# Part A

Firstly, we analyse and define the control problem to be solved. The task is to implement an MP controller for a gantry crane, capable of tracking a given square in XY (horizontal) plane. The square is to be tracked by the mass suspended from the crane and not necessarily the crane itself.

This problem can be deconstructed into 4 separate problems of moving the mass from a given point A to a given point B. The four movements are then executed in sequence, such that the mass tracks the required square in the end. This definition of the problem allows for the use of controller implemented for previous assignments with only minor changes.

Having decided to use code from previous assignments, a choice has to be made between using controller with only hard constraints and controller with soft constraints implemented. To that end, both controllers were tested in moving the weight from a given point to another given point. Both controllers were set up with the same cost matrices and constraints, apart from the angle constraint, where the soft constraints were used. This testing showed superior performance of the controller with hard constraints only. The controller with soft constraints took significantly longer to compute, since the slack variables increase the size of the system to be optimised cit. At the beginning of the simulation, the controller would not have computed the solution in time (solutions took more than 1 second with sampling time of 1/30 seconds). Moreover, the settling times of controlled variables of hard constrained controller were shorter.

We can now begin to adjust the hard-constrained controller to the square tracking task. The first step is to define the square to be tracked. Since the problem is posed as moving the crane from a given point A to a given point B, the square is defined by 4 points in its corners. These points should be far apart, to avoid problems connected with the stickiness of the crane (larger force required to begin moving it). If the controller exerts large force to overcome the stickiness, it would risk overshooting the corner of a small square. Equally, if solution is set up to heavily penalise overshooting, the crane might not reach its end state, or even start moving. The square is oriented so that its sides are parallel with the X and Y axes. This simplifies the definition of the constraints (as explained later). Moreover, this way the movement along each side is controlled by one actuator only, there is no coupling of the two actuators’ action in the movement, and consequently any oscillations are controlled more easily.

In the laboratory sessions, it was also noted that the crane experiences larger stickiness in the X-axis than in the Y-axis. This is due to the fact that in the X-axis larger mass (crane car and rail it moves on) has to be moved than in the Y-axis (crane car only). To ensure a square is tracked instead or a rectangle, a stickiness correction constant is introduced to the code. This constant is added to the higher X coordinate of the corners and subtracted from the lower X coordinate. By doing this, the controller is set to track a rectangle, but due to stickiness it will track a square. Value of this constant is best set experimentally in real hardware. In the simulations, the increased stickiness is not well modelled, and hence the value of the constant is set to zero.

After the target states (i.e. the corners of the square) are defined, the constraints are defined too. The constraints are imposed on the same states as in the previous assignments – on X and Y position and on X and Y angle. The constraints set on angle are constant. The position constraints are different for the four different target states. For each state, the position constraint is a thin rectangle with shorter sides lying on the previous and current target state and longer sides parallel to the side of the square. The constraint is defined by variable margin, which describes the distance of the longer side from side of the square.

Using the notation from lectures and previous assignments, the only matrices that are affected by the existence of 4 different constraints are the b constraint matrices. Therefore, there must be 4 sets of calculations performed in the initialisation stage of the program. The constraint matrices bb and target states are then cycled through based on the time of simulation/run of the hardware. Time of the simulation is taken, divided by distance between two adjacent states (i.e. length of the side of the square) to ensure longer time is allowed for larger squares tracked. This result is then multiplied by a constant, by which the action of the controller can be sped up or slowed down. Remainder after division by 4 is then calculated from this time control signal to pick the appropriate state and constraint matrix from the set of 4.

To evaluate the controller, a metric of “squarness” was developed. The trace of the pendulum is estimated from the simulation data (position and angle) by assuming length of the string. Even though this is not accurate calculation, it is still informative, as it involves the angular deviation of the string (i.e. oscillations). Smallest possible rectangle is then circumscribed and largest possible rectangle inscribed to the trace. The difference in the areas of these two rectangles gives then the rectangular area the pendulum sweeps. The smaller this area, the less oscillation the pendulum experiences and the more perfect is the square tracked. Note that rectangles were used in this method, since any deviation from perfect square shape can be readily solved by adjusting the stickiness correction variable.

Using this metric, the parameters of the controller were tuned using trial and error. The final set of the parameters is given in the table below.

*Use of constraints – define constraints around desired path towards the current target point. Can define 4 sets of constraints corresponding to 4 target states. Active constraint is always the path from previous target to current target. Matrices to be changed are bb (matrix of state constraints). 4 are calculated and then cycled through by target calculator.*

*Evaluate square and tune – definition of squarness and calculation. Inscribe and circumscribe a rectangle to the path tracked. Not drawing squares, since squarness problems (one side being longer than the other) can be solved by increasing the stickiness constant*

*Table of final parameters after the tuning*

*Constraint margin had to be loosened for the linear simulation to work. In lin model, if no solution is found inf/NaN is produced for input. Lin sim cannot be run with these. In non-lin sim, these values are limited*

*Discussion of tuning results as per notes*

*Linear simulation worse than non-linear – mismatch between the linear and non-linaer model. If optimised for the non-lin model, lin model will suffer in performance*

**Part B**

Discuss the practical challenges that arise with MPC in a continuous process industry plant, both (i) during the implementation phase and (ii) during the entire life cycle.

(i)

Parametrisation – running long tests

Converting the plant into the model – maths (complex dynamics of the plant) continuous processes are inherently complicated (sometimes not even properly understood [1]) as they involve many loops, consist of interconnected units – BUT techniques exist where cost is independent of the state size [2]

Model is non-linear – has to linearize it – non-linear parts computationally expensive

Lack of experts and time to do this

Significant initial investment – although costs retrieved soon

(ii)

Change in plant requires change of model – difficult

In the following section, practical challenges connected with use of MPC in continuous process industry are discussed. It is split into 2 subsections: first discussing issues during implementation phase and second challenges in maintenance of MPC controller.

The first issue can arise before the MPC design phase is commenced. Even though MPC is turning into the standard technique of industrial control and is widely accepted as an efficient and economical technique [10], management might often require a solid business case to be presented, before an investment into MPC is approved. However, engineers often only have indirect methods of estimating benefits (e.g. methods based on variance reduction), which are simplistic and based on experience, and as such do not offer a well-grounded case [9]. On the other hand, there are techniques to create a simple simulation of the MPC controlled plant and base the business case on it, which offers much more persuasive case [12].

When the investment into MPC is approved, the design phase can begin. Usually the first, and most difficult step is to devise a mathematical model of the plant to be controlled. This can account for up to 80% of the design work and investment [11]. The modelling is especially problematic, if detailed models derived from first principles are needed. The plants to be modelled often include many loops and interdependent subsystems with complex dynamics, which are difficult to analyse [2]. The system size (number of controlled and manipulated variables) can easily reach into hundreds of tightly coupled variables [4], further complicating the analysis. Moreover, in the continuous process industry, the processes to be modelled are sometimes poorly understood [1].

If only a black-box model is required, the analysis is somewhat simplified. For this, software packages capable of model identification can be used [zhu]. The model is constructed from data obtained in plant tests. However, there are challenges connected with the tests as well. Since time constants in continuous process plants can reach hours, tests might take week or months to complete [2] [12]. The choice of tests is also a problem, as the inputs that would yield the most useful information are likely to take the system out of its operating range [7].

After the model is complete, and the controller designed, the next challenge is to tune the controller parameters to achieve optimal operation. Cost matrices, soft and hard constraints can all be considered tuning parameters [10]. Since the size of the system is usually large and there can be tight coupling between the parameters, the task is inherently complicated [4]. Moreover, the tuning is mostly manual job and no effective automatization procedure exists [7]. After the tuning is complete, validation of the model can be performed, for which plant test data are again necessary.

All these factors make the design procedure extremely challenging task. The situation is further aggravated by that lack of expert control engineers with the necessary experience and skill to perform these analyses [7] [12]. This makes the modelling of the plant and design of optimal controller the single largest challenge in implementing MPC in industry. On the upside, this motivates research into the area, and some techniques to simplify and shorten the design task have been proposed [5].

Aside from the technical challenges, there are also challenges connected with the human factor. The MPC control operators need to be knowledgeable and skilled in operating the new control system. For this they need extensive training, which imposes additional financial and time cost [12]. Moreover, there are also psychological factors at play. If at the beginning of the MPC integration unrealistic expectations about its performance were formed, the operators might be later dissatisfied with the new controller. In such situation, they are more likely to not use it properly, or even turn it off completely [7]. If the user interface of the controller is complicated and not user-friendly, it can lead to similar negative consequences [8].

The challenges connected with the continuous use of MPC controller are tightly coupled with the ones solved during the design phase. This is because design decisions naturally affect the operation of the controller and its ability to cope with any emergent situations. Discussions of the following issues will therefore often reach back to the design stage.

The first issue that can be identified is variance of the inputs to the controlled plant. Naturally, in the continuous process industry the ingredients of the product will be of varying quality and characteristics (e.g. grain size, moisture, density). Due to legal requirements, the product must keep its quality irrespective of the inputs. The controller must therefore adapt to changing circumstances. This can be done for instance by allowing for a range of input qualities in the design process, or by defining several operation points of the plant based on the quality categories of the inputs [3].

Possibly the largest issue that has to be solved during the lifecycle of the MPC controller is changing characteristics of the plant. This can be attributed to slow sensor and actuator wear, process or recipe changes and replaced parts [14] [13]. For this reason, there should exists a business and engineering framework to continually review the performance of the MPC controller to assess, whether a change to the model is necessary [7] [10]. However, the MPC is usually designed by an outside specialist contractor company, which is typically not available to support the system during its entire lifecycle. The adjustments to be made are then responsibility of the in-house engineers and operators, who might lack the necessary skills [7]. This creates another consideration in the design phase, where simpler controller will be easier to maintain and adjust, however, likely more imprecise in its operation. Moreover, a model redesign will usually cause disruption of the production process, since testing is required similarly as in the initial design process [14].

An alternative approach is to design the MPC so that it is capable of adjusting its model automatically. There are solutions available which can support this. However, the automatic model adjustment relies of continuous excitation of the system to gather data based on which the model can be re-adjusted. This necessarily means some performance of the controller is sacrificed [14]. Moreover, the controller operators need to be comfortable with supporting such adaptive system, which might be problematic due to aforementioned lack of skilled engineers and costs associated with their training [10].

If the business employing MPC in its processes wants to maintain its competitive edge, it should also be following the latest technologies available and deploying them into their operations. These can be for instance integrated real-time optimisation or economic MPC solutions [12]. To be able to do this, the business naturally has to employ additional personnel involved with research and development, imposing further costs and hiring issues (due to lack of skilled labour).

Literature

[2] "multivariable dynamics of a plant composed of several interconnected units with recycle, bypass, and heat streams, which can significantly increase the complexity of the plant-wide dynamics"

system with large dimension (many state variables) difficult to control online (computation power) and difficult to estimate/measure state variables (many long tests)

this paper however, suggests a control scheme independent of the system size

[1] processes to be transformed into the model are sometimes not even understood properly - inherent difficulty in creating models

[3] variable quality of feed – need to change the model continually

Changing inputs require additional layer of control to estimate/calculate its effect on the system overall

[4] “However, as the plant size increases, the complexity of the process model increases rapidly, making process modeling and control system design very difficult and expensive”

[5] schemes proposed to reduce time and effort it takes to fit an MPC to a plant (model fitting might not be that difficult)

[6] first MPC formulations used one norm cost functions solved by linear programming LP – then it moved to quadratic costs necessitating QP (more computationally expensive) but without some problems of LP

[7] MPC depends on expert resources, which are limited – because of this MPC should be designed to that future interventions are minimised

“Difficult MPC set-up may cause less robust tuning and model mismatch due to software use errors. Chances of sustainable performance are immediately reduced.”

Choice of one MPC vs. several small, loosely coupled controllers – one can optimise whole process, several are easier to monitor

“A common problem with this approach is that the type of plant experiments that yield the best data are also likely to perturb the process beyond current operating limit”

Model re-designs often done by non-experts – higher chance of error

Trade off: simple, adjustable model vs accurate and complicated model

Controller tuning difficult – ranges of variables can be huge + size of the system, no automated way to do this

To use lin MPC in non-lin model – define several operating points and respective tuning (gain scheduling technique)

There are expectations to be managed – if operators expect miracles from MPC and don’t get them, they might lose trust

Need to have performance review framework to ensure MPC is bringing value and not deteriorating (due to sensor/actuator wearing, model changes, etc)

If model needs to be adapted, there are packages which can do it automatically, but the changed model still needs to be checked by a person

[8] operator might have problems working with MPC even after training, if the user interface is poorly designed

[9] To achieve desirable performance, it is necessary to build an accurate model and to tune control parameters appropriately. However, both are difficult in practice due to process nonlinearity and changes in process characteristics

Most APC suppliers and users are required to report the benefit to management. Benefit estimation methods based on variance reduction are still carried out, but they are sometimes rudimentary and based on experience

[10] MPC regulators need maintenance to keep their performance on point

„To set the optimization problems, constraints and weighting matrixes are added to the control and prediction horizon. All these parameters can be considered tuning parameters”

Presents method to evaluate performance of MPC

[11] 80% of MPC design spent on model development

[12] MPC limited by expert time

Takes long tests to parametrize all variables in the system

Complicated maths to create a model, some processes need to be modelled from first principles

Fit additional sensors and actuators = cost

Continuous plants usually require only linear model

[13] MPC deteriorates over time as the plant changes by virtue of its dynamics

[14] “Processes degrade over time due to wear and tear on actuators, design changes and replaced parts, to name a few factors. Eventually the difference between the current process and initial model becomes too large and the control performance suffers, often leading to distrust in the MPC and the controller being turned off.”

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