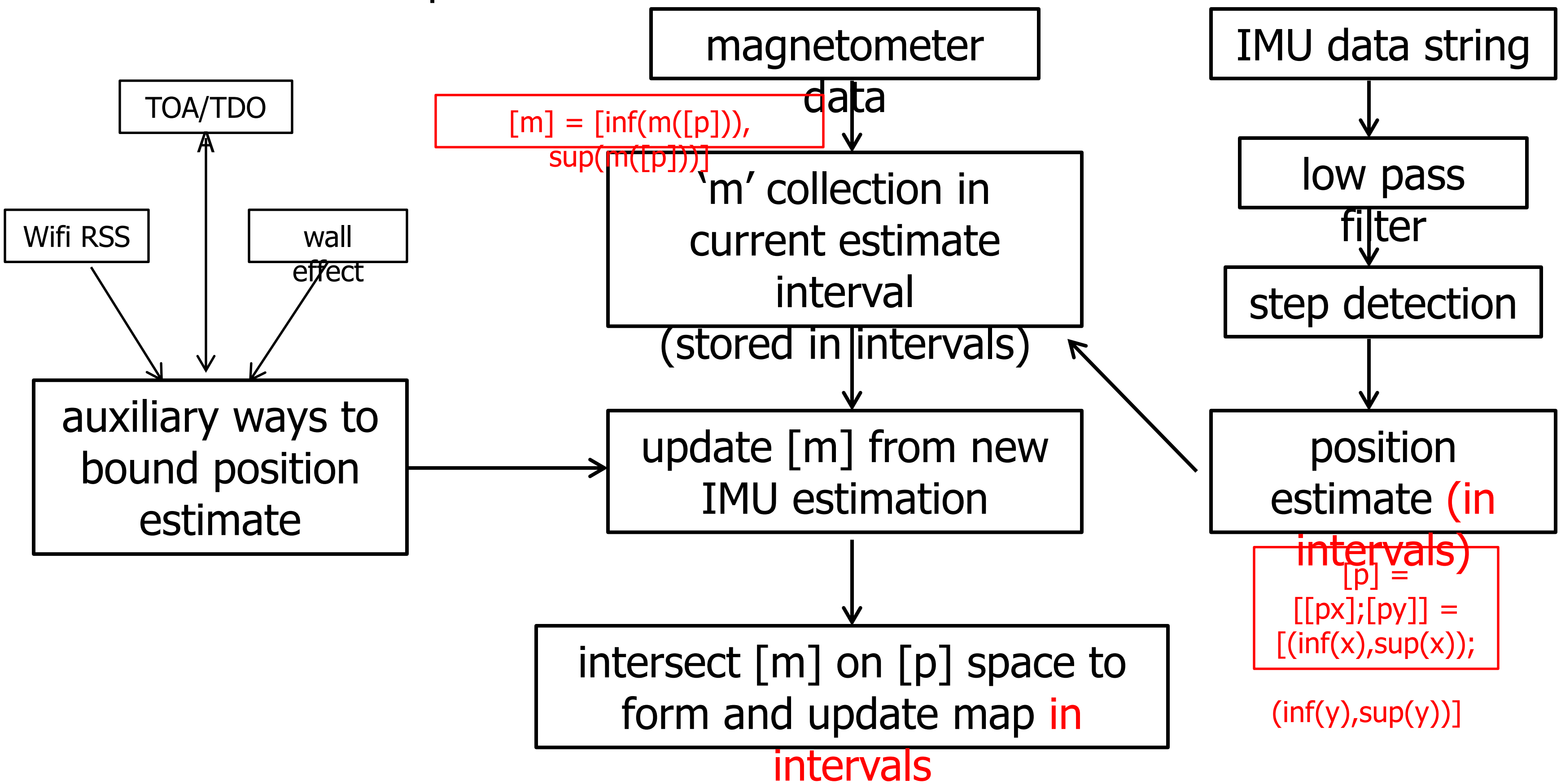
Fig.2. std value distribution of [m] on a map

Algorithm: Map Construction

```
Q = gridGenerate(mapSize, mapReso);  % generate grids, with default m value (if nothing known in prior, m = 0), and Q = [gridX; gridY; m] is 3 by 1.
while( i<length(IMU_DataString) ){
    [p(:,i)] = [[px];[py]];  % read in one position estimate
    [m] = [inf(m([p])), sup(m([p]))] ; % collect mag value
    [p_new(:,i)] = expandToGrid([p(:,i)] ,[m], mapSize, mapReso)  % expand to grids
    Q = gridUpdate(p_new(:,i))  % update m values to grids
}
```

Crowdsourcing the Map Construction

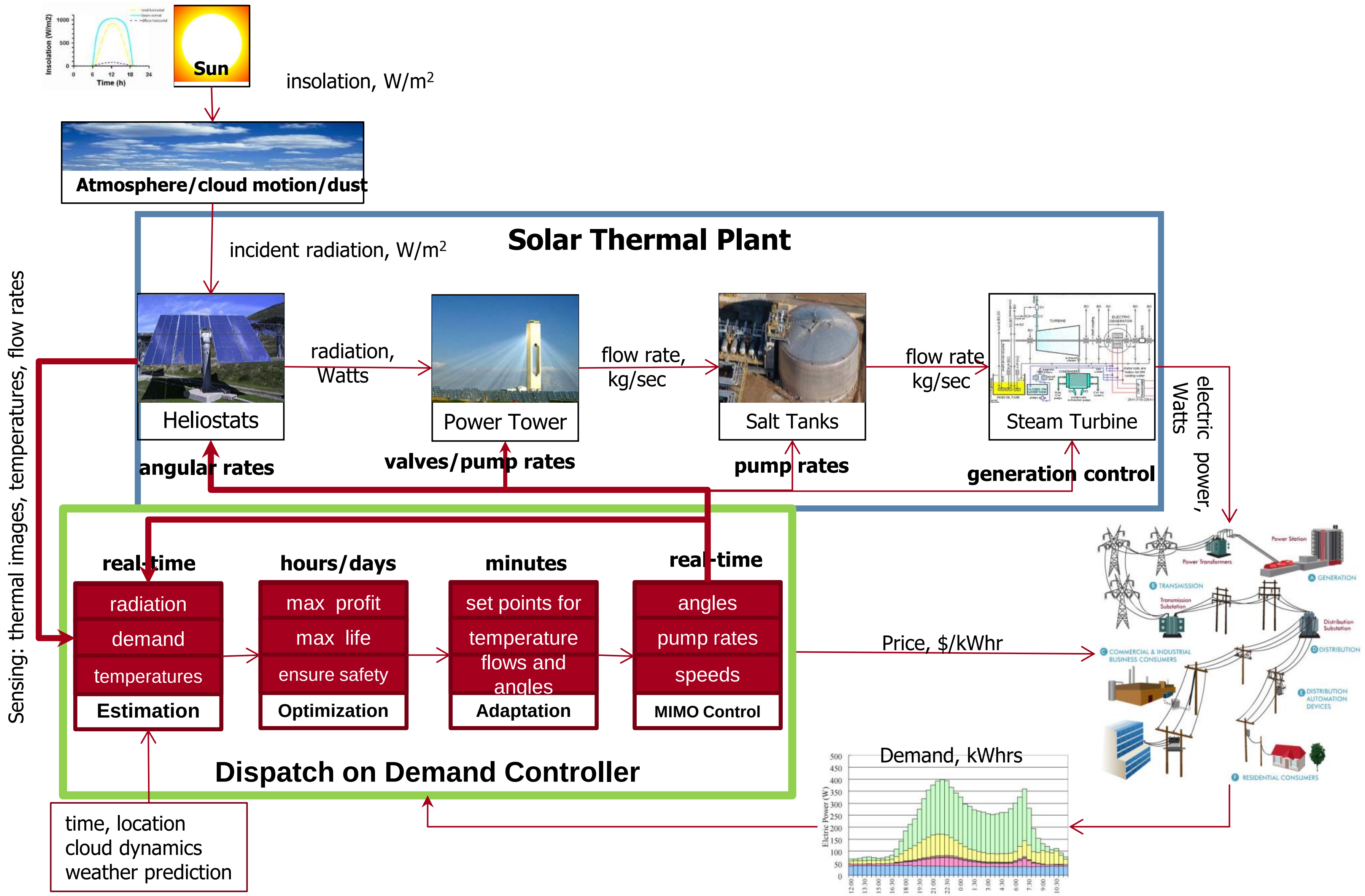
For a random floor plan:



Case 2: Control of CSP to maximize lifecycle

Collaborators:

Qi Luo



Sun
Time (h)
Insolation (W/m2)
insolation, W/m2
Atmosphere/cloud motion/dust
Solar Thermal Plant
incident radiation, W/m2
Heliostats
radiation, Watts
Power Tower
flow rate, kg/sec
Salt Tanks
flow rate kg/sec
Steam Turbine
electric power, Watts
angular rates
valves/pump rates
pump rates
generation control
Sensing: thermal images, temperatures, flow rates
real-time
hours/days
minutes
real-time
radiation
demand
temperatures
Estimation
max profit
max life
ensure safety
Optimization
set points for
temperature
flows and angles
Adaptation
angles
pump rates
speeds
MIMO Control
Price, $/kWhr
Dispatch on Demand Controller
time, location
cloud dynamics
weather prediction
Demand, kWhrs
Electric Power (W)
Power Station
Power Transformers
GENERATION
TRANSMISSION
Transmission Substation
Distribution Substation
DISTRIBUTION
COMMERCIAL & INDUSTRIAL BUSINESS CONSUMERS
DISTRIBUTION AUTOMATION DEVICES
RESIDENTIAL CONSUMERS

Dispatch on Demand Control for Concentrating Solar Thermal Plants

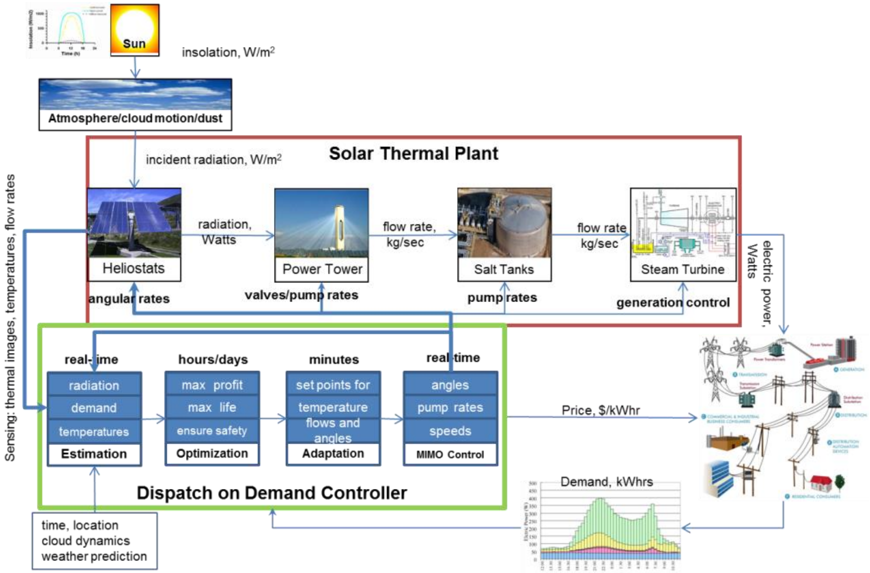
a ***three level control architecture*** for **CSP plants** that optimizes their performance on multiple time scales—

- reactive (*regulation to temperature set points*),
- tactical (*adaptation of temperature set points*), and
- strategic (*trading off fatigue life due to thermal cycling and current production*)—and can be implemented on existing plants to improve their efficiency and reliability.

Under specific technological circumstances—of sensing, control, and thermal energy storage, our architecture will make CSPs competitive with coal-thermal power plants, *reducing solar power costs down to $0.06/kWhr*, while ***responding with agility*** to both ***market dynamics*** and ***changes in solar insolation*** and producing electricity at the lowest cost.

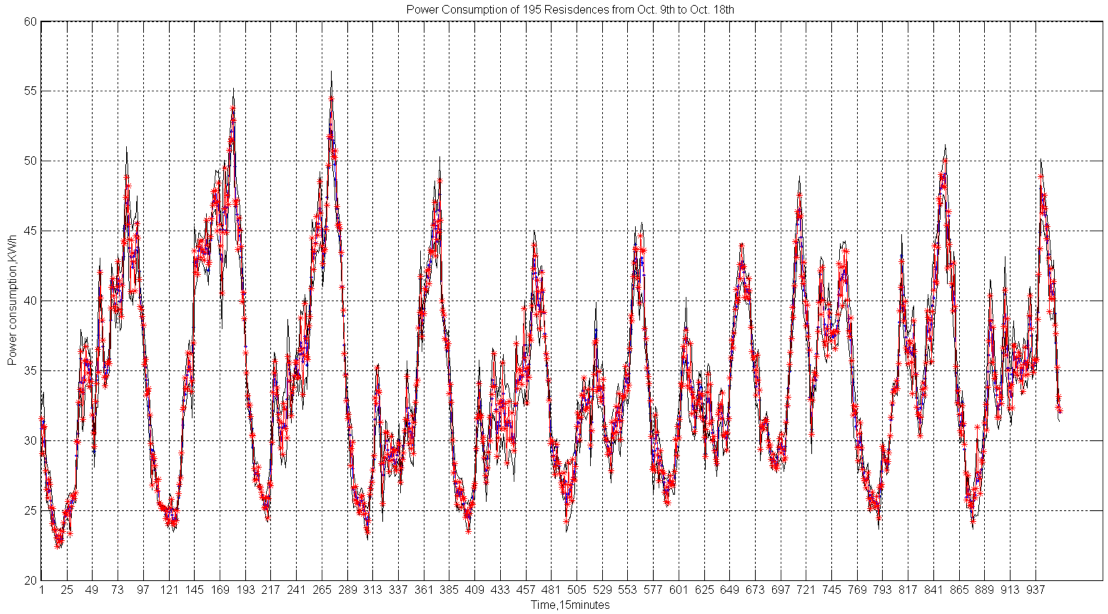
Market Impact

The model based controller will minimize failures in early stage plants and ensure early adoption of the CSP plants.



Immediate enabling of maximal system performance with component upgrades

Residential Electricity Demand



Energy consumption of 195 families in South Bend, Indiana from Oct.11 to Oct. 18,2010

- Residence of same area share similar electricity consumption patterns.
- Key factor of electricity demand is human habits.
- Second key factor is weather condition.
- The remaining demand behaves like Gaussian noise.

Influence of temperature

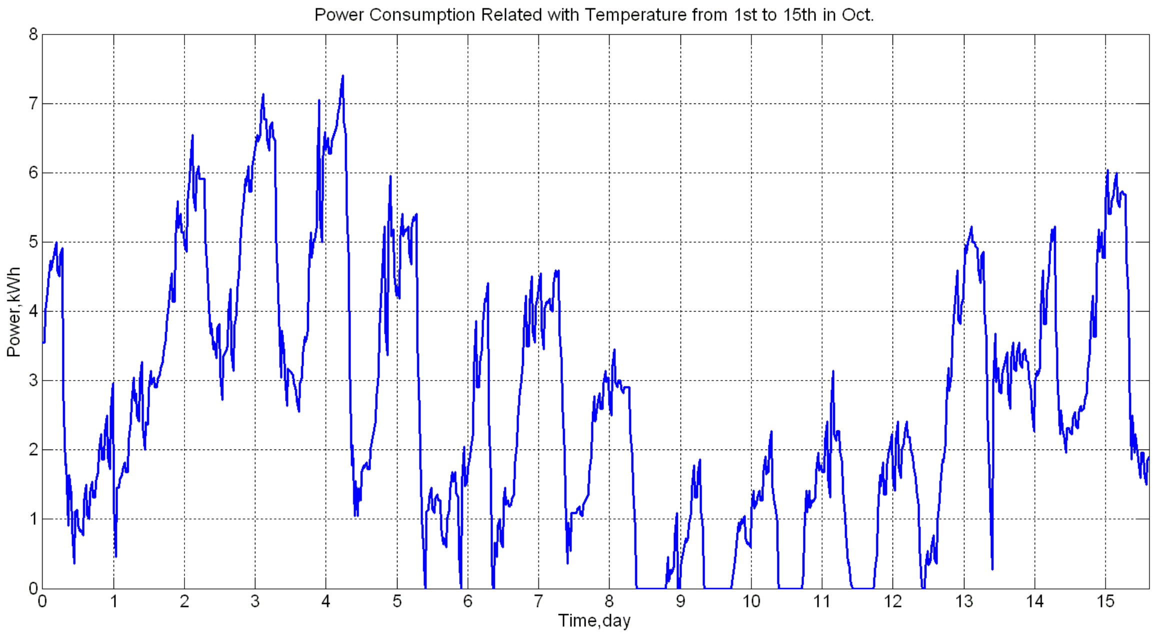
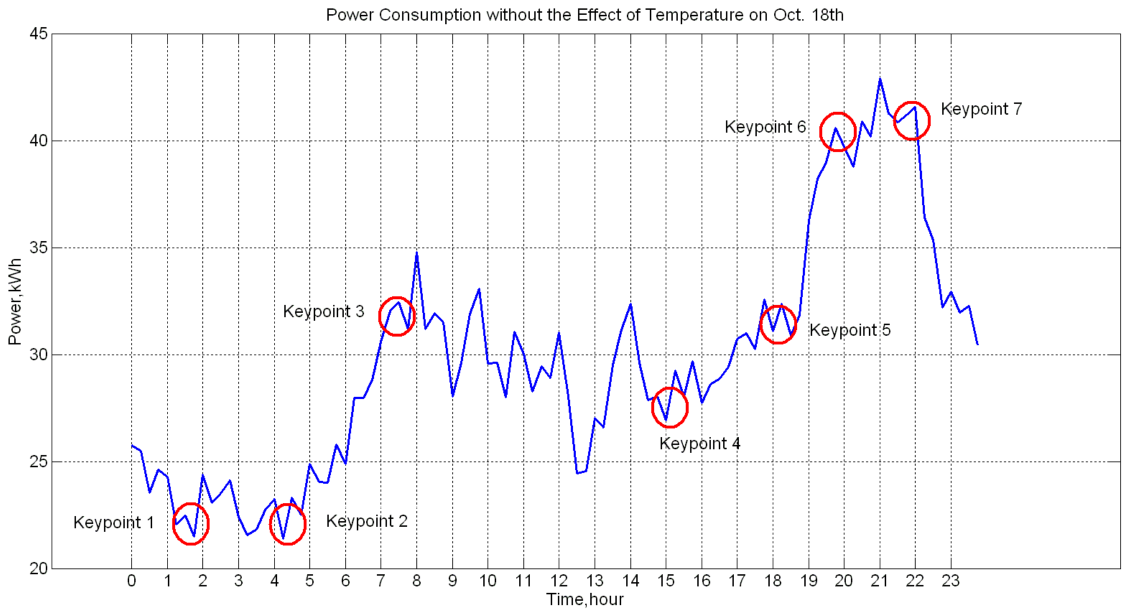


Fig. Temperature influence electricity demand.

Influence of human habits



Estimating the Condition of the CSP

- Solar receiver element

$$(mC_p)_{tube}\frac{dT_t(i,j,k)}{dt} = Q_{inc}(i,j,k) - (Q_{rad}(i,j,k) + Q_{conv}(i,j,k) + Q_{refl}(i,j,k)) - (UA)(T_t(i,j,k) - T_{HTF}(i,j,k))$$

- High temperature fluid

$$(mC_p)_{HTF}\frac{dT_{HTF}(i,j,k)}{dt} = (UA)(T_t(i,j,k) - T_{HTF}(i,j,k)) - Q_{HTF}$$

Thermal Storage Schematic

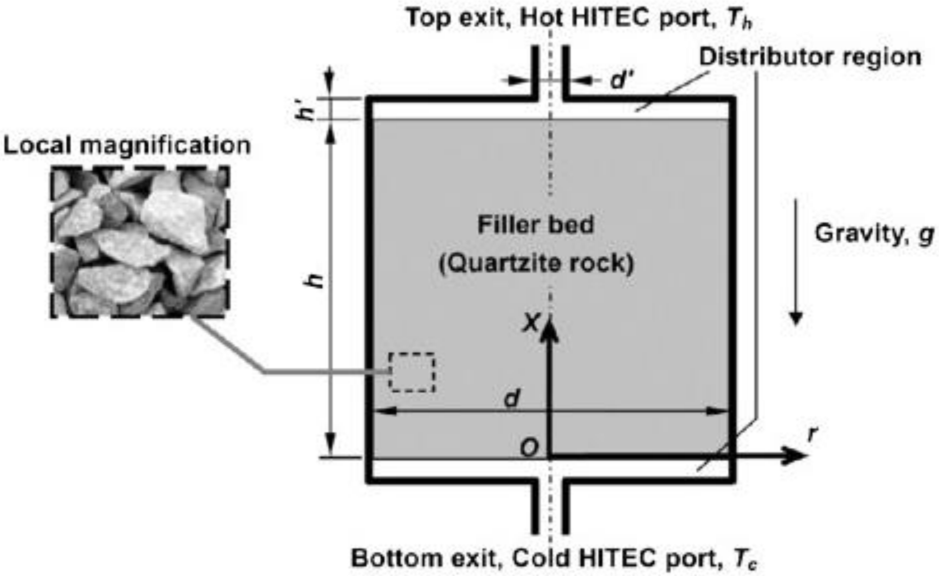


Fig: Schematic illustration of a thermocline [1]

[1] Z. Yang and S. V. Garimella, Thermal analysis of solar thermal energy storage in a molten-salt thermocline," Solar Energy, vol. 84, no. 6, pp. 974-985, 2010..

Thermal Storage Dynamics

$$\varepsilon\frac{\partial\Phi_\rho}{\partial\tau}+\nabla\cdot(\Phi_\rho\mathbf{U})=0$$

$$Re\frac{\partial\Phi_\rho}{\partial\tau}+Re\Psi\nabla\cdot(\frac{\Phi_\rho\mathbf{U}\mathbf{U}}{\varepsilon})=-\varepsilon\nabla P+\nabla\cdot\mathbf{T}+\varepsilon\Phi_\rho Gr\mathbf{e}_\mathbf{x}-\varepsilon(\frac{\Psi_\mu\mathbf{U}}{Da^2}+\frac{FRe\Psi}{Da}\Phi_\rho\mathbf{U}\mathbf{U})$$

$$\begin{aligned}&PrRe\frac{\partial}{\partial\tau}(-\varepsilon\Phi_\rho\Phi_{Cpl}\Theta_l)+PrRe\nabla\cdot(\Phi_\rho\Phi_{Cpl}\Theta_l\mathbf{U})\\&=\frac{1}{\Psi}\nabla\cdot(\Phi_{ke}\nabla\Theta_l)+2PrARe\Phi_\mu[\mathbf{S}\mathbf{S}'+\mathbf{tr}(\mathbf{S})\mathbf{tr}(\mathbf{S}')]+\Phi_{kl}Nu_i\Psi(\Theta_s-\Theta_l)\end{aligned}$$

$$PrRe\frac{\partial}{\partial\tau}[(1-\varepsilon)\Omega\Phi_{\rho s}\Phi_{Cps}\Theta_s]=-\Phi_{kl}Nu_i\Psi(\Theta_s-\Theta_l)$$

Thermal Storage Temperature Distribution

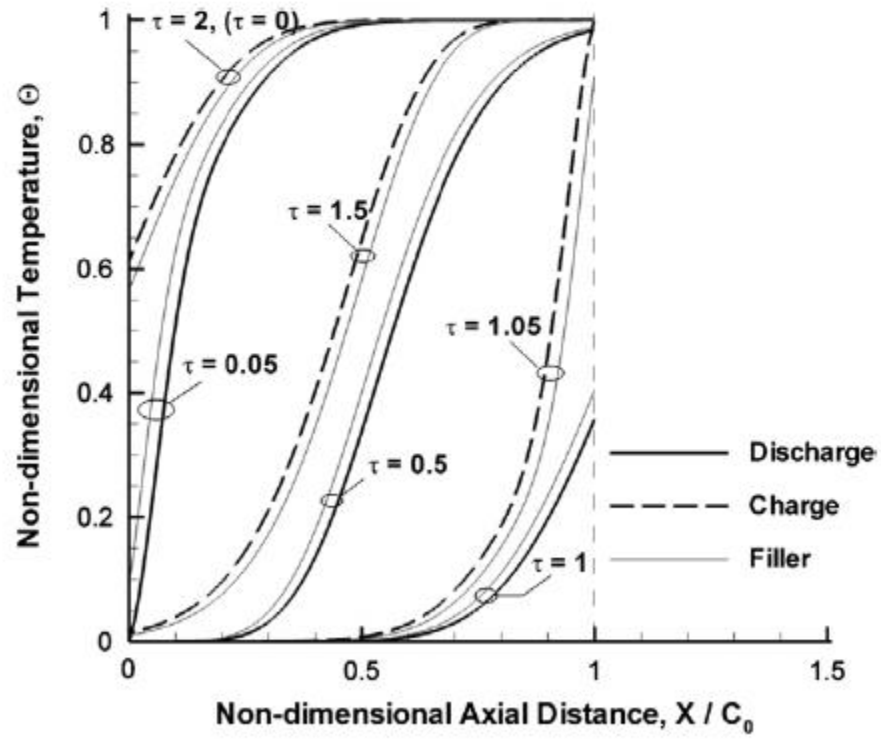


Fig: Charging-discharging process with fixed flow rate

Thermal Storage Summary

- Determine optimized thermal storage structure.
- Control input
  - Heat transfer flow rate at top/bottom in exit, q_T , q_b or non-dimentional flow velocity u.

Control output

- Thermal storage thermal distribution along axis,$T(x)$.

Disturbance

- Ambient temperature, T_{amb}.

Steam Turbine Generator

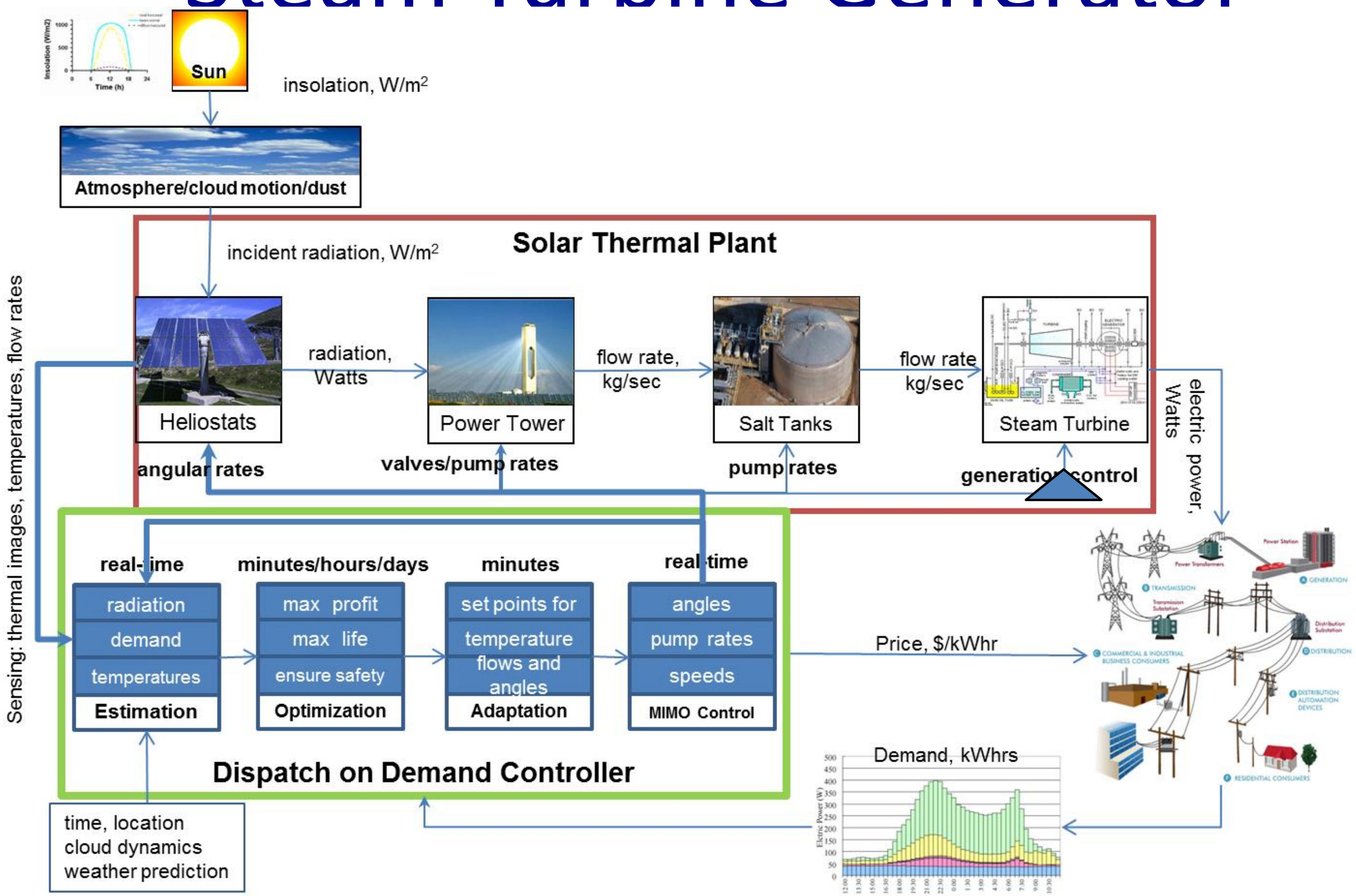


Fig: Multi-timescale control architecture

Steam Turbine Generator

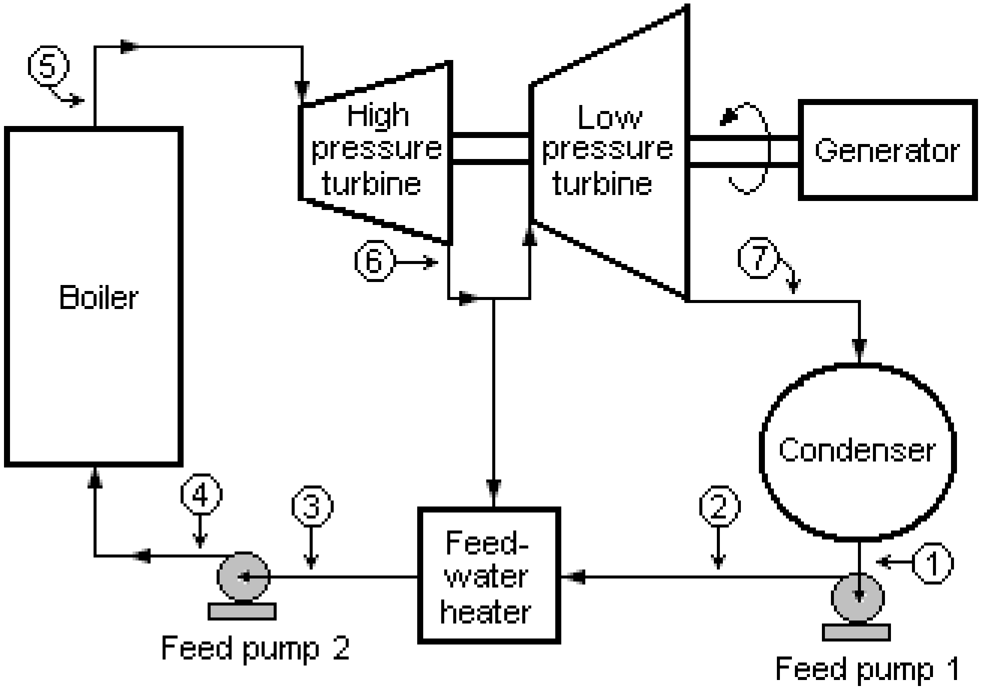


Fig: Schematic of steam turbine

Figure source:"http://thermal-powerplant.blogspot.com/2010/06/steam-turbine-driven-electric-generator.html".

Boiler Dynamics

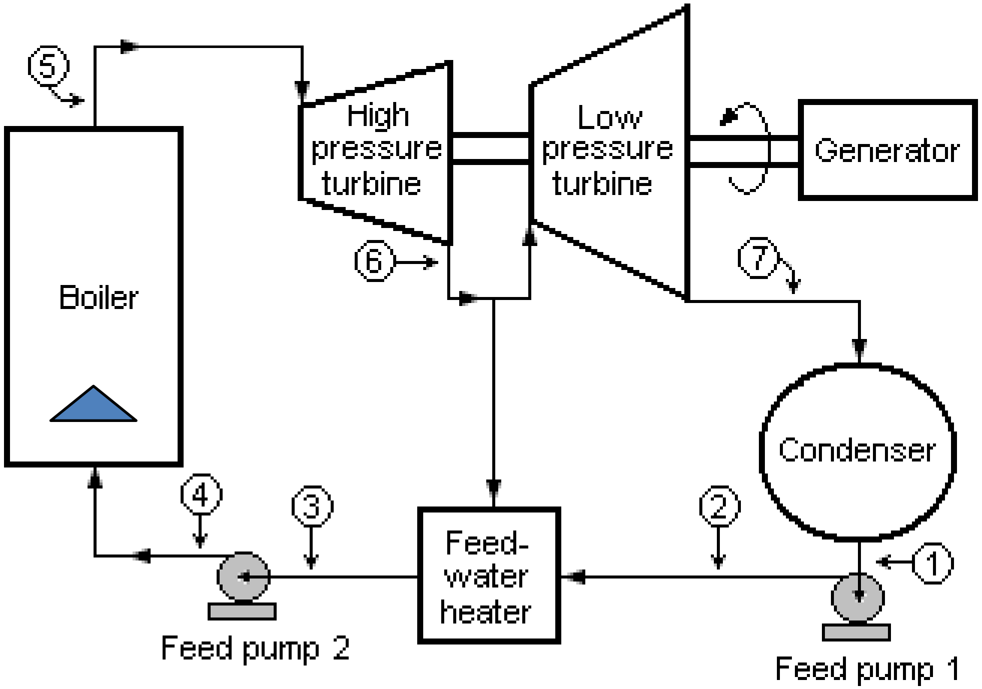
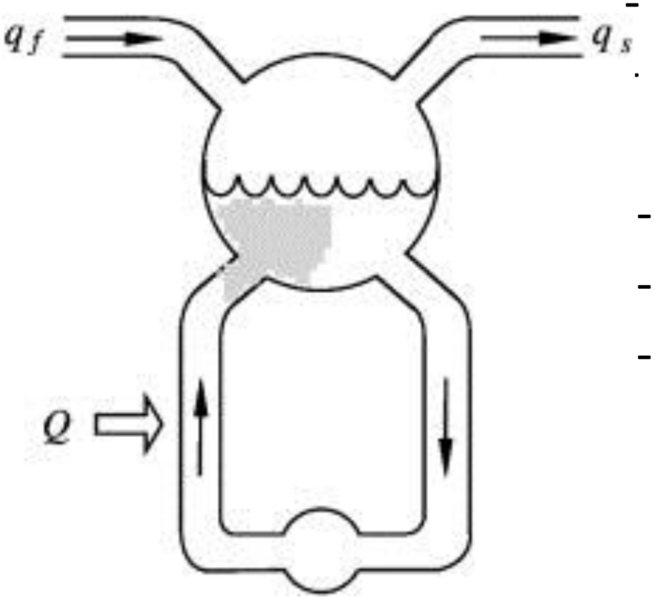


Fig: Schematic of steam turbine

Figure source:"http://thermal-powerplant.blogspot.com/2010/06/steam-turbine-driven-electric-generator.html".

Boiler System



- q_f , feed water flow rate
- q_s , heated steam flow rate
- Q, supplied energy

- p, drum pressure
- α_r, steam quality at outlet riser
- V_{wt}, total water volume in drum.
- V_{sd}, steam under liquid level.

Fig: Schematic of boiler [1]

[1] K. Astrom and R. Bell, Drum-boiler dynamics," Automatica, vol. 36, no. 3,pp. 363-378, 2000.

Boiler Dynamic Equation

$$e_{11}\frac{dV_{wt}}{dt} + e_{12}\frac{dp}{dt} = q_f - q_s$$

$$e_{21}\frac{dV_{wt}}{dt} + e_{22}\frac{dp}{dt} = Q + q_f h_f - q_s h_s$$

$$e_{32}\frac{dp}{dt} + e_{33}\frac{d\alpha_r}{dt} = Q - \alpha_r h_c q_{dc}$$

$$e_{42}\frac{dp}{dt} + e_{43}\frac{d\alpha}{dt} + e_{44}\frac{dV_{sd}}{dt} = \frac{\rho_s}{T_d}(V_{sd}^0 - V_{sd}) + \frac{h_f - h_w}{h_c} q_f$$

Steam Turbine Model

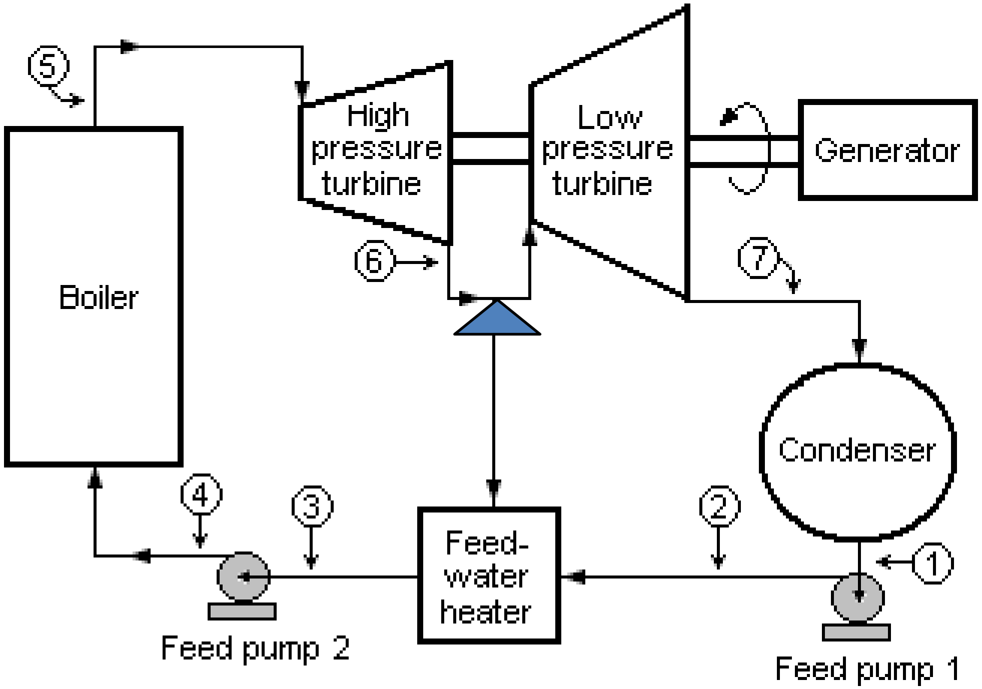


Fig: Schematic of steam turbine

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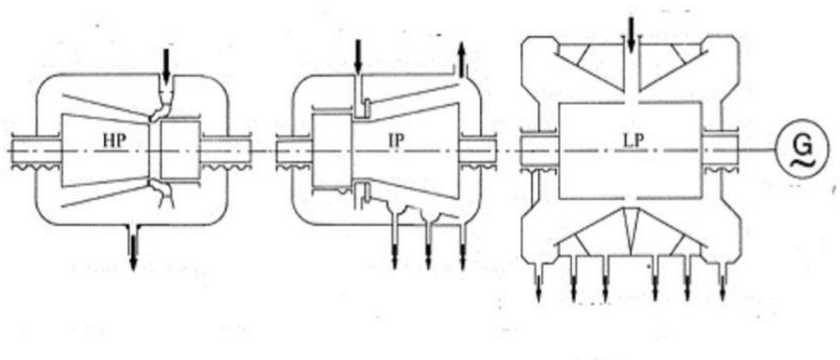
Steam Turbine Model



ıpplied torque to turbine

ar velocity of turbine

lied torque to turbine by
or.

Fig: Schematic of steam turbine [1]

[1] W. Lin, C. Tsai, and C. Lin, Analyzing the linear equivalent circuits of electromechanical systems for steam turbine generator units," Generation, Transmission Distribution, IET, vol. 5, pp. 685-693, July 2011.

Steam Turbine Dymanics

$$J_{iB}\frac{d\omega_{iB}}{dt} = \tau_{iB} - D_{iB}\omega_{iB} - K_{iB}(\theta_{iB} - \theta_i)$$

$$i = H, M, L$$

$$J_H\frac{d\omega_H}{dt} = \tau_H - D_H\omega_H - K_{HM}(\theta_H - \theta_M) - K_{HB}(\theta_H - \theta_{HB})$$

$$J_M\frac{d\omega_M}{dt} = \tau_M - D_M\omega_M - K_{ML}(\theta_M - \theta_L) - K_{HM}(\theta_M - \theta_H) - K_{MB}(\theta_M - \theta_{MB})$$

$$J_L\frac{d\omega_L}{dt} = \tau_L - D_L\omega_L - K_{LG}(\theta_L - \theta_G) - K_{ML}(\theta_L - \theta_M) - K_{LB}(\theta_L - \theta_{LB})$$

Boiler Dynamics

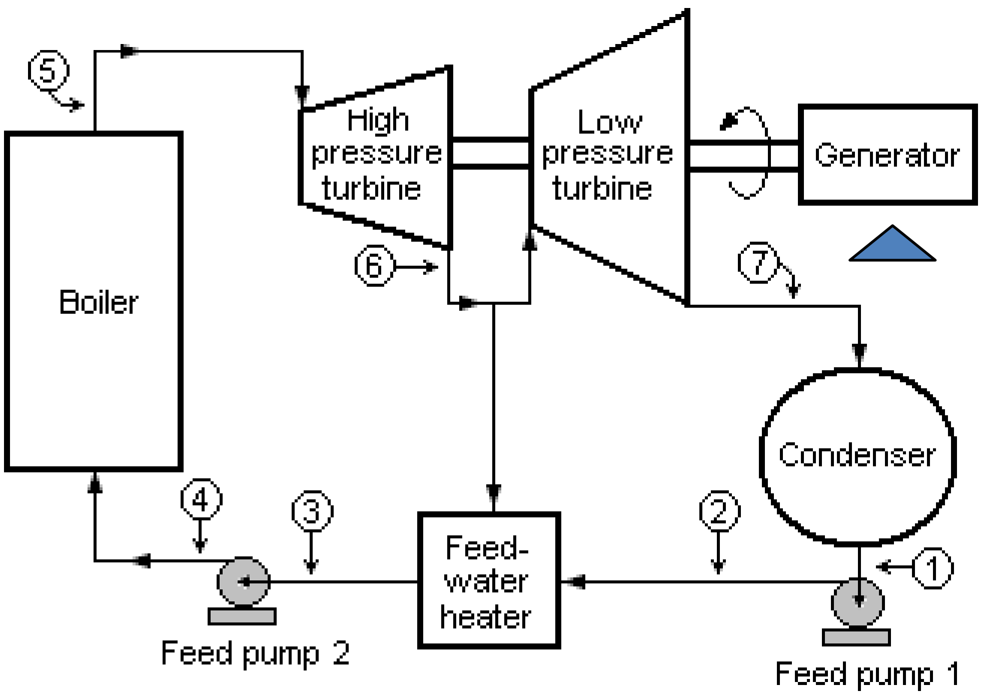
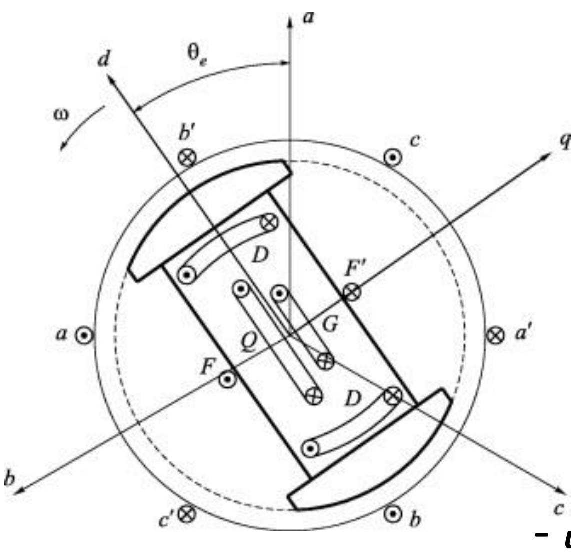


Fig: Schematic of steam turbine

Figure source:"http://thermal-powerplant.blogspot.com/2010/06/steam-turbine-driven-electric-generator.html".

Synchronous Generator System



- τ_{EM}, electromagnetic torque of generator
- V_{qs} , quadrature axis voltage
- V_{ds} , direct axis voltage
- ω_r , mechanical angular velocity.
- i_{qs} , quadrature axis current.
- i_{ds} , direct axis current.
- i_{fd} , field current.

Fig: Schematic of synchronous generator system[1]

[1] Chapter 4 - modeling and analysis of synchronous machines," in Power Quality in Power Systems and Electrical Machines (E. F. Fuchs and M. A. Masoum), pp. 155 -207, Burlington: Academic Press, 2008.

Synchronous Generator Dynamics

$$v_{ds} = (\frac{\omega_r}{\omega_b}X_q)i_{qs} + (-r_s - \frac{p}{\omega b}X_d)i_{ds} + (\frac{p}{\omega_b}X_{md})i'_{fd}$$

$$v_{qs} = (-r_s - \frac{p}{\omega b}X_q)i_{qs} + (-\frac{\omega_r}{\omega_b}X_d)i_{ds} + (\frac{\omega_r}{\omega_b}X_{md})i'_{fd}$$

$$\tau_{EM} = (\frac{3}{2})(\frac{P}{2})[L_{md}i'_{fd}i_{qs}i_{ds} + (L_{mq} - L_{md})i_{qs}i_{ds}]$$

Steam Turbine Generator Model Summary

- Control Input
  - Heat absorbed by boiler, Q, boiler feedwater flow rate, q_f

Control Output

- quadrature axis current, i_{qs} , direct axis current, i_{ds} .

Knowledge Required in Developing the Controller

- Normal CSP dynamics.
- **Measurement uncertainties and disturbance**
- Actuation limit.

System Parameters/States of Our Interest

- Sun position: α , Altitude angle; r , Azimuth angle.
- Heliostat tracking: ψ_t , Tilt angle; ψ_α , Tilt azimuth angle; τ_1Dual-axis non-orthogonal angle; μ the canting angle.
- CSP receiver: T_{amb} , Ambient temperature; $T_{HTF}(\mathrm{i,j,k})$, HTF temperature of the ith node; $T_{tube}(\mathrm{i,j,k})$, Tube temperature of the ith node; q_{HTF}, HTF flow rate.
- CSP storage: q_t, HTF top exit flow rate; q_b, HTF bottom exit flow rate; $T(x)$, Storage temperature distribution along flow axis.
- Steam Turbine Generator system: q_f , feed water flow rate; q_s , heated steam flow rate ; Q, supplied energy; p, drum pressure; α_r, steam quality at outlet riser; V_{sd}, total water volume in drum; V_{sd}, steam under liquid level. ω, angular velocity of turbine ;τ_{EM},applied torque to turbine by generator; ω_r , mechanical angular velocity; i_{qs} , quadrature axis current; i_{ds} , direct axis current.
- Energy Market: D_{DA} , Day ahead demand; D_{RT} , Real time demand; p_{DA} , Day ahead price; p_{RT} , Real time price.

Measurement of Solar Radiation

- Pyrheliometer : For direct normal solar radiation measurement.
- Pyranometer : For global horizontal radiation measurement.
  - Photodiode detectors.
  - Thermopile detectors.

Table: Comparison of solar radiation measurement instruments

	Photodiode	Thermopile
Electromagnetic Spectrum [nm]	400-1100	335-2200
Response Time	50 ms	< 15s
Operating Temp. ^{o}C	-40 to 65	-40 to 80

Measurement of Temperature

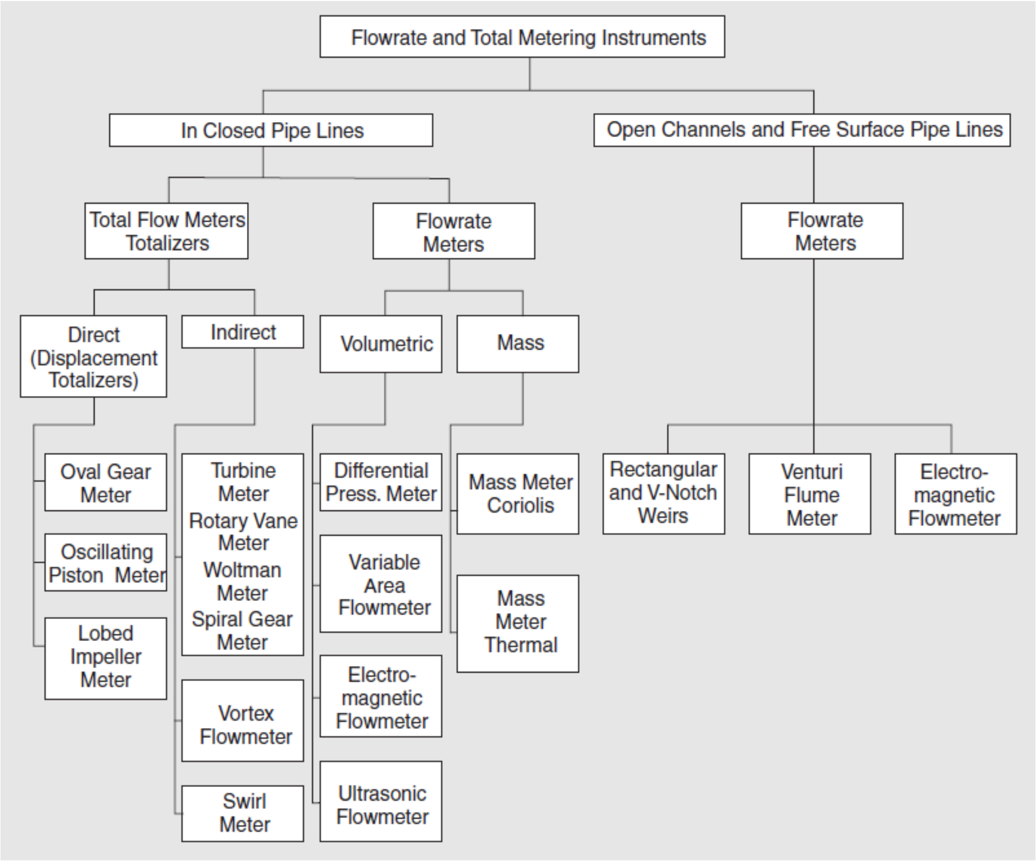
- Ambient temperature measurement : RTD, thermocouple, etc.
- CSP receiver temperature measurement: Beam Characterization System.
- HTF temperature measurement : Thermocouple.

Table: Comparison of temperature measurement instrument

Criteria	Thermocouple	RTD	Thermistor
Temp Range (^oC)	-267 to 2316	-240 to 649	-100 to 500
Accuracy	Good	Best	Good
Linearity	Better	Best	Good
Sensitivity	Good	Better	Best
Response Time	Fast	Slow	Fast
Cost	Best	Good	Better

Measure of Flow rate

- Mechanical flow meters.
- Pressure based flow meters.



Sensor Specification of Interest

- Input resolution.
- Output resolution.
- Input range. Output range.
- Maximum non-linearity.
- Maximum hysteresis.
- Reaction time.

Knowledge Required in Developing the Controller

- Normal CSP dynamics.
- Measurement uncertainties and disturbance
- **Actuation limit.**

Actuation Analysis- Motors for heliostat

- Electric motors
  - *Motors for heliostat.*
  - Motors for pumps.

Table: Comparison of solar motors for heliostat

Characteristics	Servo Motor	Stepper motor
Power Range	High	Medium
Efficiency	80%-90%	70%
Low Speed High Torque	Good	Good
High speed High Torque	Good	Bad
Power to Weight/Size ratio	Better	Good
Torque to Inertia Ratio	Better	Good
Overload Safety	Bad	Good
Repeatability	Good	Better

Actuation Analysis – Motors for pumps

- Electric motors

  - Motors for heliostat.

  - Motors for pumps.

Table: Comparison of solar motors for pumps

Characteristics	AC induction motors	AC synchronize motors
Power Range	High	Medium
Efficiency	High	Higher
Speed Accuracy	Medium	High
Load torque variation	Slight variance	None
Power factor	0.5-0.9 lagging	Flexible
Start Current	High	Low
Start torque	Low	High
Cost	Low	High

Actuation Analysis – pumps

Table: Comparison of pumps

Characteristics	Radial-flow pumps	Axial-flow pumps	Mixed-flow pumps
Enter direction	Along axial plane	Parallel to the rotating shaft	-
Exit direction	Right angles to the shaft(radially)	Parallel to the rotating shaft	-
Operation pressure	High	Low	Medium
Operation flow rate	Low	High	Medium

Actuator Specification of Interest

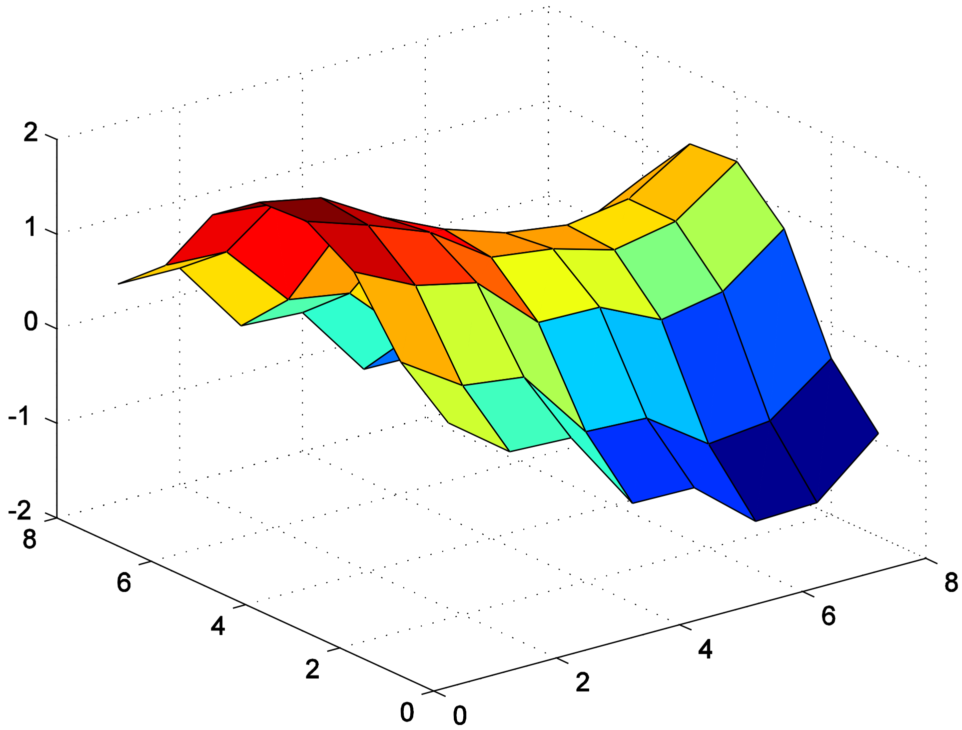
- Electric motors

  - Speed range, accuracy, saturation point, torque dynamic response, rated power, efficiency, load profile.

- Pumps

  - Operating speed, operating temperature, operating horsepower, maximum operating pressure.

Temperature distribution on power tower surface



Case 2: Control of Wind Turbines to minimize maintenance

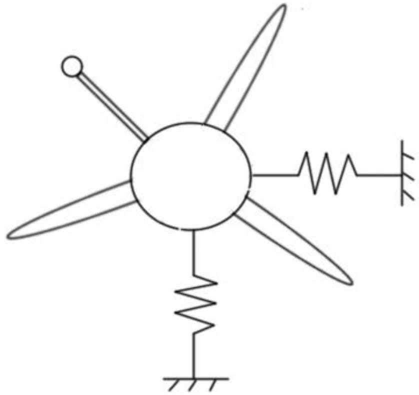
Collaborators:

Will Black

We want to detect the formation of ice on the turbine blades for two reasons. The ice can produce an imbalance in the system causing cyclic loading which ultimately leads to structural weakening and failure. Since the turbine blades are essentially designed like airfoils, a build-up of ice on the leading edge and/or the cambered section can reduce the lift coefficient to zero (rendering the system useless).

The mass imbalance affects the normal vibrational modes, which can be easily measured by a LIDAR system. Using this in collaboration with sensors embedded in the system increases the health monitoring capability of the supervisory system.

Simple Dynamic Analysis

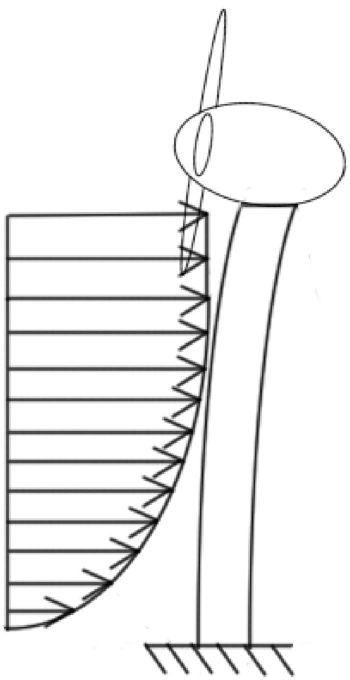


X Vibration $$(M+m)\ddot{x} + K_x x = m(\ddot{\theta} r \sin\theta + \dot{\theta}^2 r \cos\theta) + F_x$$

Y Vibration $$(M+m)\ddot{y} + K_y y = -m(\ddot{\theta} r \cos\theta + \dot{\theta}^2 r \sin\theta) - (M+m)g + F_y$$

θ Vibration $$I\ddot{\theta} + B\dot{\theta} = \tau_w + mr\sin\theta\left(\ddot{x} - \ddot{\theta} r \sin\theta - \dot{\theta}^2 r\cos\theta\right) - mr\cos\theta\left(\ddot{y} + \ddot{\theta} r\cos\theta + \dot{\theta}^2 r \sin\theta\right)$$

More Complicated Analysis



Tower Bending $$\frac{\partial}{\partial z^2}\left(EI\frac{\partial^2 w}{\partial z^2}\right) + \rho A\frac{\partial^2 w}{\partial t^2} + \frac{\partial}{\partial z}\left(P\frac{\partial w}{\partial z}\right) - f = 0$$

Tower Torsion $$Js\frac{\partial^2\theta}{\partial t^2} - 2\frac{\partial}{\partial z}\left(GI\frac{\partial\theta}{\partial z}\right) - M = 0$$

Blade Bending $$\frac{\partial^2}{\partial r^2}\left(E_b I_b\frac{\partial^2 w_b}{\partial r^2}\right) + \rho_b A_b\frac{\partial^2 w_b}{\partial t^2} + \frac{\partial}{\partial r}\left(P_b\frac{\partial w_b}{\partial r}\right) - f_b = 0$$

- Can we keep things simple and get by? Or do we need a more complicated analysis?
- Can we actually make measurements that satisfy the assumptions of a more complex model?

What do our system dynamics usually look like?

$$\dot{x} = f(x) + g(x)u + p(x)w + q(x)m + N_x(\mu, \sigma)$$

The vector fields f(x), g(x)u, p(x)w, d(x)m, and N represent our nominal system dynamics, control actuation, external disturbances, component failures, and process noise respectively.

What are the dynamics of disturbances and failures?

- Disturbances: many are linear systems
- Failures: exponential (approximately linear at first)
- Can we measure these directly?

$$\dot{\xi} = A\xi$$
$$w = C\xi$$

Do we always know the values of system parameters?

- Parameters usually unknown
- Parameters can change with time
- Check for linearity in parameters
- Can use least squares to estimate

$$y = \Phi(x, u, w, m)\theta$$

$$\hat{\theta} = (\Phi^T\Phi)^{-1}\Phi^T y$$

In system identification theory, we need a persistently exciting signal to *exactly* identify system parameters (asymptotically in time). The difficulty is that persistently exciting signals may not be feasible, or may even destroy the system!

What might specific sensor output look like?

Consider the x-axis accelerometer output of an inertial measurement unit:

$$\ddot{x}_{meas} = (1 + SF_x)\ddot{x} + SFA_x|x| + SFN_x\ddot{x}^2 + \sin(\Delta_z)\,\ddot{y} + \sin(\Delta_y)\,\ddot{z} + c + b + N_x(\mu, \sigma)$$

Our measured output is a function of the actual output subject to the limitations of the hardware. The hardware influences SF, SFA, SFN, Δ, c, b, and N represent scaling factor error, asymmetry error, nonlinear error, misalignment, offset, walking bias, and noise respectively.

Sometimes the outputs we are interested in are combinations of sensor values, and represented as:

$$y = h(x) + d(x)n + N_y(\mu, \sigma)$$

where h(x), d(x)n, and N are the nominal output, sensor faults, and sensor noise respectively.

The overall system is

$$\dot{x} = f(x) + g(x)u + p(x)w + q(x)m + N_x(\mu, \sigma)$$

$$y = h(x) + d(x)n + N_y(\mu, \sigma)$$

Can we estimate disturbance and failure processes?

Since we usually cannot directly measure disturbances or failures, we try to design observers that can provide estimates of these additional processes using elements of system theory as well as sensor measurements.

Disturbance Observer

$$\dot{\hat{\xi}} = A\hat{\xi} + L(x)(\dot{x} - f(x) - g(x)u - d(x)m - p(x)\hat{w})$$
$$\hat{w} = C\hat{\xi}$$

Fault Observer

$$\dot{\hat{\gamma}} = D\hat{\gamma} + K(x)(\dot{x} - f(x) - g(x)u - p(x)w - d(x)\hat{m})$$
$$\hat{m} = E\hat{\gamma}$$

Note: The derivative of state may not be available, but we can usually combat that with an internal state and filtered error. The above equations are examples assuming linear exogenous disturbances/faults which may not be the case.

A Fundamental Challenge in ISHM and Control

Our goal is to predict and detect faults with minimal cost to the system (e.g. sensors), but this presents a fundamental challenge. Can we differentiate between disturbances and faults? Hardware faults and sensor faults? This is not easy to prove, but if we can then we extort system theory as much as possible and reduce the cost of health monitoring significantly. If faults and disturbances cannot be separated by mathematics alone, then extra sensing is needed to alleviate this problem.

A classroom exercise in gaming

How do we get wise to the strategies of others?

Cognitive states and learning rates?

Game

- Choose a partner to play with—say you are A and the partner is B
- Each of you guess whether the partner is producing heads or tails.
- If both of you produce heads or tails**, A wins a dollar**
- If A and B produce a combination of heads and tails (HT or TH), **B wins a dollar**
- **Play this 10 times,** say 10 times, and lets find out the maximum score in the room.