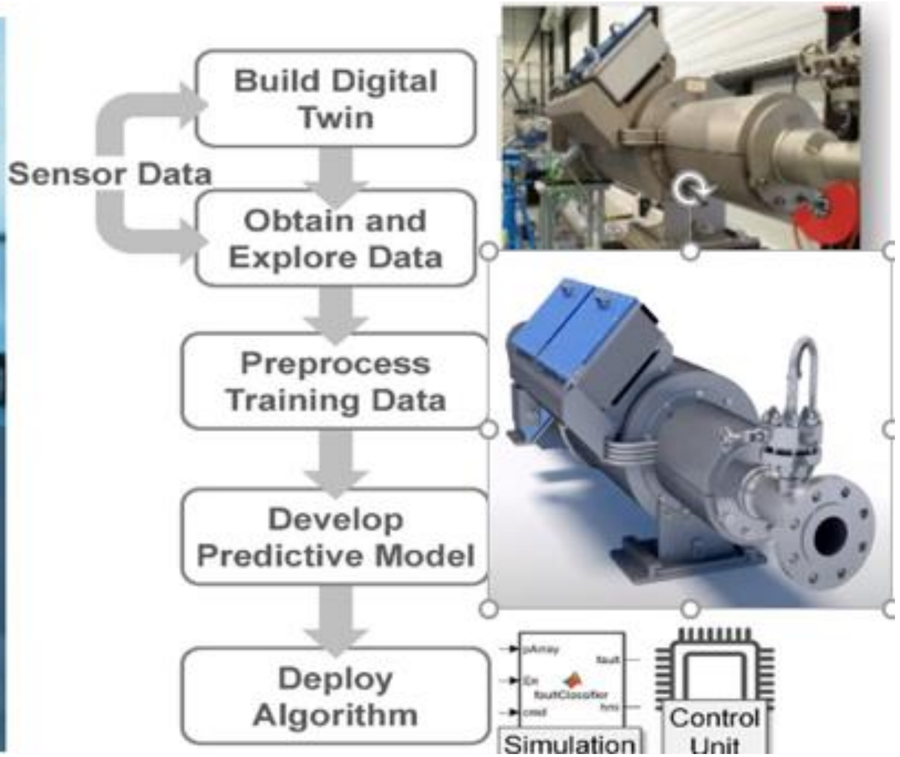
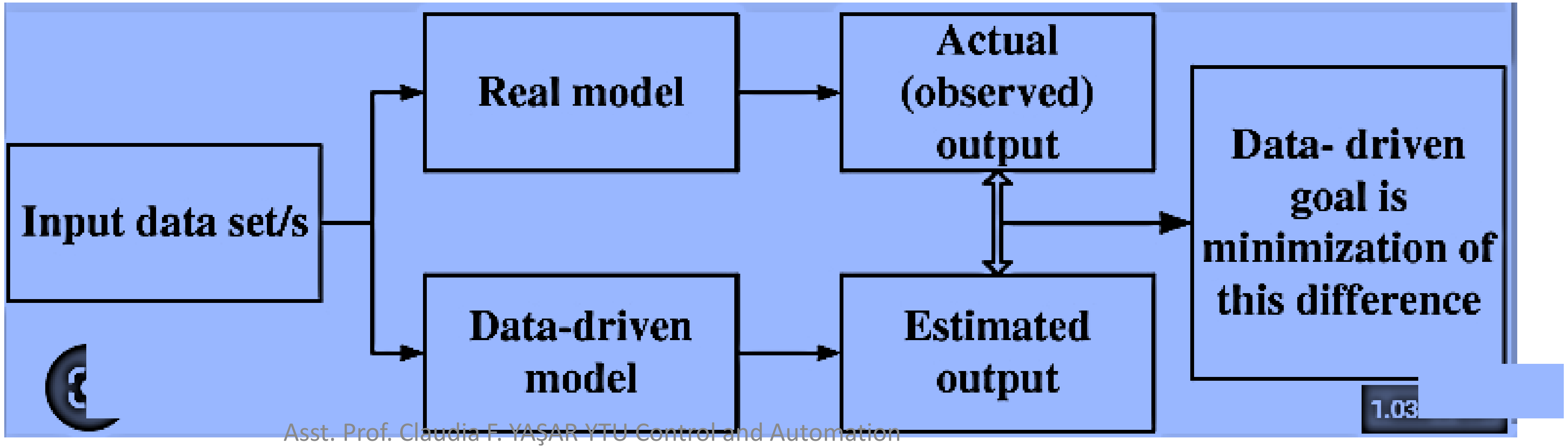
Data-Driven Modelling





	Intelligent Control System KOM 5101
1	Introduction to Intelligent Control Systems (knowledge-based vs data-driven systems)
2	Computational Thinking Tools
3	Dynamical Systems Modelling (Control System Toolbox could be used to transfer functions, state space models)
4	Model Predictive Control MPC (MPC Toolbox can be used)
5	Intro to Machine Learning (Stats & Machine Learning Toolbox could be used)
6	Data-driven Modeling -with machine learning (Stats & Machine Learning Toolbox could be used)
7	Data-driven Modeling -with system Identification (SysID toolbox could be used)
8	Midterm Exam
9	Data-driven Control Techniques -Extremum seeking (Simulink Control Design could be used)
10	Data-driven Control Techniques -Model reference adaptive control (Simulink Control Design could be used)
11	Intro to Deep Learning (Deep Learning Toolbox could be used)
12	Reinforcement Learning (RL Toolbox could be used)
13	Student's Projects
14	Student's Projects
15	Final Exam

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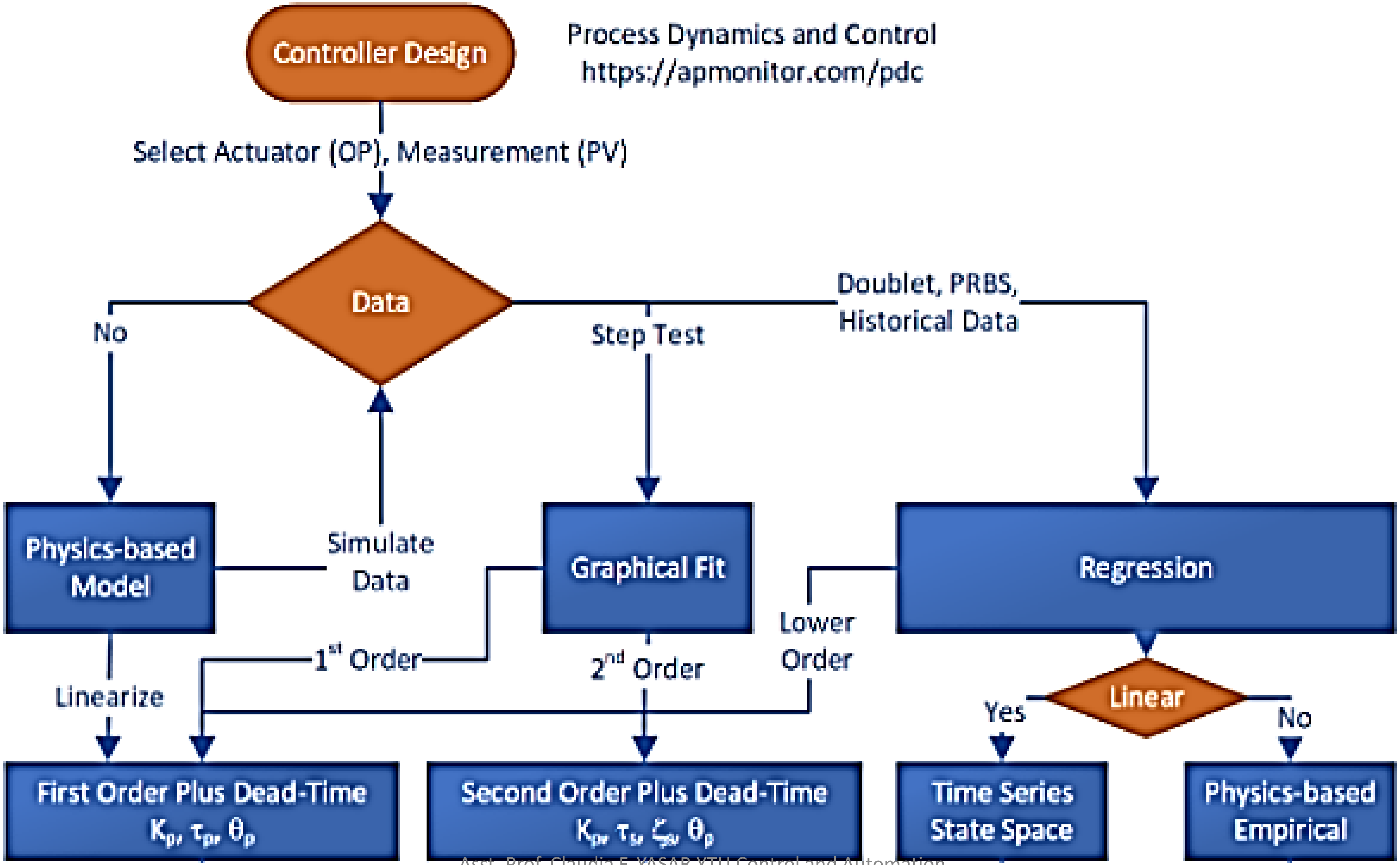
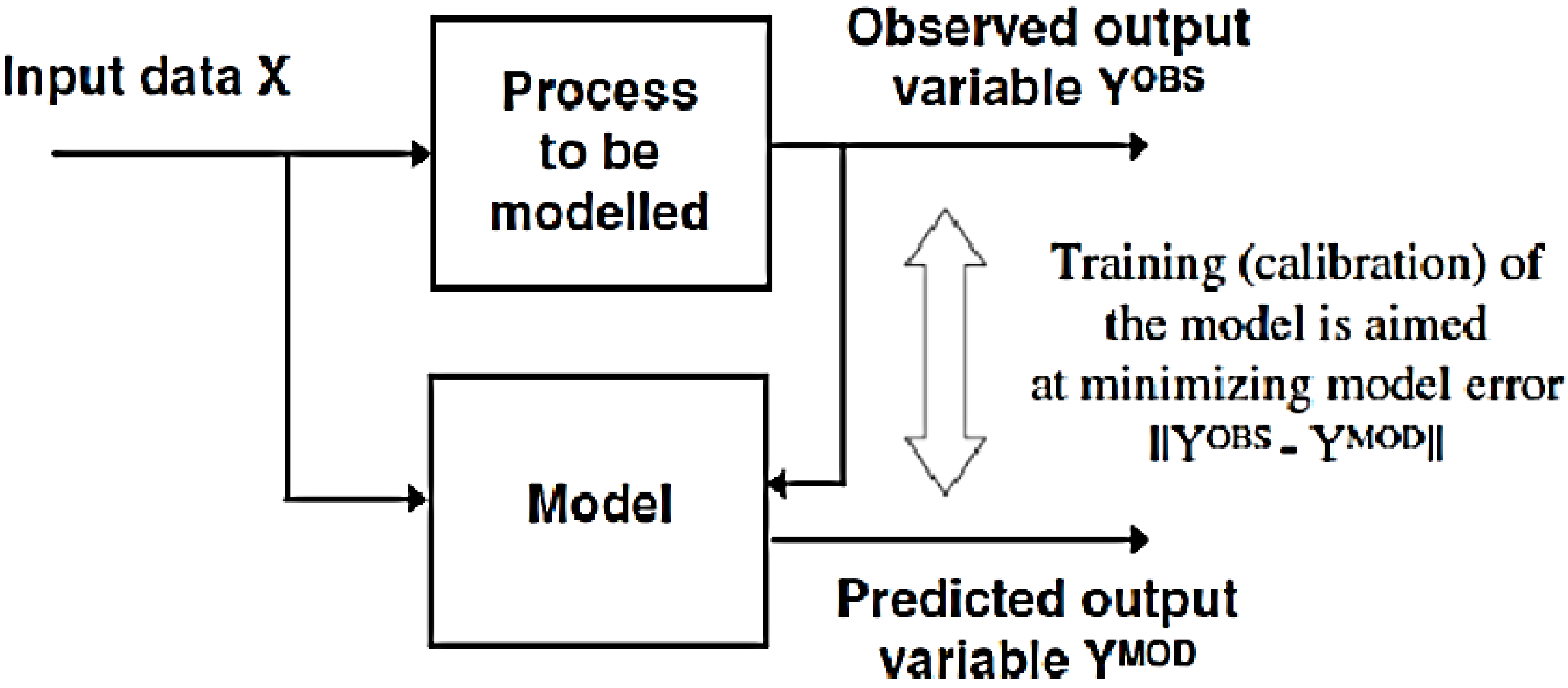
Intelligent Control Systems KOM5101	Preparation + Homework	Matlab Drive
1 Introduction to intelligent control systems (knowledge-based vs data-driven systems)	Select the project from https://github.com/mathworks/MathWorks-Excellence-in-Innovation#mathworks-excellence-in-innovation-projects	https://drive.matlab.com/sharing/c1f9073b-a0b0-4966-95b0-c107691878da
2 Computational thinking tools	Work with the Virtual Hardware and Labs for Control. Solve the following Labs Lab4_PositionAnalysis.mlx Lab3_PositionControl.mlx Lab2_VehicleModel.mlx Lab1_CruiseControl.mlx	https://drive.matlab.com/sharing/77e65af2-6ffd-4709-a0bd-c36e0fbe50df
3 Dynamical systems modelling	1. Study and Obtain the state space model of a crane system. 2. Study and Obtain the state space model of the Lateral Vehicle Dynamics bicycle model with two degrees of freedom, lateral position and yaw angle.	https://drive.matlab.com/sharing/31e0ba39-b3f8-402c-a428-6a5b9d620081
4 Model Predictive Control MPC	Study and work with the MPC models explained. Use the MPC Toolbox of Matlab and the apmonitor server. Learn how to work with the drivingScenarioDesigner. Program the MPC algorithms using Simulink and Live scripts. Modify Models and MPC parameter and settings.	https://drive.matlab.com/sharing/398fa9fa-4650-4316-ab2b-0d228b24f48c
5 Machine Learning	 Machine Learning Onramp 6 modules | 2 hours | Languages Learn the basics of practical machine learning methods for classification problems.	

Intelligent Control Systems KOM5101		Preparation + Homework	Matlab Drive
6	Data-Driven Modelling	Use the FOPDT example and do your own model estimation. Work with FOPDT live scripts **FOPDT_Lab/L06_Assignment_graphical** **Use the 2nd_order_linear model and obtain the regression parameters**	https://drive.matlab.com/sharing/71cc50d0-e79e-47e3-b91e-9ba1aa1cf78b
7	Data-Driven Modelling		


Controller Design
Process Dynamics and Control
https://apmonitor.com/pdc
Select Actuator (OP), Measurement (PV)
Data
No
Step Test
Doublet, PRBS, Historical Data
Physics-based Model
Simulate Data
Graphical Fit
Regression
1st Order
2nd Order
Lower Order
Linearize
Linear
Yes
No
First Order Plus Dead-Time
K_p, τ_p, θ_p
Second Order Plus Dead-Time
$K_p, \tau_s, \zeta_s, \theta_p$
Time Series
State Space
Physics-based
Empirical

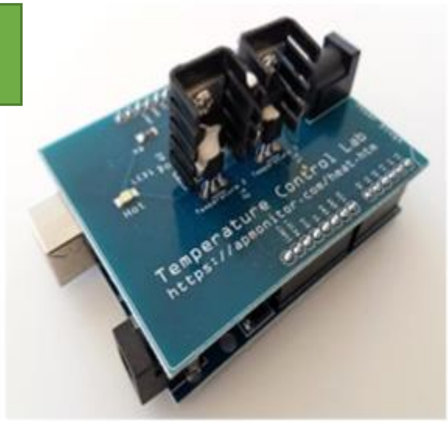
Moving Horizon Estimation 2nd order MIMO System

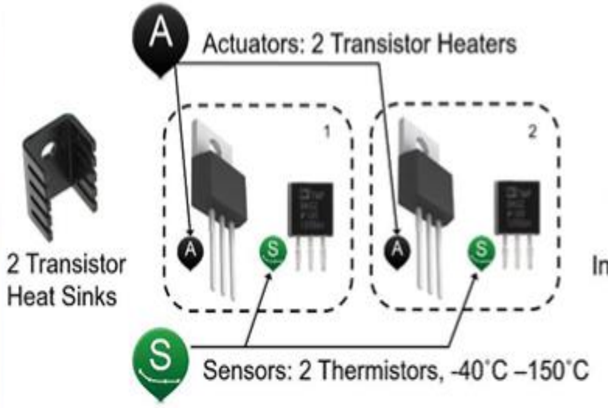


Dynamic models constructed with equations that describe physical phenomena may need to be tuned by adjusting parameters so that predicted outputs match with experimental data. Moving Horizon Estimation is an optimization approach to align dynamic models with successive measurements.

Moving Horizon Estimation 2^{nd} order MIMO System

Transient model between the two heater power outputs and the two temperature sensors. An energy balance describes the transient temperature response of heaters with temperature sensor.





This model represents the energy balance equation with convective heat transfer, radiative heat transfer, and the heater energy inputs. The additional blue terms are heat transfer

convective

radiative

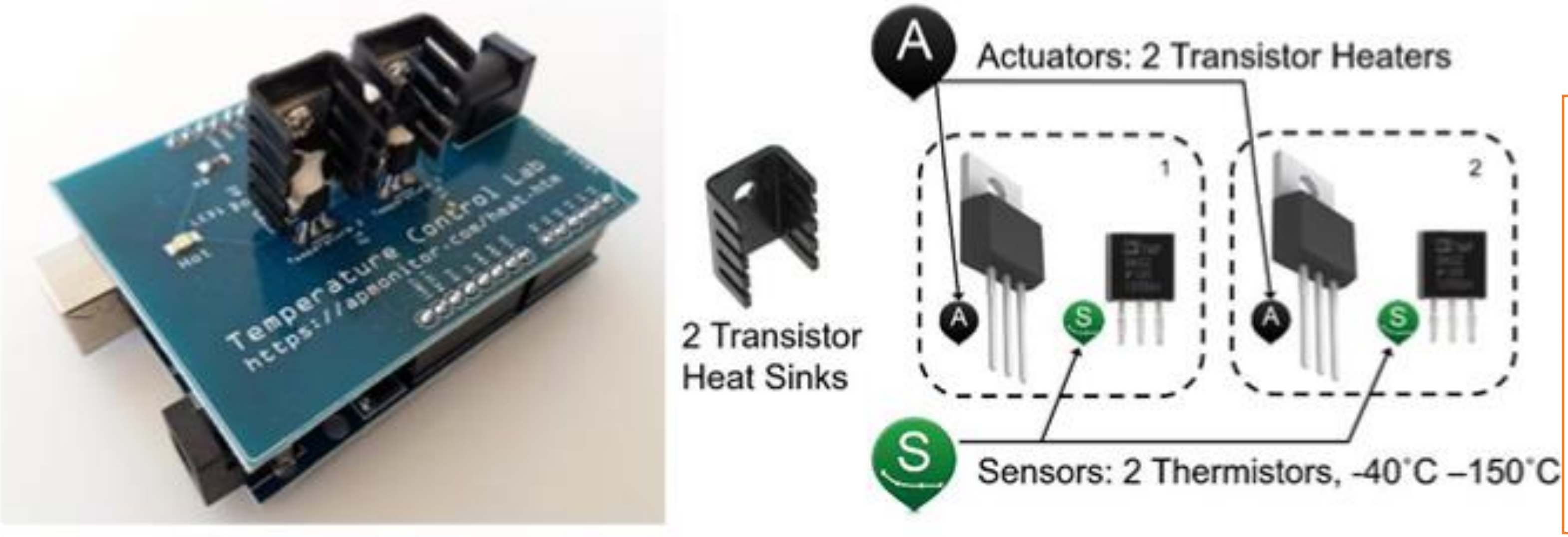
heater energy inputs

$$mC_p \frac{dT_1}{dt} = UA\,(T_\infty - T_1) + \epsilon\,\sigma\,A\,(T_\infty^4 - T_1^4) + UA_s\,(T_2 - T_1) + \epsilon\,\sigma\,A_s\,(T_2^4 - T_1^4) + Q_1$$

$$mC_p \frac{dT_2}{dt} = UA\,(T_\infty - T_2) + \epsilon\,\sigma\,A\,(T_\infty^4 - T_2^4) + \underbrace{UA_s\,(T_1 - T_2) + \epsilon\,\sigma\,A_s\,(T_1^4 - T_2^4)}_{\text{heat transfer}} + Q_2$$

Moving Horizon Estimation 2nd order MIMO System

The heater and temperature sensor are assumed to be at the same temperature.



Sensor Model

$$\tau_c \frac{dT_{C1}}{dt} = T_1 - T_{C1}$$

$$\tau_c \frac{dT_{C2}}{dt} = T_2 - T_{C2}$$

You can assume that conduction is negligible and that the only heat transferred is through radiation to the surroundings or convection or radiation to the surrounding air or from the heater nearby. The heaters are initially off and the heaters and sensors are initially at ambient temperature.

Empirical Model Estimation :

The objective is to fit **empirical and physics-based predictions** to the data for a two heater model of the temperature control lab. Parameters are adjusted to minimize the sum of integral absolute error (IAE) between the model predicted values and the measured values.

$$IAE_{model} = \sum_{i=0}^{n} \left|T_{1,meas,i} - T_{1,pred,i}\right| + \left|T_{2,meas,i} - T_{2,pred,i}\right|$$

An optimizer is used to adjust the parameters and achieve alignment between the model and the measured values.

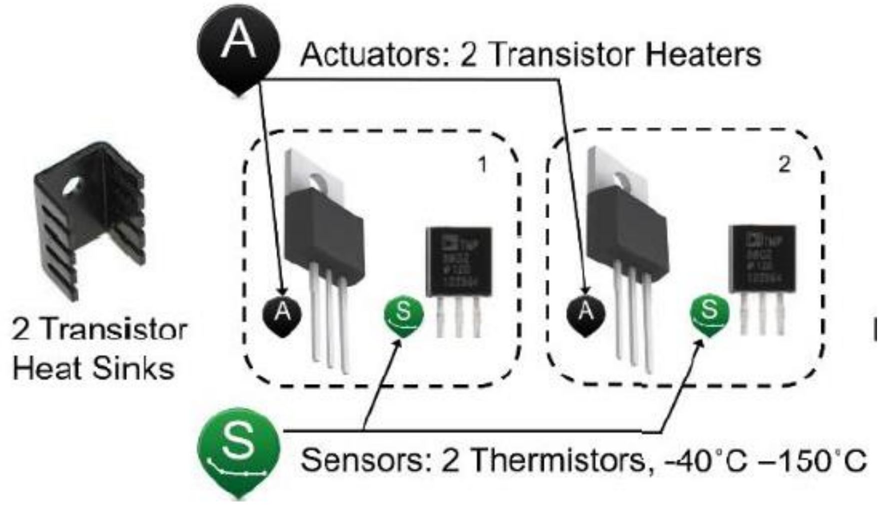
Semi-Empirical Moving Horizon Estimation

Design a Moving Horizon Estimator (MHE) for the temperature control lab to estimate the two temperatures and any necessary parameters by combining elements of fundamental and empirical modeling approaches. Create a model that will accurately predict the temperature $Th1$ and $Th2$ and can be used in a model predictive controller.

$Th1$ and $Th2$, are predicted from the equations but are not directly measured.

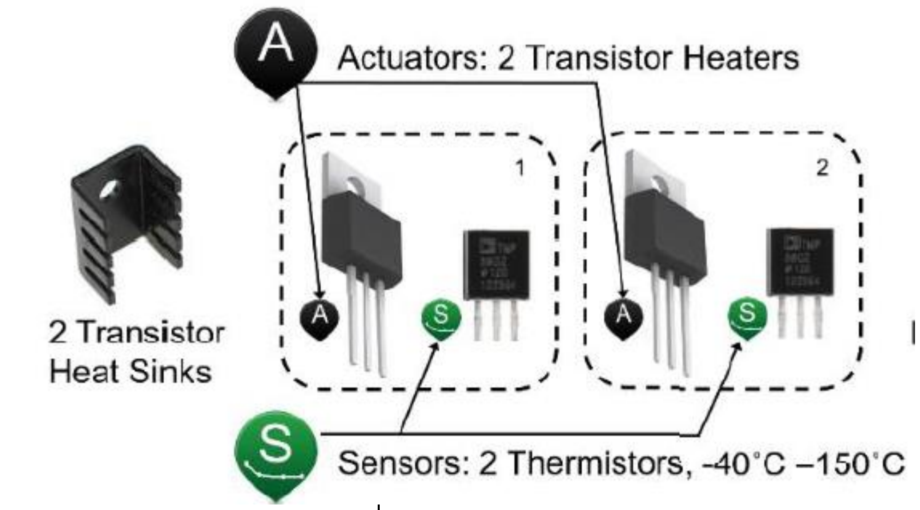
10 minute data collection period that includes rapid and slow asynchronous (staggered) steps of the heaters with varying magnitude and direction.

The estimator may not be able to determine all of the unknown or uncertain parameters in the energy balance because several of the parameters are co-linear.



https://apmonitor.com/do/index.php/Main/AdvancedTemperatureControl

Quantity	**Default Starting Values (SI Units) or Use Values from Lab C (Preferred)**
Initial temperature (T_0)	296.15 K
Ambient temperature (T_∞)	296.15 K
Heater Factor (α_1)	0.0100 W/%
Heater Output (Q_1)	0 to 100%
Heater Factor (α_2)	0.0075 W/%
Heater Output (Q_2)	0 to 100%
Heat Capacity (C_p)	500 J/kg-K
Surface Area Not Between Heat Sinks (A)	$1\text{x}10^{-3}$ m^2
Surface Area Between Heat Sinks (A_s)	$2\text{x}10^{-4}$ m^2
Mass (m)	0.004 kg
Overall Heat Transfer Coefficient (U)	10 W/m^2-K
Emissivity (ε)	0.9
Stefan Boltzmann Constant (σ)	$5.67\text{x}10^{-8}$ W/m^2-K^4



Energy Balance: Transient model between the two heater outputs and the two temperature sensors

convective

radiative

heater energy inputs

$$mC_p\frac{dT_{h1}}{dt} = UA\left(T_\infty - T_{h1}\right) + \epsilon\,\sigma\,A\left(T_\infty^4 - T_{h1}^4\right) + UA_s\left(T_{h2} - T_{h1}\right) + \epsilon\,\sigma\,A_s\left(T_{h2}^4 - T_{h1}^4\right) + \alpha_1 Q_1$$

$$mC_p\frac{dT_{h2}}{dt} = UA\left(T_\infty - T_{h2}\right) + \epsilon\,\sigma\,A\left(T_\infty^4 - T_{h2}^4\right) + \underbrace{UA_s\left(T_{h1} - T_{h2}\right) + \epsilon\,\sigma\,A_s\left(T_{h1}^4 - T_{h2}^4\right)}_{\text{heat transfer}} + \alpha_2 Q_2$$

Sensor Model

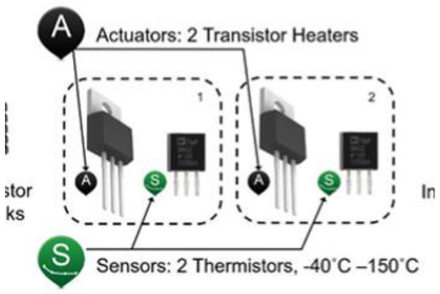
$$\tau\frac{dT_{c1}}{dt} = -T_{c1} + T_{h1} \quad \text{and} \quad \tau\frac{dT_{c2}}{dt} = -T_{c2} + T_{h2}$$

Empirical correlations

Estimated FV

```
U = 10.0
tau = 5.0
a1 = 0.01
a2 = 0.0075
```

% moving horizon estimation



data for the moving horizon estimator

	A	B
1	time	
2	0	
3	3	
4	6	
5	9	
6	12	
7	15	
8	18	
9	21	
10	24	
11	27	
12	30	
13	33	
14	36	
15	39	
16	42	
17	45	
18	48	
19	51	
20	54	
21	57	
22	60	

Values that are not going to change

Estimated parameters

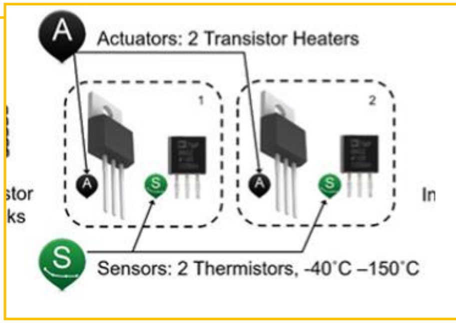
Model

```
Constants
   Ta = 23.0                              ! degC
   mass = 4.0 / 1000.0                    ! kg
   Cp = 0.5 * 1000.0                      ! J/kg-K
   A = 10.0 / 100.0^2                     ! Area not between heaters in m^2
   As = 2.0 / 100.0^2                     ! Area between heaters in m^2
   eps = 0.9                              ! Emissivity
   sigma = 5.67e-8                        ! Stefan-Boltzmann

Parameters
   Q1 = 0
   Q2 = 0

   U = 10.0
   tau = 5.0
   a1 = 0.01
   a2 = 0.0075

Variables
   TH1 = Ta
   TH2 = Ta
   TC1 = Ta
   TC2 = Ta

Intermediates
   TaK = Ta + 273.15
   T1 = TH1 + 273.15   ! degC to K
   T2 = TH2 + 273.15   ! degC to K

   Q_C12 = U*As*(T2-T1)
   Q_R12 = eps*sigma*As*(T2^4-T1^4)

Equations
   ! energy balance 1
   mass*Cp*$TH1 = U*A*(TaK-T1) &
                + eps * sigma * A * (TaK^4 - T1^4) &
                + Q_C12 + Q_R12 &
                + a1*Q1

   ! energy balance 2
   mass*Cp*$TH2 = U*A*(TaK-T2) &
                + eps * sigma * A * (TaK^4 - T2^4) &
                - Q_C12 - Q_R12 &
                + a2*Q2

   ! empirical lag 1
   tau * $TC1 = -TC1 + TH1
   ! empirical lag 2
   tau * $TC2 = -TC2 + TH2
```

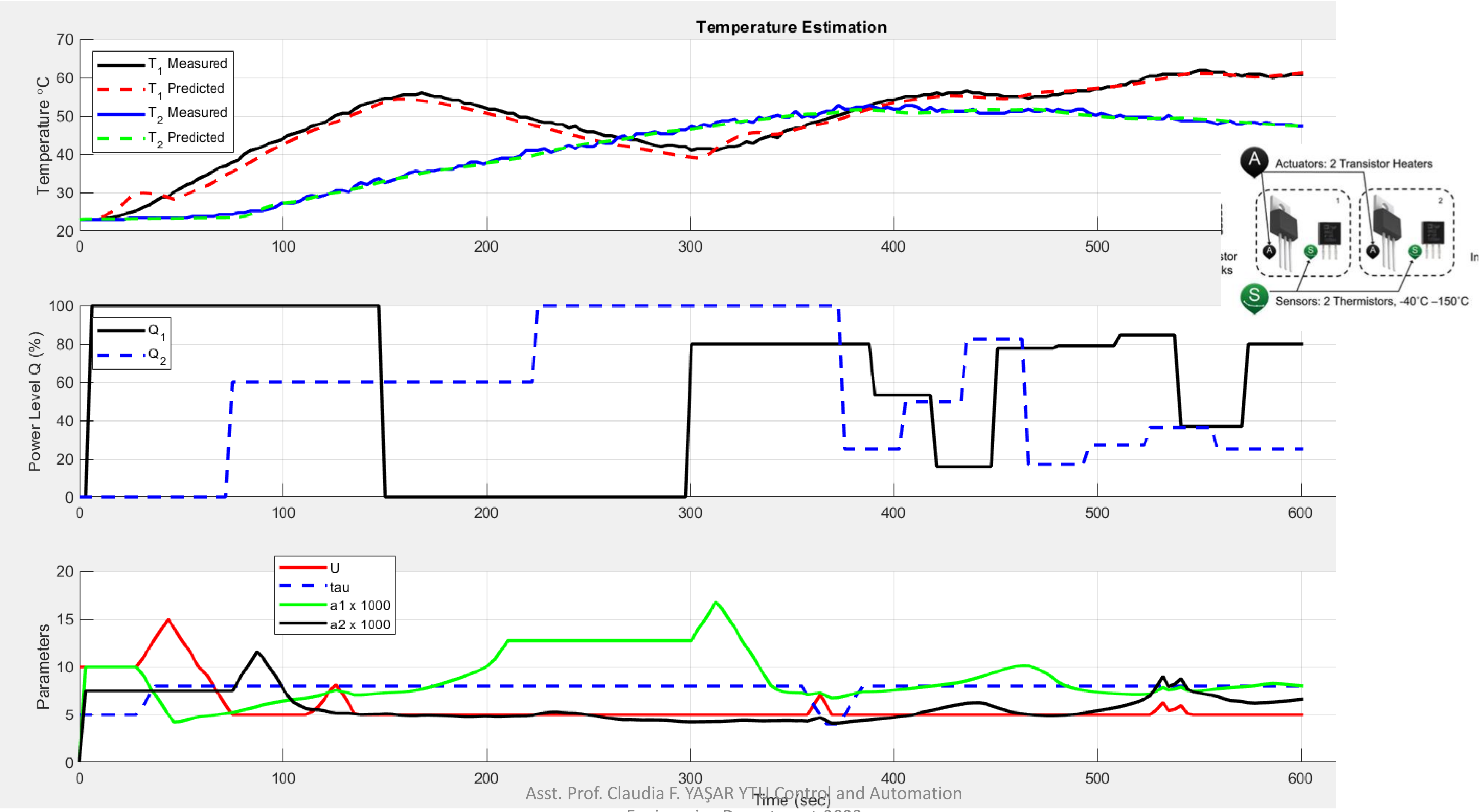
```
Variables
   TH1 = Ta
   TH2 = Ta
   TC1 = Ta
   TC2 = Ta

Intermediates
   TaK = Ta + 273.15
   T1 = TH1 + 273.15  ! degC to K
   T2 = TH2 + 273.15  ! degC to K

   Q_C12 = U*As*(T2-T1)
   Q_R12 = eps*sigma*As*(T2^4-T1^4)

Equations
   ! energy balance 1
   mass*Cp*$TH1 = U*A*(TaK-T1) &
                + eps * sigma * A * (TaK^4 - T1^4) &
                + Q_C12 + Q_R12 &
                + a1*Q1

   ! energy balance 2
   mass*Cp*$TH2 = U*A*(TaK-T2) &
                + eps * sigma * A * (TaK^4 - T2^4) &
                - Q_C12 - Q_R12 &
                + a2*Q2

   ! empirical lag 1
   tau * $TC1 = -TC1 + TH1
   ! empirical lag 2
   tau * $TC2 = -TC2 + TH2
```

$$m C_p \frac{dT_{h1}}{dt} = UA\,(T_\infty - T_{h1}) + \epsilon\,\sigma\,A\left(T_\infty^4 - T_{h1}^4\right) + UA_s\,(T_{h2} - T_{h1}) + \epsilon\,\sigma\,A_s\left(T_{h2}^4 - T_{h1}^4\right) + \alpha_1 Q_1$$

$$m C_p \frac{dT_{h2}}{dt} = UA\,(T_\infty - T_{h2}) + \epsilon\,\sigma\,A\left(T_\infty^4 - T_{h2}^4\right) + UA_s\,(T_{h1} - T_{h2}) + \epsilon\,\sigma\,A_s\left(T_{h1}^4 - T_{h2}^4\right) + \alpha_2 Q_2$$



$$\tau \frac{dT_{c1}}{dt} = -T_{c1} + T_{h1} \quad \text{and} \quad \tau \frac{dT_{c2}}{dt} = -T_{c2} + T_{h2}$$


Temperature Estimation
Temperature °C
T1 Measured
T1 Predicted
T2 Measured
T2 Predicted
Power Level Q (%)
Q1
Q2
Parameters
U
tau
a1 x 1000
a2 x 1000
Time (sec)
Actuators: 2 Transistor Heaters
Sensors: 2 Thermistors, -40°C –150°C