

Modeling from data: Physics + System Identification

plus a little Philosophy



Key Ideas

Models should be in a useful form

Linear system difference equations are good for design

Linear system plus memoryless nonlinearities OK too

Interconnections of simple components

Simplicity is a major goal

Occam's razor, parsimony or even simpler

Complexity hurts us downstream

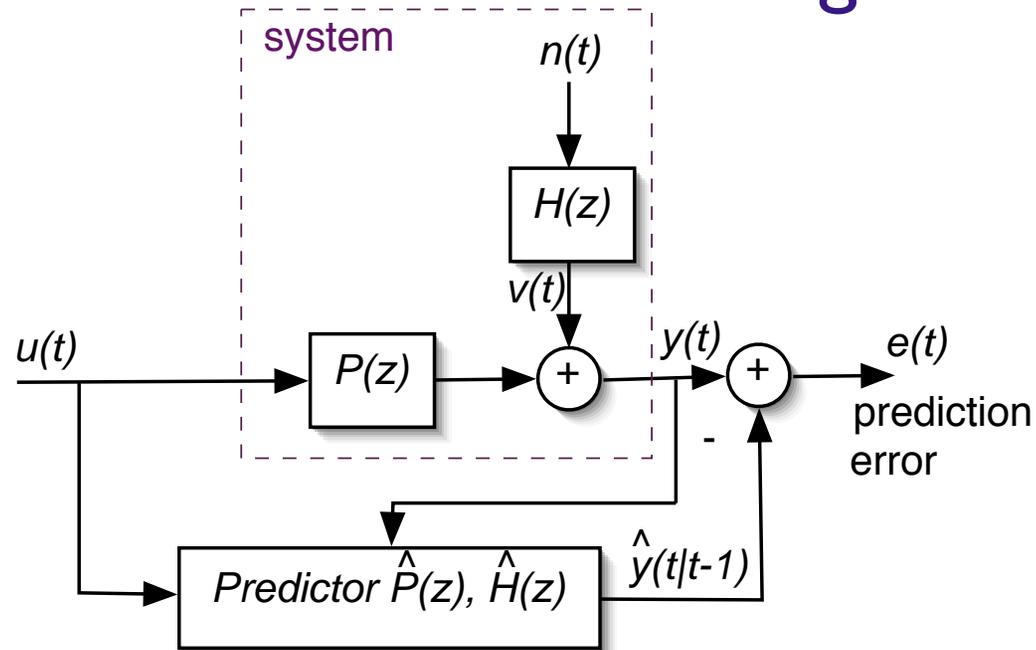
Approximation is a necessity and is desirable

No exact match is possible

Characterize model performance in a sensible way

Try to reflect the ultimate model usage

Prediction error modeling



Prediction error formalism for model selection

Good model = small prediction error

Lots of existing (linear) theory - statistics

Lots of good (linear) software - matlab toolbox

Especially useful if we want the model for prediction

What about for control?

Prediction error methods PEM

A good model predicts the plant system output well

Need to test this outside the current application

Extrapolation and not just repetition

Changing experimental conditions

Input signal

Feedback control

Acid tests to determine two things

The best model fit to the data

The quality of the fit to the data

Prediction error - some math

$$\begin{aligned} \text{model} \quad y_t &= \hat{P}(z)u_t + \hat{H}(z)n_t \\ \hat{y}_{t+1|t} &= \hat{H}(z)^{-1}\hat{P}(z)u_t + [1 - \hat{H}(z)^{-1}]y_t \end{aligned}$$

Associated predictor

Leads to the prediction error frequency-domain formula

Changing the input spectrum alters the prediction task

For control design want inputs similar to eventual controlled system

Circular problem

Sometimes prediction needs to be formulated without an input

Example coming up in combustion instability modeling

Different formulation

Similar ideas

Affecting PEM model fits

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N \{L(z)[y_k - \hat{y}_{k|k-1}]\}^2 =$$
$$\frac{1}{2\pi} \int_{-\pi}^{\pi} \left\{ \left| P(e^{j\omega} - \hat{P}(e^{j\omega}, \theta)) \right|^2 \Phi_u(\omega) + |H(e^{j\omega})|^2 \right\} \frac{|L(e^{j\omega})|^2}{|\hat{H}(e^{j\omega}, \theta)|^2} d\omega$$

Big effects on model fit over frequency

Input spectrum

Feedback controller

Correlation between input and output

Data filter

Disturbance model

Assumed known or estimated

Model structure

Closed-loop PEM formulae

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N \{L(z)[y_k - \hat{y}_{k|k-1}]\}^2 =$$
$$\frac{1}{2\pi} \int_{-\pi}^{\pi} \left\{ \frac{|P(e^{j\omega}) - \hat{P}(e^{j\omega}, \theta)|^2}{|1 + P(e^{j\omega})C(e^{j\omega})|^2} |C(e^{j\omega})|^2 \Phi_r(\omega) \right.$$
$$\left. + \frac{|1 + \hat{P}(e^{j\omega}, \theta)C(e^{j\omega})|^2}{|1 + P(e^{j\omega})C(e^{j\omega})|^2} |H(e^{j\omega})|^2 \right\} \frac{|L(e^{j\omega})|^2}{|\hat{H}(e^{j\omega}, \theta)|^2} d\omega$$

Accounts for the correlation between input and output

More complicated than open-loop PEM formula

But still comprehensible

The controller is even more evident

Connects to robust control criteria

Closed-loop modeling and control

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{k=1}^N \{L(z)[y_k - \hat{y}_{k|k-1}]\}^2 =$$

$$\frac{1}{2\pi} \int_{-\pi}^{\pi} \left\{ \frac{|P(e^{j\omega}) - \hat{P}(e^{j\omega}, \theta)|^2}{|1 + P(e^{j\omega})C(e^{j\omega})|^2} |C(e^{j\omega})|^2 \Phi_r(\omega) \right.$$

$$\left. + \frac{|1 + \hat{P}(e^{j\omega}, \theta)C(e^{j\omega})|^2}{|1 + P(e^{j\omega})C(e^{j\omega})|^2} |H(e^{j\omega})|^2 \right\} \frac{|L(e^{j\omega})|^2}{|\hat{H}(e^{j\omega}, \theta)|^2} d\omega$$

$$\left| \frac{P(e^{j\omega}) - \hat{P}(e^{j\omega}, \theta)}{P(e^{j\omega})} \times \frac{C(e^{j\omega})P(e^{j\omega})}{1 + C(e^{j\omega})P(e^{j\omega})} \right| < 1$$

The main issue is to understand which controller is $C(z)$

Current controller for identification, next controller for control

Acid tests of models

Falsificationism



Karl Popper

Propose a new experiment to test the model

Corroboration or invalidation

Hypothesis testing approach

Model invalidation

Poor prediction

Strongly correlated residuals/errors

Systematic errors

Statistical tests

Building models - some Philosophy

What can you do if the model fails?

Modify it to perform better

Deductive reasoning to include Physics

New model structure

Inductive reasoning fits the model to data

Deduction:

deriving conclusions from general or universal principles

Adjusting model structure to accommodate new experiments

Determining model structure from Physics

Induction:

deriving general conclusions from specific examples

“Let the data speak for themselves”

Fitting models and parameters to experimental data

Combustion instability modeling



Jet engines and gas turbines

Lean combustion yields economic and environmental benefits

Limited by appearance of limit cycling at low fuel-to-air ratios

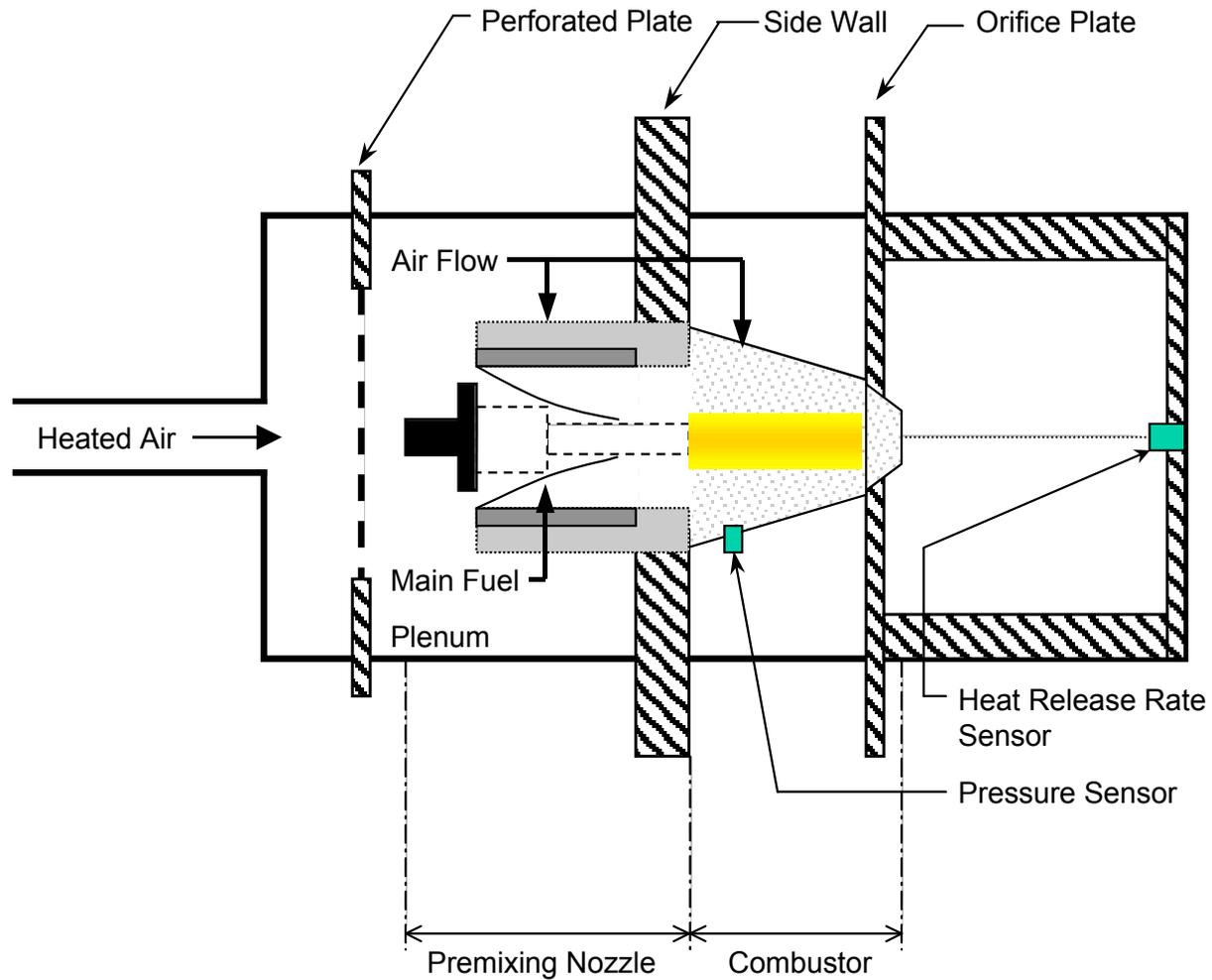
Benefits are lost

Build a model for control of the combustion instability

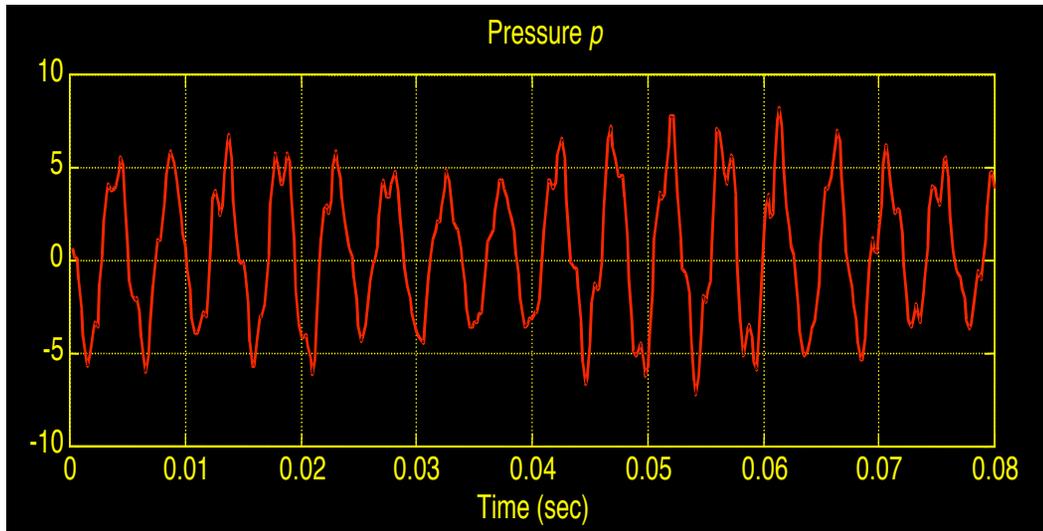
Alternating deductive and inductive stages

Stressful experimental tests of models' predictive powers

Experimental set-up



Experimental data



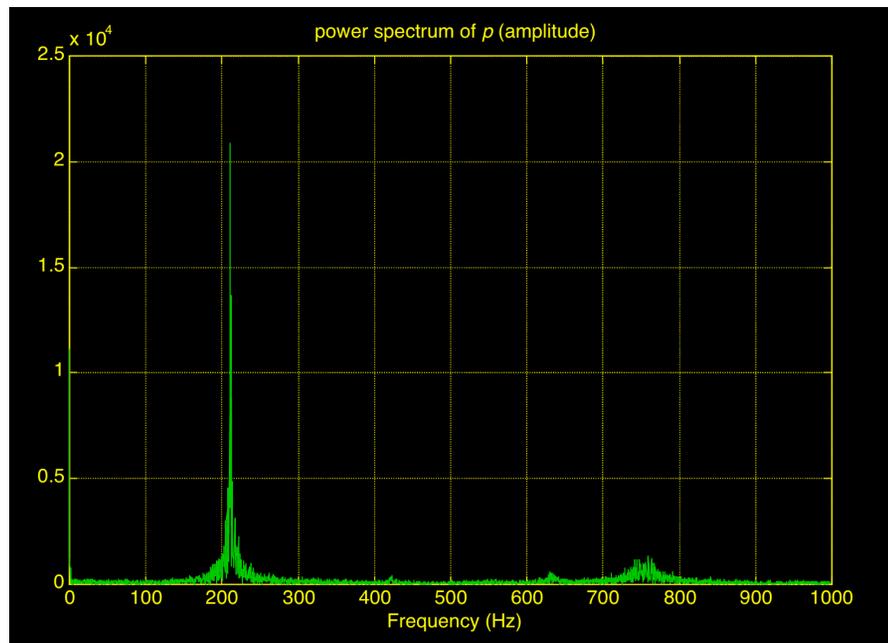
Highly periodic

Not very informative for modeling

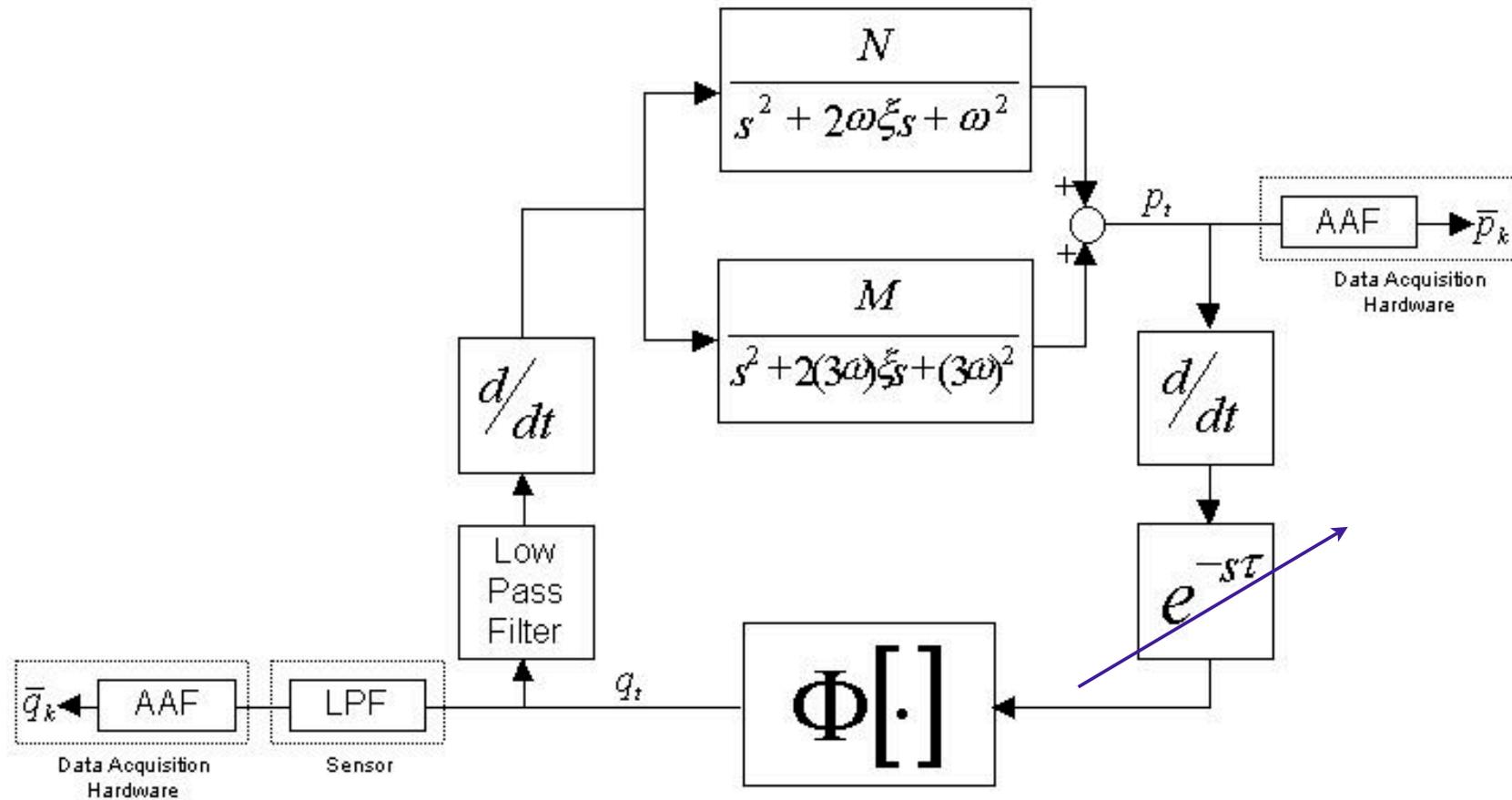
Harmonics at 210Hz, 420Hz and 630Hz

Non-harmonic component at 720Hz

Nonlinear phenomena



Model structures from Physics



Combustion chamber acoustics meet heat release rate function

Improved fidelity with model development

Parsimonious model adjustments

Model development

Peracchio & Proscia

First-order acoustics and model fit to data

Incapable of explaining multiple frequencies

Deduction

Induction

Test

More complex Physics

Third-order acoustics and model fit to data

Corroboration simulation test passed

Invalidated at multiple operating points

740Hz frequency changes with fuel-to-air ratio

Deduction

Induction

Test

Test

More simple Physics - another phenomenon included *Deduction*

Variable delay with fuel-to-air ratio and fit

Multiple-operating-point corroboration test passed

Induction

Test

Message

Modeling involves a number of processes

Deduction, induction, testing

Much of this might be classified as “Prejudice”

This embodies our understanding of the process

I call this “Idiot testing” Does the model make sense?

Modeling for use in control design has a special set of prejudices

Extraordinary simplicity

Control systems operate over only a couple of decades of frequency

Stability properties are important

Unlike when modeling for prediction

We could really model well if we know what the final controller was