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Control Performance Assessment and Benchmarking in Application: Divided-wall Distillation Column

Introduction

- ❑ Backgrounds
  - Plant description
  - The guideline
- ❑ Divided wall column example
  - SISO benchmarking procedure
  - MIMO benchmarking procedure
- ❑ Discussions

Background: Distillation Columns

Distillation is the primary separation process used in the chemical processing industries. While this unit operation has many advantages, one drawback is its significant energy requirement. The dividing-wall distillation column (DWC) offers an alternative to conventional distillation towers, with the possibility of savings in both energy and capital costs.

While theoretical studies have shown the economic advantages of DWCs in certain circumstances, industry has been hesitant to build these columns. One reason may be a lack of understanding of their design and control.

DWC - State of the Art

In 1985, BASF constructed and started up what is believed to be the first commercial DWC. BASF is also believed to be the leader in the total number of such column in existence, with over 25 DWCs operating today.

Linde AG has recently constructed the world's largest DWC for Sasol, an estimated 107-m tall and 5-m in diameter. Krupp Uhde has designed a column to remove benzene from pyrolysis gasoline for Veba Oel.

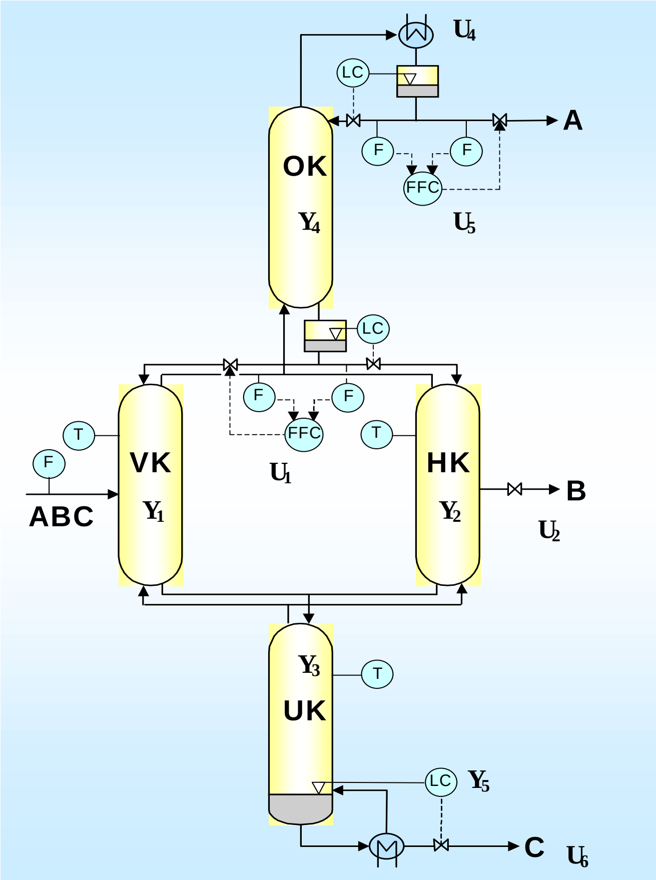
About This Case Study

In this case study, we are going to evaluate the performance of the controllers used in an industrial pilot-scale DWC.

The DWC is controlled in a multi-loop fashion.

In the following slides, we first study the control loop performance in SISO fashion. Then a MIMO study will be carried out.

Description of Divided Wall Column (DWC)



A brief description of DWC is as follows:

1. The ultimate control objective is the purity of all three components.
2. No online measurements for purity in the plant
3. Three temperatures are controlled as a substitute

DWC: Inputs/Outputs

Outputs	**Inputs**
Y1 : Temperature in VK	U1 : Split ratio between columns VK and HK
Y2 : Temperature in HK	U2 : Flow of component B
Y3 : Temperature in UK	U3 : Heating energy for component C
Y4 : Pressure in OK	U4 : Cooling energy in the condenser A
Y5 : Level in the column sump	U5 : Reflux ratio of component A
	U6 : Flow of component C

DWC Input/Output Pairings

Currently applied pairing between Mv-s and Cv-s:

T_{VK} – reflux ration of A	Y1(U5)
T_{HK} – split ratio	Y2 (U1)
T_{UK} – flow of component B	Y3(U2)
P_{OK} – cooling energy in condenser of A	Y4(U4)
Luk – flow of component C,	Y5(U6).

Characteristics of DWC

Characteristics of distillation column:

1. Stochastic sources acting on the system process,
2. The systems' outputs tend to remain around a given value for long periods of time.
3. If process variability is known and may be reduced, then it is possible to increase the process to its safe operational limits in order to improve productivity and efficiency.
4. Since maintaining a steady product concentration level near 100% is the major control objective, the variances of the controlled temperatures should be reduced as much as possible. Taking variance as measure of performance is quite applicable and really meaningful.

Comparison of SISO Benchmarks

Table 1. Comparison of benchmarking methods: benefits

Benefit	MV	GMV	RS-LQG
Control performance	✓	✓	✓
Limits actuator energy	×	✓	✓
Reflects controller structure	×	×	✓
Provides optimal controller settings	×	×	✓

Table 2. Comparison of benchmarking methods: data requirements

Type of Data	MV	GMV	RS-LQG
Loop Delay	✓	✓	✓
Loop Output Error	✓	✓	-
Actuator Input	×	✓	-
Weighting Choices	×	✓	✓
System Model	×	×	✓
Controller Structure	×	×	✓

MV Benchmark

MV: minimize the variance of the output $Var[Y(i)]$

ALGORITHM:

- Estimate the process time delay
- Estimate the minimum achievable variance
- Estimate the actual variance (or the mean square error)
- Compare these two values:

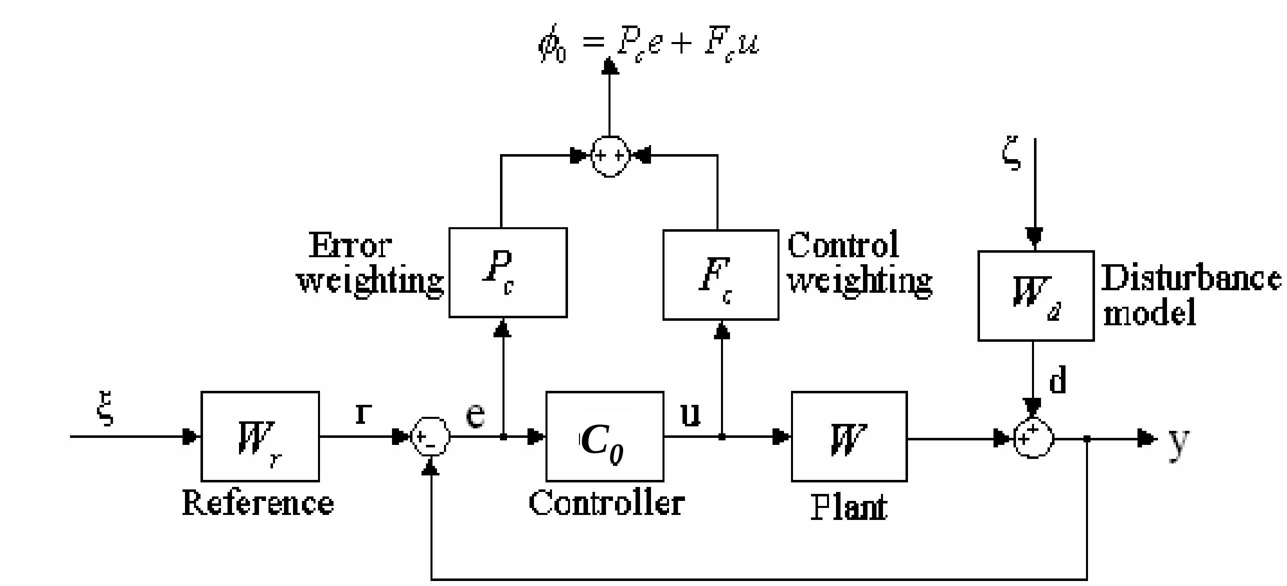
$$\hat{\eta}(k) = \frac{\hat{\sigma}_{mv}^{2}}{\hat{\sigma}_{y}^{2} + \overline{y}^{2}} \qquad \in [0,1]$$

1 MV control

0 poor control

Where $\overline{y}^{2}$ is the square of the error between the set point and the output.

GMV Benchmark



GMV: minimize the variance of the "generalized" output $f_0(t)$: $Var[\phi_0(t)]$

$$\boxed{\phi_0(t) = P_c e(t) + F_c u(t)}$$

MV/GMV Benchmark Computation

The MV and GMV benchmarking algorithms use only system data to compute the benchmark index. For both algorithms the user must define a data length and an autoregressive model length

- Data length and autoregressive model length are system specific
- Data length (n) influences the statistical confidence in the value of the performance index
- Autoregressive model length (m) should be such that the closed loop impulse response is fully captured with m-samples
- Generally (n) should be much greater than (m), typical values range from n = 150 x d, to n =1500

MV/GMV Benchmark Computation

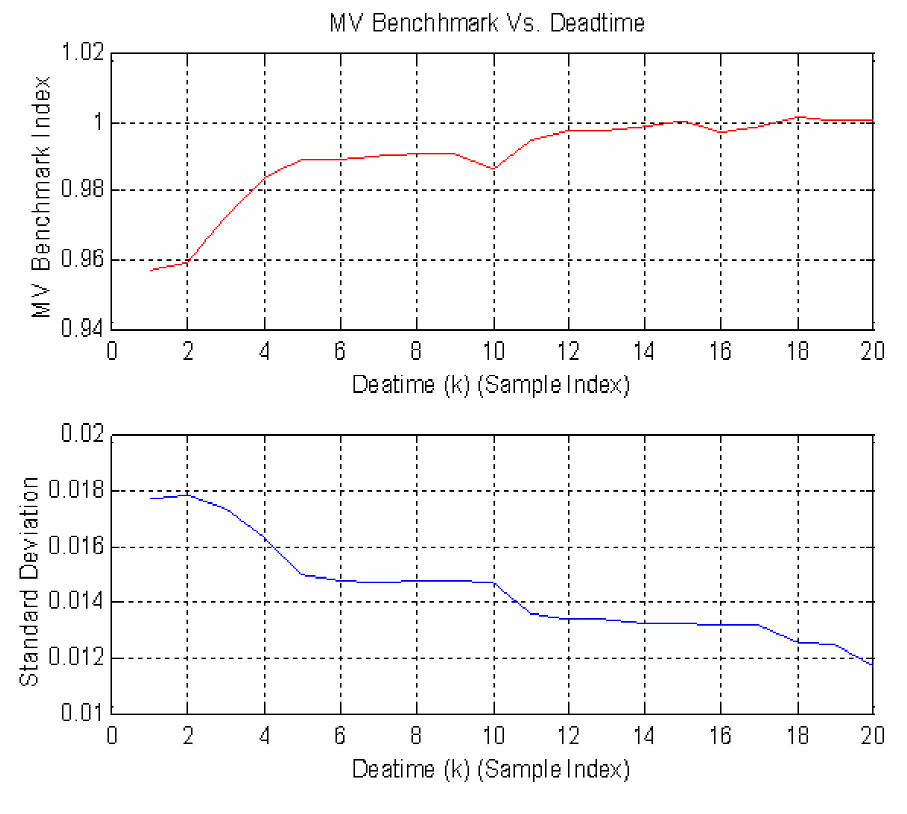
The MV and GMV algorithms require that the estimate (k) of system time delay (d) be precise, i.e $k = d$

- If $k < d$, then, estimated index < true value of the of the loop performance

- By conducting a series of test using a range of time delay values, a curve can be constructed, with the true time delay and benchmark index as a point on the curve. This curve is user defined, i.e., the process controller is required to reduce the error variance to a some value in the given interval (k)

MV Benchmark Results - Loop 2

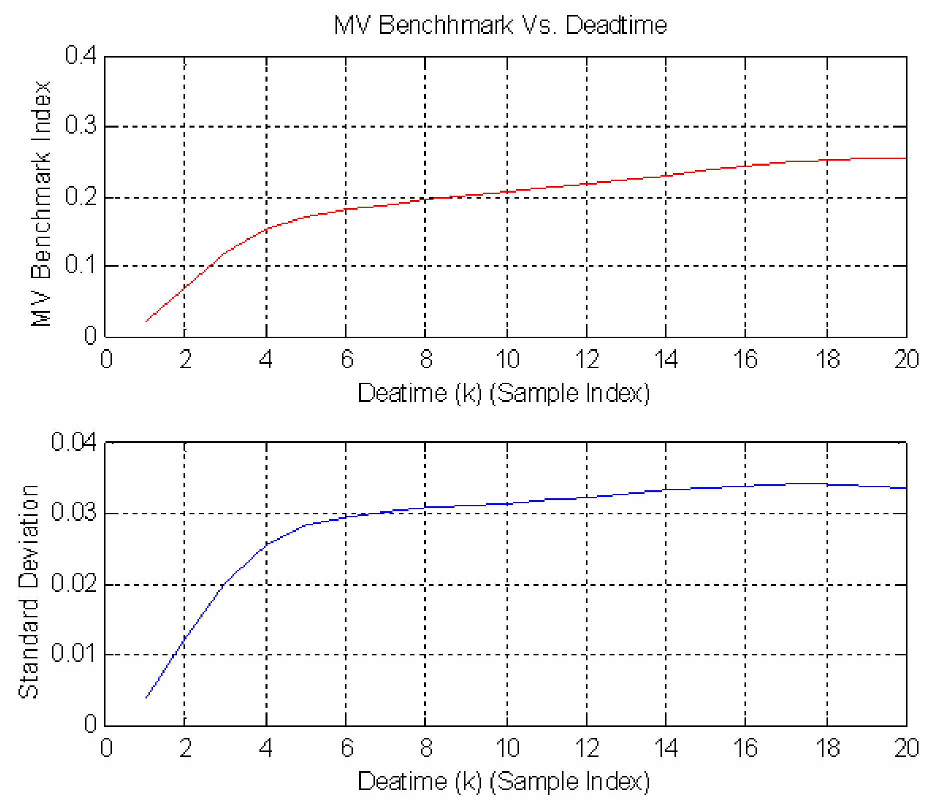
T_{HK} (Y_2) – split ratio (U_1)



1. The value of the benchmark index did not change significantly as the dead time was varied.
2. It is highly probable that
3. The dead times for these loops is either 1 or 2 sample intervals.
4. The existing controller is likely to be a MV controller

MV Benchmark Results - Loop 4

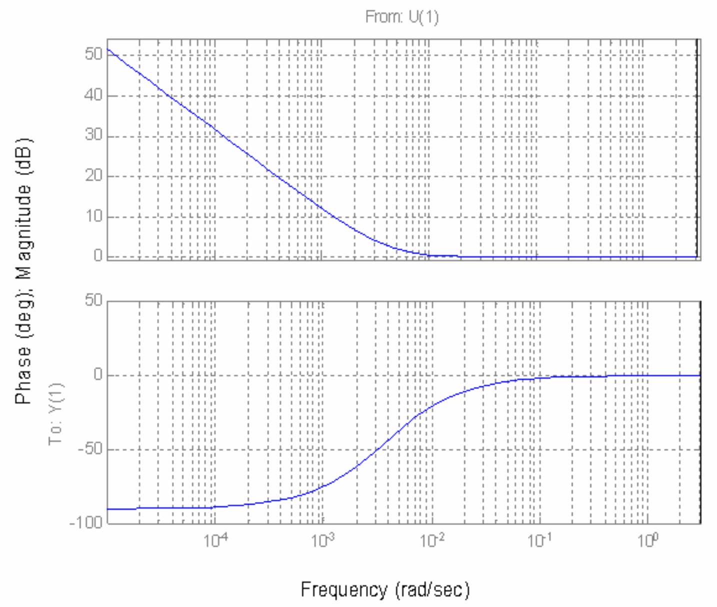
P_{OK} (Y_4) – cooling energy in condenser of A (U_4)



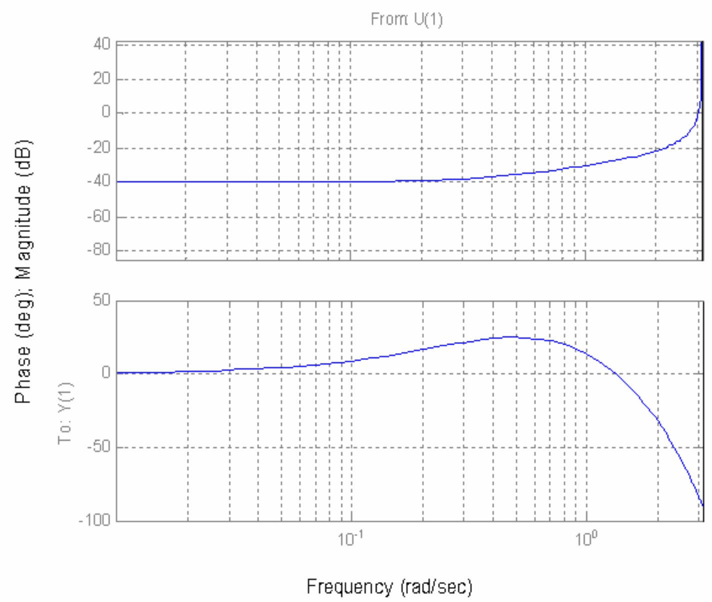
The best possible MV index under normal operating conditions is approximately 0.25, hence it can be assumed that compared to the MV controller, the controller in this loop is poorly tuned.

GMV Benchmark - Loop 2

The GMV benchmark algorithm needs a set of dynamic error and control weights to compute the performance index. These weights act as design parameters that specify the type of optimal controller required. the user is required to know and specify the optimal performance requirements for the control loop under assessment.



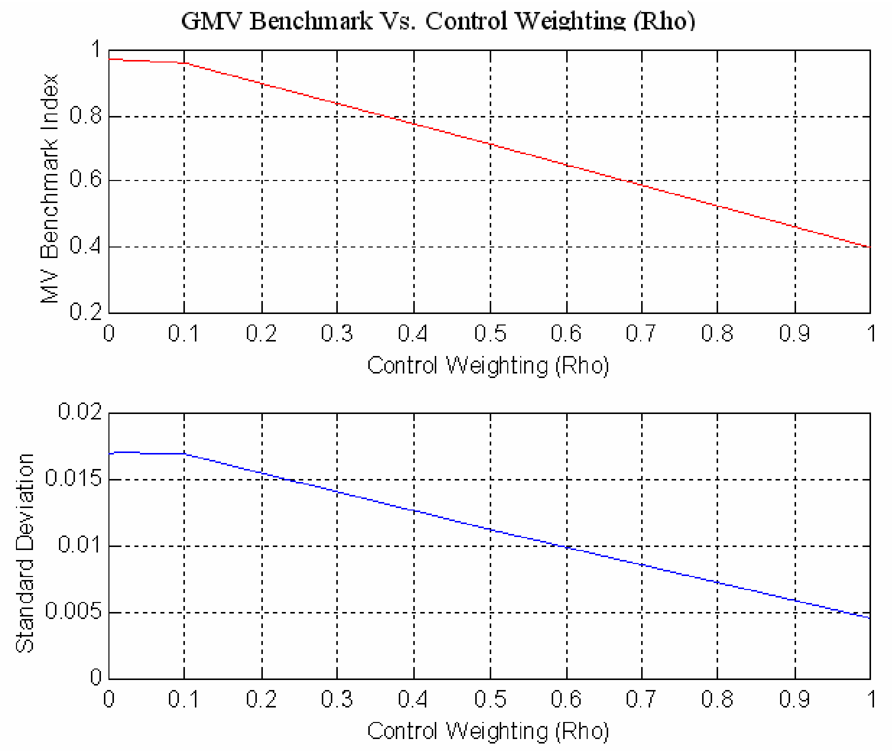
Error weighting



Control weighting

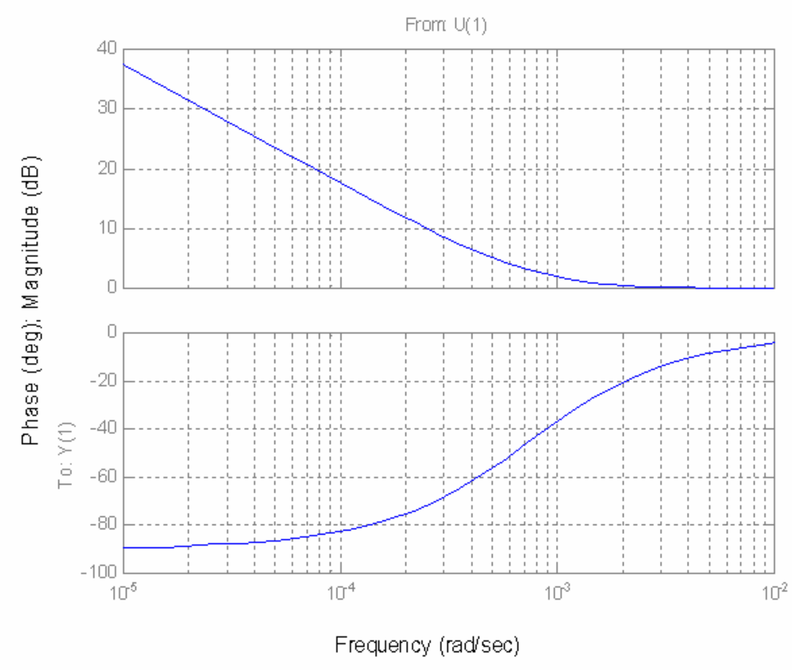
GMV Benchmark - Loop 2

In order to evaluate the control effort, we use the weighting shown in the previous slide and vary the relative weighting between them. As the weighting of control increases, more penalty is put on control action.

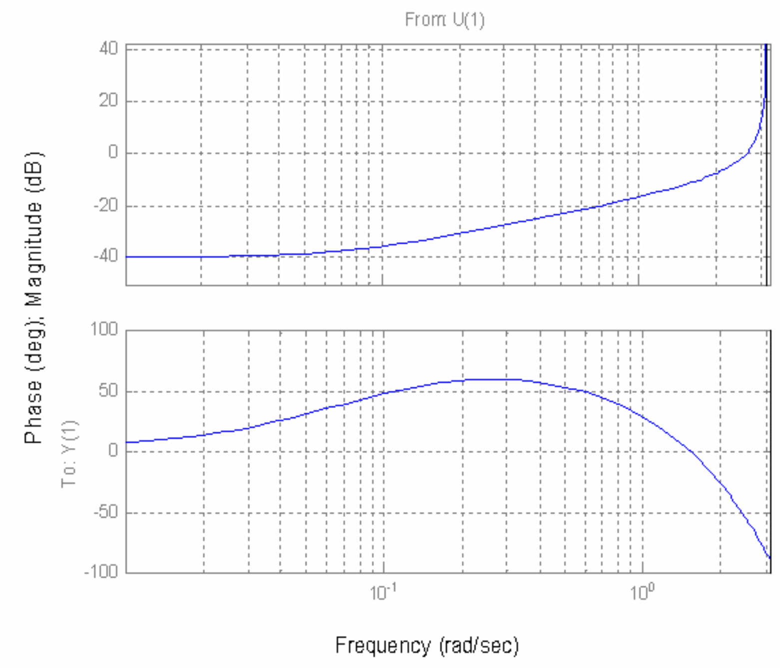


As the value of the scalar term was increased, the performance of controller can be seen to depreciate as indicated by the benchmark index. The controller is indeed a MV controller and it may be using too much control action.

GMV Benchmark - Loop 4

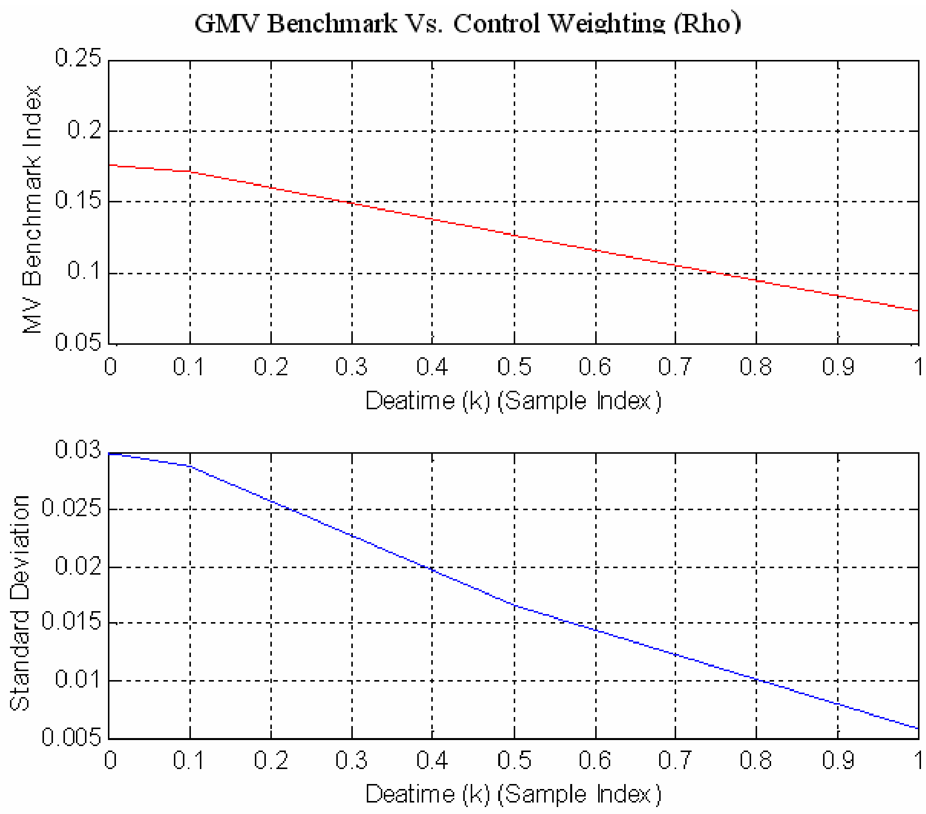


Error weighting



Control weighting

GMV Benchmark - Loop 4



In term of GMV metric, loop 4 still under-performed, it is likely that it should be re-tuned.

RS-LQG Benchmark

The RS-LQG algorithm does not use plant data to compute the benchmark index, a process model in transfer function form is required

1. Existing controller and RS controller type required (this information normally already exist).
2. Models of the system disturbance and reference in transfer function format are also required
3. The accuracy of the results returned ultimately depends on the accuracy of the model used for benchmarking

RS- LQG Benchmark

The RS-LQG algorithm requires the user to specify dynamic error and control weightings

1. Weightings determine the desired optimal controller required
2. Difficult to compare the performance results returned for the same process control loop when two different set of weightings are used
3. The choice of weightings must be consistent with the control problem, especially for RS benchmarking

In the following slides, the effect of weighting on RS-LQG will be illustrated.

RS-LQG Loop 4

Using system identification, we have:

Plant $\left(\dfrac{B_0}{A_0}\right)$ $$z^{-1}\frac{-11630+4510\,z^{-1}+5301\,z^{-2}}{1-0.6757\,z^{-1}-0.4152\,z^{-2}+0.0947\,z^{-3}+0.0009064\,z^{-4}}$$

Noise $\left(\dfrac{C_d}{A_d}\right)$ $$\frac{.005}{1-.4z^{-1}}$$

Original controller: C= -2e-6

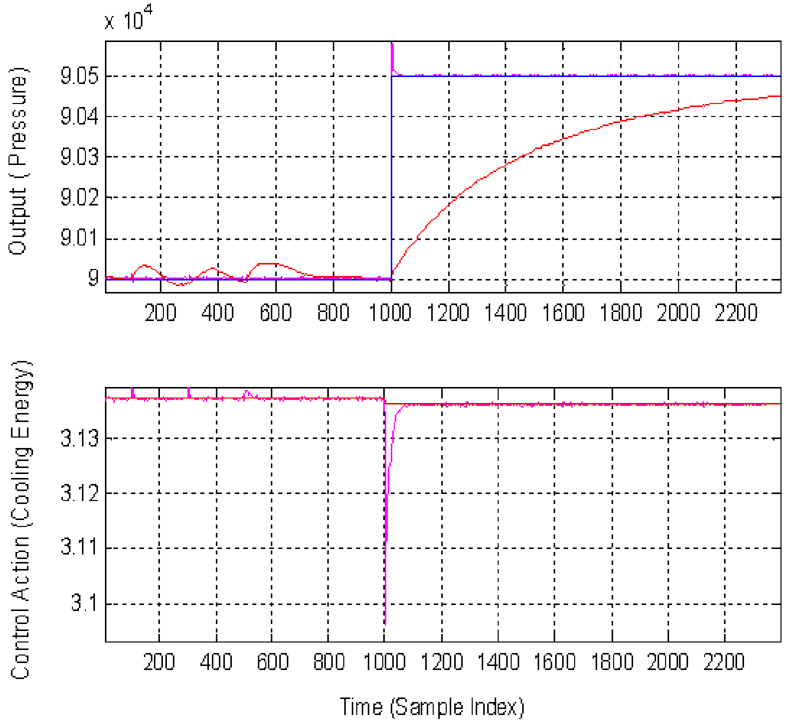
First, the error and control weighting are selected as:

Error weighting $Q_c = \dfrac{1.002-0.9985\,z^{-1}}{1-z^{-1}}$

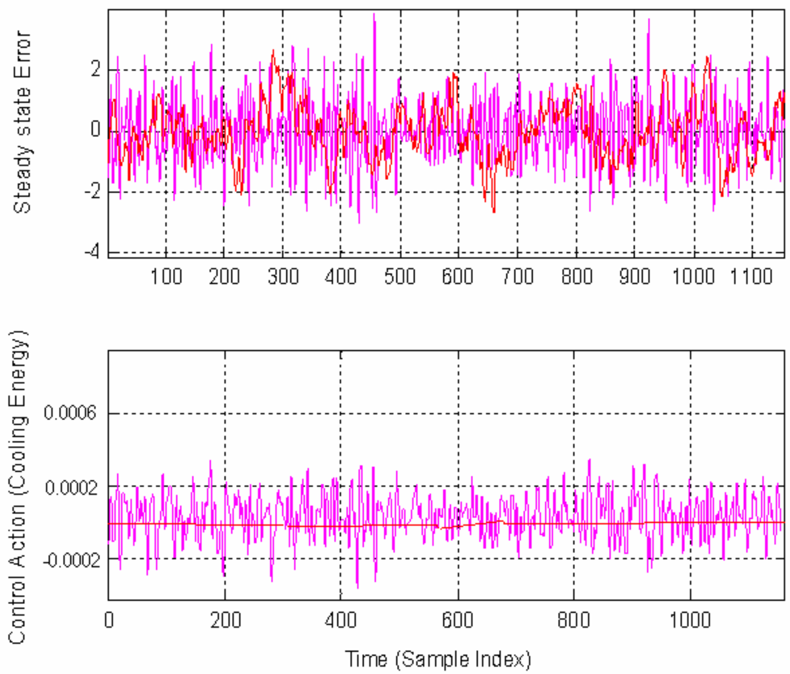
Control weighting $R_c = 0.1$

RS-LQG Benchmark - Loop 4

Red: existing Controller – Violet: re-tuned controller



Dynamics response



Steady state response

RS-LQG Benchmark - Loop 4

From the previous slide, it can be seen that the re- tuned RS-LQG has a much faster dynamic response than the original controller.

On the other hand, in term of regulation performance, the original controller is better. The control action is much less than that of the RS-LQG controller. The variance of the output is also smaller. It should be noted that the steady state results shown is after de-trending.

Now, the we change the RS-LQG weighting as follows:

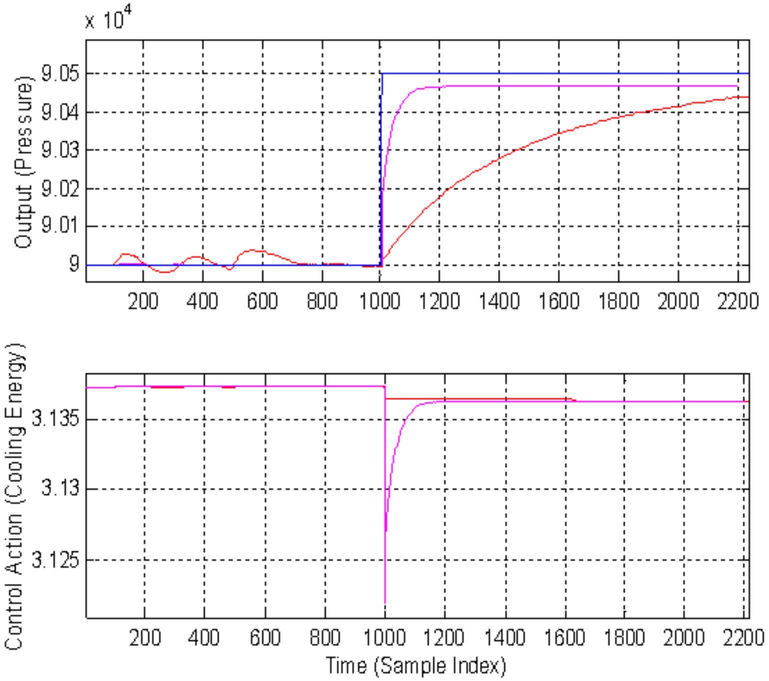
Error weighting $Q_c=1$ Control weighting $R_c= 0$

The noise is the same as before:

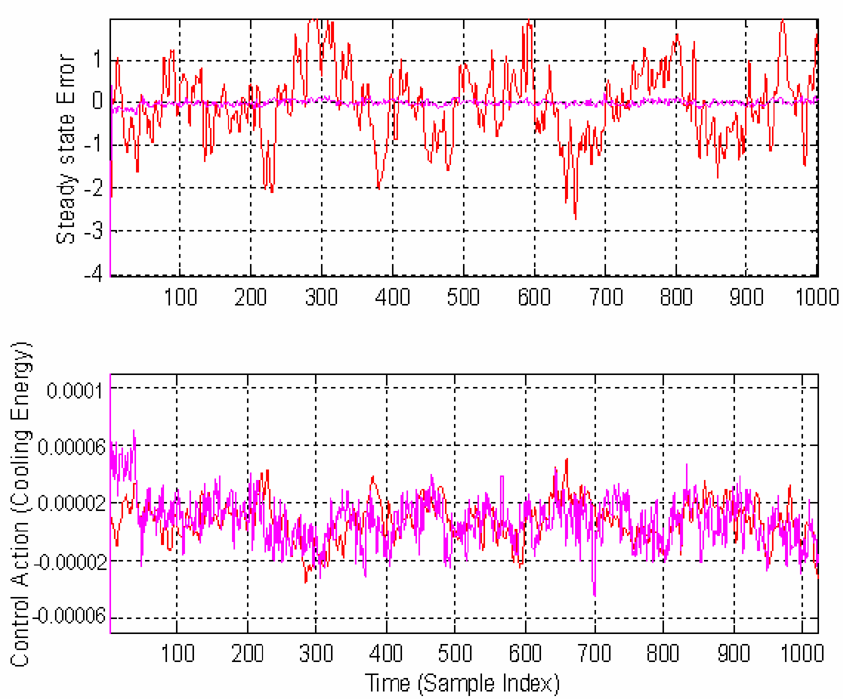
$$\text{Noise}\ \left(\frac{C_d}{A_d}\right)\ \frac{.005}{1-.4z^{-1}}$$

RS-LQG Benchmark - Loop 4

Red: existing Controller – Violet: re-tuned controller



Dynamics response



Steady state response

RS-LQG Benchmark - Loop 4

Now, the re-tuned RS-LQG controller has better performance than the original controller both in terms of dynamic response and regulation performance. In the case of the regulation performance, the new controller has greatly reduced the output variance, with a modest increase on the control effort. Since there is no integral in the error weighting, the new controller is also a proportional controller. However, the gain is greatly increased.

This clearly illustrate that the weighting selection for the RS-LQG design plays a deciding role on its success.

Brief Summary up to now

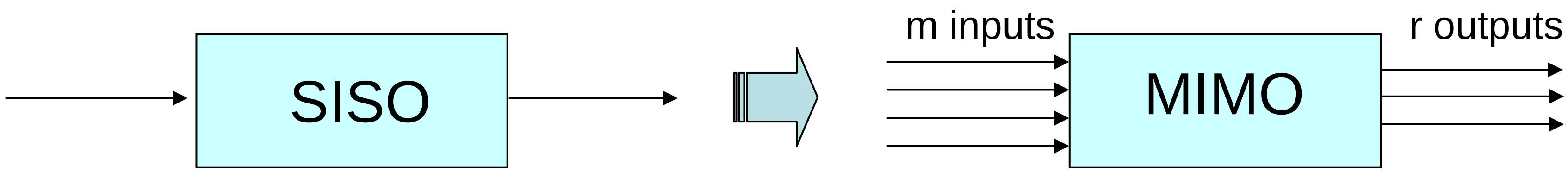
The main objective of control benchmarking is not only knowing how well the system is performing, but also on deciding whether the system performance be improved

- The MV and GMV algorithms only give an indication on how well the existing controller is performing
- No information is provided on how the controller can be re-tuned to obtain that performance
- No information provide that could aid controller re-design
- The RS-LQG algorithm gives an indication on how well the existing controller is performing as well as design information
- The RS-LQG algorithm can be used to test different optimal design scenarios

MIMO Benchmark

- MIMO systems contain loop interactions and recycles
- Optimising each loop , might lead to system instability
- SISO benchmarking indices cannot be extended to the MIMO case
- MIMO benchmark for overall sub-process required

Benchmarking of Multivariable Processes



$$W = z^{-k}\frac{B}{A}$$

$$\underset{r\times m}{W} = \underset{r\times r}{A^{-1}}\,\underset{r\times m}{B} = \underset{r\times r}{A^{-1}}\,\underset{r\times r}{D^{-1}}\,\underset{r\times m}{\tilde{B}} = \underset{r\times r}{D_r^{-1}}\,\underset{r\times r}{A_r^{-1}}\,\underset{r\times m}{\tilde{B}}$$

matrix fraction

inverse interactor matrix

Extension to multivariable systems is generally nontrivial.
Possible difficulties are a result of:

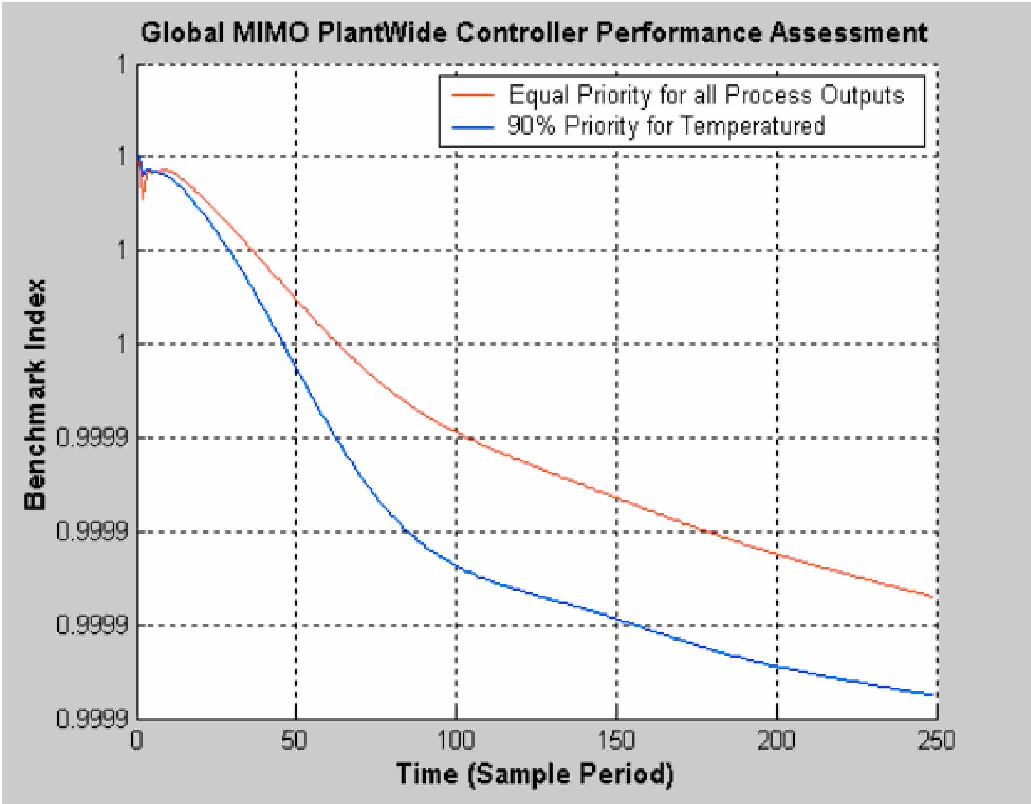
- interactions between loops
- loops need to be prioritised to obtain desired objective
- performance is also dependent on control structure

LQGPC Benchmark

1. The LQGPC algorithm does not use plant data to compute the benchmark index, a process model in state space form is required
2. Existing controller model is required
3. Models of the system disturbance are required
4. Future reference trajectory is assumed to be given
5. The accuracy of the results returned ultimately depends on the accuracy of the model used for benchmarking

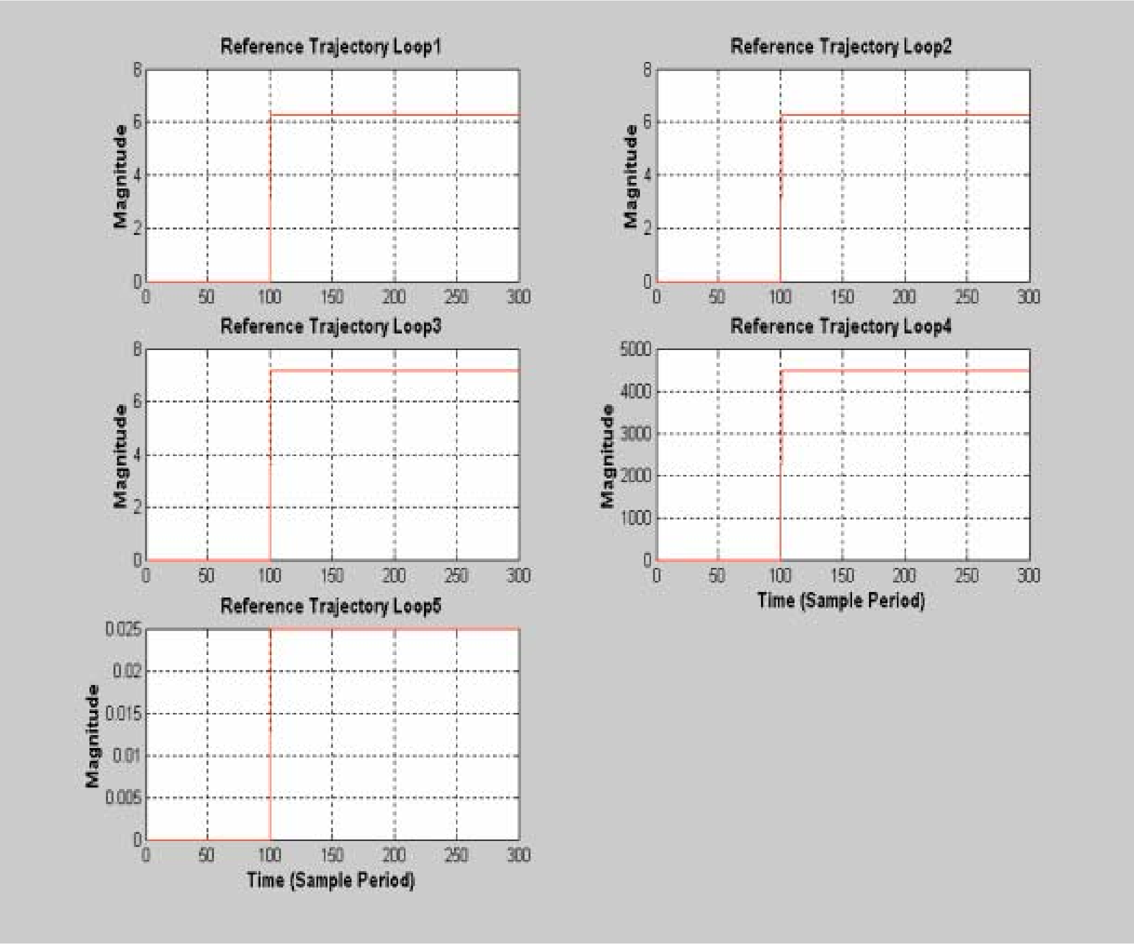
Benchmarking Results - Steady State

The control weighting is set to be zero. The LQGPC benchmark tries to minimise weighted output variance. Two error weightings are used. The result indicates that the original PID controller is operating as a MIMO MV controller



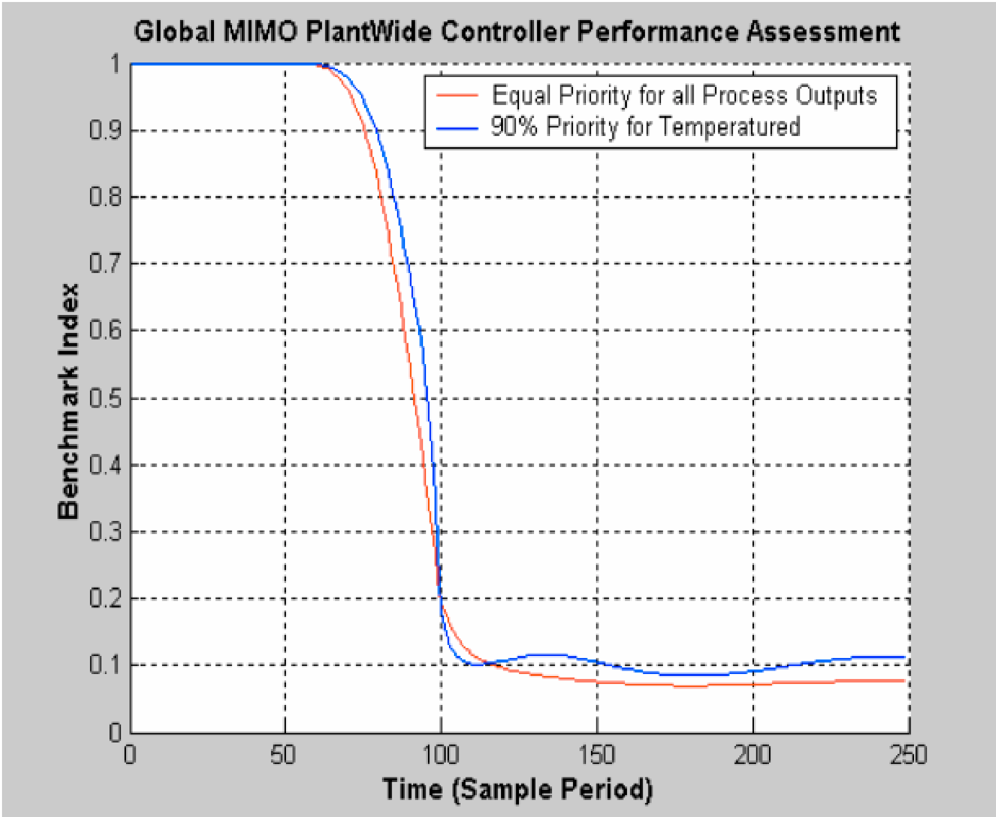
LQGPC - Transient Performance

For the following reference changes:



LQGPC - Transient Performance

The transient performance test indicates that the multi-loop PID controller is operating at only 10% of the GPC optimum.



Benchmarking Results -Transient Performance

It is obvious that, the transient performance of the existing multi-loop PID controller is relatively poor comparing with the MIMO LQGPC controller. One obvious reason is that LQGPC is able to anticipate the change of reference and as a true MIMO controller, it can co-ordinate the control action of each individual loop.

However, we can not jump to the conclusion that a change of controller is needed. Remembering that the main control objective of DWC is regulation, and existing controller is performing very well in that aspect. We need to a further study involving economic auditing to decide whether a change is needed or not

Conclusions

- SISO benchmarks provide a wealth of useful information
- The move from SISO to MIMO algorithms will provide better optimisation targets
- Engineering judgement still an essential part of the benchmarking process
- Define the control/optimisation problem, then chose the benchmark tool that best fits