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TITLE: Adaptive Model Predictive Control using Neural Networks

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ADAPTIVE MODEL PREDICTIVE CONTROL USING NEURAL NETWORKS

Chris Baum, Kevin Buescher, Vijay Hanagandi, Roger Jones, Ken Lee

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Los Alamos *Nonlinear Adaptive Computation*

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Outline of Our Work in Controlling Chemical Processes

- Developed neural networks and training procedures that are well suited to:
Small amounts of off-line training data On-line training Control of systems with substantial time lags
- Developed generic Model Predictive Control (MPC) software
- Controlled the following simulated systems using MPC:
continuously stirred tank reactor with jacket dynamics (DuPont) plasma etching model for semiconductor manufacture (TI) distillation columns (DuPont)

The CNLS Network:

(Connectionist Normalized Local Spline)

- RBF style network: linear combination of localized nonlinear functions.

models complex systems (nonlinear), trains quickly.

$$\phi(x) = \sum_{j=1}^M \left[a_j + (x - c_j)^T d_j \right] \frac{\rho_j(x)}{\sum_{k=1}^M \rho_k(x)}$$

- Differs from standard RBF in use of extra linear term, and normalization.
- Since it is local, it can operate and learn in a small region without affecting the whole (unlike Feed-Forward NN's such as the MLP.)

CNLS Training Procedures are Well Suited to Control

- On-line training reduces the required amount of off-line training data.
- Standard on-line training takes gradient steps in weight space.
- In addition to standard on-line training, the network is trained on differences between two adjacent points in the time series, and three adjacent points in a time series (normal projection training).

This allows the network to learn information on the derivatives of the plant, and to deal with highly correlated closed-loop data.

Crucial in controlling to set-point (only small portion of state space seen.)

No analogous procedures with Feed-Forward Networks.

- A method has also been devised to allow the movement and addition of centers based on center spacing, and network error.

Compensates for poor initial choice of centers (Random).

Can start with very little training data (or none).

Global behavior of network is not disrupted due to locality of basis functions.

- Training is fast since the network is linear in the adaptive parameters.

What is Model Predictive Control (MPC)?

- MPC uses a model to evaluate how control strategies will affect the future behavior of the plant.

Variable prediction and control horizons can be used.

Can deal with explicit constraints.

- After finding a good strategy, MPC pursues that strategy for one control step and then re-evaluates its strategy based on the plant's response.
- An empirical process model is used, which can be continuously updated.
- With a neural net as the model, MPC can be used to control *nonlinear plants*.

Smoothing of Approach to Setpoint

- The approach to setpoint is smoothed by plotting an exponential approach curve.

Speed of approach can be modified

- Cost function includes setpoint error and control chatter terms.
- Constraints on control and control change are included.

We Use a Two-Timescale Approach to Network Input Reduction

- Problem:

Need to sample plant outputs fast enough to measure disturbances, and update controls for fast response and disturbance rejection.

A neural net would require many inputs to correctly model dynamics occurring at slower time-scales.

Must iterate net many times to reach an adequate prediction horizon.

This necessitates a large amount of training data and training time in order to get an accurate enough model.

- Solution:

The neural network models the plant at a slower time-scale, using averages of controls, and gapped plant outputs.

Controls are still updated at the fast rate.

CSTR With Two Time Constant Delay

Realistic heat transfer added to reactor jacket.

Time constant of exothermic reaction is unchanged.

Model equations:

$$\begin{aligned}\frac{dx_1}{dt} &= -x_1 + Da(1-x_1)e^{\frac{x_2}{1+x_2/\gamma}} \\ \frac{dx_2}{dt} &= -x_2 + BDa(1-x_1)e^{\frac{x_2}{1+x_2/\gamma}} + \beta(x_2 - x_J) \\ \frac{dx_J}{dt} &= \delta_1\delta_2(x_{J0} - x_J) + \beta_J\delta_1(x_2 - x_J)\end{aligned}$$

Non-Isothermal Continuous Stirred Tank Reactor

Training Set for CSTR

Note how little data appears in the unstable regime.
 Network is trained by iterating through the training set less than 20 times.
 We start with 5 basis centers and add more as needed.

MPC Control of CSTR with On-Line Training and Input Dimension Reduction

Control Input to CSTR (Input Reduction)

MPC Control of CSTR with On-Line Training, but no Input Dimension Reduction

Control Input to CSTR (no Input Reduction)

Example: High-Purity Distillation Column

- Simulated binary column (methanol and ethanol) with 27 trays, 50–50 mole % input, 99 mole % ethanol nominal output
- Controls are reflux rate and vapor boilup rate
- Plant "outputs" are temperatures at trays 7 and 21 (these temperatures are correlated with output concentrations in steady state).
- This system is tough to control because it has

highly nonlinear behavior
a long settling time
coupled outputs
inverse response

- Distillation Column Model:

Open Loop Responses to 5% Control Changes in Distillation Column

MPC Control of Distillation Column with On-Line Training and Input Dimension Reduction -- Tray 7

MPC Control of Distillation (OLT & IDR) -- Tray 21

MPC Control of Distillation Column with Input Dimension Reduction Only -- Tray 7

MPC Control of Distillation (IDR) -- Tray 21

Conclusion and Future Work

- Produced effective modeling and control software for nonlinear systems.

On-line training and adaptive net structure.

Gapped prediction for time-lagged systems.

- Good control of nonlinear plants with little training data.
- On the way:

Improved user interface and data handling tools.

Application to cryogenic deuterium-tritium separation columns.

Four linked columns for separation of hydrogen isotopes.

Operate at cryogenic temperatures.

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