Reducing Costs Through Application of Advanced Control Methods

(reducing engineering costs)

Mike J Grimble

The ACTC and University of Strathclyde

HOW CAN ADVANCED CONTROL HELP?

- Quotation from a famous academic:
- *"It is our job to generalise and abstract problems in engineering*

  otherwise everyone would know what we are talking about"
- The gulf between practicing engineers and academics is wide and the question arises as to whether anything in the great armoury of mathematical control theory is useful to engineers in industry.
- The question is rather similar to the motor mechanic who has shelves of tools covering many different models, international standards and possibilities and the answer is probably the same. That is, *sometimes such tools are essential because nothing else will do.*

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Coordinated Control Engineering Services

ISC / ACTC / ICC University of Strathclyde

industrial systems and control

Industrial Systems and Control Ltd

- Industrial control consultancy
- Bespoke training courses
- Service contracts to provide regular training/consulting
- Wholly-owns and administers ACTC

applied control technology consortium

Applied Control Technology Consortium

- Cost effective industrial training
- Consultancy
- Regular workshops forums/meetings
- Regular academies

The University of Strathclyde in Glasgow

Industrial Control Centre

- ISC / ACTC draws on the expertise within ICC
- ICC is leading research group in control, theory and applications
- undergraduate and postgraduate degree studies, student projects etc

Why is Advanced Process Control Necessary?

Advanced Process control is needed for multivariable systems. There is a natural limit to what can be achieved with single-loop systems and classical controller structures. The improvements advanced control can provide include one or more of the following features:

- Improved performance and accuracy.
- Greater robustness and reliability
- Optimized energy usage
- Improved economics through constrained operation
- Improved disturbance rejection properties.
- Reduced interaction.

Possible Benefits

- Energy optimization and reduced energy consumption.
- Improved product yield
- Reduced environmental impact
- Increased capacity
- Improved product quality
- Better plant response time
- Improved safety and reliability.
- Process improvements
- Asset utilization
- Capacity increases
- Quality improvements.

Regulatory Control Methods

Improved control structures and tuning

(reducing engineering costs)

Feedback Control Systems

Feedback control systems are needed for the following important reason:

Feedback Control Systems Accounts For Uncertainties in a System

Uncertainties may arise due to the unknown, highly nonlinear and time-varying dynamic characteristics of processes and due to unanticipated and unmeasured disturbances.

Advantages of feedback control systems:

- Feedback controller attempts to reject impact of disturbance on a controlled variable.
- Reduces sensitivity of a controlled variable to unmeasured disturbances/process changes.

Disadvantages of feedback control systems :

- Feedback controller requires measurement (or accurate estimation) of controlled variable in order to function properly.
- Feedback controller does not anticipate disturbances that affect controlled variable. It only reacts after disturbances have made an impact upon a given controlled variable.
- Inherently stable system can be destabilised by feedback control.

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Feedforward Control Systems

Advantage of Feedforward Control Systems:

- Feedforward controller takes corrective action before controlled variable starts deviating from its set-point. Ideally, the corrective action will cancel the effects of the disturbance so that the controlled variable is not affected by the disturbance.

Disadvantages of Feedforward Control Systems:

- Feedforward control requires disturbances to be measured (or estimated).
- No corrective action is taken by feedforward controller for unmeasured disturbances.
- Feedforward controller requires presence of a process model.

Even if exact cancellation of measured disturbance is not possible, feedforward control can significantly reduce the effects of measured disturbances.

Feedforward control is normally used in combination with feedback control. Feedback rejects impact of any unmeasured disturbances whilst feedforward cancels measured disturbances.

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Predictive Control Methods

Improved control if used properly

(reducing engineering costs)

Some Predictive Control Vendor Companies Products

- **Aspentech**
  - *DMCplus*
  - *DMCplus-Model*
- **Honeywell**
  - *Robust MPC Technology (RMPCT)*
- **Adersa**
  - *Predictive Functional Control (PFC)*
  - *Hierarchical Constraint Control (HIECON)*
  - *GLIDE (Identification package)*
- **Emerson - MDC Technology**
  - *SMOC (licensed from Shell)*
  - *Delta V Predict*
- **Predictive Control Limited (Invensys)**
  - *Connoisseur*
- **ABB**
  - *3d MPC*

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Model Predictive Control

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Model Predictive Control

- Several types of industrial MPC and DMC is most widely used.
- Dynamic Matrix Control (DMC): industrial model-predictive control developed by Charlie Cutler (originally at Shell and formed DMC Corp in 1984 sold to AspenTech in 1996).
- MPC is most popular form of multivariable control.
- Handles complex sets of constraints.
- Has an optimizer on top of the MPC so that it controls against the most profitable set of constraints. This uses incremental costs (feed costs, utility costs) and incremental revenues (product values).
- For distillation example, the incremental cost of steam ($/lb), the incremental cost of feed ($/lb), and the incremental value of both products ($/lb) is needed.

Constraints

Physical systems include many *constraints:*

- Physical constraints, such as actuator limits.
- Safety constraints, such as rate, temperature and pressure limits.
- Performance constraints like overshoot and rise time.
- Unfortunately the best or optimal operating points are often near constraints.

Most Significant Advantages of MPC are Offered:

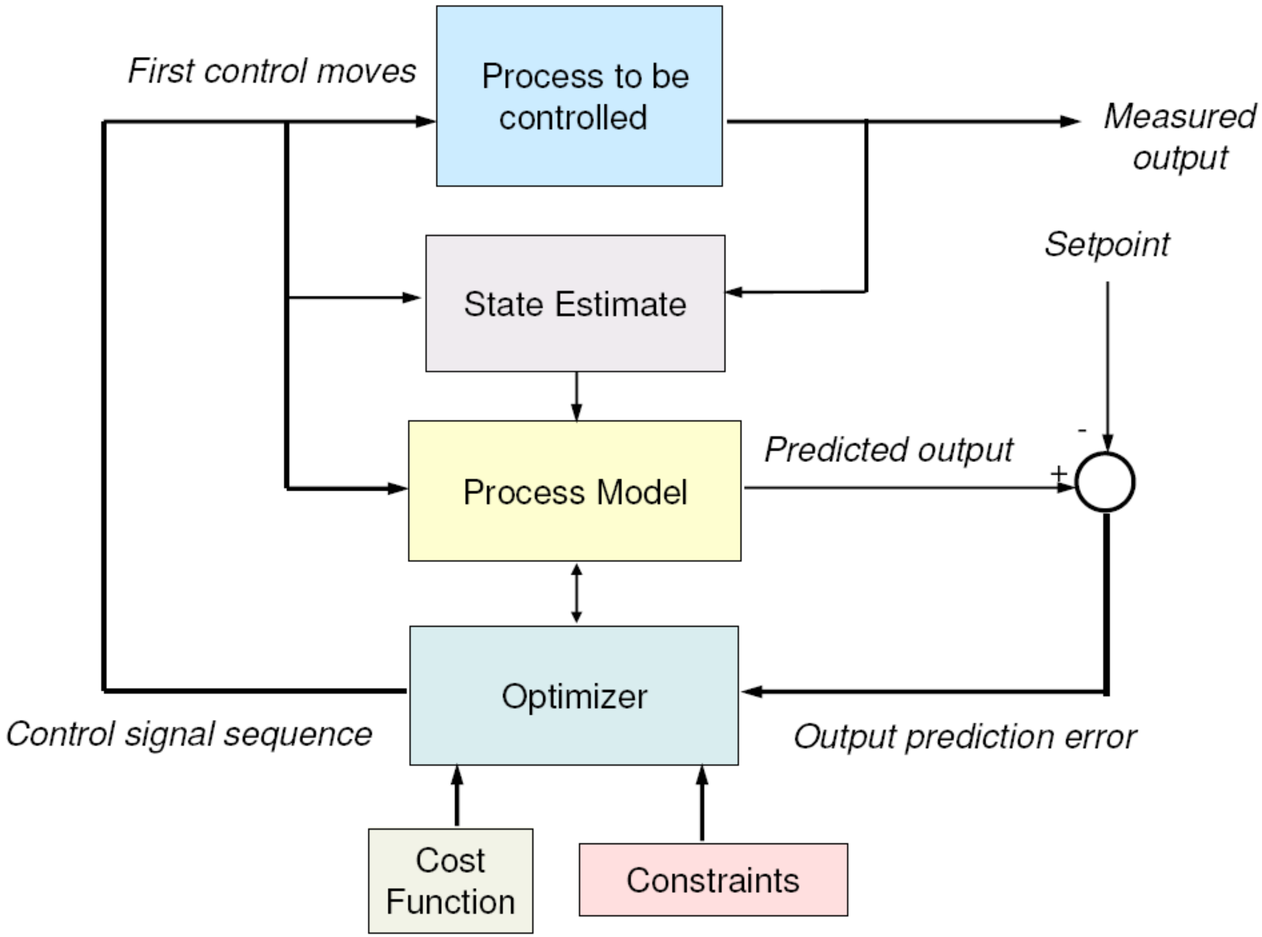
- For high volume processes, such as refineries and high volume chemical plants.
- For processes with unusual process dynamics or significant transport-delays.
- For processes where there are significant economic benefits by operating closer to constraints.
- For processes that have different active constraints depending on the product grade, changes in product values, summer/winter or day/night operation.
- For processes where it is important to have a smooth transition to new operating targets.

Model Predictive Control Structures

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Typical Model Predictive Control Structure



Source: Rihab Khalid Al Seyab,Nonlinear Model Predictive Control Using Automatic Differentiation, Cranfield University, PhD Thesis, 2006

Real-Time Optimization (RTO)

RTO solves the following optimization problem: *"Given the fixed arrangements and sizes of equipment, the quality and cost of feedstock, utilities costs, and product specifications, values, and market demands, what are the best operating conditions to give the most valuable products at the lowest operating costs?"* (Cutler and Perry).

RTO execution typically involves five main steps:

- Steady state detection
- Data reconciliation
- Parameter estimation
- Optimization
- Send optimum targets to MPC controller.

- RTO can deliver value over an MPC controller when the optimization variables have a NL relationship with the profit function and are not currently used to control constraints or specifications.
- Linear MPC controllers do not normally have the capability to determine optima for variables that have significantly NL behaviour (see Gattu et al).

REVIEW OF THE STATUS OF LINEAR MPC APPLICATIONS

(Quote taken from: G Gattu, S Palavajjhala, and D B Robertson, Bass Rock Consulting, Incorporated)

Linear MPC controllers are now installed on all major units, at most refineries in the US. An MPC controller refers here to a steady-state Linear Programme (LP) or Quadratic Programme (QP) optimizer, integrated with a linear dynamic controller. However, many MPC applications do not perform adequately or deliver the potential benefits of this technology. MPC controllers that perform well have the characteristics:

- The scope of the controller covers all key process constraints
- All key equipment, process and product specification constraints are active and are controlled at the limits
- The economic optimizer pushes against the correct combination of constraints
- Dynamic controller performance is good over a wide operating range
- Intervention from operators occurs only to handle rare conditions that were consciously not included in the design

Successful MPC applications that meet the above criteria over their lifespan are surprisingly rare. Some applications are implemented poorly and others have degraded because of inadequate maintenance, to where benefits are near zero. The application success rate is not well represented in either the public or proprietary refiners' literature because only success stories are publicized and even those are not always justified by the control-room reality. Common problems leading to poor performance are:

- Model inaccuracy
- Poor LP/QP optimizer tuning
- Lack of operator training and lack of maintenance.

Model inaccuracy can result either from poor plant-test execution or from process changes over a period of time that invalidate an initially good model. Problems may also arise because of non-linearities that have not been included in the model.

Performance monitoring tools that identify the problematic models and quantify the degradation of controller performance are necessary. Such performance monitoring tools could assist the control engineer to better maintain MPC controllers and to prioritize problem areas. Unfortunately, the currently available tools produce complex data that is confusing to most practicing engineers.

Complex LP problems contain a large number of possible active constraint sets. In these cases, encountering particular constraint trade-offs that were not considered in the MPC design can cause the application to drive the process in the wrong direction. Also, uncertainty in the empirical MPC models can create poorly conditioned LP matrices that result in highly undesirable controller behaviour. Poor understanding of this issue is the norm, so these ill-conditioned problems are rarely fixed and benefits suffer.

There are significant benefits from better implementation and maintenance of current linear MPC controllers. Justification of NL control and optimization should not be based on capturing benefits already accessible to current linear MPC technology. In fact, a well-maintained MPC controller is a pre-requisite for successful implementation of non-linear optimization.

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Quotes taken from: G Gattu, S Palavajjhala, and D B Robertson, Bass Rock Consulting, Incorporated

Linear MPC controllers are now installed on all major units, at most refineries in the US.

Successful MPC applications that meet the above criteria over their lifespan are surprisingly rare. Some applications are implemented poorly and others have degraded because of inadequate maintenance, to where benefits are near zero. The application success rate is not well represented in either the public or proprietary refiners' literature because only success stories are publicized and even those are not always justified by the control-room reality.

Common problems leading to poor performance include model inaccuracy. This can result either from poor plant-test execution or from process changes over a period that invalidate an initially good model. Problems may also arise because of non-linearities that have not been included.

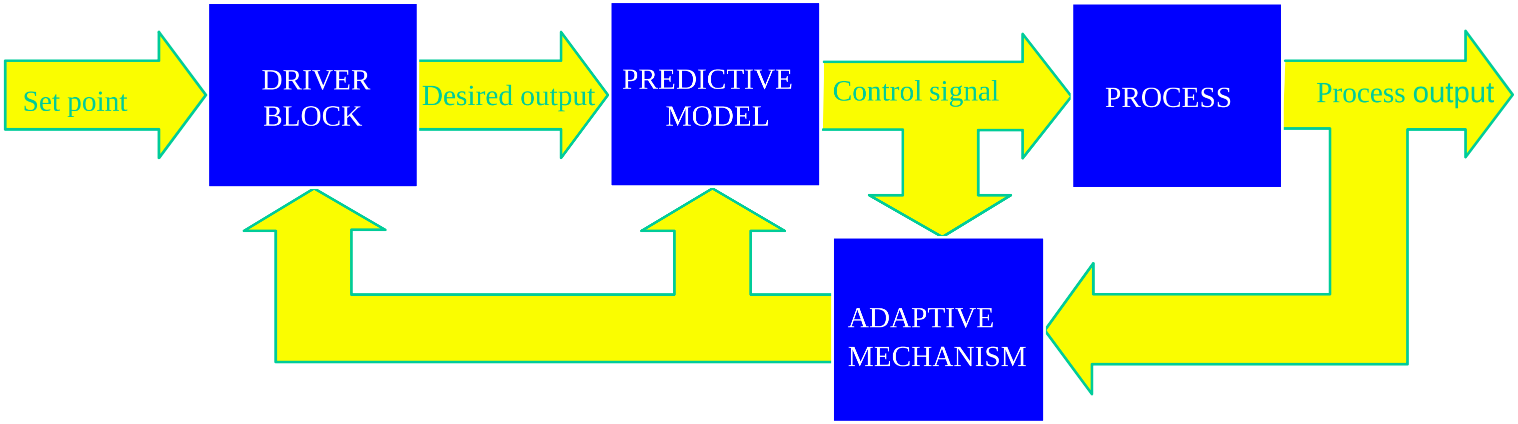
Performance monitoring tools that identify the problematic models and quantify the degradation of controller performance are necessary. Unfortunately, the currently available tools produce complex data that is confusing to most practicing engineers.

There are significant benefits from better implementation and maintenance of current linear MPC controllers. In fact, a well-maintained MPC controller is a pre-requisite for successful implementation of non-linear optimization.

Adaptive Predictive Control

(reducing engineering costs)

ADAPTIVE PREDICTIVE CONTROL



The adaptive mechanism acts on two feedback levels:

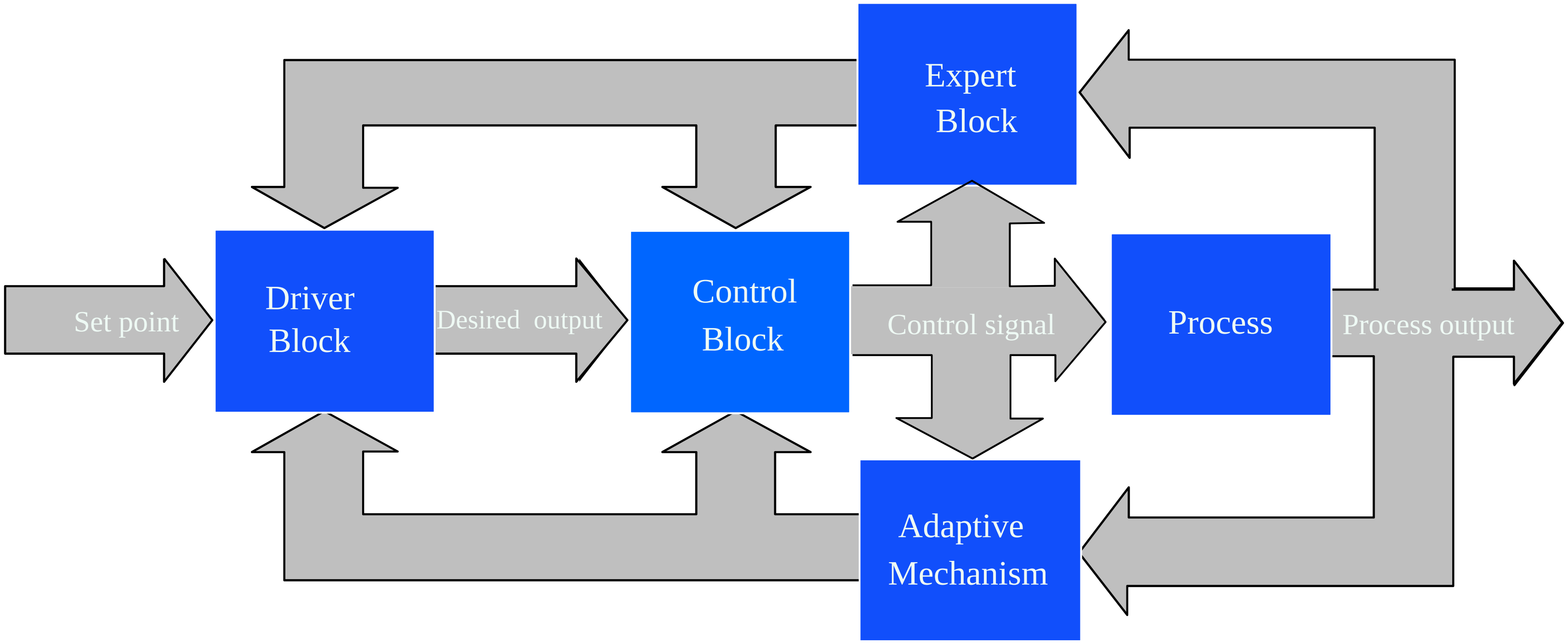
On the ***first feedback level****, from the process I/O signals and the prediction error, the adaptive mechanism* ***adjusts the predictive model parameters*** *to make the prediction error tend towards zero. On the* ***second level****, the adaptive mechanism--at every control instant,* ***informs the driver block about the current process status and of the process output deviation from the desired trajectory****. This information is used by the driver block to redefine the desired trajectory by taking into account the process status at said control instant. This second feedback level complements the first level and* ***ensures that the desired process output trajectory is always consistent with the current process status****.*

Adaptive predictive control applied, has demonstrated an excellent control performance when applied to industrial processes ***as long as there is a cause-effect relationship*** *that determines the process dynamics and that this relationship can be identified by means of a model. Usually the cause-effect relationship of a process is present in certain domains of operations, while in others it fails to exist or cannot reliably be modelled in real time.*

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

ADEX BLOCK DIAGRAM

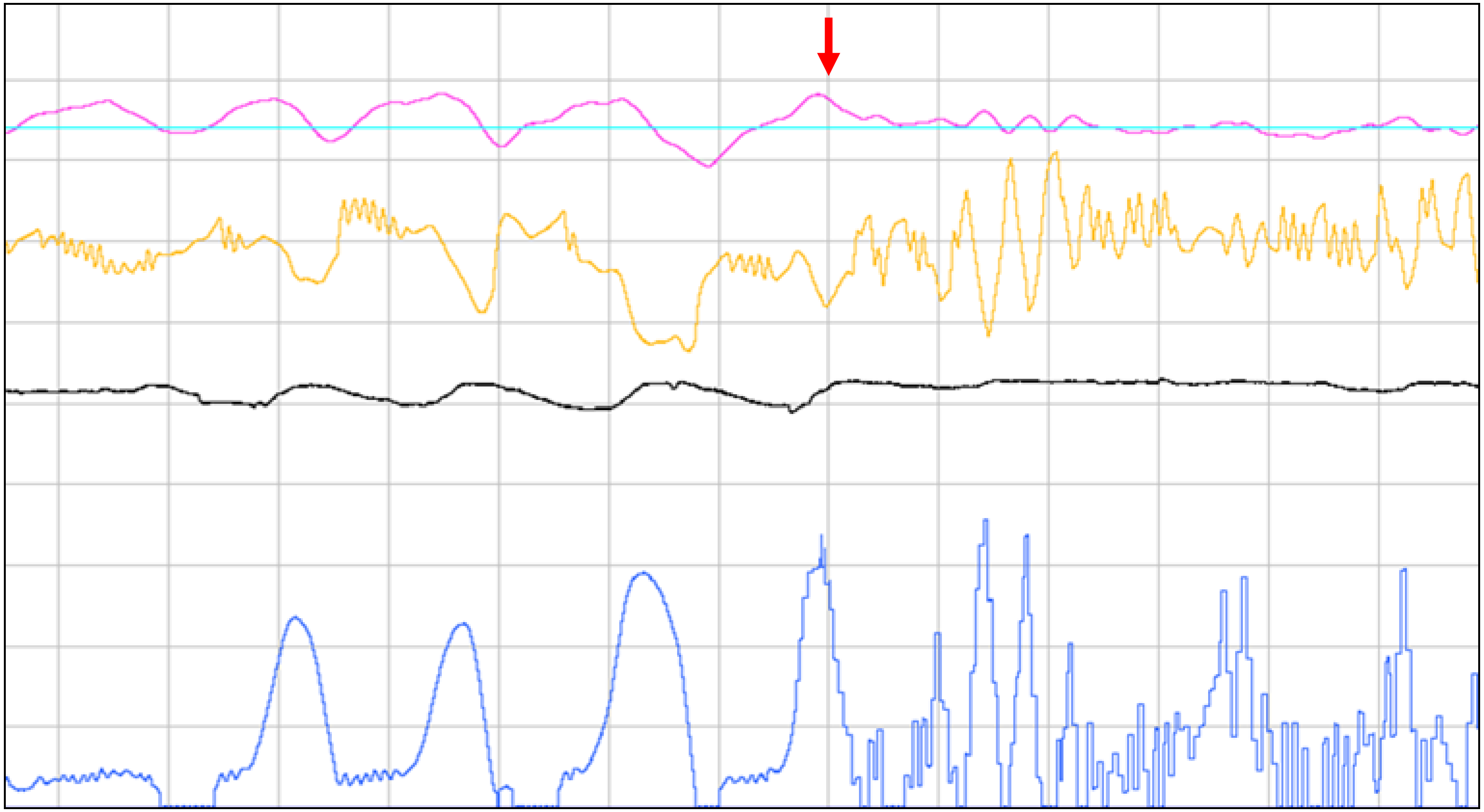


*An **expert block has been added** to the upper portion of the diagram and this, based on rules and on the evolution of the process variables, determines and/or modifies the operation of the control block, driver block, and adaptive mechanism.*
*Depending on the domain of operation the **EXPERT BLOCK** will determine if the **CONTROL BLOCK** is going to be a predictive model applying adaptive predictive control or an expert system applying expert control.*

When adaptive predictive control is applied:
*(i) The **EXPERT BLOCK** may modify the performance criterion to generate the desired trajectory within the **DRIVER BLOCK**, accommodating in this way the desired performance of ADEX to different domains of operation;*
*(ii) The **EXPERT BLOCK** determines when the adaptation is executed, taking into account the operating conditions; and*
*(iii) The **EXPERT BLOCK** makes full use of the available knowledge of the process (and it's dynamics) to decide when and how to apply APC, and when and how to apply expert control.*

The ACTC and University of Strathclyde
THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Adaptive Control switched on



- **ISC/ADEX Project:** *Here live plant showing commercial adaptive controller switched in place of poorly operating PI controller (difficult to tune due to changeable operating points)*
- *The benefits are that the adaptive controller required little in the way of configuration as it learnt the underlying model and it was able to provide improved performance over the whole operating range*
- *Red =set-point SP;   green = process variable PV;   orange = controller output OP;*
  blue/white = other PVs not direct under control
- *Cannot mention any more about the process due to confidentiality issues.*
- *Operators could easily revert back to their familiar PI – but they like it as it means less intervention for them.*
- *Has been running without problem for a 2 months, through plant shuts and start-ups.*

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

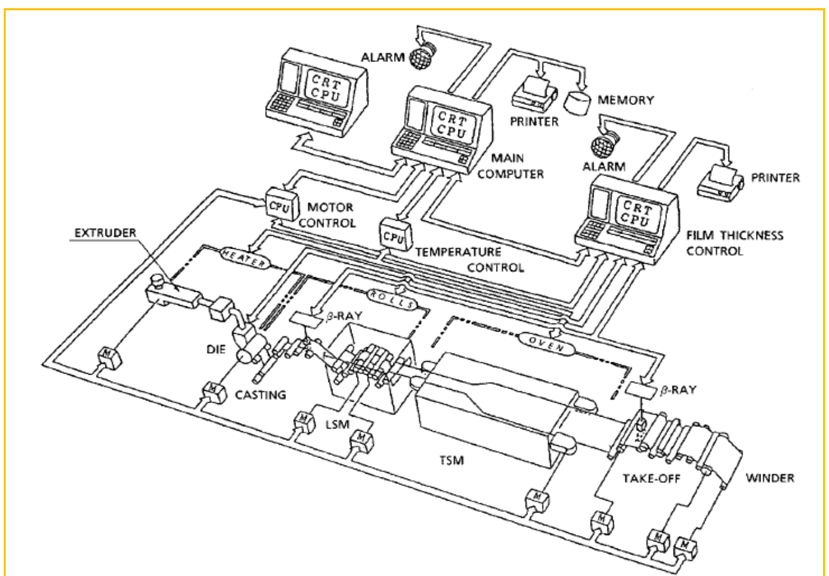
Importance of Modelling

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

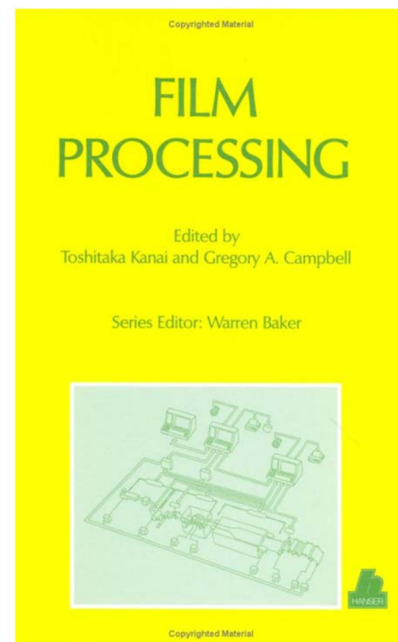
Plastic Film Making Process

1. **Die:** converts the melt with a circular cross section to uniformly thick melt
2. **Casting Drum:** cools down the melt and produces continuous film
3. **Slow-nip, Heating, Fast-nip, Cooling Rolls:** stretch film in the machine direction
4. **Coaters:** add colours when required
5. **Stenter Oven:** includes Sideways-draw and Crystallisation
6. **Winder:** rolls the finished product.



Thanks to Dupont

Figure is from a book "Film Processing" by T. Kanai and G. Campbell (1999).

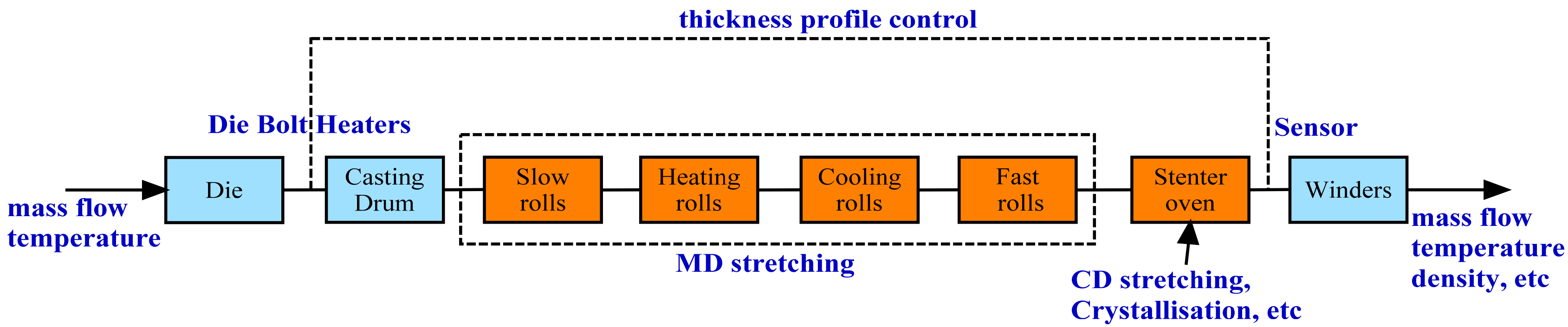


The ACTC and University of Strathclyde

The ACTC and University of Strathclyde

Overview of First-Principles Model

Model Structure



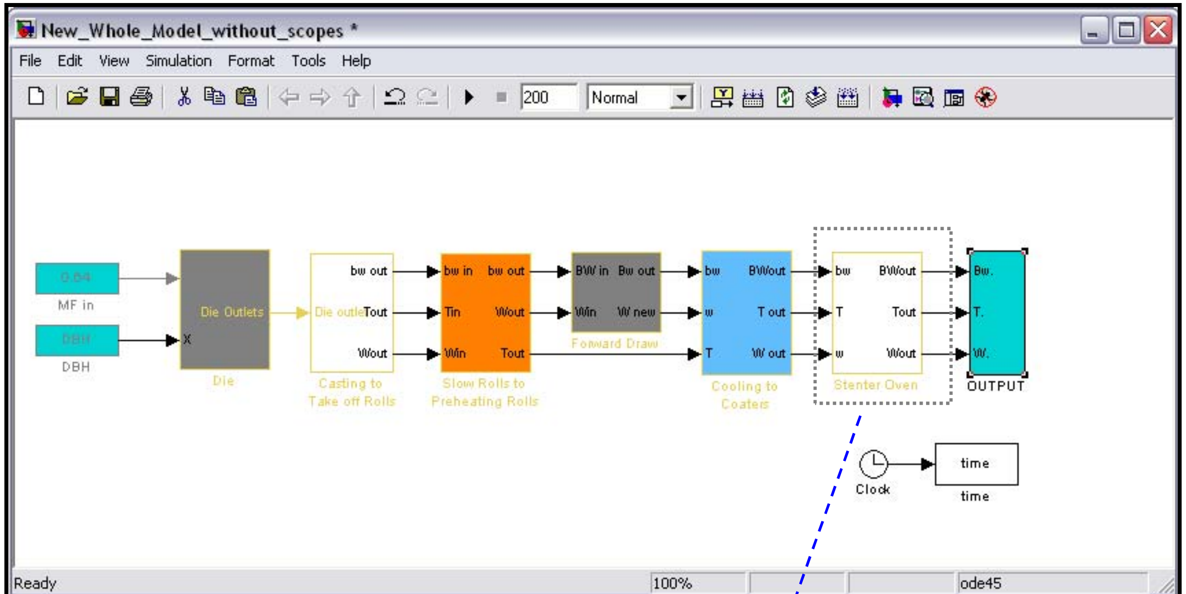
- The model is implemented in MATLAB/SIMULINK
- For the purpose of modelling, the plastic film extrusion process is divided into a number of unit operations, e.g. die, casting drum, etc
- One of the main features is to track changes in the film thickness, temperature, etc, throughout the process
- The whole process model consists of a number of unit operations; each of the unit operations consists of a number of sub-models, such as deformation, heat transfer, mass transfer sub-models.

Origin and Thanks to Dupont

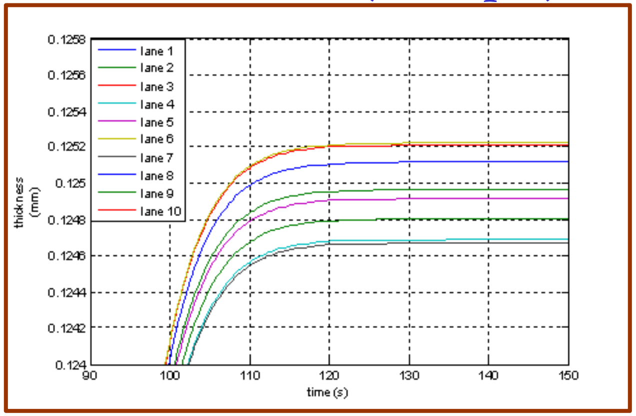
THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Model in SIMULINK

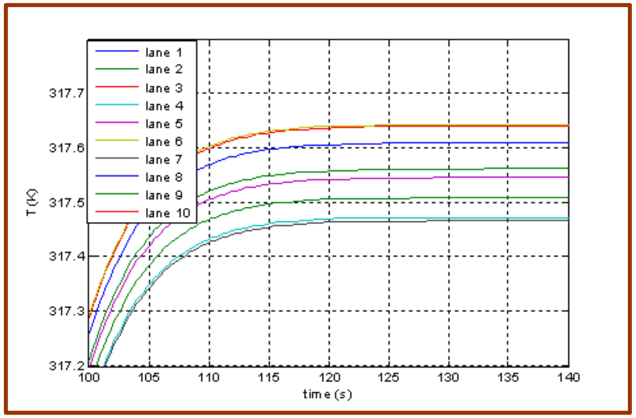
Simulink interface

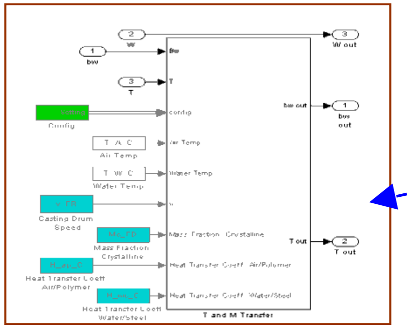


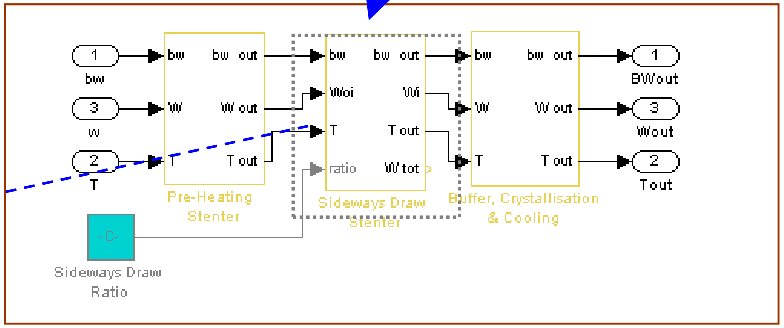
Thickness (example)



Temperature (example)







- Thickness, temperature, etc can be tracked at almost any locations
- Inside the blocks, we have m-files of all the equations, parameters, etc
- There are initialisation files for all the geometrical and operational data, etc

Origin and Thanks to Dupont

Advanced Modelling Methods

higher fidelity models

(reducing engineering costs)

Linear Parameter Varying (LPV) Modelling and Control

Introduction to Linear Parameter Varying Modelling

- The system parameters in some nonlinear systems are varying with the operating conditions that can be described by some variables.
- For such plants, including some subsystems in engines, they can be approximated by input output *LPV* systems with variables which can be measured online for scheduling.
- The variables can be used for a gain scheduled controller.
- If the parameters are not known before or are time-varying online estimation is necessary.

The University of Strathclyde in Glasgow

Scheduling Controller Tuning

- Can be effective when either a measured disturbance or the controlled variable correlates with nonlinear process changes.
- Sometimes possible to tune the controller at different levels of the scheduling parameter and combine the results so that the controller tuning parameters vary over the full operating range.

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

LPV Systems in an Input-Output Form

In addition to these state-space based methods, some authors have considered LPV systems in an input-output form:

$$A(q, p_k)y_k = B(q, p_k)u_k$$

with

$$\begin{aligned} A(q, p_k) &:= 1 + a_1(p_k)q^{-1} + a_2(p_k)q^{-2} + \cdots + a_{n_a}(p_k)q^{-n_a} \\ B(q, p_k) &:= \mathrm{b}_0(p_k) + b_1(p_k)q^{-1} + b_2(p_k)q^{-2} + \cdots + b_{n_a}(p_k)q^{-n_b} \end{aligned}$$

Where q is the shift operator. Bamieh and Giarre (1999) considered the special case where the parameters $a_i(p_k), b_i(p_k)$ are polynomials in the time-varying parameter p_k. They showed that the coefficients of these polynomials can be determined by solving a linear least-squares problem and they derived least mean-square (LMS) and recursive least-squares (RLS) identification algorithms.

State Dependent Systems

A state dependent system involves state equation matrices that are time varying depending upon the states also upon control input:

$$x(t+1) = \mathcal{A}(x,u)x(t) + \mathcal{B}(x,u)u(t) + \mathcal{G}(x,u)d(t)$$
$$y(t) = \mathcal{C}(x,u)x(t) + \mathcal{D}(x,u)u(t)$$

State dependent systems arise when parametric uncertainty is present in a model or when the actual *NL* system can be approximated by a state dependent system and an *LTI* model is a very poor approximation.

The ACTC and University of Strathclyde

State Dependent/LPV Systems

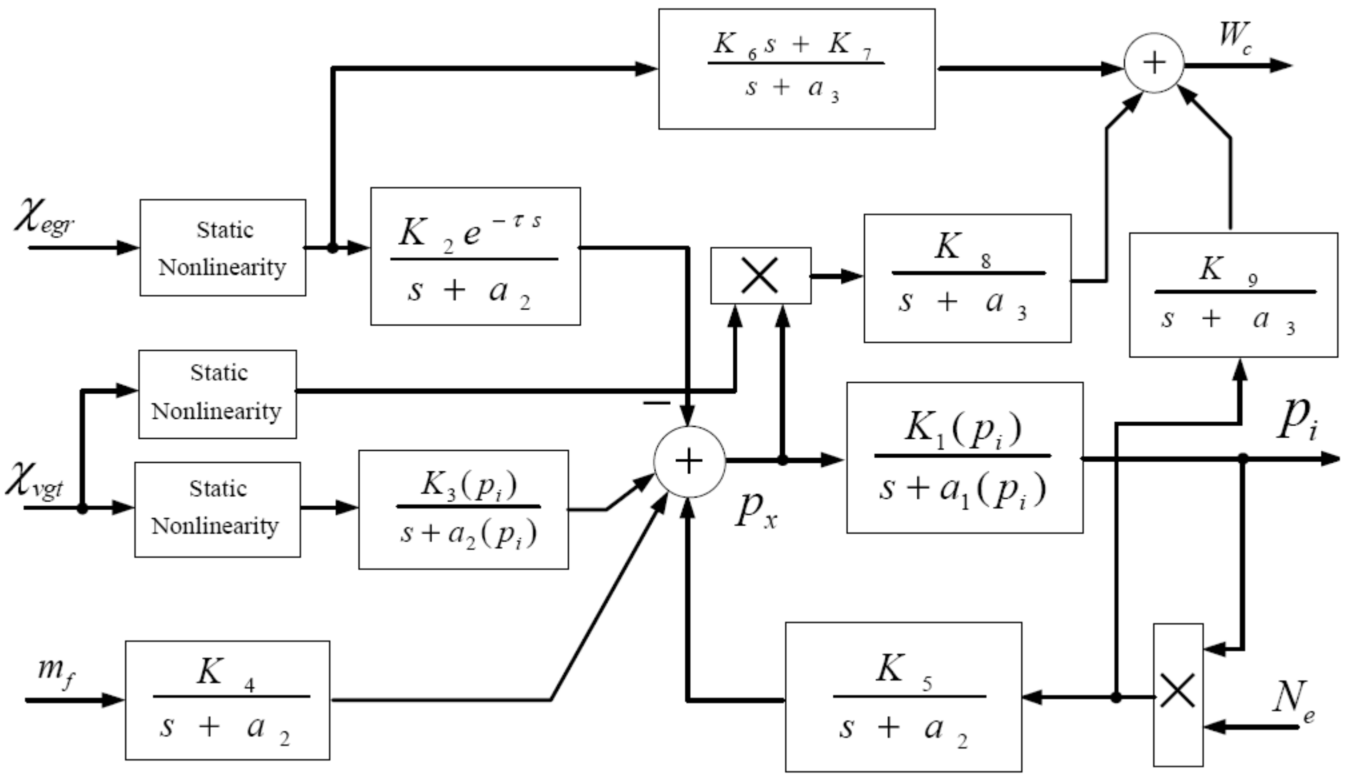
A state dependent, input dependent and LPV system involves state equation matrices that are time varying and depend on the states, inputs and parameters:

$$x(t+1) = \mathcal{A}(x,u,p)x(t) + \mathcal{B}(x,u,p)u(t) + \mathcal{G}(x,u,p)d(t)$$
$$y(t) = \mathcal{C}(x,u,p)x(t) + \mathcal{D}(x,u,p)u(t)$$

State dependent systems can also represent a class of Hybrid systems.

The ACTC and University of Strathclyde

LPV Model of the Air Path System



The system states depend on the engine speed which is a typical scheduling variables in the production ECU for regulating the VGT vane position, which is one of the system inputs.

Based on Johanne S Kepler Universit at Linz, Thesis: Advanced LPV Techniques for Diesel Engines

LPV System Identification and Advantages

- LPV robust control approach for a class LPV systems has attractive properties relative to the LTV approach.
- The LPV model takes advantage of the exogenous signal variables.
- The result is that it is closely related to the working point conditions so that it can have smaller prediction errors
- The LPV model parameters can converge to constant values.
- For the LTV case the estimated parameters are always varying with different working points.
- Better control performance and robustness can originate from using the more precise model structure of LPV models.

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Nonlinear Control Methods

Improved control if very nonlinear

(reducing engineering costs)

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Simple Controller for Nonlinear Systems

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Need for Nonlinear Control

The main areas where nonlinear control is needed are:

- Regulator control problems where the process is subject to large frequent disturbances and hence exhibits a strong degree of nonlinearity,
- Servo control problems where the operation points change frequently and span a sufficiently wide range of the process dynamics.

Both cases are present in most modern chemical processes.

" the extension to nonlinear model based predictive control has not been very successful despite a significant amount of research effort having been put into this area. The main hurdle facing the extension of LMPC to NMPC is the significant computational burden especially in the case of large dimension, fast time response, and highly nonlinear processes. Any strategy that can be devised to alleviate computation burden is therefore desirable".

Quoted Source: Rihab Khalid Al Seyab,Nonlinear Model Predictive Control Using Automatic Differentiation, Cranfield University, PhD Thesis, 2006

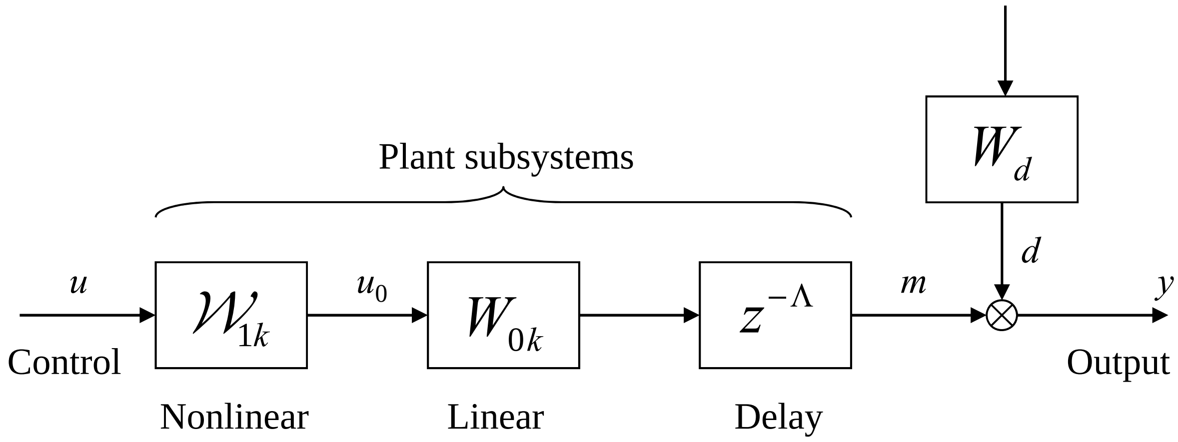
Nonlinear Plant Model

Plant model may be given in a very general form, e.g.:

- *state-space formulation*
- *neural network / neuro-fuzzy model*
- *look-up table*
- *Fortran/C code*

$$f(u, y) = 0$$

- Only need to compute the output to given input signal
- Can include linear/NL components, e.g. Hammerstein model with static input NL's



- Only knowledge of NL plant model required is *ability to compute an output* for a given control sequence.

The ACTC and University of Strathclyde

NGMV Problem Formulation

- General NGMV cost function to be minimized:

$$J_{NGMV} = E[\phi_0^2(t)]$$

with

$$\phi_0(t) = P_c e(t) + (\mathcal{F}_c u)(t)$$

$$P_c = P_{cn} P_{cd}^{-1}$$ - *linear error weighting (matrix fraction)*

$$(\mathcal{F}_{\mathrm{c}} u)(t) = z^{-\Lambda} (\mathcal{F}_{\mathrm{c}k} u)(t)$$ - *control weighting (possibly nonlinear)*

- Control weighting assumed invertible and potentially nonlinear to compensate for plant nonlinearities in appropriate cases
- Weighting selection is restricted by closed-loop stability needs

The ACTC and University of Strathclyde

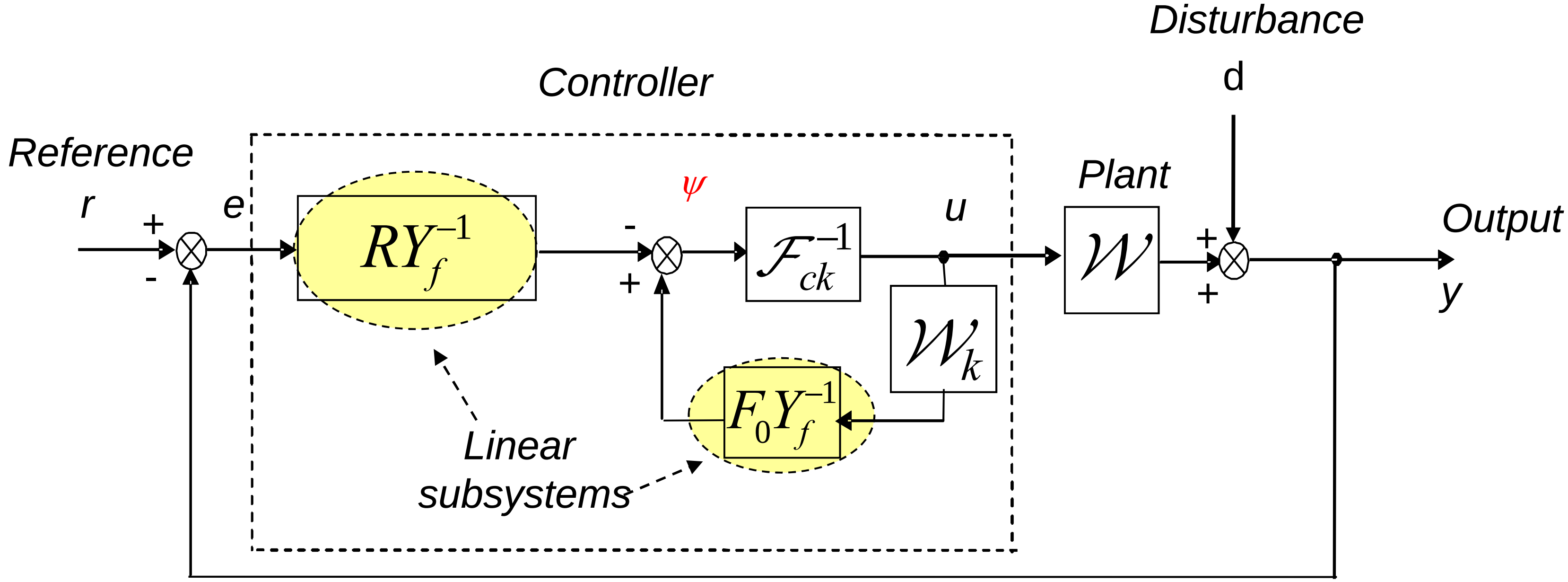
THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Implementation of the NGMV Control

$$u(t) = \mathcal{F}_{ck}^{-1}\left(RY_f^{-1}(y(t) - \mathcal{W}_k u(t-\Lambda) - r(t)) + P_c \mathcal{W}_k u(t)\right)$$

where $P_c - z^{-\Lambda} R Y_f^{-1} = F_0 Y_f^{-1}$

$$\boxed{u(t) = \mathcal{F}_f^{-1}\left(RY_f^{-1}(y(t) - r(t)) + F_0 Y_f^{-1} \mathcal{W}_k u(t)\right)}$$

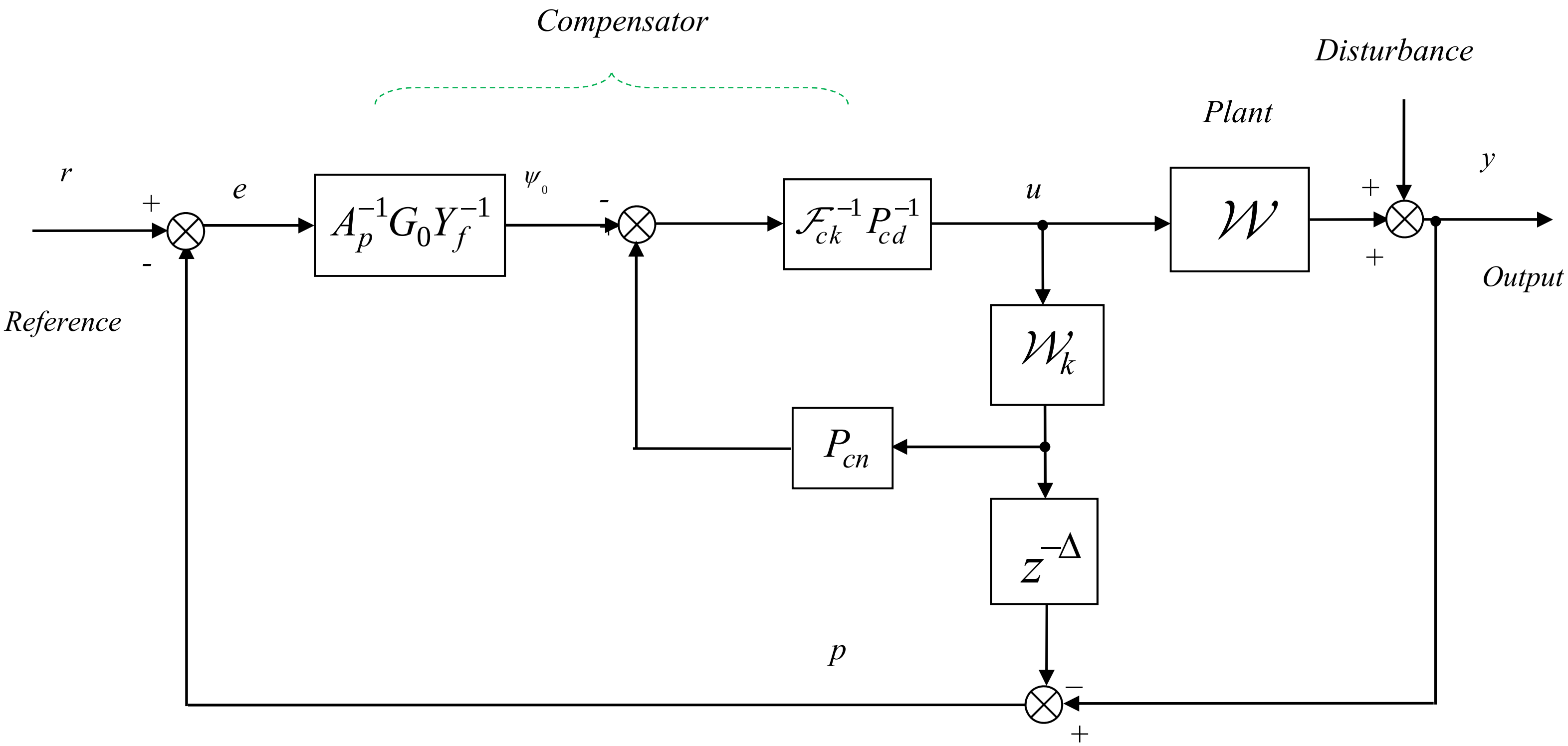


- *The controller is nonlinear but fixed!*

The ACTC and University of Strathclyde

Smith Predictor Form of NGMV Controller

- *System may be redrawn and compensator rearranged as shown below*



The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Advanced Condition Monitoring Methods

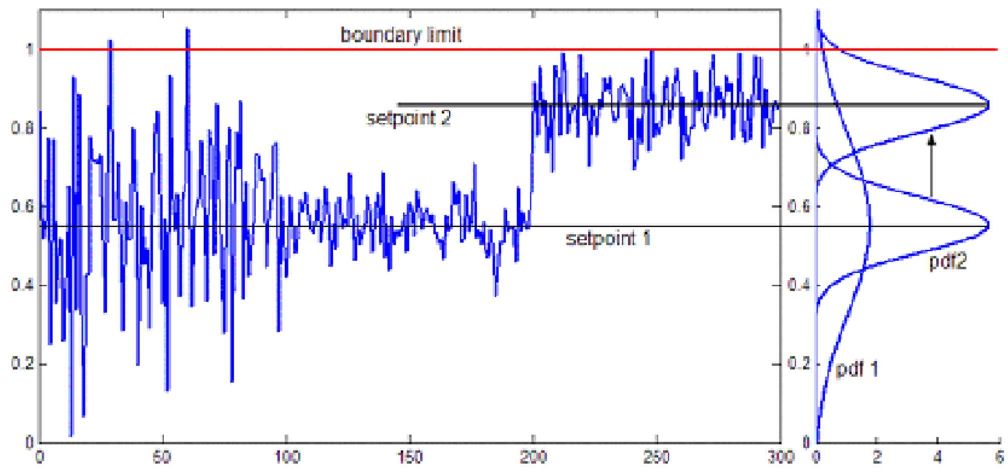
Improved control by aided tuning

(reducing engineering costs)

Minimum Variance Benchmark

- Comparing current performance with theoretical best

Minimum Variance Controller



- *Uses standard plant operating data*
- *Process variability is linked to process economics*

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

MV Benchmark Limitations

Minimum variance analysis highlights deficiencient loops, but:

- Actuator *movement is not penalised*
- Assumes *unlimited controller order*

…which results in a *pessimistic* benchmark.

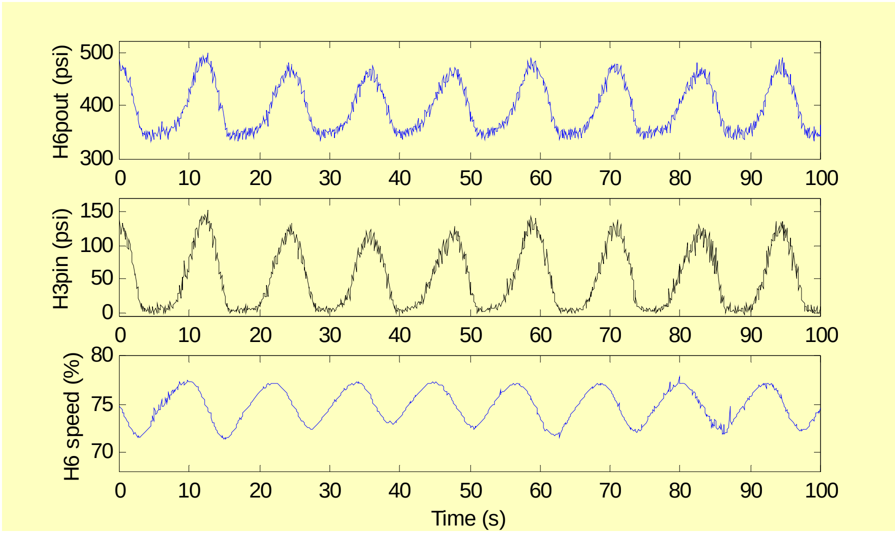
Also:

- Raw data is required – not archived/compressed data
- Difficult to link loop variability with process economics
- Only works on a loop by loop basis

The ACTC and University of Strathclyde

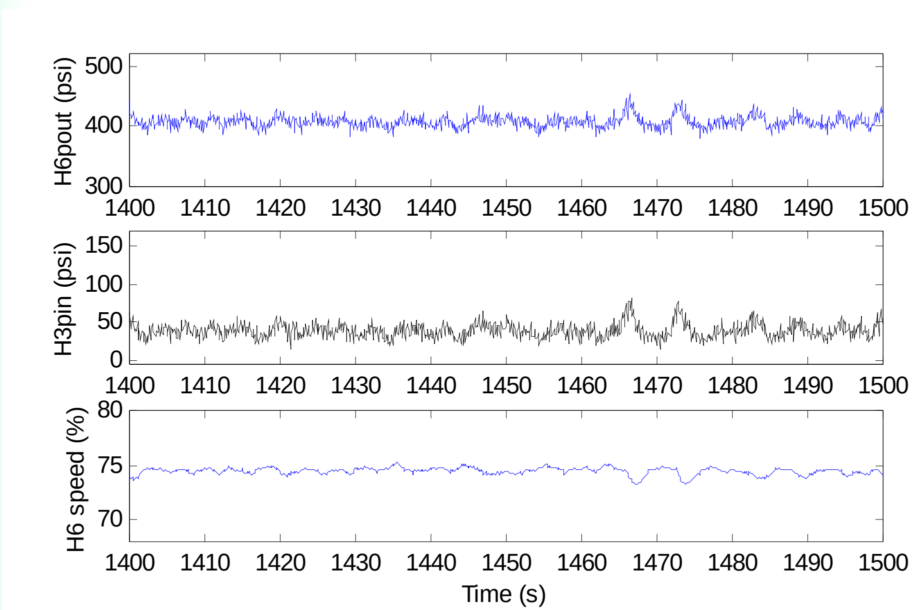
Illustrative Industrial Examples

Food Homogenisation (ISC Ltd.)



$\eta = 10.9\%$

Original System Responses causing excessive wear



$\eta = 79.6\%$

Improved System Responses following ISC investigation

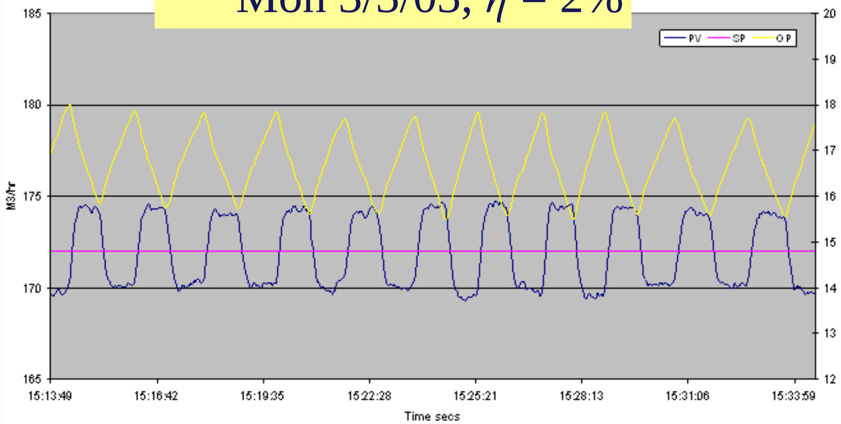
Here are the results of using a benchmark before and after a control loop investigation and improvement exercise. Whilst the benchmark was not used to identify the poor performance (it was the excessive maintenance costs by the pressure variations), the metric clearly reveals the improvements in control that were made.

The ACTC and University of Strathclyde

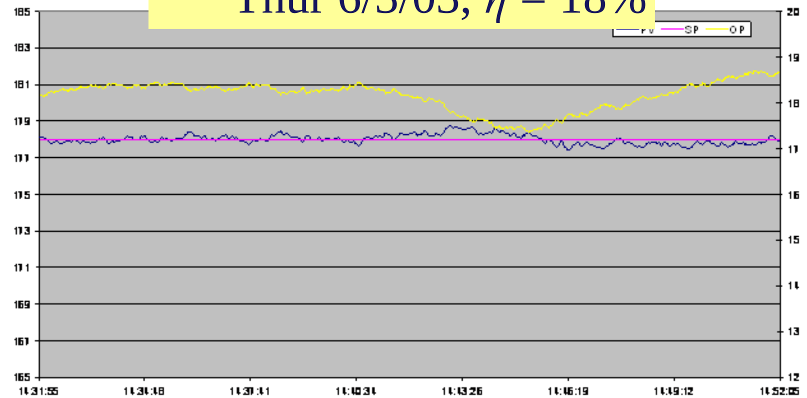
THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

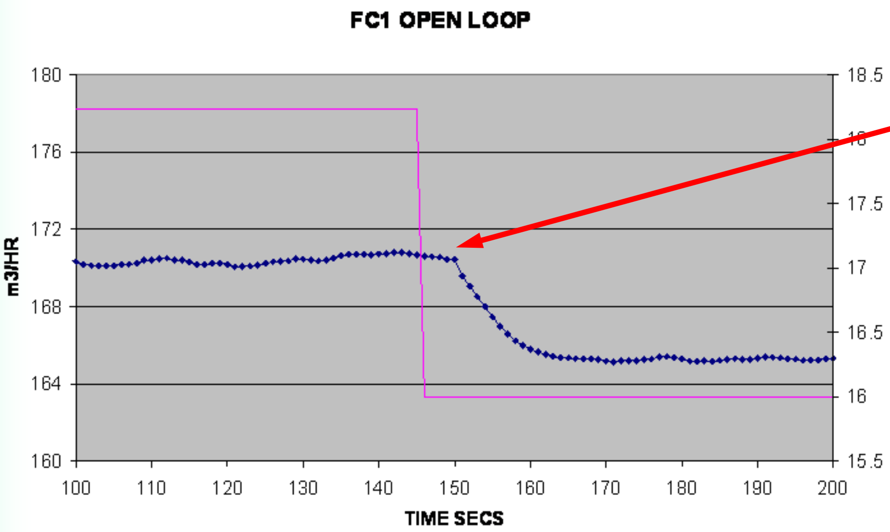
Refinery Flow Loop (ISC Ltd.)

Mon 3/3/03, η = 2%



Thur 6/3/03, η = 18%





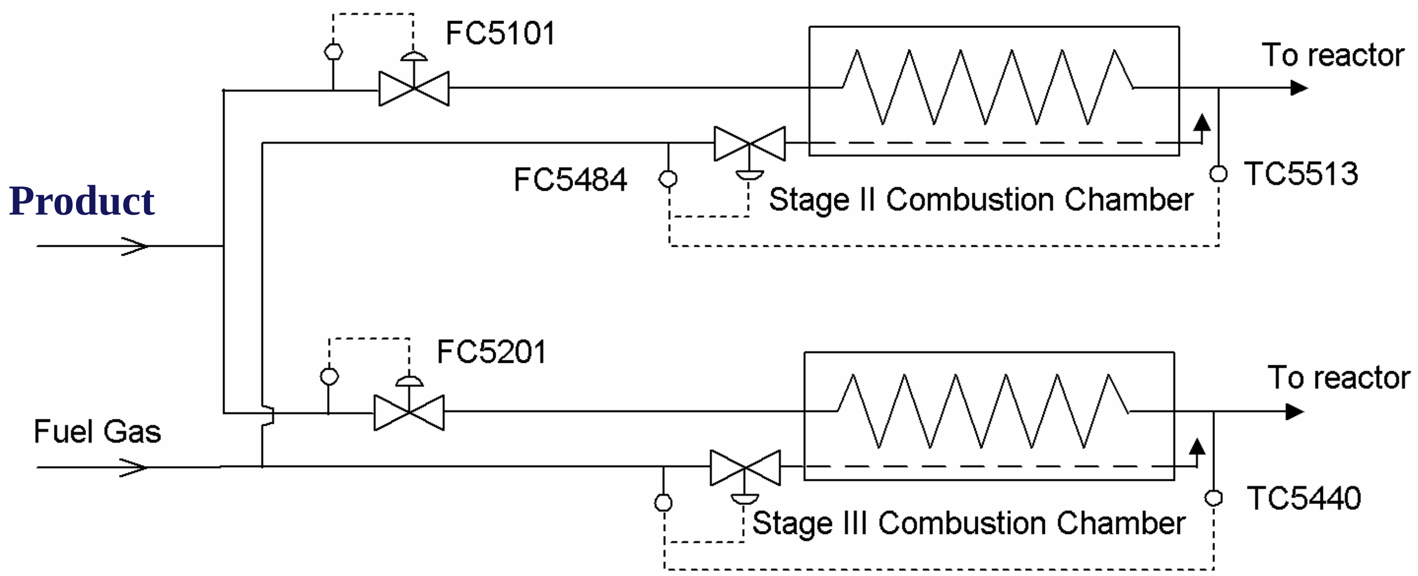
loop delay = 4 secs

- *1st data set shows oscillations (limit cycles) in controlled flow – very poor performance metric*
- *2nd data set – cause of limit cycles (most probably a sticking valve) have been removed and improvement in performance is clear, though could still possible do better.*

In this case step tests were possible to obtain loop delay to a high degree of confidence. It is clear from looking at the trend of the first data set that it has problems but benchmarking is an automatic way of calculating loop performance.

The figure of merit is related to a theoretical minimum. If only looking at past variance (i.e. like SPC) then one might think that the 2nd data set is good (compared to the variance from 1st data set). However, the Poor MV benchmark shows that this loop is still underperforming and plenty of opportunity for improvement.

Furnace Temperature Control (ISC Ltd.)



- Furnace exit temperature is critical:
  - product quality, re-work and energy consumption
- Depends on good control

… but which loops are underperforming ?

Consider a simple furnace example of two parallel streams of product being heated to a desired temperature. There are six control loops in total, 3 on each stream:

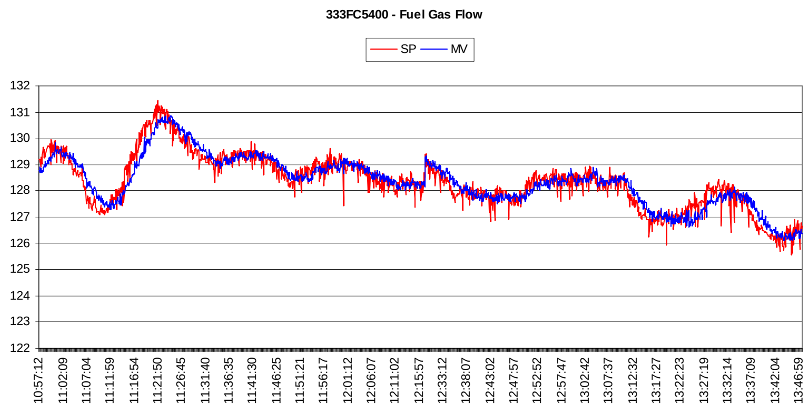
- *Product flow controller*
- *Fuel gas flow controller*
- *Product temperature controller – required temperature = 380 degC*

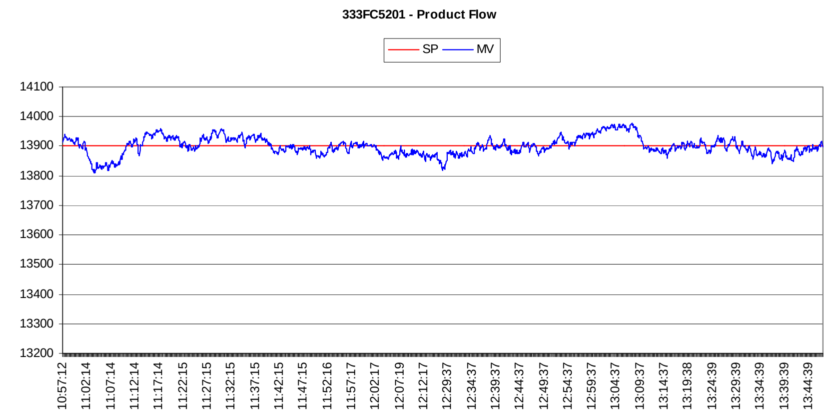
The final temperature depends upon all control loops, since variations in the product and fuel gas flow controllers will influence the final temperature. Such variations may arise due to changes in pressures and also coupling between common parts of process.

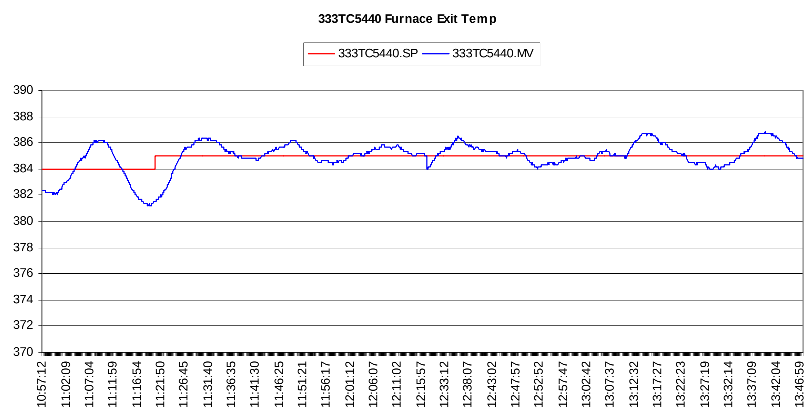
The ACTC and University of Strathclyde

Furnace Temperature Control (ISC Ltd.)

Normal operating data:







Trend showing Fuel Gas Flow

1. *It is in cascade control – hence the varying SP.*
2. *Trend showing Product Flow.*
3. *Trend showing Furnace Exit Temperature*

The loop delays also need to be known:

- *For flow loops this was assumed to be 5secs*
- *For temperature loop – historical data showed this to be 30secs.*

The ACTC and University of Strathclyde

The University of Strathclyde in Glasgow

Furnace Temperature Control (ISC Ltd.)

- Results from MV Benchmark:
  - Fuel Gas Flow Loop = 50%
  - Temperature Loop = 15%
  - Product Flow Loop = 2%
- Poor product flow control!!
- Agreed with a formal investigation of the process.

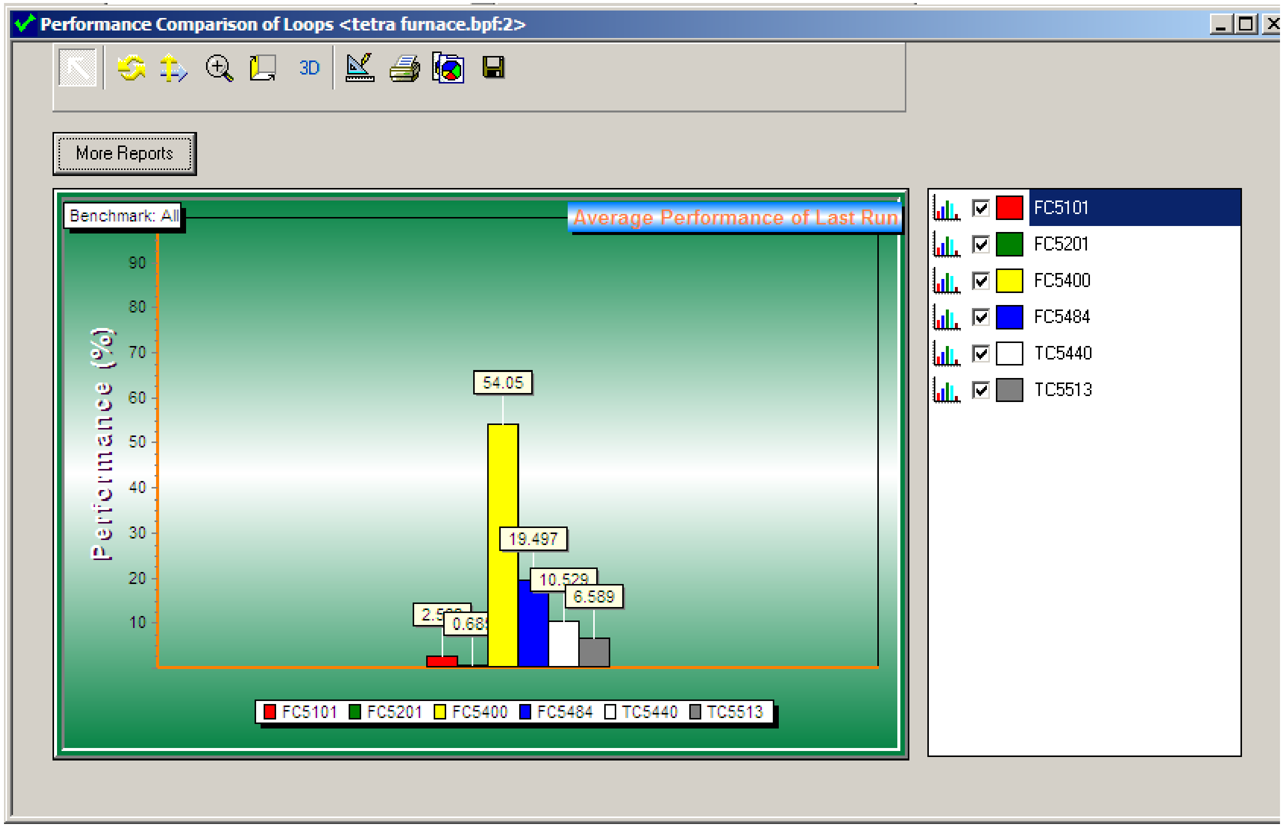
Results obtained from running the data through the basic algorithm clearly shows which loops are underperforming.

These performance indices were not linked to the economics of the plant, but just relate to pure variability.

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW

Furnace Temperature Control (ISC Ltd.)



- *This image shows the graphical output of the results in the PROBE prototype software developed under the ETSU project*
- *This really emphasises which loops are performing well and those that are not.*

The ACTC and University of Strathclyde

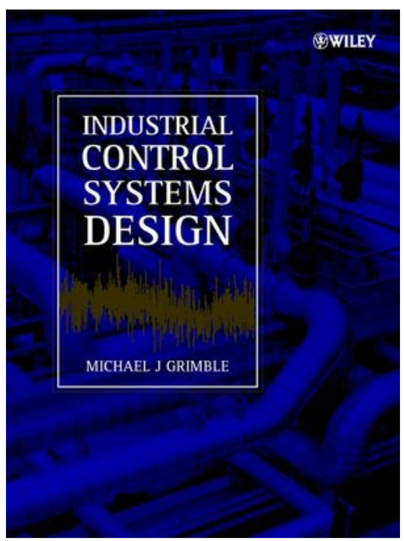
The University of Strathclyde in Glasgow

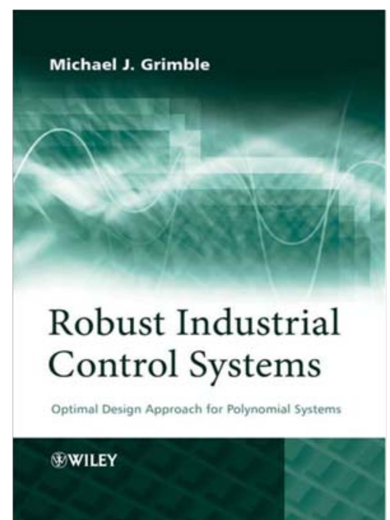
Final Remarks

- For difficult control problems modelling and simulation are often essential otherwise we are blindly attempting to cross a motorway.
- Many ways treating nonlinearities and uncertainties, leading to different design methods.
- Performance often falls when improving robustness but proper treatment of nonlinearities can lead to significant improvements in performance and robustness.
- Low order controllers have natural benefits and robust behaviour.
- New LPV models and control methods have considerable potential for applications not fully explored in the process industries.

Acknowledgements

- *We gratefully acknowledge the support of the plastic film process research by DuPont Teijin Films UK Ltd and UK EPSRC.*
- *The cooperation and help of Sung-ho Hur, Dr Reza Katebi of the ICC and Dr Andrew R Taylor of DuPont is also gratefully acknowledged.*





References

- Cutler, C. R., and Perry, R. T., "Real Time Optimization with Multivariable Control is Required to Maximize Profits", *Computers and Chemical Engineering, Vol. 7, No* 5, pp. 663-667, 1983.
- Gangadhar Gattu, Srinivas Palavajjhala, and Doug B Robertson, *Are Oil Refineries Ready for Non-Linear Control and Optimization*?, Bass Rock Consulting, Inc.
- Camacho E F and Bordons C, Model Predictive Control, Springer, 1999.
- Dutton K, Thompson S and Barraclough B, The Art of Control Engineering, Addison Wesley, 1997.
- Marlin T, Process Control: Designing Processes and Control Systems for Dynamic Performance, McGraw Hill, 1995.
- Ogunnaike B A and Ray W H, Process Dynamics, Modelling and Control, Oxford University Press, 1994.
- M.Paulonis, J.Cox, "A Practical Approach for Large-Scale Controller Performance Assessment, Diagnosis and Improvement", Journal of Process Control, Vol. 13, pp.155-168, 2003
- G.Dumont, "Tools for Monitoring and Tuning Advanced Process Control Systems", ECC Workshop, Portugal, Sep 2001
- B.Huang, S.Shah, "Performance Assessment of Control Loops: Theory and Application", Springer Verlag, Oct 1999, ISBN 1-85233-639-0
- N.Thornhill, M Oettinger, P.Fedenczuk, "Refinery-wide Control Loop Performance Assessment" , Journal of Process Control, Vol. 9, pp.109-124, 1999
- N.Thornhill and T Hagglund, "Detection and Diagnosis or Oscillation in Control Loops", Journal of Control Engineering Practice, Vol. 5, pp. 1343-1354, 1997

The ACTC and University of Strathclyde

THE UNIVERSITY OF STRATHCLYDE IN GLASGOW