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Industrial IT and Automation

**Developing and Testing of an MPC strategy for a four
tanks multivariable process using Emerson Delta V
system.**

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Summary:

With the advancement of control system, Model Predictive Control has taken over the mainstream PID controller because of its more efficient and advanced control over the multivariable process. The Quadruple Tank process represents the multivariable process, which has 2 input, 2 output and 4 states. The complexity of the control system is handled in a more optimal way with the help of DeltaV MPC system.

The main goal of the thesis is to develop a model that handles the disturbance and the constraints parameter of the Quadruple Tank process. The DeltaV offers a robust controller after successfully developing the model. The controller handles the interaction between the process variables in the best possible way to reach its desired output. The setpoint and the disturbance are handled in a quite satisfactory manner. The step response model for the model developed in the DeltaV system can give a wide operational range, which helps to develop a more robust controller for any situation. After successfully performing the test process, the DeltaV uses the FIR and ARX model to identify the step response model, which will eventually create the optimal controller for the process.

Even though the model showed a satisfactory result but some more development can be achieved by manipulating the instruments such as the pump or the sensor, which will enlarge the operational region as well as handling the disturbances more profoundly.

Preface

The thesis entitled Developing and Testing an MPC strategy for a four-tank multivariable process using Emerson Delta V system was performed and written in USN Prosgrunn and Emerson Porsgrunn. The task description and objectives can be found in Appendix A.

Most of the works regarding testing and implementing the MPC have been performed in Emerson office at Porsgrunn.

The DeltaV book online has been the primary reference for the MPC strategy described here in this thesis. Other resources have been referenced in its best possible way.

I would like to thank my Supervisor, Carlos F. Pfeiffer, for allocating me to this thesis, which is an extension of my previous master project on Beer Lab. He has guided me throughout the thesis with lots of resources and proper guidelines to complete the work. A special thanks to the Emerson office to let me continue my work with them after my master's project, which helped me gain a better knowledge of their DeltaV system. A very special thanks to Rune Anderson from Emerson who has cordially helped and mentored me throughout the whole journey of my thesis by providing me resources as well as training on the MPC system on DeltaV. In addition, a lot of thanks to Per.Fylkesnes who helped to build a platform to communicate the Quadruple tank system with the DeltaV as well as calibrating the sensors and the HMI for the process.

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Nomenclature

γ = The coefficient for the flow proportion of three-way valve

q_i = Flow from the tanks

K_p = Pump gain

\dot{m} = Mass flow

\dot{V} = Volumetric flowrate

a_d = Cross-sectional area of the valve

c_d = valve coefficient

δp = valve pressures drop

A = Tank area

L = Prediction horizon

x_k = state of the process

J_k = Objective function

C_i = extended controllability matrix

DC_M = impulse response matrices

u = process input

y = process output

d = Dead time

E_p = The error vector of dimension p

Γ^u = Penalty matrix for POM

Γ^y = Penalty matrix for POE

ARX- Auto-Regressive with eXternal inputs

AV- Constraint Variable

CV- Controlled Variable

DV- Disturbance Variable

FIR- Finite Impulse Response

LP- Linear Programming

MIMO- Multiple Input Multiple Output

MPC - Model Predictive Control

MV- Manipulated Variable

P&ID- Piping and Instrumentation Diagram

POM- Penalty on Moves

POE- Penalty on Error

SISO- Single Input Single Output

SP- Setpoint

TSS- Time to Steady State

1 Introduction

In the 21st century, global engineering has evolved for multidimensional purposes. With the evolvement of engineering, the industrial process has gained its peak at its highest. Multifunctional equipment introduced MIMO process, which can efficiently take control of the system. But conventional PID has its own limitation to control the multivariable process along with cross-coupling as it can generally work on a single-loop controller because of their limitation over receiving information of one process variable. With time industrial interest has moved to a multivariable process to make production and control systems more convenient. With the rising interest in the multivariable control system, Karl Henrik Johanson introduced the Quadruple tank process back in 1998. The quadruple tank process is a multivariable process with four cross-connected tanks which can induce multivariable characteristics.

In this introductory chapter, an overview of the quadruple tank process and its functionality, how it can be controlled with Model predictive control, especially with the DeltaV control system, will be discussed.

1.1 Background

The oil, gas, chemical industries, refineries, food industries have developed their control system to bring out more efficiency. To make this happen process control section has introduced MIMO (Multiple Input Multiple Output). The process got complex with more than one input and output. Each input can control multiple output signals. So the complexity of the control system because of multiple interactions between input and output makes it difficult in comparison to the general SISO system. So to understand the problem and make it easily accessible as mentioned earlier, The four tank system has been introduced. The simulation results of the quadruple tank process have been presented in [1]. Experimental results of the quadruple tank process have been published by e.g David Di Ruscio who presented a Model Predictive Control algorithm with integral action with experimental results obtained from the quadruple tank process in [2]. A linear discrete-time state-space realization of the Kalman filter used on the quadruple tank process was presented in [3].

System identification and model predictive control of the quadruple tank process model

was covered in [4], and system identification has also been covered in [5].

In USN, the four-tank system has been developed, and a different controller along with Multivariable PI(D) had been introduced to solve different linear and non-linear models [3]. Besides different control module has been tested on the rig such as IMC(Internal Model control), DMC(Dynamic Matrix Control) and also The model predictive controller with integral action.

Even though the previously different controller has been working on the Quadruple tank, a proper DeltaV controller with MPC pro has never been introduced to test with. So, the thesis will lead to a proper investigation of how the controller will handle the multivariable system.

1.2 Objectives

The main objective is to find a proper model that can control the four-tank system efficiently with the DeltaV controller's MPC Pro block. As the quadruple tank has 2 output, 2 input, and 4 states, it is necessary to have a proper model to control the system in a way that can handle all the parameter changes as especially the disturbance. With the help of the MPC Pro block in DeltaV, the system-wide range of data will be gathered, and with the state estimation and step response model, a proper model is needed to be developed. And to make sure the model which has been created has to be robust for any circumstances. So, in detail, the objectives can be achieved by ensuring the proper control variable, manipulated variable, disturbance variable, and a proper constraint, which will lead to the design of a controller by the MPC pro block for the advance control system. A proper stable system has to be achieved with manual calibration to start the test section. After the test process, a proper system identification in DeltaV from the subspace model will be made. This will give a model that will generate the controller for the quadruple tank system. The main goal is to have a controller that will handle any kind of sudden change or a wider operational range for practical use in industry.

1.3 Thesis Outline

The whole thesis description will be discussing the whole scenario from the development of model establishment to practical implementation of the model to the DeltaV. Each part of the description will be divided into a different section.

Chapter 1 will provide an overview of the outline for the quadruple tanks system and the previous work that had been done on this system.

Chapter 2 will give a detailed overview of the quadruple tank system describing the hardware as well as the behaviour of the process

In chapter 3 describes the model development of the MPC from the non-linear and non-linear model.

Chapter 4 will give a brief discussion about the MPC strategy in DeltaV.

In chapter 5, the Configuration of MPC in DeltaV has been discussed. The step test strategies have been discussed precisely in this chapter

Chapter 6 will give an in-depth comparison of different model verification and its result

Chapter 7 will discuss the results, and the problem has been faced as a discussion throughout the thesis

In chapter 8 concludes the overall thesis result finishing with some recommendations for future work.

2 System overview

This chapter will give an overview of the Quadruple tank process describing the comprehensive overall aspects of the physical system as well as its mathematical functions, the hardware descriptions, and the software that will be used. The process is located at Emerson's Porsgrunn office. To have a proper module, all the physical equipment must be tested properly so that they do not have any difficulties, and that will lead to developing a controller for the system with the DeltaV MPC after developing a proper module.

2.1 Quadruple Tank process

The physical rig of the quadruple tank process consists of four tanks, which is a multivariable process. The four-tank system is built in a way so that they are cross-coupled. The input for the process, which is controlling the overall system, is two pumps. The system has a reservoir, which is shown in figure 2.1, reserves the liquid for the whole system. Each pump work on the reservoir to pump water to one upper tank as well as one diagonally implemented lower tank. Two valves work as three-way valves to distribute the water to all the tanks. Each valve is connected to an upper tank and a diagonally situated lower tank. The distribution of water is determined or controlled by the position of the three-way valve. A signal to the three-way valve controls the opening of the valves for the upper tank. Every tank has discharge valves which can be manipulated manually. The upper tank will flow out the water to the lower tank, which will eventually introduce the disturbance to the system. The lower tank flows out the water to the reservoir.

2 System overview

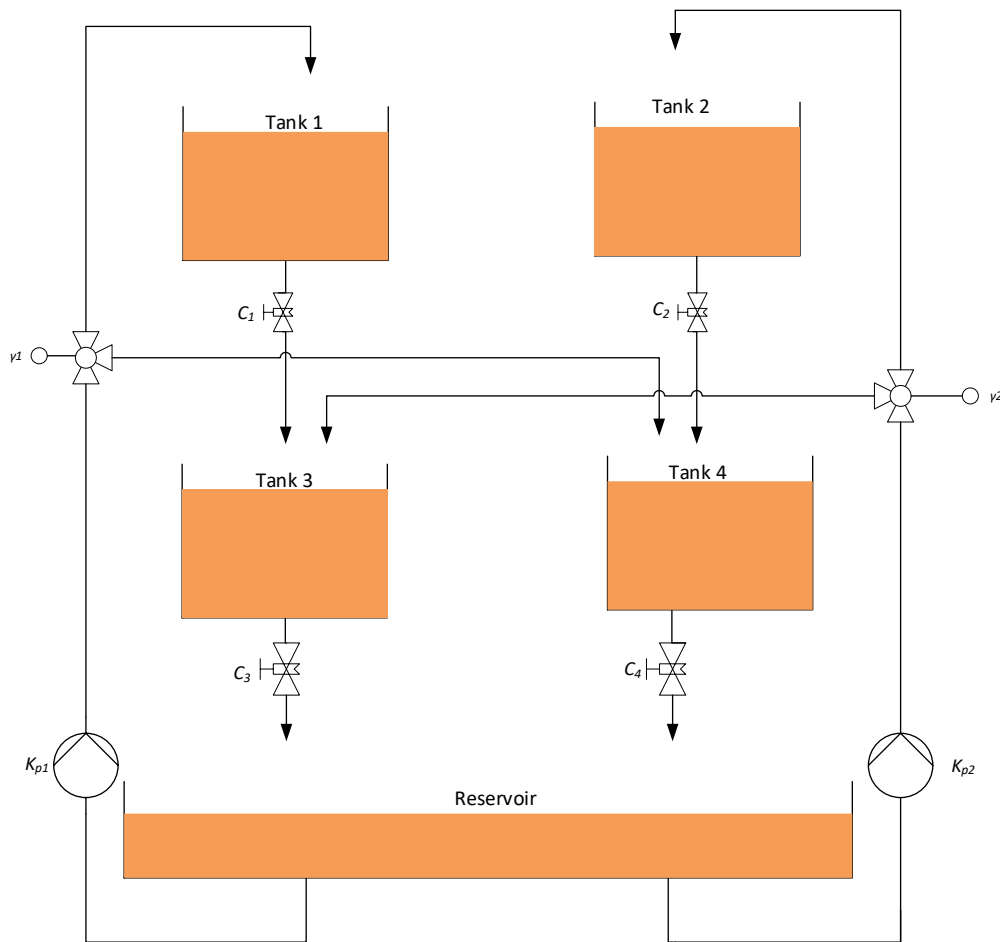


Figure 2.1 Quadruple tank process diagram

Each valves discharge coefficient for the water discharge can be defined cw_i for the discharge valve i ., the gain for the pump can be defined as K_p . The coefficient for the flow proportion of the three-way valve is γ . Where $\gamma=0$ means all the flow of water will go to the upper tank, and $\gamma=1$ means all the flow will go to the lower tank. So, for each valve, the γ can be defined as the equation mentioned in (2.1)

$$\gamma_1 = \frac{q_1}{q_1 + q_4}, \gamma_2 = \frac{q_2}{q_2 + q_3} \quad (2.1)$$

2 System overview

Where q_i described as the flow from the tanks, and i defined as the tank number. As a result, the upper tank flow can be described as $0 \leq \gamma \leq 1$, and that gives us the proportion for the lower tanks is $(1-\gamma)$.

As the primary concern is to control the lower tanks, including the disturbance added by the upper tanks, so the lower tanks parameter is considered as the controlled variable. Among the two pumps, the pump 1 delivers water to tank 1 and 4, and on the other hand, pump 2 provides the water to the tank 2 and 3. So the cross-coupling process gives us a complex multivariable process.

2.2 Hardware

The hardware of the quadruple tank consists of 2 pumps, 4 tanks, 4 level sensors, 6 flow sensors, and a two three-way valve. The measurement of the water level is captured by the ultrasonic sensors, which represent the level with voltage from 0 to 10v that has been converted to 0 to 332 mm as level. The flow sensor operates with frequency from 0 Hz to 60 Hz, and then it has been translated to a voltage signal of operating range between 0v to 5v using an Arduino. The manipulated variable is the pumps that can be controlled with the voltage range of 0V to 10V. To operate the pump a Boolean signal is sent. The ideal speed of the pump is equivalent to 2v. The three-way valve is used by translating its operating voltage to app measurement, which indicates the range from 0 to 1. As discussed earlier, if the operating point is 1 it means only the lower tank is opened. But with the increased signal from zero to 1, the three-way valve distributes water to the upper tank as well. And the discharge valve of each tank is kept in a proper position so that the tank does not go empty or fulfilled while it's in its controlled operation mode.

P&ID symbol list has been discussed here

Tag	Description	Comment
LT1	Level transmitter 1	Measures level in tank 1
LT2	Level transmitter 2	Measures level in tank 2
LT3	Level transmitter 3	Measures level in tank 3
LT4	Level transmitter 4	Measures level in tank 4
FT1	Flow transmitter 1	Measures flow to tank 1
FT2	Flow transmitter 2	Measures flow to tank 2
FT3	Flow transmitter 3	Measures flow to tank 3
F14	Flow transmitter 4	Measures flow to tank 4
FI5	Flow transmitter 5	Measures flow from pump 1
FT6	Flow transmitter 6	Measures flow from pump 2
γ 1	Three-way valve 1	Splits flow from pump 1
γ 2	Three-way valve 2	Splits flow from pump 2
P1	Pump 1	Pumps water to tank 1 and 4
P2	Pump 2	Pumps water to tank 2 and 3

3 Model development

This section will cover the theoretical model development of the system. It will be divided into two sections. One will describe the non-linear model development, and the other will describe the linear model development.

3.1 Non-linear model

Different model has been established for the quadruple tank system in different works of literature.

The four-tank system is a dynamic process means which will change with time, so it is compulsory to have proper knowledge of how the system behaves with time. The primary model that has been established here is obtained from the first principle of the law of mass. With the similarities between the mass flow equation and the process of the quadruple tank, it can easily be said that the accumulated mass of a tank is equal to mass flow into the tank minus the mass flow out of the tank. As the water in each tank has a constant density, so the level of the water follows the accumulated mass of the tanks water, which gives us the equation 3.1

$$\frac{dm}{dt} = \dot{m}_{in} - \dot{m}_{out} \quad (3.1)$$

\dot{m}_{in} = mass flow into the tank

\dot{m}_{out} = mass flow out of the tank

Converting the mass terms to the volumetric flow gives us

$$\begin{aligned} \rho \frac{dV}{dt} &= \dot{V}_{in}\rho - \dot{V}_{out}\rho \\ A \frac{dh}{dt} &= \dot{V}_{in} - \dot{V}_{out} \\ \frac{dh}{dt} &= \frac{\dot{V}_{in} - \dot{V}_{out}}{A} \end{aligned} \quad (3.2)$$

3 Model development

h = water level of the tank

\dot{V}_{in} = incoming volumetric flow rate to the tank

\dot{V}_{out} = outgoing volumetric flow rate of the tank

A = area of the tank

As the system consisting of the four tanks has the same area, so $A_1=A_2=A_3=A_4=A$.

To establish the model, it is necessary to have a clear idea about the inflow and outflow of the tanks. The upper tank gets the water through the pump from the reservoir. The flow into the upper tanks is the ratio of the distributed water coming from the pump through the three-way valve, and the flow out of the upper tank is the water going through the discharge valve connected to the end of the tank. The lower tank also has distributed water through the three-way valve in addition to the discharge flow of the upper tank, and the flow out for the lower tank can be described as the discharge flow of water through the discharge valve. So, it is necessary to include the pumps, three-way valves, and the discharge valves.

Using the Bernoullis equation [6], the flow can be determined through the discharge valve.

$$\dot{V} = a_d c_d \sqrt{\frac{2}{\rho} \delta p} \quad (3.3)$$

\dot{V} = volumetric flow rate of the valve

a_d = cross-sectional area of the valve

c_d = valve coefficient

δp = valve pressures drop

The pressure drop must be considered here, which is equal to the hydrostatic pressure of the bottom of the tank because of the atmospheric pressure which is present above the water column and on the outlet of the valve.

So, after simplifying the valve equation and collecting all the constants, the resulting equation developed in the equation (3.4). The flow here is dependent on the level.

$$\dot{V} = c\sqrt{h} \quad (3.4)$$

$c = a_d c_d \sqrt{2g}$ where g = gravity constant.

As the pump step response is not infinitely fast, the pump dynamics must be considered. But through the test process, it showed that even though the pump reaches its steady states fast enough to the related controlled variable of the tanks water level, which takes higher time to reach its stable states. So, neglecting the pump dynamics will reduce 2 extra states to establish the model. Considering the input and the output response, which is almost linear with a constant gain of the pump, each tank has been modelled separately, and the combination of the expressions merged into one gives the following continuous-time model for the tanks.

$$\begin{aligned} \frac{dh_1(t)}{dt} &= \frac{1}{A} [K_{p1}(1 - \gamma_1)u_1(t) - c_1\sqrt{h_1(t)}] \\ \frac{dh_2(t)}{dt} &= \frac{1}{A} [K_{p2}(1 - \gamma_2)u_2(t) - c_2\sqrt{h_2(t)}] \\ \frac{dh_3(t)}{dt} &= \frac{1}{A} [K_{p2}\gamma_2 u_2(t) + c_1\sqrt{h_1(t)} - c_3\sqrt{h_3(t)}] \\ \frac{dh_4(t)}{dt} &= \frac{1}{A} [K_{p1}\gamma_1 u_1(t) + c_2\sqrt{h_2(t)} - c_4\sqrt{h_4(t)}] \end{aligned} \quad (3.5)$$

As it is stated on Johansson [7] the quadruple tank process has its minimum and its non-minimum phase depending on the multivariable zero's location.

The system is at its minimum phase when the corresponding equation in (3.6) satisfied

$$0 < \gamma_1 + \gamma_2 < 1 \quad (3.6)$$

and the system to its non-minimum phase when equation (3.7) is satisfied

$$1 < \gamma_1 + \gamma_2 \leq 2 \quad (3.7)$$

As per Johansson statement the controllability of the tank is easy when it is in its minimum phase. For the whole experiment, the γ_1 & γ_2 is kept 0.7 and 0.8 for all simulations.

As the model is in its continuous form but to implement it should be transformed into the discrete form. As a continuous-time model can be discretized using the forward Euler's method shown in equation (3.8)

$$\frac{dh(t)}{dt} = \frac{h_{(k+1)} - h_{(k)}}{\Delta t} \quad (3.8)$$

$h_{(k+1)}$ = next time step

$h_{(k)}$ = present time step

Δt = step size

Applying the Euler's method to the equation (3.5) gives the equation (3.7)

$$\begin{aligned} h_{1(k+1)} &= h_{1(k)} + \frac{\Delta t}{A} \left[K_{p1}(1 - \gamma_1)u_{1(k)} - c_1 \sqrt{h_{1(k)}} \right] \\ h_{2(k+1)} &= h_{2(k)} + \frac{\Delta t}{A} \left[K_{p2}(1 - \gamma_2)u_{2(k)} - c_2 \sqrt{h_{2(k)}} \right] \\ h_{3(k+1)} &= h_{3(k)} + \frac{\Delta t}{A} \left[K_{p2}\gamma_2 u_{2(k)} + c_1 \sqrt{h_{1(k)}} - c_3 \sqrt{h_{3(k)}} \right] \\ h_{4(k+1)} &= h_{4(k)} + \frac{\Delta t}{A} \left(K_{p1}\gamma_1 u_{1(k)} + c_2 \sqrt{h_{2(k)}} - c_4 \sqrt{h_{4(k)}} \right) \end{aligned} \quad (3.9)$$

So, equation (3.7) gives the non-linear model of the system.

3.2 Linear model

To have a linear MPC, it is necessary to develop a linear approximation of the non-linear model. To obtain the model the non-linear model has been 1st linearized and then discretized. The linearization can be achieved by the approximation of the non-linear continuous-time differential equations. With the implementation of the first two-term of the Taylor series expansion [8] time differential equation of the continuous linear model is developed in equation (3.10)

$$\frac{dh(t)}{dt} = f(h^o, u^o) + \left. \frac{\partial f}{\partial h} \right|_{(h^o, u^o)} (h(t) - h^o) + \left. \frac{\partial f}{\partial u} \right|_{(h^o, u^o)} (u(t) - u^o) \quad 3.10$$

3 Model development

h^o = nominal value of state h

u^o = nominal value of state u

The value of h^o & u^o refers to the operating point of the corresponding states. The equation (3.10) can be rewritten by putting the values of $h(t) = (\delta h(t) + h^o)$ and $u(t) = (\delta u(t) + u^o)$.

$$\frac{d\delta h(t)}{dt} = \left. \frac{\partial f}{\partial h} \right|_{(h^o, u^o)} \delta h(t) + \left. \frac{\partial f}{\partial u} \right|_{(h^o, u^o)} \delta u(t) \quad (3.11)$$

The approximation of the non-linear differential equation that has been shown in (3.11) gives the linear model equation in (3.12).

$$\begin{aligned} \frac{d\delta h_1(t)}{dt} &= \frac{1}{A} \left[K_{p1}(1 - \gamma_1)\delta u_1(t) - \frac{c_1}{2\sqrt{h_1^o}} \delta h_1(t) \right] \\ \frac{d\delta h_2(t)}{dt} &= \frac{1}{A} \left[K_{p2}(1 - \gamma_2)\delta u_2(t) - \frac{c_2}{2\sqrt{h_2^o}} \delta h_2(t) \right] \\ \frac{d\delta h_3(t)}{dt} &= \frac{1}{A} \left[K_{p2}u_2\gamma_2\delta u_2(t) + \frac{c_1}{2\sqrt{h_1^o}} \delta h_1(t) - \frac{c_3}{2\sqrt{h_3^o}} \delta h_3(t) \right] \\ \frac{d\delta h_4(t)}{dt} &= \frac{1}{A} \left[K_{p1}\gamma_1\delta u_1(t) + \frac{c_2}{2\sqrt{h_2^o}} \delta h_2(t) - \frac{c_4}{2\sqrt{h_4^o}} \delta h_4(t) \right] \end{aligned} \quad (3.12)$$

The equation is expressed as the linear model equation, whereas if it needed to be described as a linear state-space model, the states, the derivatives, and the outputs as well as the input has to be expressed as a vector, and all the coefficient needs to be transformed into matrices which gives the state-space model.

Applying the continuous-time state-space model, which is

$$\begin{aligned} \dot{x} &= A_c x + B_c u \\ y &= C_c x \end{aligned}$$

Where

$$\dot{x} = \begin{bmatrix} \frac{d\delta h_1(t)}{dt} \\ \frac{d\delta h_2(t)}{dt} \\ \frac{d\delta h_3(t)}{dt} \\ \frac{d\delta h_4(t)}{dt} \end{bmatrix}, x = \begin{bmatrix} \delta h_1(t) \\ \delta h_2(t) \\ \delta h_3(t) \\ \delta h_4(t) \end{bmatrix}, u = \begin{bmatrix} \delta u_1(t) \\ \delta u_2(t) \end{bmatrix}, y = \begin{bmatrix} \delta y_1(t) \\ \delta y_2(t) \end{bmatrix}, C_c = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_c = \begin{bmatrix} -\frac{c_1}{2A\sqrt{h_1^o}} & 0 & 0 & 0 \\ 0 & -\frac{c_2}{2A\sqrt{h_2^o}} & 0 & 0 \\ \frac{c_1}{2A\sqrt{h_1^o}} & 0 & -\frac{c_3}{2A\sqrt{h_3}} & 0 \\ 0 & \frac{c_2}{2A\sqrt{h_2}} & 0 & -\frac{c_4}{2A\sqrt{h_4^2}} \end{bmatrix}, B_c = \begin{bmatrix} \frac{K_{p1}(1-\gamma_1)}{A} & 0 \\ 0 & \frac{K_{p2}(1-\gamma_2)}{A} \\ 0 & \frac{K_{p2}\gamma_2}{A} \\ \frac{K_{p1}\gamma}{A} & 0 \end{bmatrix}$$

Using the Forward Euler's method on this state-space model discretized model has been achieved in equation (3.13)

$$\begin{aligned} x_{(k+1)} &= x_{(k)} + \Delta t [A_c x_{(k)} + B_c u_{(k)}] \\ y_{(k)} &= C_c x_{(k)} \end{aligned} \tag{3.13}$$

$$\begin{aligned} x_{(k+1)} &= (I + \Delta t A_c) x_{(k)} + \Delta t B_c u_{(k)} \\ y_{(k)} &= C_c x_{(k)} \end{aligned}$$

Comparing the model with the standard form, which is

$$\begin{aligned} x_{(k+1)} &= A_d x_{(k)} + B_d u_{(k)} \\ y_{(k)} &= C_d x_{(k)} \end{aligned} \tag{3.14}$$

The A_d, B_d, C_d can be written as following $A_d = (I + \Delta t A_c), B_d = \Delta t B_c$ and $C_d = C_c$.

4 Model predictive control

This chapter will represent the concept of MPC with an explanation and illustration. The basic concept of MPC and its theory is going to be explained along with the explanation of how the prediction model is derived from the state-space model. In this chapter, the DeltaV MPC system will be introduced as well, along with the implementation algorithm of MPC in DeltaV. For the DeltaV MPC algorithm explanation, the DeltaV online is the reference document here. Most of the theory represented here for the model development of MPC in DeltaV is described with the help of DeltaV book online [9].

4.1 Introduction to MPC

The evolution of MPC starts with the concept of optimal control theory developed back in 1960 by Kalman et al [10]. In 1970 implementation of various MPC control had been reported. At that time, the technology was developed on the base of DMC (Dynamic matrix controller) and IDCOM (Identification and command) concept. The strategy behind the MPC was to develop a control system that could give a prediction on the systems' dynamic behaviour on the basis of its future control action with the help of keeping its predicted error minimized that subjects to process constraints. Later the QDMC (Quadratic Dynamic Matrix Control) had been developed and added to the MPC back in 1980. In 1990 a lot of strategies such as PCT, SMOC (Shell Multivariable Optimizing Controller), Predictive Control Strategy, HIECON (Hierarchical constraint control), RMPC (Robust model predictive control) had been included in MPC. Later in 1998, besides all these Dynamic Model Control Package, DMC- plus had been introduced to MPC.

MPC works by defining each time step and using on those time steps to create and solve a new optimization problem. It makes a model by observing the system's dynamic behaviour over time and including all constraints and disturbances as well. The MPC can predict future states and outputs from the current scenario. With the help of a constructed model for the MPC optimization, it can predict the model's behaviour, like how the outputs should be changed for the future over a prediction horizon. When the model has been developed, the MPC works over it to understand its dynamic behaviour and act over each control interval over the predicted

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horizon by including new control input according to the change of the system due to any disturbance or sudden changes and fed it into the control system at each time step considering the constraints. Previously the PID control system has its popularity for its robust control system over SISO. But as the MIMO system has been introduced and it included the constraints, the PID couldn't cope up with its limitation, and MPC takes over the place as it can easily handle constraints that are integrated into the MPC system. MPC can also control the MIMO system in a better way because of its advanced control architecture on handling the interaction of controller variables as well as delays.

The traditional feedback loop controller determines the errors by measuring the difference between the setpoint and the process value and adjust thereby. On the other hand, MPC adjusts the error by determining the future setpoint, and the future predicted values (Blevins et al, 2013).

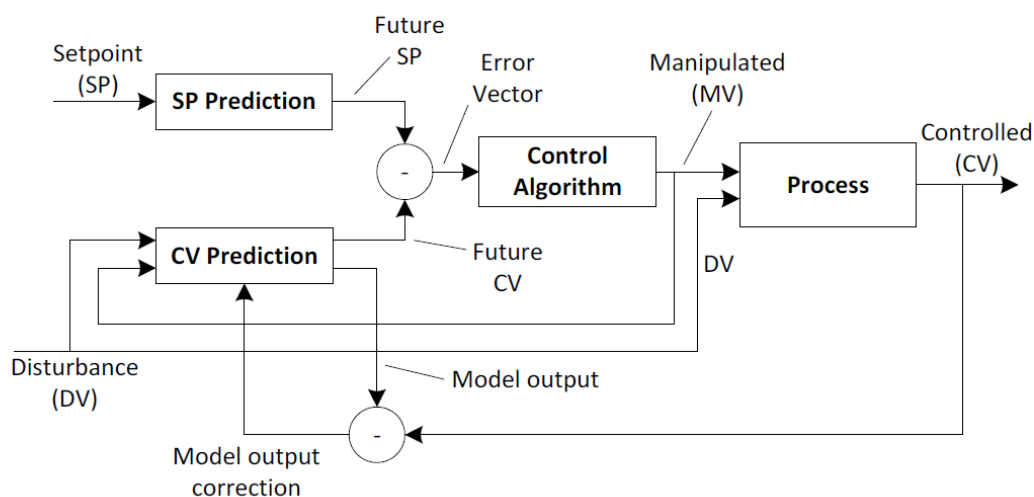


Figure 4.1: MPC Controller operation principle (Blevins et al, 2013)

Figure 4.1 demonstrates the MPC controller principle where the feedback flow indicates two process inputs being the manipulated variable (MV) and the disturbance variable (DV), and the output process variable is the control variable (CV). The figure shows the CV prediction works on the process model over a prediction horizon, which gives the output of the CV. Then the SP prediction goes along with the same prediction horizon as earlier. Then comes the control algorithm where it detects the error by measuring the difference between the SP prediction and

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CV prediction, and at the same time, the algorithm works on keeping the error as minimum as possible with proper optimization.

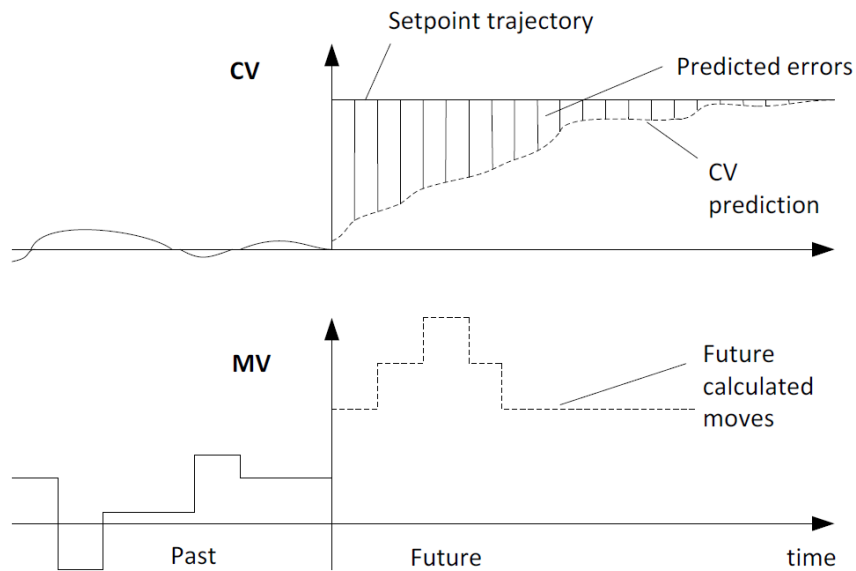


Figure 4.2: Illustration of MPC controller operation (Blevins et al, 2013).

Depending on the present scenario and calculation, the MPC controller predicts the dynamic behaviour of the process and calculate thereby. The future calculation does not change even the control horizon ends, which is defined by the sample number in a prediction horizon. When the prediction horizon moves forward, the MPC controller depending upon the model had been created, and the current situation predicts the future process output again and changes thereby.

The major drawback of the MPC system is the model must be developed before the controller is implemented, which takes a lot of time. Furthermore, the computational time as well as real-time applications on the implementation, is really an issue here.

According to the (Di Ruscio, 2012) the MPC algorithm consists of the following:

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- Cost Function

The cost function or also known as the control objective defines the criteria by maximizing the product value while keeping the material cost minimum or in different approach in the control system is where the future output and specified reference helps to track an error which needs to be minimum. In both scenarios, the main objective function is solved by two famous methods, which are Linear Programming (LP) and Quadratic Programming (QP). In LP, the solution can be found in the inequality constraints and in QP does not depends that much on inequality constraints.

- Constraints

Constraints can be defined as the limitation of a model or system that has to be fulfilled or satisfy. MPC has the ability to handle constraints as it is integrated into the system. In general, the constraints can be classified into two kinds- one is equality, and another one is inequality constraints. The equality constraints define the dynamic behaviour of the system, and the inequality constraints define the upper and the lower bound

For example, the system input amplitude constraints can be written mathematically as

$$\Delta u_{k|L}^{min} \leq u_{k|L} \leq \Delta u_{k|L}^{max} \quad (4.1)$$

Also, the process output constraints can also be written as

$$y^{min} \leq y_{k+1|L} \leq y^{max} \quad (4.2)$$

Here

L= prediction horizon.

- Process model

The MPC process model includes a future prediction control over a prediction horizon. The relation between the future process output and the input is described in the process prediction model. The Process Model can be developed through a different procedure such as impulse response model, step response, state-space model, DRX, ARMAX model etc. It is an integrated part of the process.

4.1.1 Prediction model from the state-space model

Among the popular methods of the MPC State-space model is the favoured one because of its straightforward derivation. Other models like ARX, transfer function, Finite Impulse Response (FIR) need to be transformed into the state-space model, and it's relatively more comfortable to use in MPC.

The general form of the state-space model followed by

$$\begin{aligned}x_{k+1} &= Ax_k + Bu_k \\y_k &= Dx_k\end{aligned}\tag{4.2}$$

And the prediction model goes by

$$y_{k+1|L} = F_L u_{k|L} + p_L\tag{4.3}$$

Here

$$\begin{aligned}F_L &= [O_L B \quad H_L^d] \\p_L &= O_L Ax_k\end{aligned}$$

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x_k = state of the process, which can be calculated simply from the known past inputs and outputs as shown by Di Ruscio [11]

O_L = observability matrix of A and D

L = Prediction Horizon

$F_L \in \mathbb{R}^{Lm \times Lr}$ which is a matrix derived from the process model

H_L^d = Toeplitz matrix of the impulse response

$p_L \in \mathbb{R}^{Lm}$ is a vector of inputs and outputs

If it is not possible to measure the state or compute it, then estimation using the state observer, for example, Kalman filter, is also an option.

The objective function defined as follows

$$J_k = (y_{k+1|L} - r_{k+1|L})^T Q (y_{k+1|L} - r_{k+1|L}) + u_{k|L}^T P u_{k|L} \quad (4.4)$$

Here

$u_{k|L}$ and $y_{k|L}$ is the process input and output

J_k = Objective function

| $r_{k|L}$ = reference

Q | and P are symmetric and positive weighting matrices

By reducing the standard form to a quadratic form and substituting p_L in the function, the following form is

$$J_k = u_{k|L}^T H u_{k|L} + 2f^T u_{k|L} + J_0 \quad (4.5)$$

Here

$$H = F_L^T Q F_L + P$$

$$f = F_L^T Q (P_L - r_{k+1|L})$$

$$J_0 = (P_L - r_{k+1|L})^T Q (P_L - r_{k+1|L})$$

By minimizing the J_k objective function with respect to $u_{k|L}$ the optimization problem can be achieved. Here $u_{k|L}^* = -H^{-1}f$.

4.1.2 Prediction model from FIR and Step response model

Another way of developing model of prediction is FIR and step response model. The state-space model defined earlier gives an expression for

$$y_k = DA^i x_{k-i} + DC_i u_{k-i|i} \quad (4.6)$$

C_i = extended controllability matrix

If the system is stable, then $A^M \approx 0$ when $M = i \geq 1$ is large, which gives the following

$$y_k = DC_M u_{k-M|M} \quad (4.7)$$

Here

DC_M = impulse response matrices

M = model horizon

The equation gives the FIR model. The model can express y_{k+1} and subtracting y_k from the equation gives

$$y_{k+1} = y_k + C_M \Delta u_{k+1-M|M} \quad (4.8)$$

$$\Delta u_{k+1-M|M} = u_{k+1-M|M} - u_{k-M|M} \tag{4.9}$$

Equation (4.8) and (4.9) gives the prediction model

4.2 Introduction to DeltaV MPC strategy

DeltaV is a DCS automated platform for process management by Emerson. It has a very reliable platform to work in process interaction in a robust technical environment. DeltaV has a unique option to deal with the advanced control system. In advance control system, it has MPC block, which can deal with the interactive process, which needs to be controlled by keeping the disturbances as well as constraints into consideration.

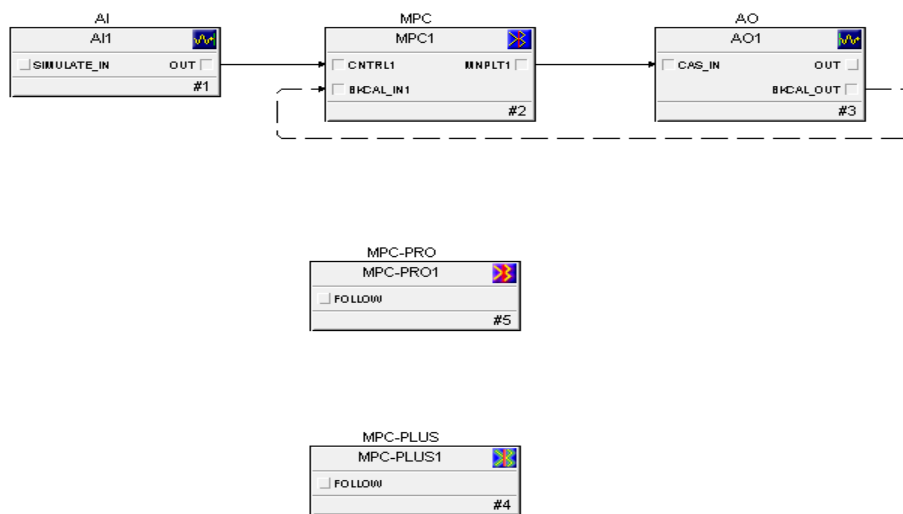


Figure 4.3 MPC blocks in DeltaV

Figure 4.3 shows the three kinds of MPC block available in DeltaV explorer, which are MPC (DeltaV v7 or later), MPCPro (DeltaV v9 or later) and MPCPlus (DeltaV v12 or later).

The MPC block uses a wiring connection regarding the input and output, whereas MPC-Pro or MPC-Plus uses the user reference to indicate the input and output. In the DeltaV the advance

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control system is consists of DeltaV predict, which includes the MPC block, and the other one is DeltaV predict pro, which consists of the MPC-pro and MPC-plus. All the MPC blocks have the dynamic controller, which calculates the control output, keeping error (the difference between the setpoint and the model prediction) minimum through linear modelling. Both DeltaV predicts, and the predict pro has a different application; for example, the DeltaV predict opens up in the control studio where it connects and defines the variables such as Control Variable, Disturbances or the Manipulated Variable through the wiring mainly in cascade system on the other side the DeltaV predict Pro includes the block in the control studio and define the variables through references. The variables have been described in the DeltaV explorer. Both have an advance control or advance control pro platform where the test procedure, as well as the development of the model can be configured. They also have different window such as the expert to manipulate the process variables and the simulation window as well.

The DeltaV Predict Pro can handle more process interaction than the DeltaV Predict, and it also has more optimization capabilities, which makes it more convenient when it comes to advance control. The MPC block in the DeltaV Predict has capacities up to 8x8 input/output process variable configuration. It has the capability of pushing the process variable to its maximized ability by maintaining the process with its constraints. It runs in the controller studio or in the application station. The DeltaV Predict Pro has more extensive capabilities when it comes to processing the variables as it has a 40x80 input/output configuration. The MPC Pro and MPC Plus have Linear programming embedded in the system to support the process optimization. They can define at most 5-objective function. As the MPC- plus can work online, it has the ability to determine any changes or operating constraints or integrating process. MPC-plus can execute only in the application station.

The MPC block consists of the following input

- Controlled variable (CNTRL): The MPC input which has to maintain the setpoint by manipulating the MV
- Disturbance (DSTRB): The input which has impact on constraints and the controlled parameter.

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- Constraint (CNSTR): the constraints variable is the operating limit for the controlled variable

And the output is the following one

- Manipulated variable (MNPLT): the MPC output, which is adjusted for the desired controlled setpoint, needs to be achieved automatically or manually by the operator.

4.2.1 Model development and identification in DeltaV

In the DeltaV predict or predict pro application, the model development goes through the step response method, which is configured in the application. The application runs a test process that has an automated step response to work on the process and gives the data for the model development. But external data can also generate the model.

For the SISO system, the prediction model for the process output can be written in the general form as follows-

$$x_{k+1} = Ax_k + B\Delta u_k + F\Delta w_k \quad (4.10)$$

$$y_k = Cx_k \quad (4.11)$$

Here

- $x_k = [y_0, y_1, y_i, \dots, y_{p-1}]^1$ is the vector for the future prediction at time $k = 0, 1, \dots, i, \dots, p-1$ steps ahead.
- A is here the shift operator which is $Ax_k = [y_1, y_2, \dots, y_i, \dots, y_{p-1}, y_{p-1}]^T$
- B is the vector for the step response coefficient of p where $B = [b_0, b_1, \dots, b_i, \dots, b_{p-1}]^T$
- $\Delta u_k = u_k - u_{k-1}$ is process input/output change in controller output at constant time k

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- $\Delta w_k = y^p - y^m$ is considered as the noise or the disturbance or model inaccuracy measured by calculating the difference between process output measurement and model output.
- $F = [f_0, f_1, f_i \dots f_{p-1}]$, $0 < f_i < 1$ is the filter for Δw_k
- C is defined as $y_0 = C x_{k+1}$ the operator for the current model output

For m input and n output process vector x_k has $n \times p$ dimension. B vector is then converted into a matrix of dimension $n \times p$ rows and m columns.

In DeltaV Finite Impulse Response (FIR) and Auto-Regressive with eXternal inputs (ARX) methods are used to identify the step response model for the model development. These methods are used for step response models, which define the future process output and future control process input relationship. The two modelling techniques are used to transfer the identified information from the FIR to ARX. FIR has the upper hand while it comes to required preliminary knowledge, which is not needed here, while ARX makes the calculation easier as it uses fewer coefficients. FIR, for example, can give overfitting problems if it needs to deal with the full default prediction horizon in DeltaV.

But using a shorter prediction horizon, FIR can identify dead time measurement, and ARX can determine better. For the SISO process, the FIR model can be described as follows

$$\Delta y_k = \sum_{i=1}^p h_i \Delta u_{k-1} \quad (4.12)$$

Here

Δy_k = change in process output at a time constant k .

h_i = coefficient of the identified model impulse response

Δu_{k-1} = change of process input at time $k-1$ and p in prediction horizon.

And for the SISO model ARX model is defined as follows

$$y_k = \sum_{i=1}^V a_i y_{k-1} + \sum_{i=1}^A b_i u_{k-d-i} \quad (4.13)$$

u = process input

y = process output

A and V are the autoregressive and moving average order of the ARX model, which has a default value of 4

a_i and b_i = model coefficient

d = Deadtime

if the process is a MIMO process in both input and output, Superposition is applied in FIR and ARX model.

4.2.2 Dynamic Controller

While developing the controller in the MPC or MPC Pro block, the number of MV should be equal or greater than the number of CV so that the dynamic controller become square. If the MV's are fewer than the CV's, it will provide limited compensation for the block. But in the MPC plus, the MV does not need to greater or equal as all the output and input will go to the controller. The previous chapter described the dynamic relationship between the input and outputs. Even though the implementation might differ in a different block, but the dynamic controller is the same.

A step response vector can be created in every Δt seconds, which can be defined as a vector of a like following:

$$a = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ \vdots \\ a_n \end{bmatrix}$$

The a vector should be identified in every pair of input/output. In DeltaV $n= 120$ and $\Delta t = (\text{Time to Steady State (TSS)}) / n$, here, TSS is defined as a change of time when the MV starts after CV hits the steady-state value.

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The future values of the output CV are predicted from the vector a . A Prediction vector has been created upon the change in input MV regarding the response of CV which defines the future changes in CV. $\Delta CV(t+p)$ is defined in the incremental form as following:

$$\Delta CV(t+p) = \begin{bmatrix} \Delta CV_1 \\ \Delta CV_2 \\ \Delta CV_3 \\ \vdots \\ \vdots \\ \Delta CV_n \end{bmatrix}$$

Here n defines the prediction changes in the prediction horizon.

The process steady state can be redefined by considering the prediction horizon p and the control horizon c as follows.

$$\Delta CV(t+p) = A * \Delta MV(t+c) \quad (4.15)$$

Here

A= gain matrix

A can also be referred as the dynamic matrix

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \cdots & \cdots & \cdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix}$$

The move plan can be defined as $\Delta MV(t+c)$ vector of changes in manipulating variable m

$$\Delta MV(t+c) = \begin{bmatrix} \Delta mv_1 \\ \Delta mv_2 \\ \Delta mv_3 \\ \vdots \\ \vdots \\ \Delta mv_m \end{bmatrix} \quad (4.15)$$

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For every change of controller output mv_i over the control horizon is defined as

$$\Delta mv_i = \sum_{j=1} \Delta mv_i(t+j), i = 1,2,3, \dots, m \quad (4.16)$$

The changes should satisfy on both MV's limits

$$\Delta MV_{min} \leq \Delta MV_{current} + \Delta MV(t+c) \leq \Delta MV_{max} \quad (4.17)$$

And CV's defines following

$$\Delta CV_{min} \leq \Delta CV_{current} + \Delta CV(t+p) \leq \Delta CV_{max} \quad (4.18)$$

The $\Delta MV(t+c)$ has shown the credential and the A has been used to calculate the $\Delta CV(t+p)$. The $\Delta MV(k)$ vector of future moves needs to be found which minimize the deviation between the setpoint trajectory $R(k)$ and the prediction vector $\Delta CV(k)$:

$$\min[(\Delta CV(k) - R(k))^2], k = 1,2,3, \dots, p \quad (4.19)$$

It can also be defined as the following one by substituting $\Delta CV(k)$

$$\min[(A * \Delta MV(k) - R(k))^2] \quad (4.20)$$

This referred to a dynamic objective function including a least square problem and that gives the solution as:

$$\Delta MV = (A^T A)^{-1} A^T E_p(k) \quad (4.21)$$

Here

E_p is the error vector of dimension p .

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By adding a penalty on $\Delta MV(k)$ this solution often leads to a oscillatory moves which gives more stable solution as the following:

$$\min[(A * \Delta MV(k) - R(k))^2 + (\Gamma^u \Delta MV(k))^2] \quad (4.22)$$

Here

$\Gamma^u = \text{diag}(\Gamma_{1,\dots,c}^u)$ is the penalty matrix for the Penalty of moves (POM) which is used to decrease the element changes in $\Delta MV(k)$, $k = 1, 2, 3, \dots, c$.

By introducing a penalty on the error for the prediction and setpoint the objective function becomes the following

$$\min[(\Gamma^y (A * \Delta MV(k) - R(k)))^2 + (\Gamma^u \Delta MV(k))^2] \quad (4.23)$$

Here

$\Gamma^y = \text{diag}(\Gamma_{1,\dots,p}^y)$ is the Penalty matrix o the Penalty on Error (POE)

The new dynamic objective function solution refers to the MPC algorithm which is unconstrained and gives the following

$$\Delta MV = (A^T \Gamma^{yT} \Gamma^y A + \Gamma^{uT} \Gamma^u)^{-1} A^T \Gamma^{yT} \Gamma^y E_p(k) \quad (4.24)$$

Here

$$\Delta MV = (\Delta MV(k), \Delta MV(k + 1), \Delta MV(k + 2), \dots, \Delta MV(k + c))$$

The equation (4.24) describes all the step response models of inputs and outputs and it is useful for controlling the process.

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The two factors of penalty here (POM) and (POE) are known as the tuning parameters to adjust the models robustness and the response speed. If the objective function needs to be smaller, the following the (POM) and (POE) has to be changed like the (POM) Γ^u needs to be increased during each element of $\Delta MV(k)$ needs to be decreased. This will make the controller less aggressive. But if the controller needs to be more aggressive, POE Γ^l has to be increased by keeping the $\Delta MV(k)$ larger, and this will make the objective function smaller.

The equation in (4.24) can be applied for the MPC and MPC Pro block. After generating or defining the step response method, then the model can be generated. In MPC or MPC Pro, after generating the model, the POM or the POE cannot be changed in MPC or in the MPC pro block online. If they need to be changed, they must be done by modifying the model again and regenerating and downloading the model.

As in the MPC plus block, the dynamic controller's subsection does not need to be squared mentioned earlier, and all the MV inputs directly go into the dynamic controller; the objective function for the MPC Plus block differs slightly than the usual equation of objective function defined in (4.23). So, the difference has a change in the interaction between the optimizer and the dynamic controller. The MPC pro and the MPC plus blocks optimizer calculate a steady-state for each MV. Referring to the constrained MPC algorithm, the dynamic objective function for the MPC plus must be modified as follows:

$$\min \left[(\Gamma^y(A * \Delta MV(k) - R(k)))^2 + (\Gamma^u \Delta MV(k))^2 + (\Gamma^0(\sum \Delta MV(k) - \Delta MVT))^2 \right] \quad (4.25)$$

Here

ΔMVT = Optimal target change of MV, which is calculated by the optimizer.

Γ^0 = Large penalty on error parameter and not usually used in the tuning parameter.

Then the optimizer calculates all the steady-state values through the modification, which forces the dynamic controller. ΔMVT can drive the process to its optimized state by changing all the

inputs. As the MPC Plus block works on the equation (4.24) in every execution it then allows the POE and the POM to change online. In PMC Plus, all the step gain can also be changed while the model is online in DeltaV.

4.2.3 Optimization

The main objective of optimization for a process is to maximize the product value and to minimize the production cost. The MPC block in the DeltaV is designed in a way to have the pusher capability, which allows the parameter either to be maximized or to be minimized through a simple optimization method. If the target rate is changed in the process, the MPC controller will push the parameters so that the target is achieved.

Handling of Output Constraint

The MPC controller handles the constraints in a way that if the predicted constraints break the limit, it changes the working setpoint of the controlled variables as following

$$\Delta SP_{CV} = -r G_{CV-AV} \Delta AV \quad (4.26)$$

Here

- ΔSP_{CV} = change of setpoint of the CV
- ΔAV = predicted steady-state constraint violation magnitude
- $G_{CV-AV} = G_{CV-MV} / G_{AVAV}$ is the gain relationship between AV and CV, fixed CV's setpoint for any violation of the constraints.
- r = relaxation factor

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In the optimization process if the limits of the constraints violated the return of the working setpoint changes in a sequence, for example, a process has 3 MV's and 2 CV's, so the third MV will work as the optimizing MV while another CV will be working as the virtual parameter as the shadow of the third MV.

The following steps are taken if the stated problem occurs

1. The First MV values go out of limit as it does not match the number of CV
2. To obtain the controllability, the CV setpoint is moved out from the optimal state by sacrificing the optimal control
3. The Excessive MV needs to move so that it can achieve the new setpoint for the virtual CV
4. As the excessive MV moves so, it causes a change in both 1st and 2nd CV
5. By pushing the 1st and 2nd CV back to its setpoints, the first MV moves to the point of limit direction.

The Linear Programming (LP) is embedded in the MPC block for process optimization.

The objective function is mainly used to express the profit and so the general problem can be described as (Lie,2013).

$$\min f(x) = c^T x \quad (4.27)$$

Subjects to,

$$\begin{aligned} A_e x &= b_e \\ A_i x &\leq b_i \\ x_L &\leq x \leq x_H \end{aligned} \quad (4.28)$$

Where

$f(x)$ = objective function

C = cost or profit vector

x = optimization variable

$A_e x = b_e$ are the equality constraints

$A_e x \leq b_e$ are the inequality constraints

$x_L \leq x \leq x_H$ is known as bounds which is also a kind of inequality constraint.

So the objective function for maximizing product or minimizing raw material cost can be defined following way:

$$Q_{min} = -UCV^T * \Delta CV(t + p) + UMV^T * \Delta MV(t + c) \quad (4.29)$$

Here

UCV = cost vector for a unit change in CV process value

UMV = cost vector for a unit change in MV process value.

Now applying the objective function regarding the MV gives the following equation

$$Q_{min} = -UCV^{-*} A^* \Delta MV(t + c) + UMV^T * \Delta MV(t + c) \quad (4.30)$$

For a two-dimensional problem such as 2 input and 2 output process, the LP solution is always located at one of the vertices. The following figure describes the problem

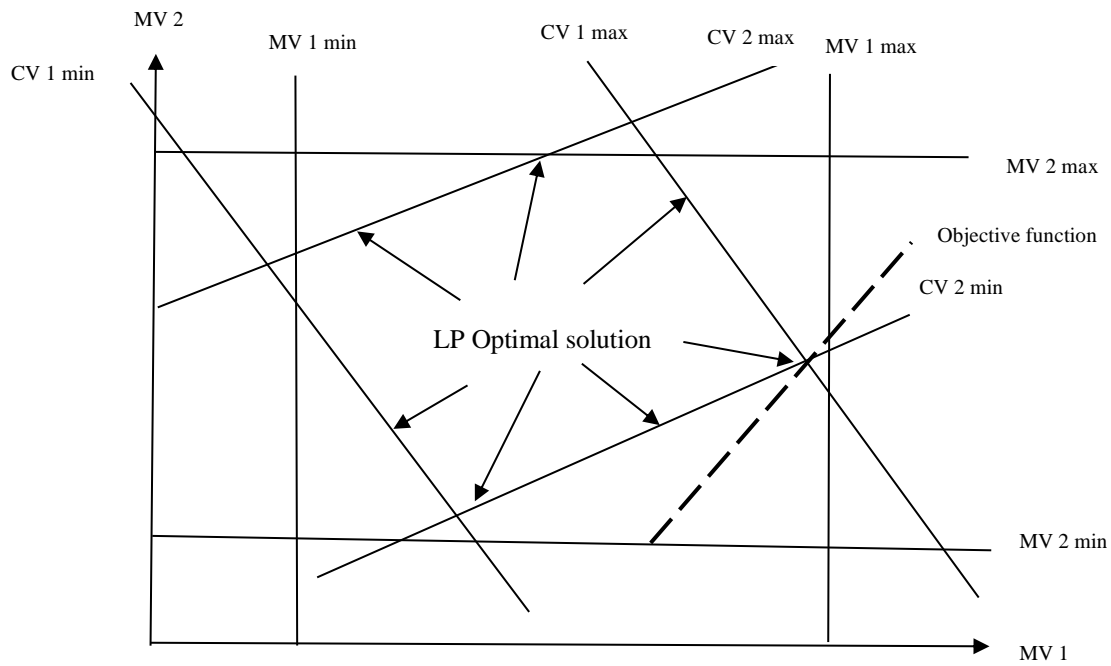


Figure 4.4 Optimization problem of a two-dimensional system

The straight lines represent the two Control variables (CV) and the two Manipulated variables (MV), and they represent the following equations:

$$CV1_{min} = a_{11}MV1 + a_{12}MV2 \quad CV1_{max} = a_{11}MV1 + a_{12}MV2 \quad (4.31)$$

$$CV2_{min} = a_{21}MV1 + a_{22}MV2 \quad CV2_{max} = a_{21}MV1 + a_{22}MV2 \quad (4.32)$$

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The optimal solution is located at one of the vertices marked by arrows. To find this solution, the LP algorithm calculates the objective function for an initial vertex and improves the solution every step until it determines the vertex with the maximum (or minimum) value of the objective function as the optimal solution. In addition to constraints and economic objectives, the Predict Pro Optimizer also accounts for controlled objectives that include target setpoints for any selected CV, preferred settling values and equalizing for selected MVs.

Optimal MV values are applied to the MPC Pro control as the target MV values to be achieved within the control horizon. If the MPC controller is squared as in the MPC Pro block, the number of MVs is equal to the number of CVs; then, MV targets can be effectively achieved by changing the CV value. The CV values then follow:

$$\Delta CV = A * \Delta MVT \quad (4.33)$$

Here

ΔMVT = optimal MV target

ΔCV = the change of CV to achieve the optimal MV

The MPC Plus controller applies both CV and MV targets as optimizer objectives with any configuration. This approach improves constraint handling. Additionally, MPC Plus generates the controller online, which accounts for actual constraints and objectives.

The option to include both CV and MV targets can be selected as well for offline MPC Pro controller generation. This improves constraint handling; however, since the controller is generated offline, it may not perform as well as the MPC Plus controller. Specifically, the MPC Pro controller will not use unconstrained MVs to compensate for constrained MVs, including MVs that are constrained by the Rate of Change (Max MV Move Per Sec) limit.

The MPC Pro algorithm working with the optimizer has two main objectives:

- Minimize CV control error with minimal MV moves within operational constraints
- Achieve optimal steady state MV values set up by the optimizer and target CV values calculated directly from MV values.

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In operation, the optimizer sets up and updates the steady state targets for the MPC unconstrained controller at every scan, thus MPC controller executes the unconstrained MPC Pro algorithm or the constrained MPC Plus algorithm. Since the targets are set in a manner that accounts for constraints, as long as a feasible solution exists, the controller works within constraint limits. Optimization, therefore, is an integral part of the MPC controller. The integrated MPC controller and optimizer performs the following sequence of operations each scan:

1. Update CV and DV measurement
2. Update CV prediction
3. Determine optimal MV steady-state targets and calculate CV targets by running LP optimizer
4. Determine dynamic MV outputs accounting for CV and MV targets by running the MPC controller
5. Update CV

The figure below gives an overview of the communication between the optimizer and MPC algorithm as well as the integrated operation

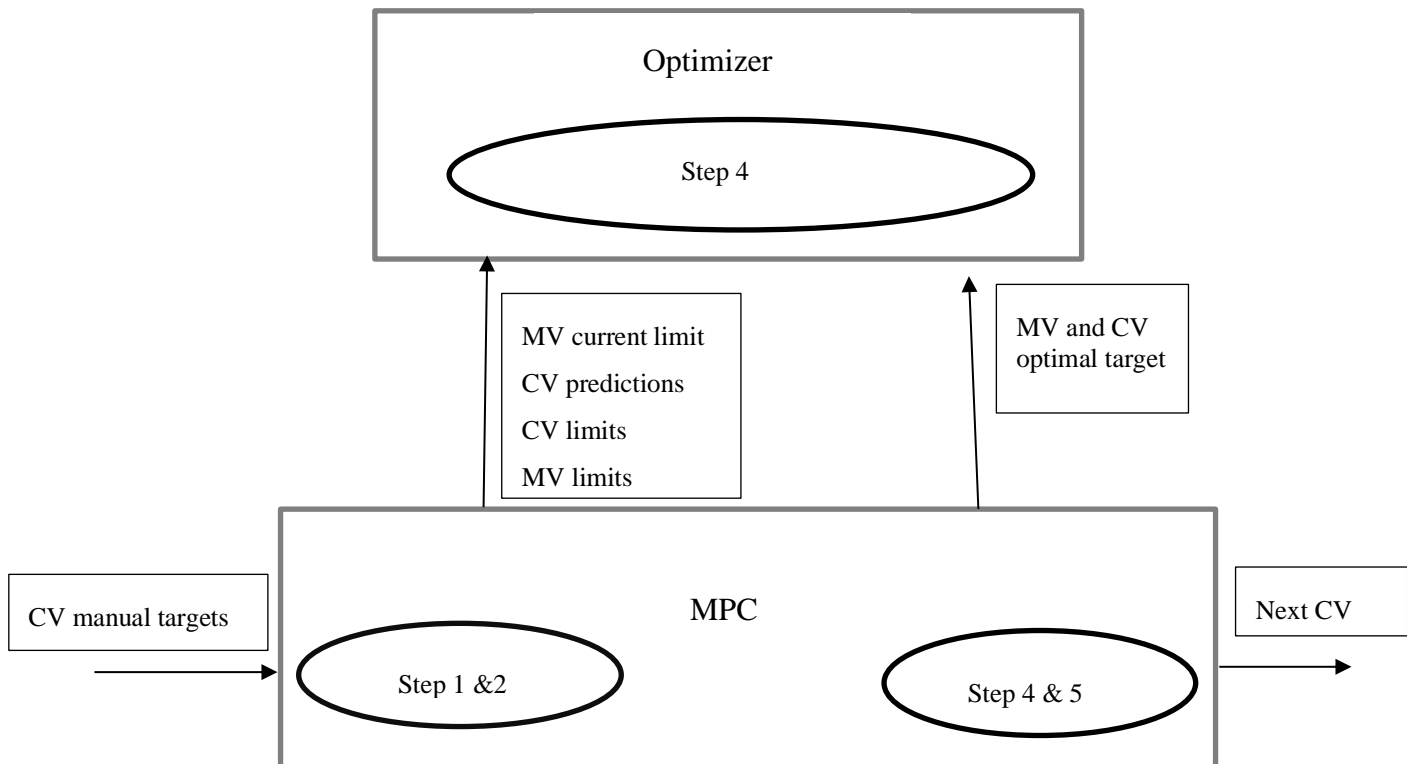


Figure 4.5 MPC and Optimizer communication

In some situations, the optimizer cannot find the optimal solution as the constraints limit is so tight. In such cases, the optimizer relaxes the system constraints by changing set points to range control (if defined) and/or abandoning some lower priority constraints.

Poor conditioning is another typical problem an optimizer has to deal with. As with the MPC algorithm, poor conditioning manifests itself as excessive changes in calculated MV targets, even for minor correction of constraints. In this approach, poor conditioning can be removed dynamically by changing the configuration of active constraints (abandoning some constraints) or by removing the association between Constraint or Controlled variables and Manipulated variables that have excessive moves.

4.2.4 Offline controller (MPC Pro)

After the model has been generated using the process model and the controller design, the MPC Pro controller has been generated. It can minimize the square error of controller variables and also the squared values of the changes in a manipulated variable over the control horizon prediction by providing stable operation and acceptable performance over a wide range of process parameter changes.

The POM parameter is the most convenient tuning parameter for the controller. The higher the value of POM gives a slow controller with a wide stability margin. This setting makes the controller insensitive to change if the process has errors. But with low POM makes the controller fast with a narrow stability margin. The dead time should be considered as a major factor for calculating the POM. Gain also influence the POM. The following equation the controller is designed for the worst-case, ensuring its robust controller operation:

$$POM_i = 3 \left(1 + \frac{6(DT_i + \Delta DT_i)}{p} + \frac{3(G_i + \Delta G_i)(DT_i + \Delta DT_i)}{p} \right) \quad (4.34)$$

5 Configuring MPC in DeltaV

This chapter will briefly discuss the MPC configuration in the DeltaV. From configuring the MPC Pro block following by configuring the model parameters as well as configuring the step test procedure.

5.1 Configuring the MPC Pro block

In this thesis, the MPC pro has been used. The MPC block has only an optimization option for CV, but MPC pro or the MPC plus can handle MV, CV and even the AV. In MPC Pro or the MPC plus optimization objectives can easily be changed as well as the parameter properties can also be redefined.

At the very first, the MPC Pro block has been appointed under a new area Named FOUR_TANK_MPC as MPC_LOOP_1

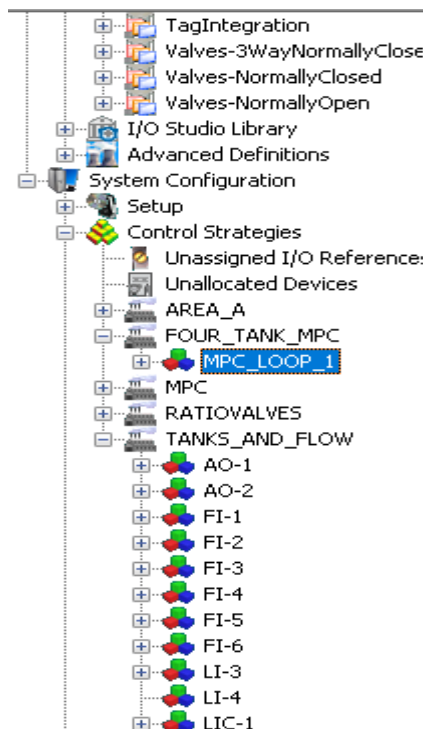


Figure 5.1 MPC assignment under area

After getting into the control studio of MPC_LOOP_1 other parameter can be assigned

Which has been discussed in the following section

5.2 Parameter configuration

After going to the configuration of the MPC pro block parameter such as CV, DV, MV, AV has been assigned through the reference for the output or input.

All the input and output such as Pump 1 and 2, Ultrasonic level sensor, two three-way valve and the flow transmitters have been configured before under area TANKS_AND_FLOW

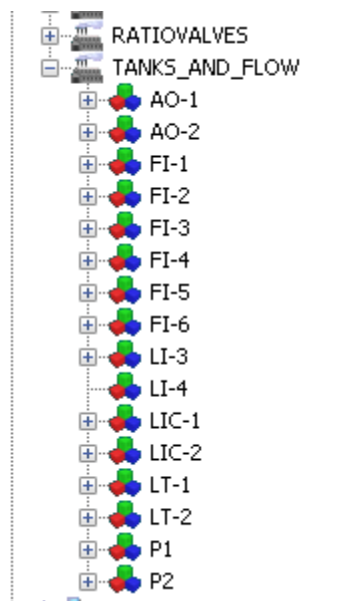


Figure 5.2 all different inputs and outputs

In this test, the control variables mean the tanks water level needs to be controlled are tank 3 and tank 4. The CV 1 and CV 2 are following by the tank3 and tank 4 level parameters. The reference has been taken from the alarm parameter of tank level denote as LI-3 and LI-4 as the alarm value has been forwarded to the parameter value (PV) from output from the level sensor.

5 Configuring MPC in DeltaV

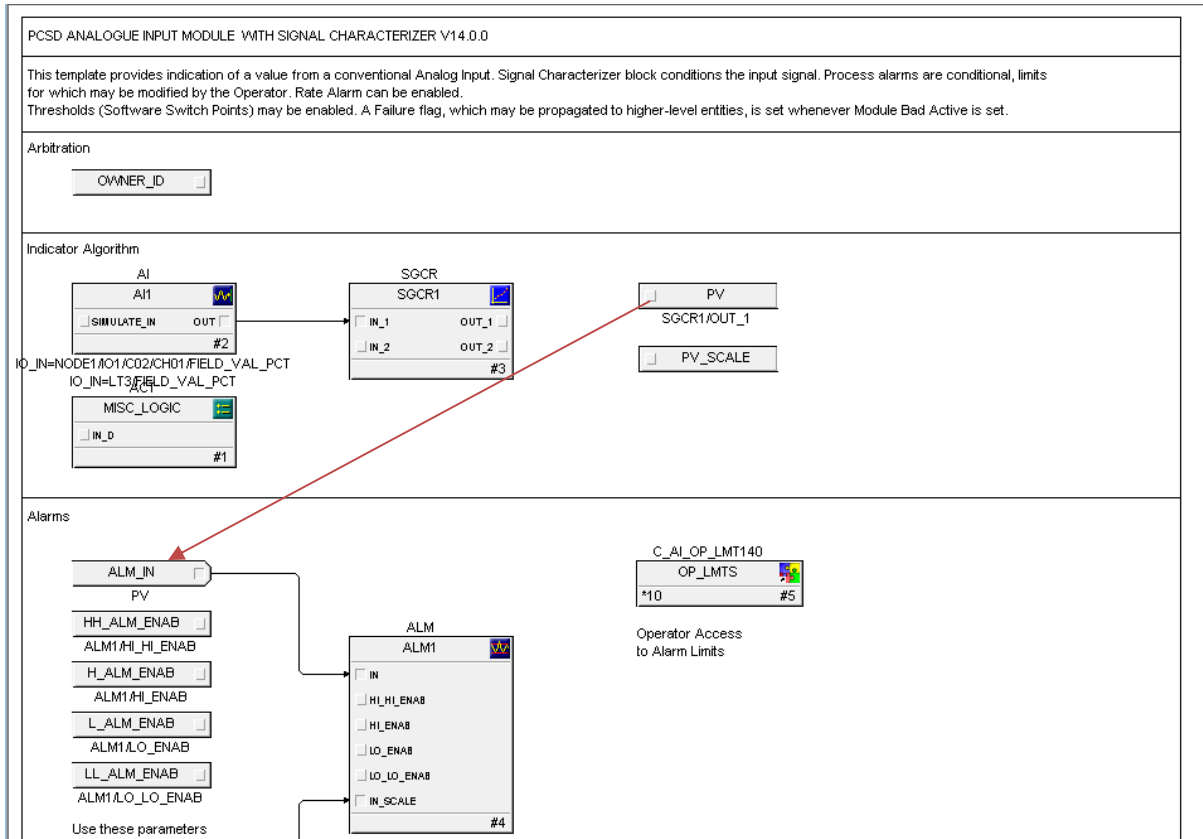


Figure 5.3 reference for CV

So the reference for the CV has been referred to as the ALM_IN for the MPC Pro parameter.

MPC-PRO1 Properties

Controlled Manipulated Disturbance Constraint Deleted Items

Description	Track SP	Respon...	SP Low...	SP High...	Path
Tank 3 Level	Yes	0	0	332	//LI-3//ALM1//IN
Tank 4 level	Yes	0	0	332	//LI-4//ALM1//IN

Total number of process inputs: 4 Total number of process outputs: 4 History sample rate: 1 sec

Close Add... Move Modify... Delete Advanced >>

Figure 5.4 CV output for the MPC block configuration

5 Configuring MPC in DeltaV

Manipulated variables are the Pump output of Pump 1 and 2. Here for the reference output RCAS_IN has been used. This mode is similar to the CAS, except the setpoint is supplied by an external program.

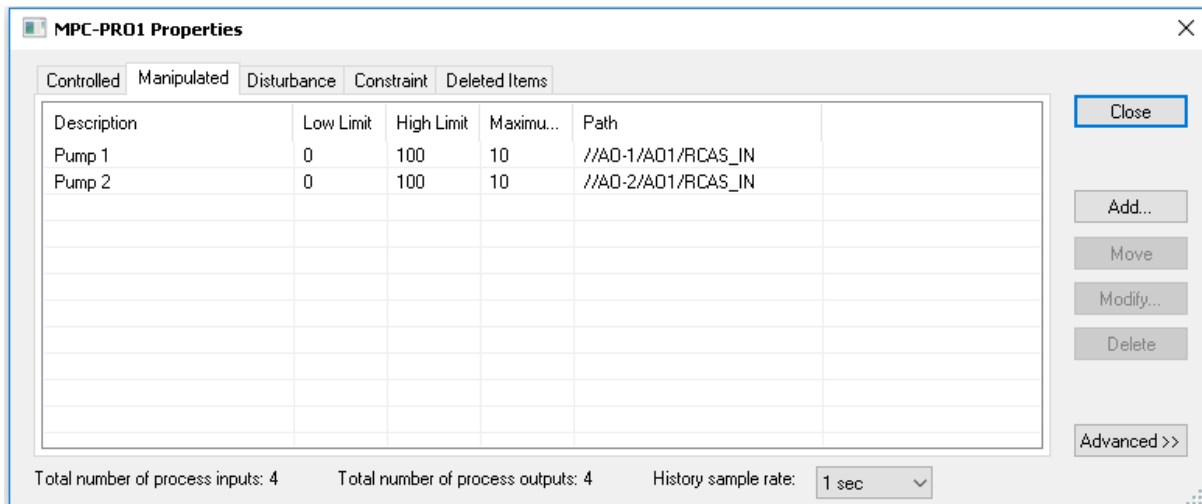


Figure 5.5 MV output for the MPC block configuration

The disturbances are the incoming water from the tank 1 and 2 through their discharge valve. The discharge valve has been kept in a constant position.

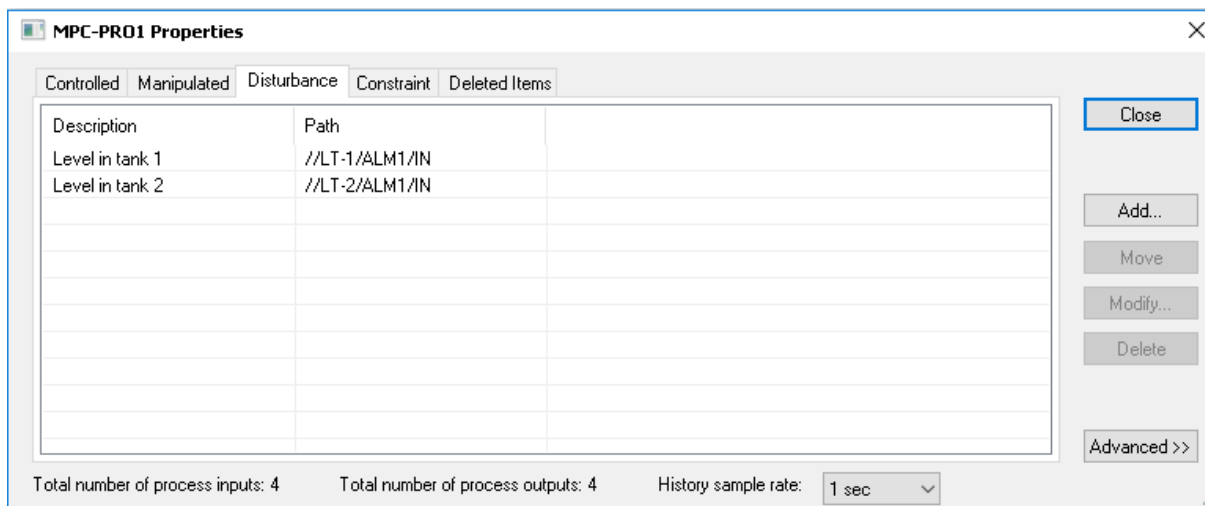


Figure 5.6 DV output for MPC block configuration.

In this model, the constraints could be ignored as the tank level needed to be controlled. But still, the constraints had been configured the level of tank 3 and 4 and configured as

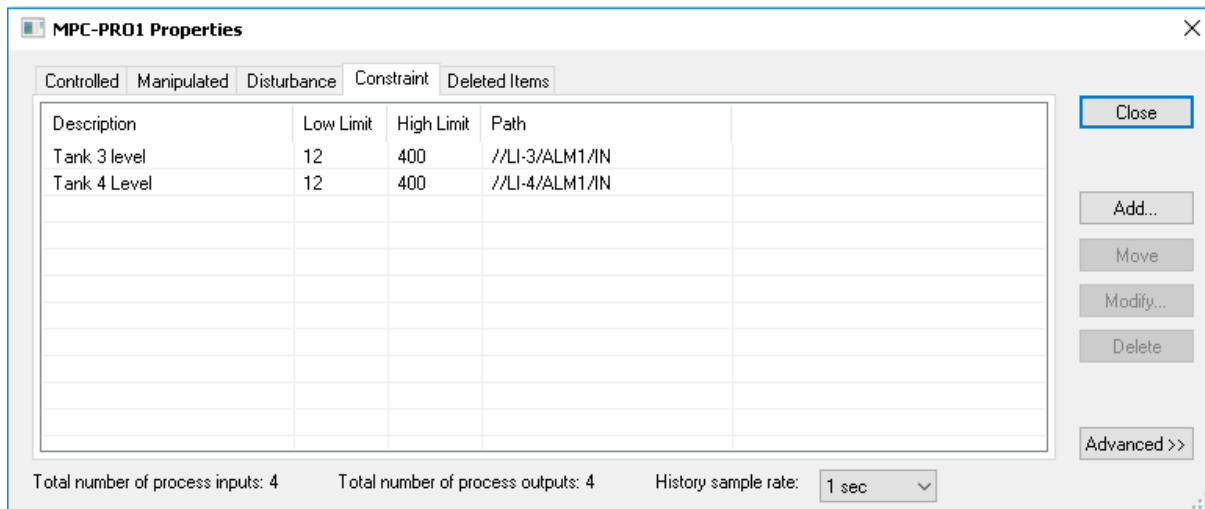


Figure 5.7 AV parameters for MPC configuration

5.3 Step test setup

After completing all the parameter configuration in the MPC Pro block, the test procedure has been set up. In the Advance control system- the test setup window had been configured with all the input-output parameters. After selecting all the parameters, the time to steady-state (TSS) had been given to 500 sec. The TSS is the estimated time to respond to the input change for the process. The DeltaV gives a recommended TSS of 39 minutes for all the tests. The step size had been given differently at a different time for the testing process to get the most reliable model. The more the step size, the wider the range can be controlled by the model. Initially, the step size had been selected 5% for all the variables. Later it had been increased by following sequence 5,8,10,12. In the end, the 12% step change shows the highest wider range for the model and had been used for further test and model generation.

6 Modelling and verification

This chapter will be discussing the step test, verification of the model. In the step test, an automatic step testing procedure will be conducting. It will result in creating a model using the methods discussed in chapter 4. After the testing process, the MPC pro will generate the model. For the model verification outputs of the actual process and the predicted process output is compared.

6.1 Step test

To develop the model step test is the most crucial one. A step test will provide a random square time step change for the model to estimate the model parameter to develop a proper model. Different step test has been tested to find a proper model. Before running the test, the model is kept to its most possible steady-state. The results of different step test will be discussed later in this chapter. A green area will appear after the test is completed, which indicates the data area that has been taken into consideration to develop the model. For the final model development, 12% step size has been selected for wider model development. Even though different level for tank 3 and tank 4 has been balanced to find the most optimal model but 20 cm or the 200mm has shown the most optimal solution for creating the better model.

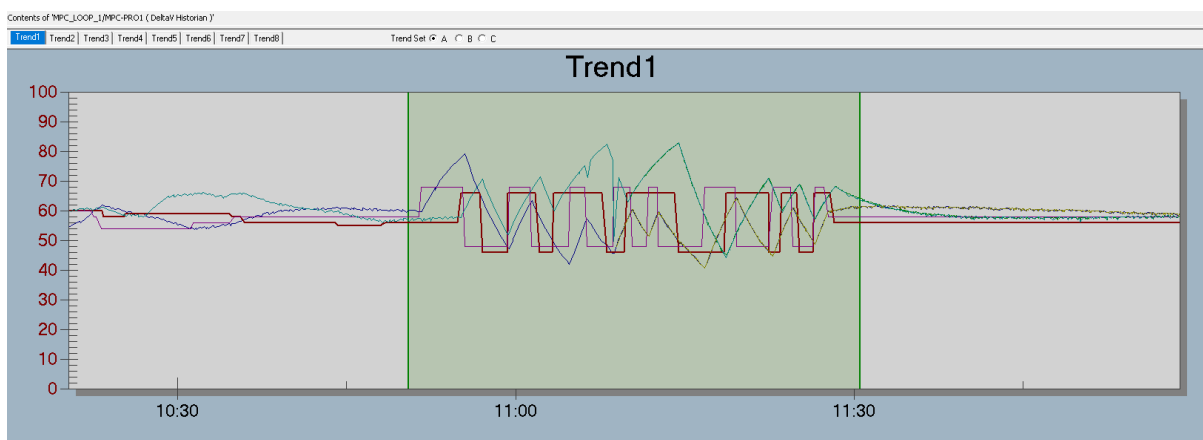


Figure 6.1 step test for model development

In figure 6.1 the green area indicated the time for the test. It can also be manually adjusted if a particular portion of the test user wants to get rid of or include if it's wanted.

6.2 Model verification

After generating a different model, they have compared for the optimal model by their error and gain parameters. In this chapter, all the identified models in the different scenarios are verified to find out the prediction model accuracy. Model accuracy is determined by comparing how much close is the real value to its prediction value. Even the consistency for several running of the test procedure under unchanged conditions shows the accuracy of the model. The model identification is solved by DeltaV Predict Pro with its embedded functions. For the model verification in this test, original data has been used for model verification. The DeltaV Predict Pro can also gather data from an external source or can manipulate the data. The model accuracy is normally determined by errors such as mean squared error, which is the square of error of the difference between real and the process value. The step response model can be expressed by a first-order transfer function model, which is followed by

$$H(s) = \frac{K}{\tau s + 1} e^{-T_d s} \quad (6.1)$$

Here

K= process gain

τ = time constant

$e^{-T_d s}$ = time delay

For the step test various test has been performed which is described in brief here

6.2.1 Model without disturbance (test-1)

In this test, no disturbance had been added just to assure that the model has been created properly.

6 Modelling and verification

In figure 6.2, the hierarchic structure of the model is shown. As for this test, the procedure constraint is not that important that had been discussed earlier, so the main focus will be on the control section.

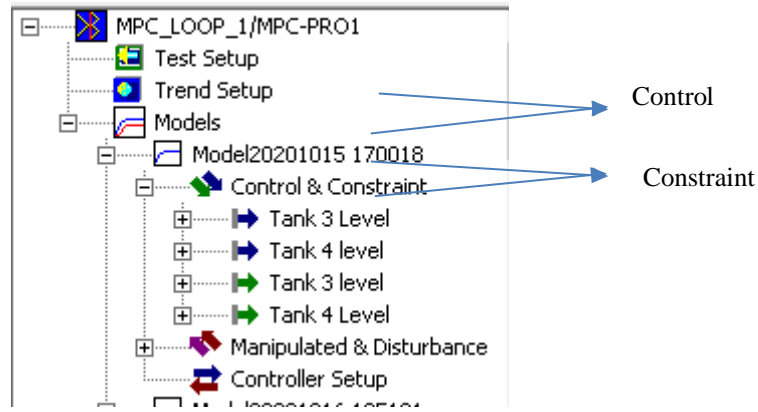


Figure 6.2 Hierarchic structure for model 1

Figure 6.3 shows the identification for the control parameter of tank 3 for test 1. This looks a good precision as the prediction and the actual process follows each other with a minimal squared error of 7.93.

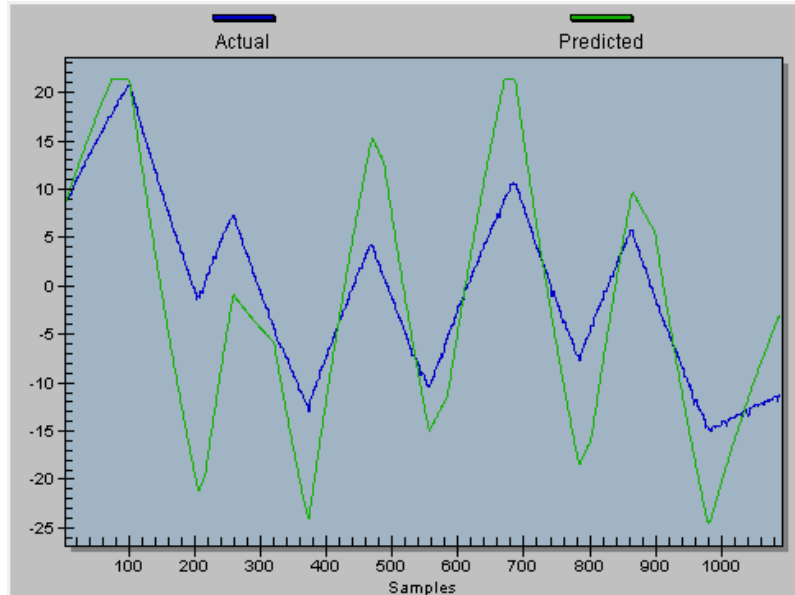


Figure 6.3 Tank 3 identification

Figure 6.4 shows the identified control variable of tank 4, which looks like a good model as its gain and error is satisfactory. The square error for this control parameter is 8.24.

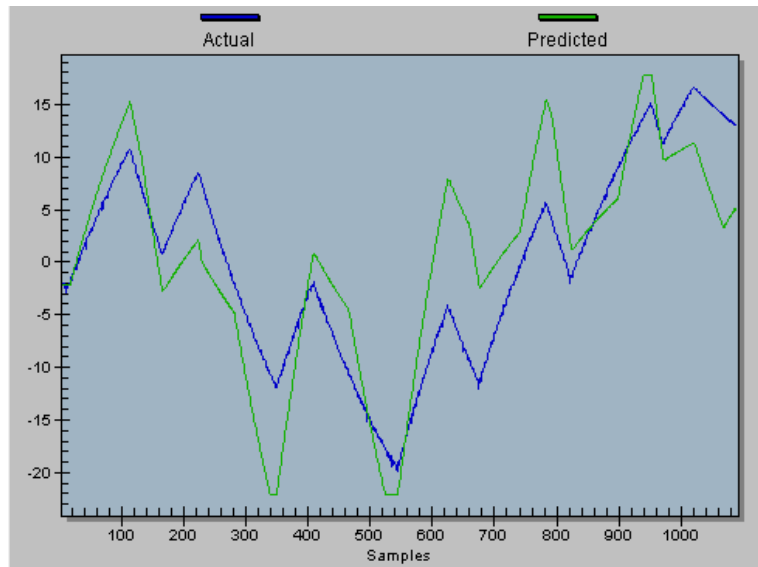


Figure 6.4 tank 4 identification

6.2.2 Model with low-level balance (test 2)

From this test, the disturbance had been added. For this particular test, the balance point has been kept quite low, which is almost 15 cm or 150 mm. But this test gives a lot of problems as the pump could not cope up with the low input signal. This will be discussed more in brief in the discussion. Figure 6.5 shows the tank 3 identification, which is quite poor with squared error of 28.45.

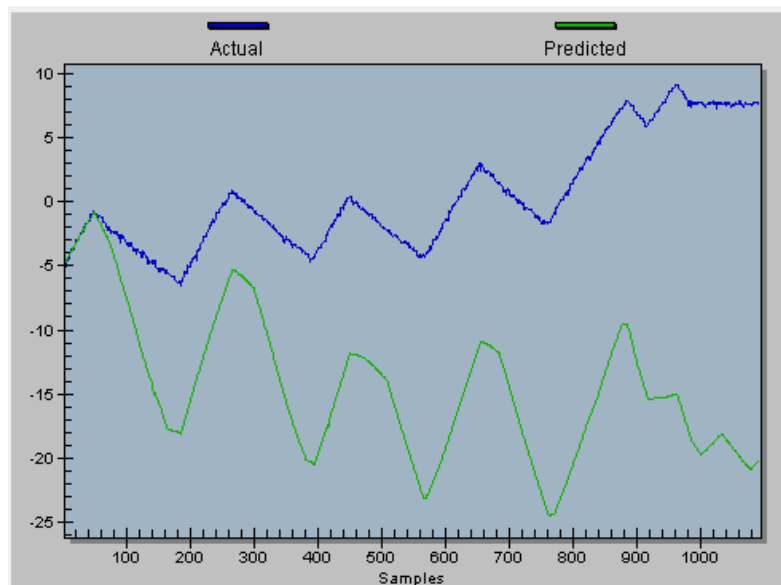


Figure 6.5 Tank 3 identification (test-2)

6 Modelling and verification

The following figure 6.6 shows the verification of the control parameter of tank 4 having a square error of 25.73.

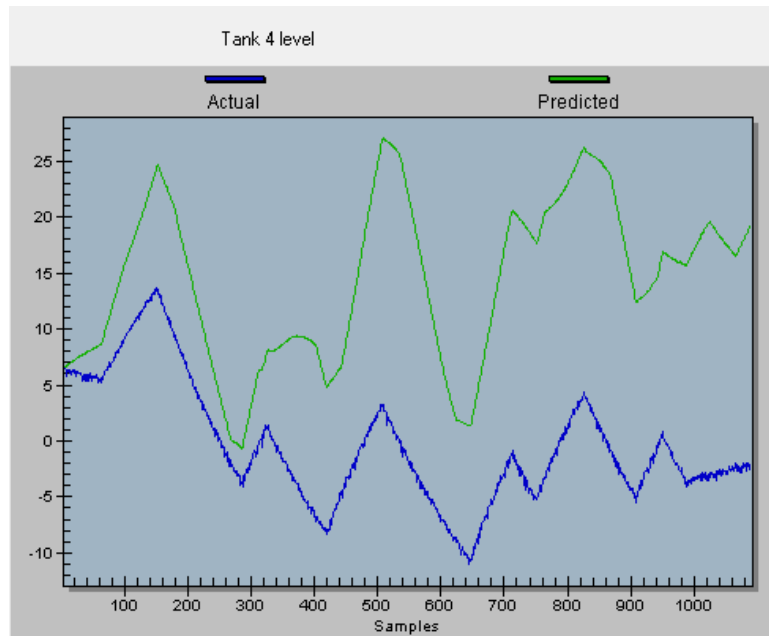


Figure 6.6 tank 4 identification (test-2)

Even though it shows the prediction follows the actual parameter, but as the pump could not pump enough water to the disturbance tank, so for this test, the whole disturbance was almost neglected. Only when the step change was used to give a higher peak, for example, from 43% to 55% of the pump output signal, the disturbance could only be added as it had a supply of water on a higher input signal for the pump. But for the lower step-change step, which went lower than 35%, could not introduce disturbance.

6.2.3 Model with midpoint balance (test 3)

For this test, the level for both tanks had been kept to its middle portion, which was 20 cm. to maintain the level for 20 cm in both tank 3 and tank 4, pump 1 and pump 2 respectively maintained an input signal of 58% for both of them.

Figure 6.7 shows the hierarchy of model. Here the question mark shows the step response has not been identified properly or has identified poorly, which needs to be corrected.

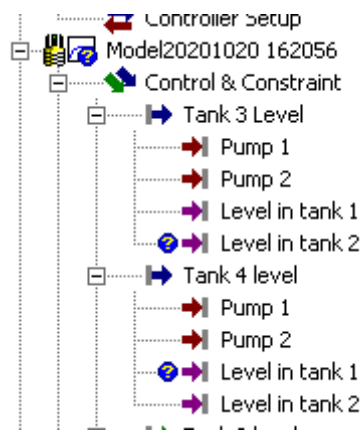


Figure 6.7 Hierarchy of test 3

But this can also be neglected here. Because for tank 3 it shows a question mark on the level in tank 2 means for tank 3, tank 2 could not contribute enough, which resulted in poor identification. But this does make sense as for the control of level in the tank the tank 2 level does not have that much importance, and this also explains the further question marks.

Figure 6.8 shows the identification of the tank 3 control parameter, which looks quite good with a lower square error of 5.24. and the figure also shows how good the prediction follows the actual values here.

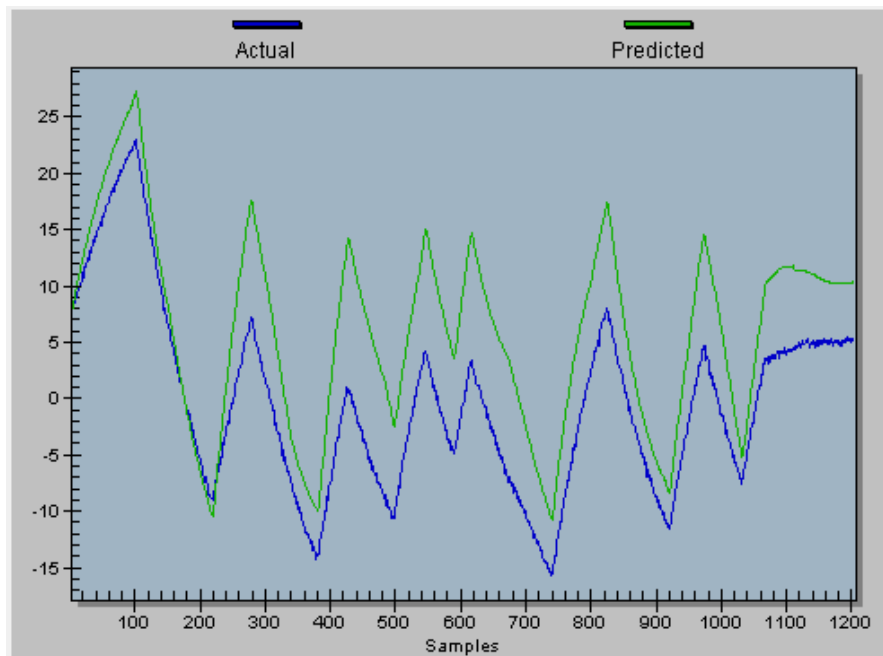


Figure 6.8 Tank 3 identification (test-3)

6 Modelling and verification

And when it comes to the identification of tank 4, figure 6.9 shows a low square error of 7.36.

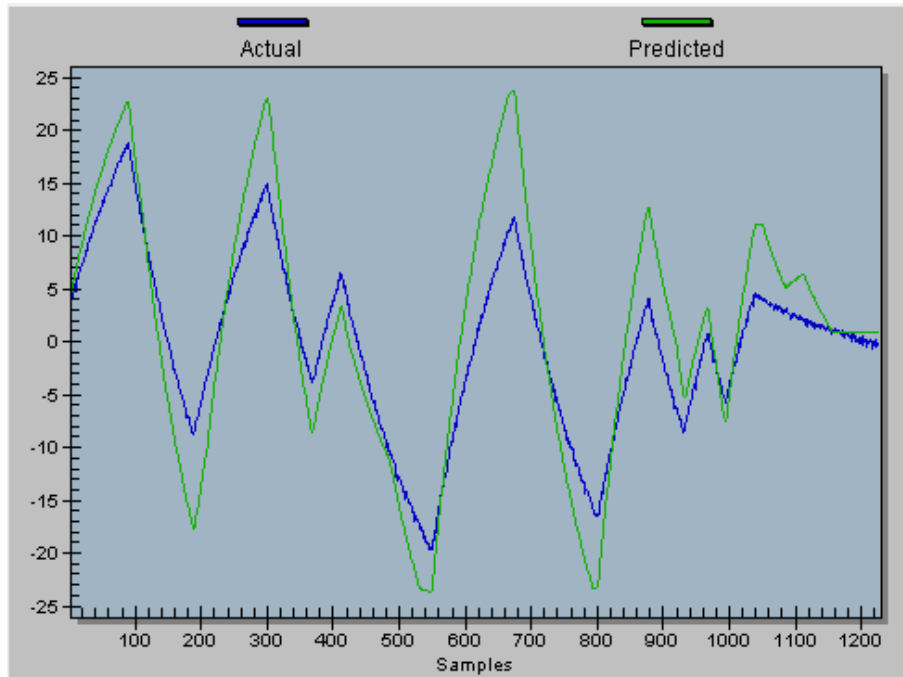


Figure 6.9 tank 4 identification (test-3)

Figure 6.10 shows the tank 3 response model. The red area of pump 2 indicates that this model has been identified as the most significant for the control process variable. As discussed earlier, the pump 2 is responsible for controlling the level of tank 3 so it validates the statement. The blue area shows that this parameter is also identified for the process control parameter.

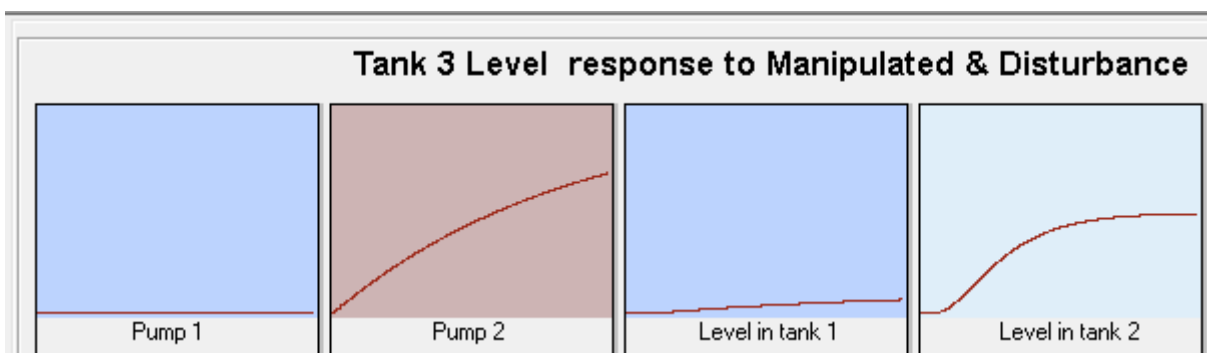


Figure 6.10 Step response of tank 3 (test-3)

The lighter blue colour identifies that the parameter is questionable.

Figure 6.11 shows the tank 4 response model. The pump 1 identified as the most significant parameter as the pump 1 control the tank 4.

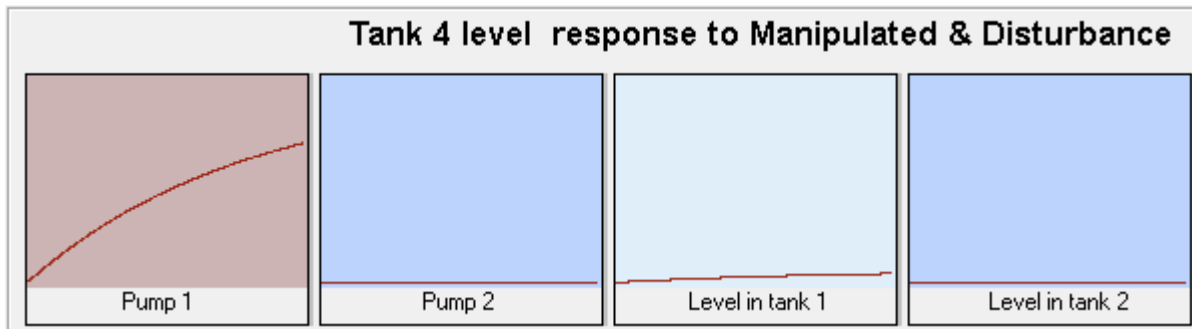


Figure 6.11 Step response of tank 4 (test-3)

6.2.4 Model with high-level balance (test 4)

For the last test, the level for both tanks had been kept high. It had been kept to 25 cm, which is almost 250 mm. to maintain this level pump input signal was almost 65%.

Figure 6.12 shows the identification of the control variable of tank 3. Even though the level had been kept quite high, it still shows a satisfactory result. The square error for tank 3 is 7.85, which is comparatively higher than test 3 but lower than test 2.

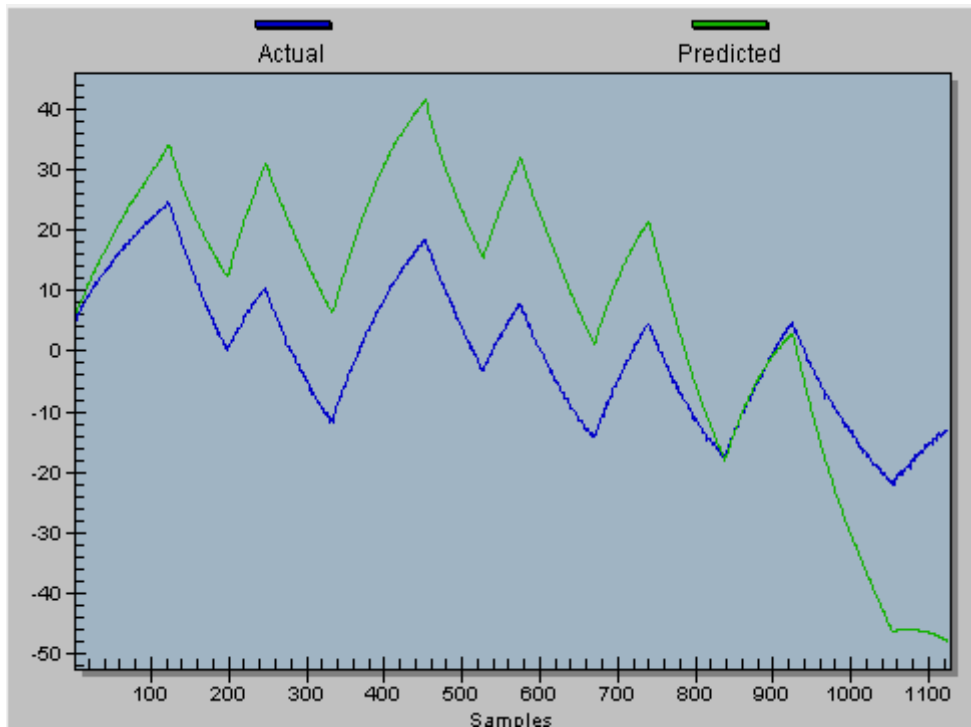


Figure 6.12 identification of tank 3 (test 4)

Figure 6.13 shows the identification of tank 4 with a square error of 16.74.

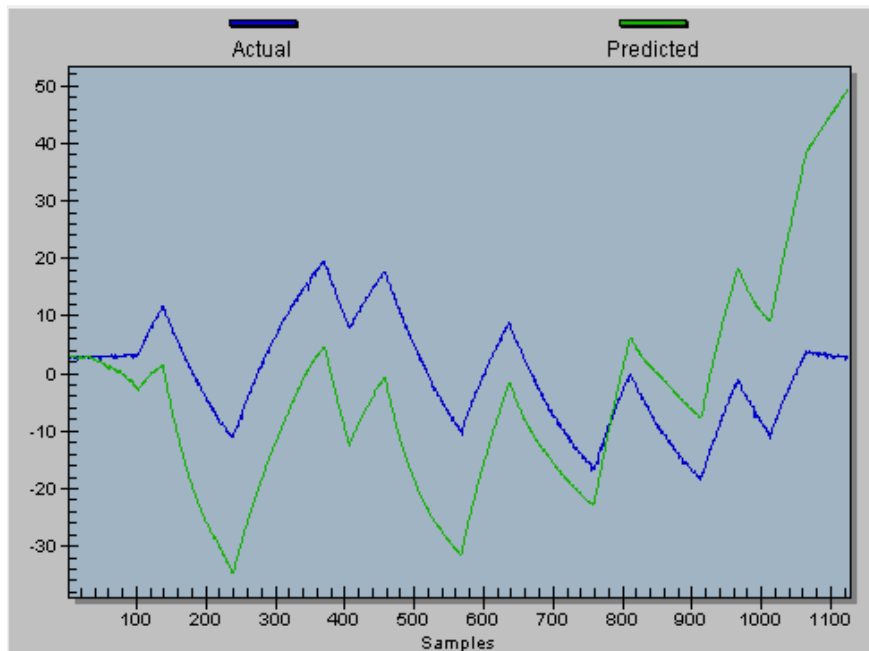


Figure 6.13 Identification of tank 4 (test 4)

The response model for tank 3 is displayed in figure 6.14. Even though the most significant manipulated variable has been identified properly, but it has a question mark on other variable parameters. Other blue areas can indicate the inconsistent related to the control parameter tank 3.

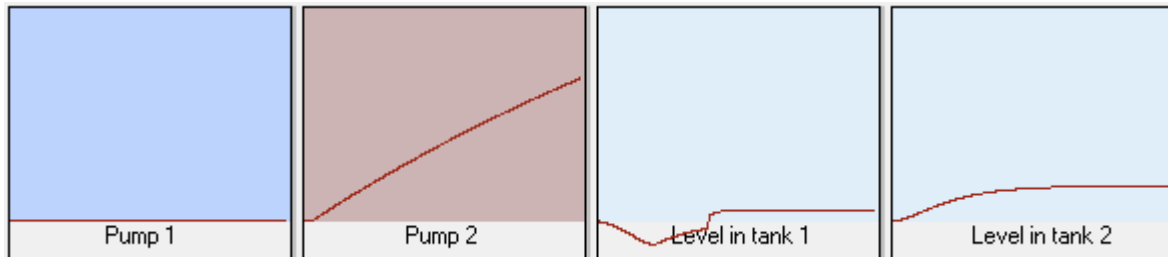


Figure 6.14 Step response of tank 3 (test 4)

Figure 6.15 shows the response model of tank 4. Like the previous one, pump 1 has been identified properly as the most significant variable, but other parameters could not be identified properly.

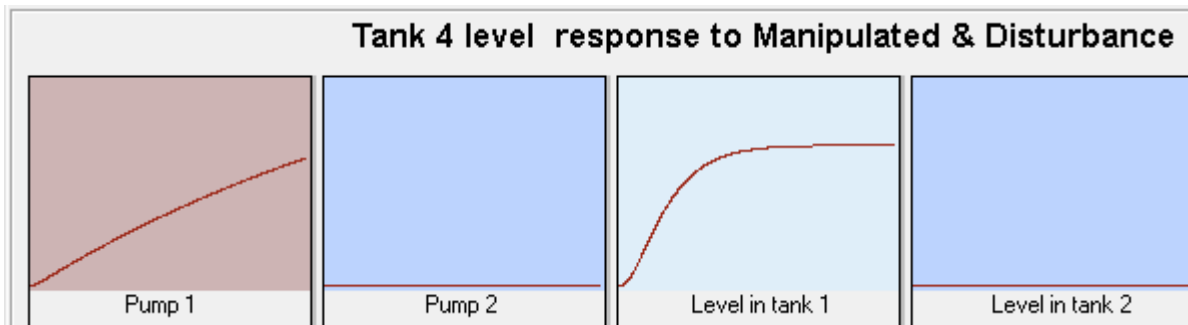


Figure 6.15 Response model of tank 4 (test 4)

6.3 Overview of the model verification

Several models have been created to find the most optimal one. In this chapter, the main three scenarios have been highlighted, even though for each scenario, several tests had been

6 Modelling and verification

performed. Many tests have to be excluded from reporting as those tests gave unsatisfactory results, including unnecessary or abnormal process values used to occur. Testing on a real process is always challenging as the operating condition varies so often. Even in this real process, the sensor also gave some problems regarding data output, which will be discussed in the discussion.

1. Test 2: For test 2, the balance level was kept low, gave comparatively the worst model among the three. Because of the Pumps shortcoming, it affected the whole model prediction. Even though the prediction parameter follows the actual values, but the square error is quite high for this model. The gain, which is shown later, is also moderate. But because of the high square error the model accuracy is poor.
2. Test 3: This test gives the most optimal solution for the model. It has the highest accuracy with relatively better gain. Even the response model also shows a better prediction in this test scenario.
3. Test 4: the test scenario gives a moderate model. The identified control variable shows moderates precision and accuracy. But the gain factor is poor as well as the square error is comparatively poor to test 3. The response model shows a lot of questionable factors, as well.

Table 6.1: Comparing gain and time constant for different test

	Test 2	Test 3	Test 4
Tank 3	K=1.63 $\tau= 47.36$	K= 1.52 $\tau= 52.13$	K=2.31 $\tau= 41.62$
Tank 4	K=1.83 $\tau= 49.42$	K=1.24 $\tau= 45.71$	K=1.83 $\tau= 48.60$

6.4 Test case simulation

This subsection will describe the simulation done on the simulator as well as on the real process. All the tests had gone through a simulator to find out which model gives the most reliable and optimal solution.

The test 3 scenario has been taken into consideration for the final model. In this model, the balance level is 20 cm or the 200mm. The three-way valve had been kept to 0.8 for both of them to have the flow of water in all the tanks. The POM has been set to 0.50 initially for the simulator, and later in the real process, the POM has been raised 0.65, which gives the robustness a more aggressive and better model.

6.4.1 Setpoint response with a simulator

With the DeltaV Predict Pro the simulator is used to determine the robustness of the model. The simulator actually gives a real process like a scenario in which the operator can predict how the model will behave in the real process. It is recommended to test the model through the simulator for a safe run.

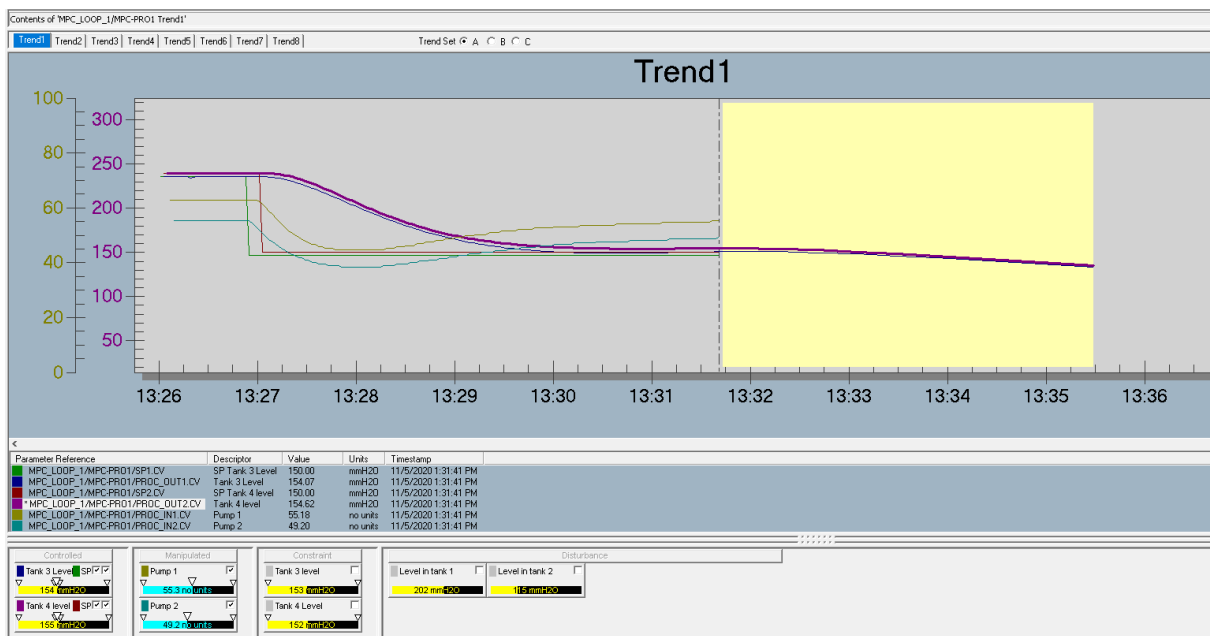


Figure 6.16 Simulation of test case 3 in the simulator

6 Modelling and verification

Initially the level for both tank 3 and tank 4 had been 245 mm. By taking the mode from manual to auto in the simulator app gives the user accessibility to give a setpoint. To perform the simulation the setpoint had been set to 150mm in both tank 3 and tank 4. The model has reached the setpoint within 2.5 minute. The manipulated variable also changes accordingly to reach the setpoint.

6.4.2 Setpoint handling in real process

After successfully testing the model in the simulator, the model has been tested on the real process. All the test scenario has been tested for the model development but as the test 3 gives the most optimal model even though all the model that had been generated from the tests only the one that has been taken under consideration is shown here.

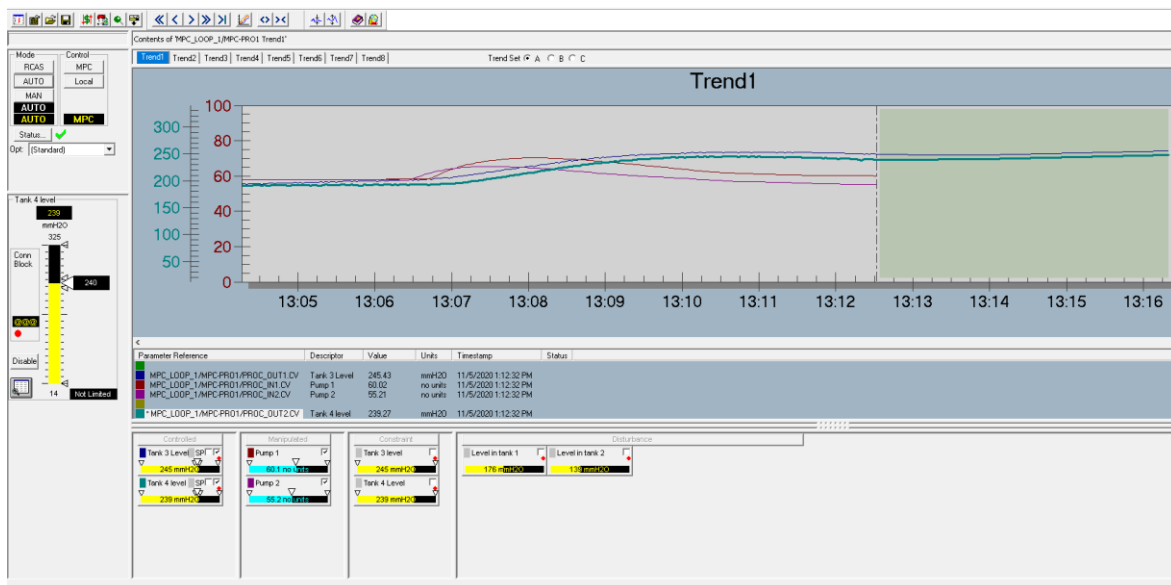


Figure 6.17 shows how the model can handle the real process

The level was steady at 190 mm. the setpoint has been set to 240 by changing the operating mode to auto. The setpoint also takes almost 2.5 minutes to reach its desire value. In this particular simulation, the disturbance has not changed.

6.4.3 Setpoint handling with changing disturbance in the real process

This test has been performed to see how the model can handle the situation when the disturbance is changed. The disturbance is added from the upper tanks. And the three-way valve here plays a vital role as when the input to the valves decreases to zero from 1, the water supply increases in the upper tank and decreases in the lower tank. Figure 6.18 shows the setpoint handling with changing disturbance.

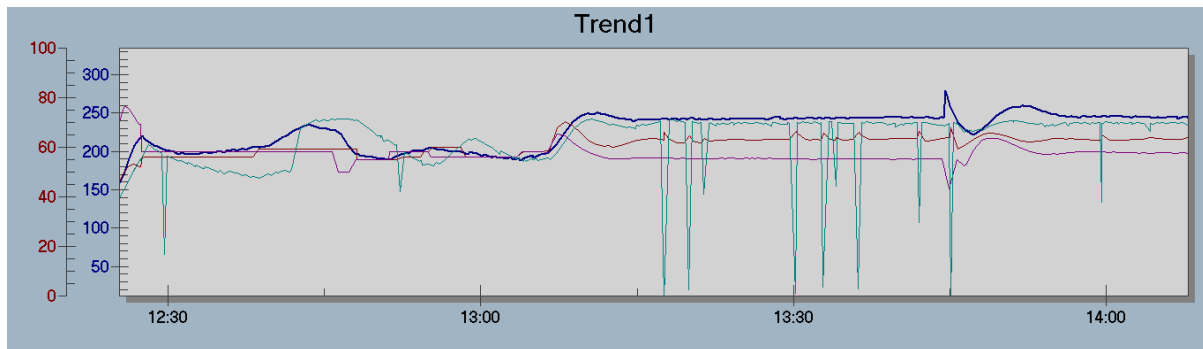


Figure 6.18 Simulation for setpoint tracking with disturbance changes in the real process

Because of the problem in data reading in sensor 4 for tank 5 there are lots of drops-in level measurements. This situation has occurred at the last moment. It shows that when the disturbance, which is eventually the input signal to the three-way valve, has been decreased to 0.45 the model changes its parameter to reach its setpoint.

7 Results and discussion

This chapter will give an overview of the outcome results and the discussion.

The model prediction process in DeltaV uses the step response model. So, identifying the proper step size is a crucial part of the model development. If the step size is too small, it will make the model a narrower one, which will not be able to handle a wide range of changes regards to water level. It will hinder the output changes as the step size was small, so it cannot develop the model for a sudden big change in the parameter. If the step size is too big, the model will introduce non-linear effects, which will also affect the model. So different step size has been tested over several test scenarios, and it shows 12% step size gives the most optimal solution to build the model. Test 2, with middle point steady water level, gives the most sophisticated model, which has been identified as the final model. Other tests have been ignored for its unusual or irregular parameters. Step test 2 has been selected for its lower square error and better gain parameter. Even though the integrated and recommended robustness for the final model had been set to 0.5, but raising it to 0.65 gives better stability with lower dead time to reach the setpoint more easily and quickly.

The simulator test shows that the model takes almost 2.5minute to reach its setpoint when the disturbance is constant. In the real process, the model also shows a similar result where it takes almost 2.5 minutes to reach the setpoint. But different noise affects the model as well. For example, when the disturbance has been changed, it shows a longer period to reach its setpoint.

The whole model development process faced a lot of problems. Some major problems and shortcoming is discussed through the bullet point:

- As the ultrasonic sensor's output value varies from 4-20 mA it's not feasible to show the output value in the process. So, the output value has been scaled to mm.
- The ultrasonic level sensor has a Deadband, which is 12mm for the lower limit and 335mm for the higher limit. The sensor cannot read beyond this level from its mounting point in the real process.

7 Results and discussion

- The pumps don't give proper output if the signal goes lower than 35%. This created a lot of problems while testing the step response. And if the input signal goes lower than 42% it cannot supply water to the upper tanks even though the signal to the three-way valves has been changed from .80 to .60.
- The sensor for tank 4 was giving a reading with a sudden drop in values. This problem has been identified as a hardware issue. Several connection issues such as loose connection to the mainboard had been fixed, but still, the problem did not solve. Figure 6.17 shows a sudden drop in value reading in the sensor of tank 4.
- As the test procedure has been done at the end of the time period, it was not possible to introduce a filter to the tank 4 sensors. Even though the Moving Average Filter has been set to every sensor, but a band filter would solve the problem more easily. Or a different approach can also be eliminating the error values from the data by accessing the data server. Accessing the historian data might solve the problem which was not possible due to the time limitation.
- While trying to test some more scenarios such as low level on tank 4 and high level on tank 4 or high level on tank 3 and low level on tank 4 became troublesome because of the tank 4 sensors faulty reading. Even though the sudden drop in the data does not affect the whole data that much, but still this does not give a proper model. so such a scenario had to avoid because of time limitation.
- When the disturbance is changed by changing the input signal of the three-way valve, the model can operate up to its input signal to 0.4. if the signal goes lower than 0.4 the model becomes unstable. This problem could be solved by testing in a different scenario where the three-way valve input signal is kept to 0.3. but as the pump cannot deliver water to the upper tank.

8 Conclusion and future work

Conclusion along with the future work which will refurbish the model for more robustness is discussed here.

8.1 Conclusion

The quadruple tank process represents the multivariable process very well. The MPC model has been created on the base of the first principle of the linear model. the MPC system is embedded in the DeltaV system with integral action gives a moderate model to develop the controller for the four-tank rig. Different test scenario leads the way to develop the most optimal model. after so many test a reasonable moderate model has been selected for generating the controller. The results have shown the success of the controller both in the simulator as well as in the real-life process. Although some difficulties have occurred during the process on which some of them took a lot of time to solve, and some showed future work which will lead the improvement in the future, a satisfactory model has been implemented. The step response model showed some questionable parts, which were also solved by manipulating some data. A satisfactory operational range also showed success while operating the controller. But due to some lacking of sensors as well as on the pump, different scenarios could not give a satisfactory result. Test 3 has been confirmed as the final model, which showed a minimum square error with good process gain. It also shows minimal process time to reach the setpoint.

8.2 Future work

Some changes over the model and the rig will give a more robust model such as

- Solving the problem with the motor, which had been discussed earlier that it could not deliver water to the upper tank at low voltage, will give a wider range and more stable model for sudden disturbance
- The sensor on tank 4 needs to be fixed for a more accurate model.

8 Conclusion and future work

- The MPC Plus block might give some better models as it can handle the constraint and other process parameters online rather than offline.
- Working on the lower input value for the three-way valve will give a more robust model for a higher disturbance.

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Appendices

Appendix A Project task description

 **University of
South-Eastern Norway**
Faculty of Technology, Natural Sciences and Maritime Sciences, Campus Porsgrunn

FMH606 Master's Thesis

Title: Developing and Testing of a MPC strategy for a four tanks multivariable process using Emerson Delta V system.

USN supervisor: Carlos F. Pfeiffer

Research group: TMCC

External partner: Emerson, Porsgrunn. Contact: Rune Andersen (Rune.Anderson@Emerson.com).

Description:

Model based control techniques, especially Model Predictive Control, have been reported used as supervisory "master" controllers to calculate the set points to dedicated single loops PID controllers [1,2].

In order to test the controllers, the models should be developed which will accurately represent the plant. The DeltaV control system has embedded MPC where the model mimics the behaviour of the real process. The model is based on first principles, statistical modelling, systems identification using step response. In all cases, the models require careful calibration with real data, if the model should mimic the plant behaviour.

Task description:

- The student should do a literature review on the topic of different approaches for process modelling of MPC system.
- The student should build a proper model of an experimental four tanks rig system, by proposing different model scenario and carefully tuning them with experimental data.
- A proper depth research on DeltaV MPC strategy and find out how it can handle the practical rig.
- The candidate should test the model experimentally, for different scenarios (reference changes, disturbances, process parameters changes), in the Multivariable Four Tanks Experimental Rig and/or other pilot processes.

Candidate category: The candidate should have a master degree in industrial automation, process control, or equivalent. Excellent competence using Matlab and programming in a general-purpose language (C, Python, etc.) is a strong requirement.

Practical arrangements:

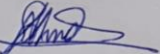
- The experimental work will be carried using the Four Tanks Ring located in the process hall, and the Delta V Industrial Control System provided and supported by Emerson, Porsgrunn.
- Emerson, Porsgrunn, will provide basic training on the Delta V system.

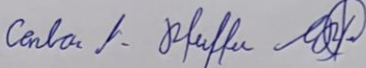
References:

[1] Bemporad, A., & Morari, M. (1999). Robust model predictive control: A survey. In A. Garulli, A. Tesi & A. Vicino (Eds.), Robustness in identification and control (pp. 207–226). Berlin: Springer.

[2] Qin, Joe & Badgwell, Thomas. (2003). A Survey of Industrial Model Predictive Control Technology. Control engineering practice. 11. 733-764.

[3] Bahadır Saltık, M & Ozkan, Leyla & H.A. Ludlage, Jobert & Weiland, Siep & Van den Hof, Paul. (2018). An outlook on robust model predictive control algorithms: Reflections on performance and computational aspects. Journal of Process Control. 61. 77-102.

Student (Date and Signature):  09.11.20

Supervisor (Date and Signature):  9.11.2020