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Abstract:

This thesis work is about developing and testing different control strategies for a four-tank laboratory process. It aims at comparing the performances of the conventional Proportional Integral controller with an advanced control strategy (Model Predictive Controller) on the laboratory process. The four-tank laboratory process is a multivariable control system consisting of four interconnected tanks, two pumps, two level sensors and two valves. A simulator that is a prototype of the real process is designed based on the non-linear model developed from physical data about the process. The linearized dynamics of the system has a multivariable transmission zero that possibly moves along the real axis by changing the valve position, giving it the minimum phase and non-phase operating points. The Proportional Integral controller and Model-based Predictive Controller have been implemented to control the system as well as the simulator respectively. A Kalman filter estimator was implemented to estimate the levels of the tanks that were not measured, and this estimates were satisfactory with the model measurements. It is then reliable to have the estimator as a kind of back-up for situations of sensor failures.
The controllers are been compared with respect to their stability, influence of process interactions and time varying dynamics. And the model predictive controller is considered more reliable regarding stability, in as much as it is difficult to tune. The changes in the input variables are smoother in MPC. And it is able to detect, correct the effects as well as influences arising from process interaction. It is a good educational laboratory thesis written to illustrate the effects of controllers on a multivariable process.

Contents

Preface

This thesis work is written as part of the requirements for the award of the Master's degree in Systems and Control Engineering at the Telemark University College (Høgskolen i Telemark, Porsgrunn) in Norway. The report is written based on the requirements for the development of Advanced Control strategies for a 4-tank laboratory Process, that is meant to be used by undergraduate students' study of multivariable process. The entire work has been carried out on the campus of Telemark University College (HiT). Some of the necessary technical information and data's needed have been obtained from the previous bachelor thesis report presented for the designed "4-tank laboratory Process". The entire implementation has been done using LabVIEW 2009 and the labVIEW codes are attached in the Appendix (Part III) of the report.

I would like to thank my supervisor, Hans-Petter Halvorsen at the Department of Electrical, Information Technology and Cybernetics for his kinded advices and suggestions during my masters thesis. His ideas have been a great motivation.

My special thanks to Associate Professor Finn Haugen and Associate Professor David Di Ruscio for all the fruitful conversations, email correspondences, and their patience to answer my questions even on very tight schedules.

Porsgrunn, June 2010.

Ademu, Victor Okpanachi.

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Part I

Introduction and Theoritical studies

Chapter 1

Introduction

1.1 Introduction

The application of controllers in the process industry has dated far back as before the $1940's$ when John G. Zeigler and Nathaniel Nichols started their pioneer research about the behaviours of controllers as well as trying to develop good methods to be used in the tunning of the controller parameters. Afterwards, more recent advances in the application of control theory emerged as a result of various problems that needed to be resolved. A good example of recent control advancement is the use of optimal control methods that are formulated using the state-space models [1], and other varying formulations that are based on the process model (step and impulse responses), disturbance type (altered white noise, decaying and constant) as well as adaptation to time varying models. There is usually an optimal balance between the control error and the "amount" of control power used, and certain optimal criterion are being minimized in this case of optimal solution.

As at the 1980's, when the first set of commercial adaptive PID controllers were introduced into the market, they were made such that the process model is continually estimated and the PID parameters been adjusted automatically from the model(Haugen, 2004b). And getting into the middle of 1980's, there have been so much industry interest on the use of advanced control strategies. The requirements for these advanced strategies are because of the various changes arising in the petrochemical industry, very strict environmental regulations and the incorporation of intelligent safety systems. The industry, then pave its way into acquiring reliable advanced control strategies with the ability to integrate the requirements to reduce operating costs, use energy resources effectively whilst reducing environmental emissions as well.

Developing efficient control strategies that would be well suited for the control of multivariable systems has been quite challenging in many areas of engineering due to the cost and large amount of time spent on model identification. It is very important to have a prototype of the real process, so that the controller will inherently have knowledge about the process it will control.

According to (Ogunnaike and Ray, 1994), model identification is clearly the "Achilles heel" of model-based controller design. And the total time spent on identifying the model most times could be more than half of the project time. Accurate dynamic models that will enhance the performance of a model-based controller is so challenging and if not found, will so much inhibit the performance of the controller.

It is assumed that Model-based predictive controller (as MPC) would be preferred for most of the difficult control problems in the process and petrochemical industries, since it has so much impact on most industrial controls. The increased industries interest to use advanced control strategies which are robust and capable of achieving improved performance of complex industrial processes that are multivariable in nature, has made it an area of concern in the academia. And the engineering undergraduates and researchers, while in the quest for more understanding of the rigorous mathematics and modeling principles studied with pen and paper, they seem to get more knowledge and understanding of the behaviors of the complex industrial processes by performing experiments and at the same time making judgments with their own prior ideas.

This report starts with some basic theoritical concepts of control system that are quite relevant to designing control strategy in Chapter 3. The development of non-linear models of the four-tank laboratory process, its linearization were also carried out in Chapter 3. In chapter 4, the description of control strategies to be implemented are discussed with regards to their effects and possible challenges as applied to the this multivariable process. There is also the possible estimation of unmeasured levels of the process in Chapter 4. In Chapter 5, a brief description of the interconnectivity of implemented

[1] State-space model: State-space model is a set of first order differential equations that are used in describing a system.

strategies with the physical process is described as well as allocation of the Input-Output device channels respectively. In Chapter 6, the implementation of the PI controller with focus on its performances at varying operating points were done. At Chapter 7, the Model Predictive Controller is implemented and the parameters required for its optimum performance been identified. In Chapter 8, the entire project involvement, findings from the implemented strategies as applied to the process and general evaluation of these strategies are highlighted. And Chapter 9 is a concise description of the results and achievements in this thesis work.

1.2 Objective

In this thesis work, the objective is to develop and test different control strategies on a four-tank laboratory process in order to achieve good performance and stability in the system. It is required and expected that the implemented control strategies be able to handle the multivariable system effectively not minding any process limitation. The implemented strategies would be compared, that is the model predictive controller (MPC) and the PID controller and their various performances would be analysed. And since the interests is to analyse the implemented strategies and making it available for further studies such that would enrich the users hands on experience, it is then important to make the implemented program more user friendly as regards the user interfaces. Also, a simple and detailed *"User training Kit"* is provided as in Appendix 2, this is to give the users of the program good guidance on handling the strategies. On the long run, using a training kit or manual would help in the teaching of the advanced control strategy and will also improve the learning abilities of the users concerned.

1.3 Background

Alot of industries in the late 1980s suddenly developed so much interest in applying multivariable control techniques which was due to the growing complexity in their plants, and the performance of conventional PID controller which has solely governed the control of the process industry was becoming limited. The adoption of the advanced strategies is to enhance the achievement of improved performances in the complex industrial process plants. Therefore, making it enough reason to include multivariable control teaching in undergraduate and postgraduate study curricula in the 1990s. It emphatically promoted the research areas of linear and non-linear design methods. It was deemed very important that a good automation and control engineering study be accompanied by some hands-on practical experiments. According to Johansson, et al.(2009) in 1990s, it became necessarily challenging to illustrate multivariable performances in feedback systems that would describe the process industry. There are quite some examples of multivariable laboratory processes which are available on commercial purposes like; Educational Control products in the US, Feedback Instruments and TecQuipment in U.K. Some of the product vendours have immensly made the awareness of the advanced strategies such that they have almost become the standards in petrochemical, chemical, refining, food processing and pulp paper. In Johansson, et al. (2009), the development and design of the 4-tank laboratory process is described such that it is very suitable for teaching the fundamentals of multivariable control. Also, in Dan-Krister et al. (2009), the 4-tank laboratory process is built by a group of undergraduate students as their bachelor project and is the main start up point for this thesis work.

This laboratory process is a prototype of a real life process plant. It consists of two pumps which are used in conveying water from the reservoir underneath to the four tanks in the overhead. There is drain from the upper two tanks into the lower two tanks. The pipes in here are connected such that each pump has an effect on the level of both measured tanks. The target here is to control the water levels in the two lower tanks using the two pumps. The control of the water levels in the two lower tanks was achieved by two (2) PID controllers. This thesis is focused on extending the control of these levels by more advanced control strategy, evaluating the strategies for the most proficient and to provide documented directives and suggestions on the usage of the developed programs.

Chapter 2

Problem description

The concept of developing advanced control strategies for a 4-tank laboratory process that would be used in undergraduate study to facilitate the knowledge of multivariable control system on a small-scale process, is a prototype of a complex real life situation. Considering the importance of good understanding of the interconnectivity between the connected process, how measurement techniques with the required hardware components as well as the various control algorithms are developed. Regulation and flow levels are quite familiar problems that attract much attention in the process industries, water supply systems and the petrochemical industry. Mostly, in fluid transport and storage scenarios that require level control, there is a kind of interaction between the connected tanks and the level needs to be properly controlled. The main idea of this work is to develop mathematical model and strategies for the 4-tank laboratory process as well as controlling the water levels in the tanks. Although, the water levels in the upper tanks seems to be disturbances to the measured level in the lower tanks.

This 4-tank laboratory process consists of two double-tank processes, with two pumps, two level sensors on the lower tanks as well as two valves that are used in determining the flow ratios in the apparatus.

Some of the goals of this thesis work are listed here but formal documentation is in Appendix 1;;

1. Designing and testing of control strategies to illustrate their performances and reliabilities.
2. Comparison of the proficiencies of developed strategies.
3. Documentation of appropriate "Training Kit" that would be a study guide for further teaching and use of the designed laboratory unit.

The laboratory process has greatly exhibited interesting characteristics within the process industry and research of advanced control strategies, hence the use of a training kit or user manual alongside conventional computer-aids in teaching cannot be underestimated since it provides very much easier and more users' friendly means of understanding the various control system strategies. The incorporation of training kit/ user manual and interactive graphical tools based on "LabVIEW[1] 2009" enhances the learning abilities of the users.

It would be a forum for an easy way of comprehending some concepts as linearization, effects of time delay and effects of nonlinearities, which have all been modeled to help the students or learners to have ideas about the behavior of complex systems as this 4-tank laboratory process. Having a training kit for the process, is a very good check on the students or learners as they always try to practice their ideas while interacting with the process.

[1]LabVIEW: Is an abbreviation for Laboratory Virtual Instrumentation Engineering Workbench;, which is a development system used for experimental, industrial, and educational measurement and automation applications solely based on graphical programming. And it is produced by National Instrument.

Chapter 3

Theory

In the implementation of various control strategies ranging from the conventional PID controller to the advanced control strategy (MPC) as applied in the multivariable systems of process control industries, it is appreciated to have a very good approach for familiarizing the automation and control scholars with the control structures commonly used in modern process control industries. Hence, different control concepts is expected to be found on the finger tips of the control students and/or engineers.

According to (DiRuscio, 2008), if we want the output of say y of a steady state process to be close to a setpoint value, r, then we may simply use a feedback control strategy with an Integral (I) controller in the feedback loop. The real world processes usually are not static, but could be approximated as a steady state (static) process. Hence, a PI controller is used instead of an Ideal Integral controller. An example is this case of designing local or advanced controller for the control actuator itself. Consider a flow controller where u is the pump opening and y is the mass flow out of the pump. It would then be reasonable to model y as a function that describes the behaviour of the pump.

Some useful concepts and terminologies used in this thesis work are as follows;

1. **Variables;**

   - *Manipulated variables:* These are usually the flow rate that are entering or leaving a process that is controlled in order to control a process. In this case, the manipulated variables are the valve positioning and the pump flow rates.
   - *Controlled variables:* This is the level in the process that we are trying to control, which could either be to keep it constant or make it follow a desired manner.
   - *Load disturbances:* This is usually the flow rate that is entering the 4-tank process. They are usually set by the upstream or downstream parts of the process which is at the valve position. And our control system should be designed in such a way as to keep the 4-tank process under controlled not been influenced by the disturbances.

2. **Dynamics;** This is regarded as the time-dependent behavior of the process. Although when there is a controller in the process, the behavior would be regarded as a "closed loop" response. When there is no controller in the system, it is termed "open loop" response(Luyben and Luyben, 1997)

3. **Feedback Control;** This is regarded as the very common way of controlling a process by measuring the variable meant to be controlled, comparing its value to a reference value (that is the set point or reference of the controller) and the difference (error) sent into a feedback controller which is responsible for altering the manipulated variable that helps drives the controlled variable to the specified value. Feedback controller always tries to correct the process value after a disturbance has made utterances and a non-zero error signal has been generated. See Figure 3.1 for a schematic illustration.

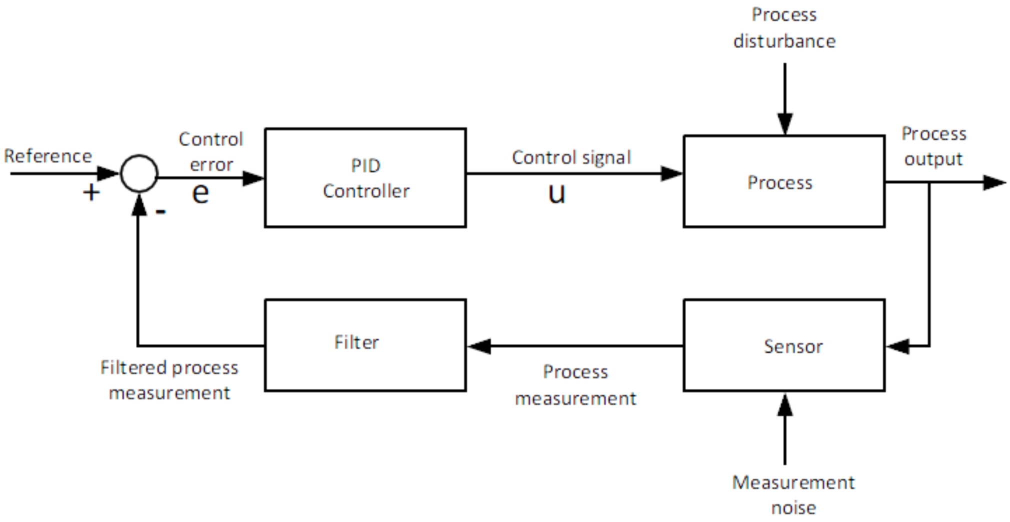

Figure 3.1: Schematic of feedback control using a PID.

4. **Feedforward Control;** This is mostly utilized in situations where the feedback control is not satisfactory, so the feedforward control is meant to act as an additive to the feedback controller in order to achieve a significant improvement in the control system.The adjustment of the control variable is not error-based, it is rather on the knowledge of the process in terms of its mathematical model as well as the measurements obtained from the disturbances to the process. Feedforward control is made very effective by the addition of measured or estimated disturbances in the system, for example the flows from the two upper tanks. Hence, the main variables that could possibly be used as feedforward control parameters are the flows from tanks 3 and 4. See Figure 3.2 for illustration of feedforward control.

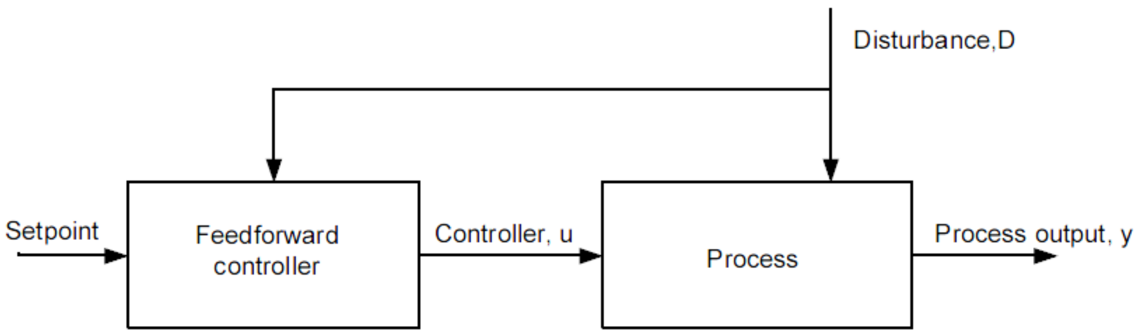

Figure 3.2: Simplified block diagram of feedforward control.

It is a fundamental requirement that the disturbances be measured or estimated (i.e. using the Kalman Filter, State observer etc). In advanced control strategies as the MPC[1] and LQC[2], the feedforward control from the reference is very much involved. Some frequently associated challenges with the Feedforward control technique are;

- Difficulty in measuring the disturbance variables on-line.
- The availability of an approximate model of the process as the quality of the feedforward control is dependent on the process model.

5. **Multi-loop control;** In this case, each of the manipulated variables depend on only a single controlled variable. i.e. a set of conventional feedback controllers.

[1] Model Predictive Controller
[2] Linear Quadratic Controller

6. **Process Interactions and Control loop Interactions;** In MIMO[3] systems, the control problem is actually more complex than in SISO[4] systems. This is a resulting effect from the process interactions that occurs between the manipulated and the controlled variables. Thus, any change in a manipulated variable like u_1, will affect all the controlled variables in the process. Due to this process interactions, the choice of the best pairing of the controlled and the manipulable variables for a multiloop control scheme becomes difficult. So, for any control problem having n controlled variables and n manipulated variables, there is n multiloop control configurations.

7. **Decoupling control;** This is one of the early approaches to multivariable control that is implemented by having additional controllers called decouplers in a conventional multiloop configuration. It is aimed at reducing control loop interactions. Other types of decoupling control methods are, partial decoupling and static decoupling and there are different situations in which their implementations are beneficial. Some of the important benefits of implementing decoupling control schemes are;

- The change of set-point for one controlled variable do not affect other controlled variables.
- It helps in eliminating control loop interactions. Hence, the stability of the closed-loop system is determined solely by the stability characteristics of the individual feedback control loops.

3.1 The Four-Tank laboratory Process

The conceptualization of the 4-tank process as a multivariable control entity is originally proposed by (Johansson, 2000) and it is made up of four interconnected tanks in two (2) pairs each, two (2) pumps, two (2) valves and two (2) level sensors connected to the two (2) lower tanks, see Figures 3.3 and 3.4 for clarifications.

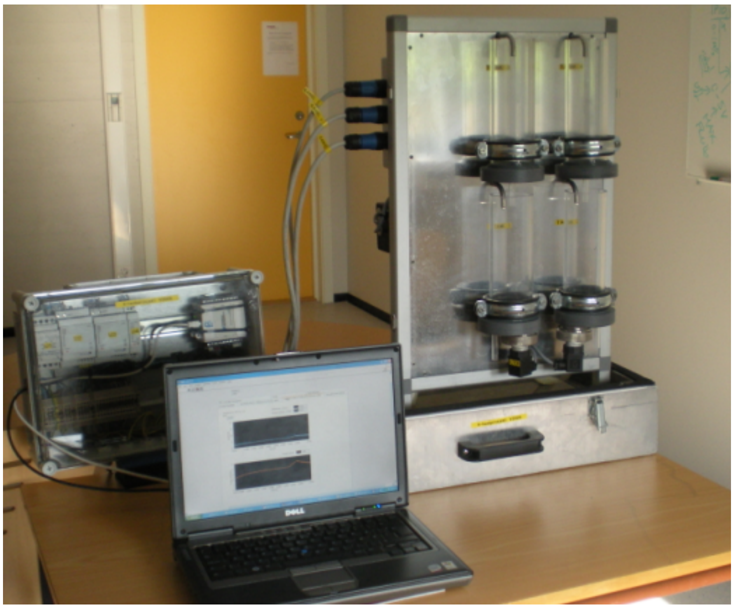

Figure 3.3: Typical four-tank laboratory process.

Pump 1 (LCP01) extracts water from the reservoir beneath the system and pours into tank 1 and tank 4, while Pump 2 (LCP02) pours into tank 2 and tank 3. The voltages to the two (2) valves (LCV01 and LCV02) as in Figure 3.4 are manipulated such that they determine the proportion of the flow that goes into any of the tanks pair. The output flow from the pumps (LCP01 and LCP02) are splitted into two by using the three-way valve. The proportion of the output flow into the tanks is determined or controlled by the valves position, as any change in the valve position will alter the quantity or proportion of flow into the tanks. The regulation of this process is designed using a PI controller, but it has been concluded based on several researches that the splitting of water flow from the pump into all the four (4)

[3]MIMO: Multiple input-Multiple output
[4]SISO: Single input-Single ouput

tanks causes process interactions and control loop interactions. In Figure 3.4, T1, T2, T3 and T4 are the abbreviations for Tank 1, Tank 2, Tank 3 and Tank 4 respectively to suit the schematic diagram.

The selection of equipments and devices that makes up the complete four (4)-tank laboratory process is based on its requirements for portability, efficient design robustness and functionality. It consists of a bottom reservoir with a plant surface as described earlier. See Figures 3.8 and 3.4 for clarification and the devices are further explained in the next sections.

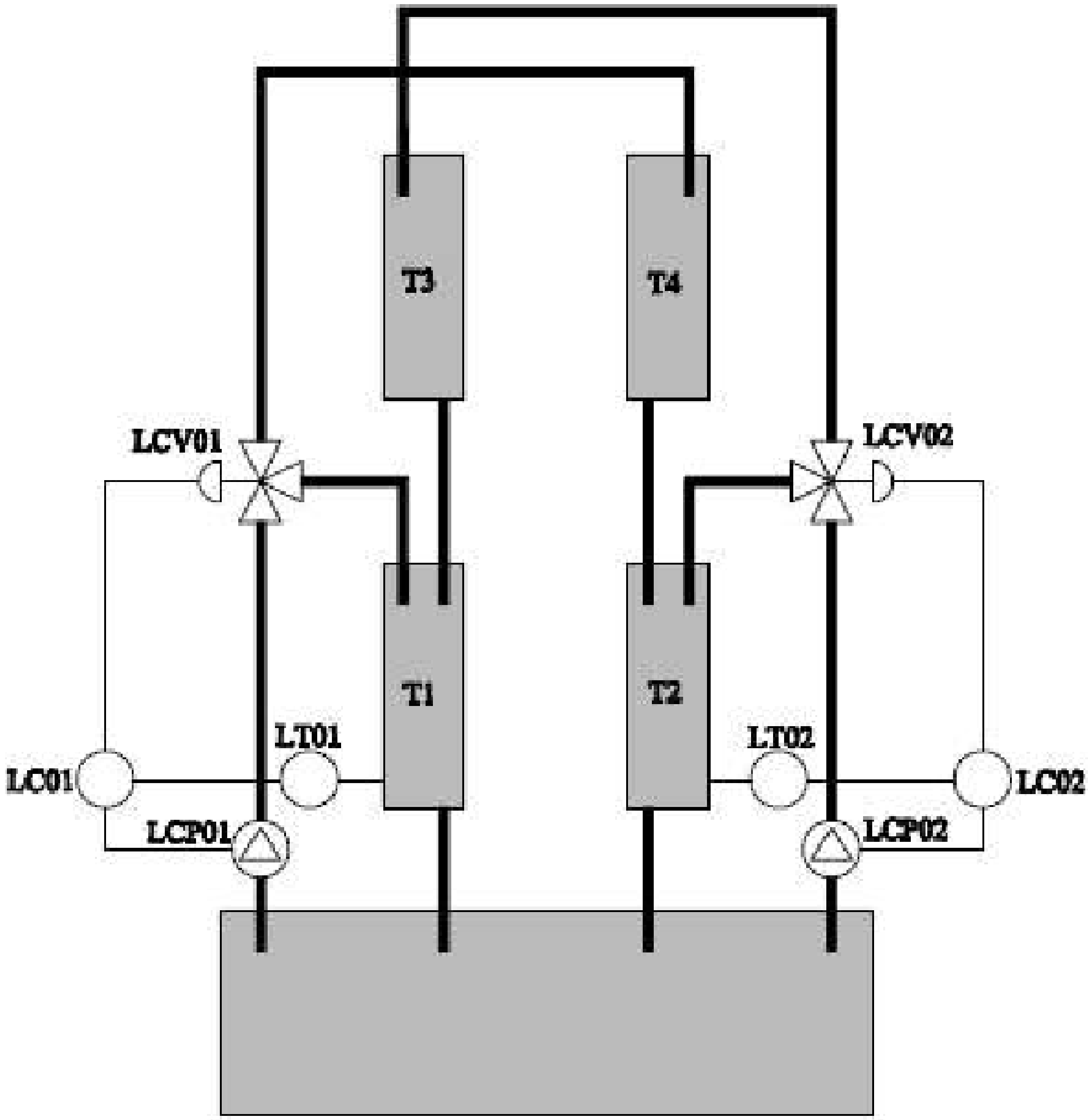

Figure 3.4: P&ID schematic of the 4-Tank laboratory process (Gøthesen Dan-Krister and Semb, 2009)

3.1.1 Bottom Reservoir

The four-tank system has been built such away that the plant surface can be attached to the bottom reservoir to form a briefcase giving it a high sense of portability. The reservoir and plant surfaces have all been designed with Aluminium giving it very light weight and resistance to corrosion and rust that could result from water reactions. The bottom reservoir consists of two compactments, a water reservoir containing majority of water and a smaller room where two (2) pumps are positioned in the water adjacent to themselves as in the lower part of Figure 3.4 and Figure 3.3 respectively. The small pump room has a thick glass plate which serves as a lid for the room, and plant interface is a standing body with aluminium disc on both front and back.

3.1.2 Pumps

The pumps used in this equipment are two Johnson impeller pumps labelled LCP01 and LCP02 in Figure 3.4 respectively. They are $12[V]$ DC pumps being regulated from $0[V]$ to $12[V]$ using self-produced amplifiers. The pumps are positioned separately in the smaller compactment of the water reservoir, and are beneath the water level in the reservoir. Designing the process facility in this way helps to avoid problems of air pumps, the impeller pumps has the disadvantage that they do not work while having air in the system. Other challenge with this pumps is that they need to have a certain rotation speed for lifting the water up to the desired height. The adjustment range of the pumps is in practice within $6.5[V] - 12[V]$. Since the signal for controlling the pumps is $0[V] - 12[V]$, it is then required to use two amplifiers to amplify the $0[V] - 5[V]$ signals from the USB devices to $0[V] - 12[V]$. Hence, two (2) amplifiers are built in , and these amplifiers each needs voltage supply of $-15[V]$ and $+15[V]$. The necessary equipments for sufficient signal conditioning are;

- $2 \times 0 - 12[V]$ DC pumps.
- $2\times$ Amplifiers for converting $0 - 5[V]$ to $0 - 12[V]$
- $-15[V]$ and $+15[V]$ DC voltage supplies to amplifiers.
- $2\times$ Analogue outputs in the I/O devices.

The pumps are controlled from the LabVIEW program user interface by setting the controller output within $0 - 100\%$ which corresponds to $0 - 12[V]$ signal to the pump. The signal flow of the pumps is illustrated in Figure 3.5.

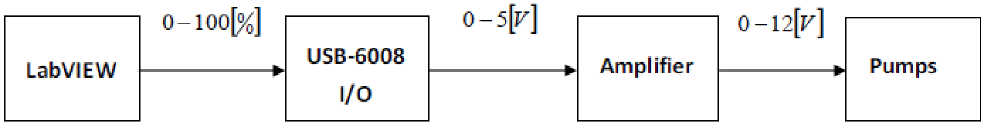

Figure 3.5: Signal flow of the pumps.

3.1.3 Valves

The water from the pumps is distributed to the four (4) tanks by the two three-way valves. The valves are adjusted linearly from small opening to fully open positions, and they are controlled from the LabVIEW user interface. Considering these properties, two Samson three-way valves with electrical actuators have been chosen having labels of LCV01 and LCV02 as in Figure 3.4. The control signal controls the opening of the valve position between the two (2) tanks, and these signals to the valves are $0 - 5[V]$. The supply voltage to the valves is $0-24[V]$ AC, and the response signals in the range of $0-5[V]$ indicates the position of the valves. They are monitored and controlled using the USB devices. The necessary requirements for the valve signal conditioning are as follows;

- $2 \times 0 - 5[V]$ control signal to valves.
- $2 \times 0 - 5[V]$ feedback signal from the valves.
- $24[V]$ AC power supply to the valves.
- $2\times$ USB analogue inputs that monitors the valve positions.
- $2\times$ USB analogue outputs used for controlling the valves.

The signal flow of the valves is illustrated in Figure 3.6.

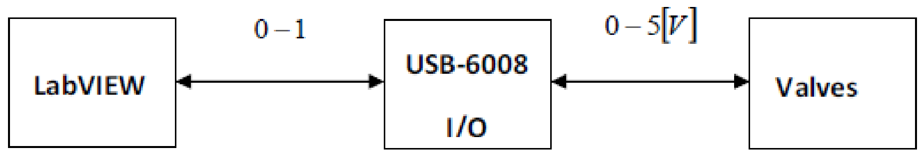

Figure 3.6: Signal flow of the valves.

3.1.4 Level sensors

The measurement of the levels in the two lower tanks (tank 1 and tank 2) are much of interest. Although the size and transparency of the tanks puts requirement for the design of the sensors. There are two *"Screw type"* pressure transmitters from BD Sensors with labels of LCT01 and LCT02 in Figure 3.4. The measurement range of these sensors is $0 - 40[mbar]$ corresponding to $0 - 400[mmH_2o]$, this is within acceptable accuracy limits of the process. In the report by Gøthesen et al.(2009) , the pressure gauges give out $4 - 20[mA]$ current signal, meaning that the signals from pressure gauges will only vary within $4 - 12[mA]$. Also, considering the fact that the analogue input of the I/O device been used is to enable the reading of the voltage signals, thus a 500Ω resistor is inserted in the circuit. The voltage across the resistor will vary between $2 - 6[V]$, hence the voltage level in LabVIEW is scaled between $0 - 20[cm]$ of the tanks height. The level of the bottom two tanks are shown graphically in LabVIEW. The level sensors require $12 - 36[V]$ DC supply. The signal conditioning requirements for the sensors are;

- $2 \times 0 - 40[mbar]$ pressure sensors of $4 - 20[mA]$.
- $2 \times 500\Omega$ resistor.
- $24[V]$ DC supply.

The signal flow of the Level sensors is illustrated in Figure 3.7.

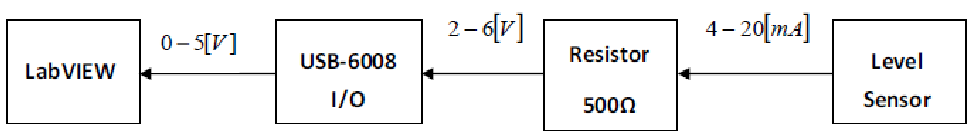

Figure 3.7: Signal flow of the Level sensors.

3.1.5 Data Acquisition-I/O device

The data communication with the four-tank laboratory process and the computer takes place through the two NI USB-6008 devices. The USB-6008 devices have Analogue Inputs and Analogue Outputs and both are used as required, see Figure 3.8. Each of the USB devices has four A/Is[5] and two A/Os[6], one (1) A/I and two (2) A/Os are used from each of the USB devices. And they are configured using the MAX[7] application.

[5] A/Is: Analogue Inputs
[6] A/Os: Analogue Outputs
[7] MAX: Measurement and Automation eXplorer

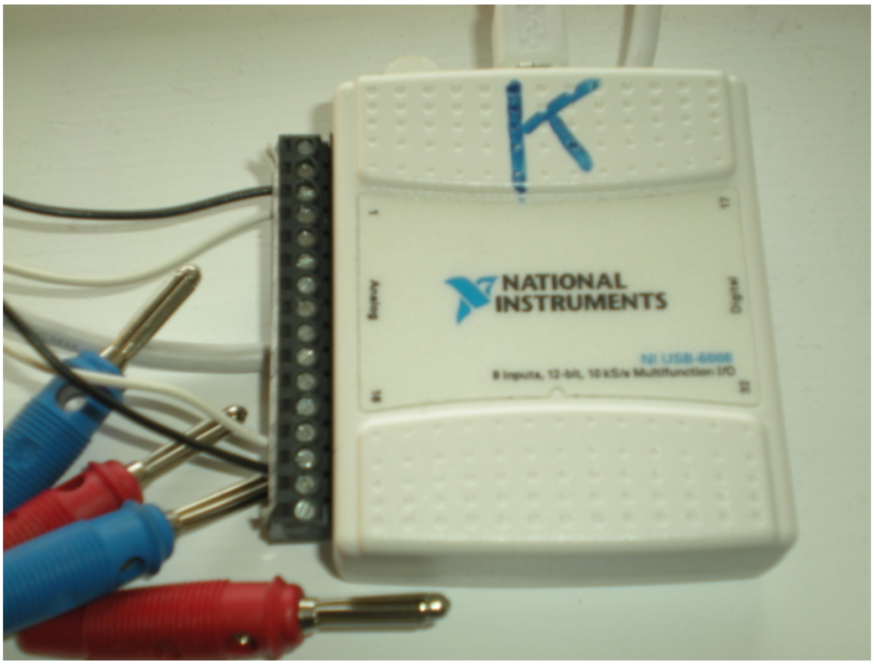

Figure 3.8: USB-6008 I/O.

For Analogue Inputs:

1. $2 - 6[V]$ from the Level sensors 1 and 2 which indicates the levels in tank 1 and tank 2 respectively.

For Analogue Outputs:

1. $0 - 5[V]$ which is for controlling flows from pumps 1 and 2.
2. $0 - 5[V]$ which is used for controlling position of valves 1 and 2.

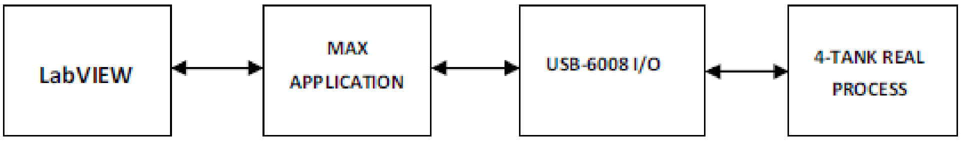

Figure 3.9: Block diagram illustrating data communication.

The block diagram illustrating the data communication between the computer and the process is shown in Figure 3.9. In order for LabVIEW to access data from the USB-6008 devices, tasks are set in National Instrument's Measurement and Automation Explorer (MAX).

3.2 Physical Model

In deriving the mathematical model for the four-tank process from physical data, while having on mind that the target is the control of the levels in the two lower tanks. There is just one way of developing the model of the liquid interaction in the 4-tank process, and the model would be simulated in order to compare the simulation result with the real process result. The inputs to the process (input voltages to the pumps) are designated as v_1 and v_2; while the outputs which are levels to be controlled are designated as y_1 and y_2 respectively (the voltages from level measurement sensors). If we consider the mass balance for just one of the tanks as reported by (Johansson, 2000), we have;

$$A\frac{dh}{dt} = -q_{out} + q_{in} \tag{3.1}$$

Where A is the cross-sectional area of the tank, $h \geq 0$ is the water level, $q_{in} \geq 0$ and $q_{out} \geq 0$ are the inflow and outflow of the tank respectively. Bernoulli's law yields; $q_{out} = a\sqrt{2gh}$, where a is the cross-sectional area of the outlet hole and g is the acceleration due to gravity. The flow from each of the pumps is splitted proportional to the valve position setting, see Figure 3.4. Assuming the flow generated by any of the pumps is proportional to its applied voltage v, and let q_L be the flow into the lower tank and q_U be the flow into the upper tank. Therefore,

$q_L = \gamma kv, q_U = (1-\gamma)kv, \gamma \in [0,1]$.

Now, the mass balace and the Bernoulli's law are extended to other tanks to obtain a non-linear model which is described by the system differential equations as follows;

$$\frac{dh_1}{dt} = \frac{-a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{\gamma_1 k_1}{A_1}v_1 \tag{3.2}$$

$$\frac{dh_2}{dt} = \frac{-a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{\gamma_2 k_2}{A_2}v_2 \tag{3.3}$$

$$\frac{dh_3}{dt} = \frac{-a_3}{A_3}\sqrt{2gh_3} + \frac{(1-\gamma_2)k_2}{A_3}v_2 \tag{3.4}$$

$$\frac{dh_4}{dt} = \frac{-a_4}{A_4}\sqrt{2gh_4} + \frac{(1-\gamma_1)k_1}{A_4}v_1 \tag{3.5}$$

Where the parameters used above are;

A_i	cross-sectional area of Tank i
a_i	cross-sectional area of the outlet hole
h_i	the water level in Tank i
v_i	voltage applied to pump i
$k_i v_i$	flow from pump i
g	acceleration due to gravity

Usually, there is a structured way of writting differential equations for a system which is known as the state-space model. It is mostly seen as an end to requirements for block diagram constructions, linearization of non-linear models, calculating time-responses ranging from analytical to numerical methods (Haugen, 2004a). It is also regarded as a very important tool in Observability and Controllability analysis, the design of control strategies as Optimal control, Model-based predictive control as well as designing estimators as the Kalman filter. A general and compact form of the state-space model is;

$$\dot{x} = Ax + Bu \tag{3.6}$$

$$y = Cx + Du \tag{3.7}$$

Where x is the state vector and u the input vector to the system. A is refered to as the system matrix, and it is usually a square matrix. In this case of the 4-tank laboratory process, the system has four state variables, h_1, h_2, h_3 and h_4, which are denoted as x. The two input variables, v_1 and v_2, are denoted as u correspondingly. Matrix $D = 0$, Equations (3.2, 3.3, 3.4 and 3.5) can be written on a matrix-vector form that corresponds to Equations (3.6) and (3.7).

3.2.1 Linearization of non-linear models

In order to enhance proficient stability analysis and controller design, it is necessary to linearize the model such a way that approximates the original non-linear model. Now, the non-linear model of Equations (3.2, 3.3, 3.4 and 3.5) can be linearized around the chosen working point given by the level in the tanks $h_1^0, h_2^0, h_3^0$and h_4^0 as in 3.1. A deviation state-space model form of $x_i = h_i - h_i^0$ is considered, while the control variables would be $u_i = v_i - v_i^0$ as well.

Table 3.1: Nominal Operating Conditions and Parameter values.

Symbol	State/Parameters	Values
$h_1^0, h_2^0, h_3^0, h_4^0[cm]$	Nominal levels	$11.8, 12.5, 5.5, 9.5$
$v_1^0, v_2^0[V]$	Nominal pump settings	$3.75, 3.75$
$A_i[cm^2]$	Areas of the tanks	28
$a_i[cm^2]$	Area of the drain in tank i	$0.16, 0.13, 0.16, 0.13$
γ_i	Ratio of flows in the valves	$0.4, 0.4$
$k_i[cm^3/Vs]$	Pump proportionality constant	$0.67, 0.74$
$g[cm/s^2]$	Gravitational constant	981
$T_i[s]$	Time constant in the linearized model	$27.78, 35.56, 18.54, 30.94$

Thus, with the application of the Taylor series; a linearized state-space model for Equations (3.2, 3.3, 3.4 and 3.5) is presented in Equation (3.8) and (3.9) respectively:

$$\dot{x} = \begin{bmatrix} -\frac{1}{T_1} & 0 & \frac{a_3}{a_1 T_3} & 0 \\ 0 & -\frac{1}{T_2} & 0 & \frac{a_4}{a_2 T_4} \\ 0 & 0 & -\frac{1}{T_3} & 0 \\ 0 & 0 & 0 & -\frac{1}{T_4} \end{bmatrix} x + \begin{bmatrix} \frac{\gamma_1 k_1}{A_1} & 0 \\ 0 & \frac{\gamma_2 k_2}{A_2} \\ 0 & \frac{(1-\gamma_2)k_2}{A_3} \\ \frac{(1-\gamma_1)k_1}{A_4} & 0 \end{bmatrix} u \tag{3.8}$$

$$y = \begin{bmatrix} k_c & 0 & 0 & 0 \\ 0 & k_c & 0 & 0 \end{bmatrix} x \tag{3.9}$$

Where $x = \begin{bmatrix} h_1 & h_2 & h_3 & h_4 \end{bmatrix}^T$, $u = \begin{bmatrix} v_1 & v_2 \end{bmatrix}^T$ and $y = \begin{bmatrix} h_1 & h_2 \end{bmatrix}^T$, also k_c is a calibration constant that is usually choosen to be 1. And the time constants for the tanks T_i, are found by the expression given in (3.10).

$$T_i = \frac{A_i}{a_i}\sqrt{\frac{2h_i^0}{g}}, fori = 1, ..4 \tag{3.10}$$

γ_1, $\gamma_2 \in [0, 1]$ are determined from the valves setting before the startup of an experiment for tanks 2 and 3 and corresponding Tanks 1 and 4 respectively. Also, the measured level signals are $y_1 = k_c h_1$ and $y_2 = k_c h_2$. The level sensors are calibrated such that, $k_c = k_c = 1$. The amount of flow that goes into tank 1 is $\gamma_1 k_1 v_1$ and the flow to tank 4 is $(1 - \gamma_1)k_1 v_1$. Likewise the flow to Tank 2 is $\gamma_2 k_2 v_2$ and the flow to Tank 3 is $(1 - \gamma_2)k_2 v_2$.

In the reports by (Numsomran A, 2008) and (Johansson, 2000), the linear transfer function matrix is calculated for the four-tank process as follows;

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = G(s) \times \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} \tag{3.11}$$

$$G(s) = C(sI - A)^{-1}B \tag{3.12}$$

$$G(s) = \begin{bmatrix} g_{11}(s) & g_{12}(s) \\ g_{21}(s) & g_{22}(s) \end{bmatrix} \tag{3.13}$$

$$G(s) = \begin{bmatrix} \frac{\gamma_1 c_{11}}{(T_1 s+1)} & \frac{(1-\gamma_2)c_{12}}{(T_1 s+1)(T_3 s+1)} \\ \frac{(1-\gamma_1)c_{21}}{(T_2 s+1)(T_4 s+1)} & \frac{\gamma_2 c_{22}}{(T_2 s+1)} \end{bmatrix} \tag{3.14}$$

Where $c_{11} = (T_1 k_1 k_c/A_1)$, $c_{12} = (a_3 T_1 k_2 k_c/a_1 A_3)$, $c_{21} = (a_4 T_2 k_1 k_c/a_2 A_4)$and $c_{22} = (T_2 k_2 k_c/A_2)$ and T_i is as defined in Equation (3.10).

The four (4) process transfer functions that comprises of the system transfer function as in (3.14), is a complete characteristics of the dynamics of the system. For the fact that it is a two input by two output control problem with four states, the transfer function is used to determine how any change in either $u_1(v_1)$ or $u_2(v_2)$ affects the system outputs $y_1(h_1)$ or $y_2(h_2)$. According to the principle of superposition as stated in (Seborg E. Dale and Mellichamp, 2003), simultaneous changes in u_1 and u_2 have a kind of additive effect on each controlled variable. Thus, the input-output relations considering the transfer function becomes as follows;

$$y_1(s) = g_{11}(s).u_1(s) + g_{12}(s).u_2(s) \tag{3.15}$$

$$y_2(2) = g_{21}(s).u_1(s) + g_{22}(s).u_2(s) \tag{3.16}$$

Also, the vector-matrix notation of these two (2) input-output relations is equivalent to (3.11). In this control scheme of the four-tank process, $y_1$is controlled by the adjustment of $u_1$and y_2 is also controlled by the adjustment of u_2. There is also an indication that process interactions can cause undersirable interactions between the control loops. Assuming a disturbance moves $y_1$from its setpoint, the following events would arise:

- The controller for loop 1 adjusts $u_1$in order to force y_1 back to the setpoint, also $u_1$affects y_2 through the transfer function g_{21}.
- For the fact that $y_2$has been altered, loop 2 controller would also adjust u_2 ensuring that it brings y_2 back to its setpoint. All thesame, any change in u_2 will affect y_1 through the transfer function g_{12} .

These controller actions continues simultaneously about when a steady state is attained..

3.3 Control System

The incorporation of Control system into already designed real plants or prototypes of chemical process plants originally evolved from the basic fact that everything in the world is changing continuously. This has given us the idea of the dynamic nature of the process plants. For large-scale; continuous plants like the chemical process plants in which a lot of process variables are measured very frequently, in order to have a guaranteed continual safe and optimized operation, it is very important that these many process variables be effectively controlled. Hence, the fundamental reason for developing control system.

Choosing a Control strategy and how it is designed are mostly dependent on our knowledge of the process, experience gained as well as insight. And for the control system to work effectively, some of the settings on the controller need to be adjusted, and this is termed "Controller tuning". This tuning is usually best achieved by a trial and error approach most times.

In this thesis, a model of the 4-tank process has been developed, and it is been used in a simulator to evaluate control strategies and their comparative efficiencies. An example, is a situation where important measurement changes value erratically and continuously. Like the bubbling of water, overflow of water in the 4-tank laboratory process.

In this multivariable process, the most important reason for control, is to keep the level of the two lower tanks at a desired level, although disturbances to this system is the flow from the two upper tanks in the equipment. And these disturbances are actually undesirable, so there is very much need for the controller to be adjusted in order to compensate for its influence on the systems' output. These disturbances could be determined by adjusting the two connected valves in the 4-tank process.

3.3.1 Multivariable Control

The existence of almost all complex chemical and industrial process plants are quit best described using the multivariable system. Although these system variables could be interacting or non-interacting in some cases, and the idea of using multiple single-loop controllers is one of the earliest methods that have been employed in the industrial control systems. Its structure appears simple and easy to understand.

In the four-tank multivariable process, there are some control variables that are adjusted or manipulated to keep the different levels of the tank process at a setpoint of interest. The control variables in this case are the pump 1 and pump 2 voltage values which are derived from the controller outputs, as well as the two valve positions. There are sensor measurements from the tanks which enables us to evaluate the system's performance.

In (Seborg E. Dale and Mellichamp, 2003) and reports by Johansson et al. (2009), there are good descriptions of proficient approaches for controlling such a multivariable process. Control methods as Decoupling and the Model Predictive Control were suggested as very good alternatives. The correct model of the 4-tank process should be utilized in order to improve the control system. The two (2) control variables, that is; the voltages of pump 1 and pump 2 are both influencing the water levels in the four tanks h_1, h_2, h_3 and h_4.

In Multivariable systems, certain characteristics as a result of the interaction between the manipulating variable with more than just one controlled variable results in the challenges of selecting the most preferred pairing of the control and manipulated variables for a multiloop control scheme as discussed in (Seborg E. Dale and Mellichamp, 2003) and (Luyben and Luyben, 1997). For convenience most times, the number of manipulated variables are equal to the number of controlled variables. This is majorly to allow the pairing of a single manipulated variable through a feedback controller. In this case, there is process interaction between controlled and the manipulated variables. For each controlled variable, it is expected that a setpoint be given while the manipulated variables are achieved by the controller function, and each process output variable has a single control loop for itself. Some typical examples of multivariable processes are;

- A distillation column where the top and bottom concentration shall be controlled.
- A heated liquid tank where both the level and the temperature are to be controlled.
- A chemical reactor that its concentration and temperature need be controlled.

Figure 3.10 is a schematic illustration of the input and output of a multivariable control system of the 4-tank laboratory process and Figure (3.11) illustrates a MIMO system.

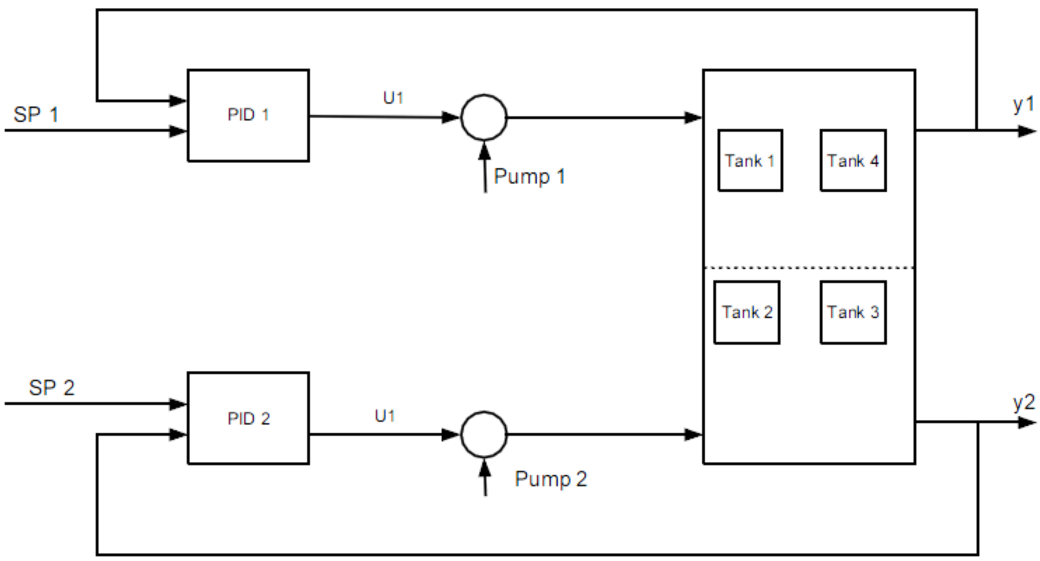

Figure 3.10: Schematic diagram of the multivariable control system

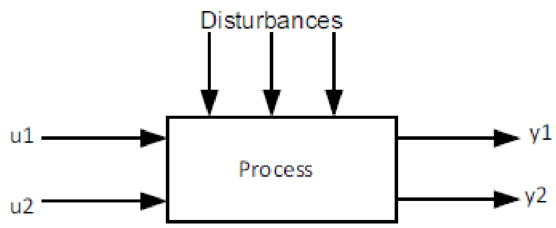

Figure 3.11: MIMO system

In this thesis work, interest is on the level measurement of the two (2) lower tanks and which are fed back to the controllers. Two different control approaches have been evaluated. They are the Conventional PID Controller and the Model Predictive Controller.

Chapter 4

Control Strategies

The need for operating very complex plants like the chemical process plants, oil refineries and pulp mills in a profitable and safer form has really necessitated the development of various control strategies.

In order to develop proficient control strategies, the designers really need to bear in mind that there must be stated control objectives which should be based on the operational requirements of the plant of interest. For various plants or process systems, there are varying control objectives and some of the general objectives according to (Seborg E. Dale and Mellichamp, 2003) are as follows;

1. Stable Operation of the Plant: The control system should be capable of facilitating a stable operation of the process plant without any significant oscillation in the major process variables. Thus, it is very much desirable to have fast recovery from process plant disturbances like changes in feed composition.

2. Safety: It is quite an obligation that industrial process plants be operated safely to ensure the promotion of the well-being of the people/equipment in the neighborhood.

3. Environmental Regulations: The Industrial Plants should adhere strictly to the environmental regulations regarding discharges/wastes beyond the boundaries of the plant.

Haven stated the control objectives as above, the control system strategies can be designed and the steps involved are as follows:

1. Select controlled, manipulated and measured variables.

2. Choose the control strategy and control structure.

3. Specify controller settings.

Usually, the control and manipulated variables can be measured on-line. In cases when controlled variable cannot be measured, it could then be estimated from other process variables using the *"Soft sensor"* approach.

The easiest and most common way for controlling a multivariable process is by using *"single loop control"* with PID controllers. There is usually one control loop for each of the process output variable meant to be controlled. The most common process control strategy is the *"multi-loop control"* which consists of a set of PI or PID controllers, usually one for each controlled variable. This "multiloop PI control" is to an extent proven satisfactory for a couple of control problems. Although, some common control problems in which advanced control strategy would be best option are stated as follows;

- **Process that is having very strong interactions between the process variables:** when there is strong interaction between the process variables, "multivariable control" strategies would be the most effective.

- **Process having slow dynamics and measurable disturbances:** This is the type of problem that requires the addition of feedforward control to the multiloop control.

- **Processes that exhibit strongly nonlinear behavior:** These are the type of problems where nonlinear control techniques like "Fuzzy Logic" are considered.

- **Processes in which constraints on the variables must be satisfied:** This is a situation where certain limits are imposed on the controlled and manipulated variables for certain reasons. Example is when the maximum flow rate is limited by the pump or control valve setting. Thus, inequality constraints could be accommodated by using *model predictive control* (Seborg E. Dale and Mellichamp, 2003).

4.1 Conventional PID Controller

The PID controller is a three-mode controller often times regarded as one of the feedback control algorithms that are predominantly used in commercial quantities dated back as in the early 1930s (Haugen, 2004b).

The controller output is used in adjusting the process variable, ensuring it to be in an acceptable range. It typically means that the steady-state or static error is zero (Haugen, 2004b).

Since our utmost interest is to adjust the control variables ensuring that controller output, changes sensitively to the deviations between the controlled variables and the set-point. Hence, the process would be influenced by a control signal thereby affecting the control variable. The control challenge here is to compare the process variable with the set-point value, which will in-turn be used as a determinant factor for the control signal. A simple block illustrating the PID control action is in Figure 3.1.

The two single control loops used for each of the levels in the tanks are each manipulating the flows through the pumps respectively. The level sensors in the lower two tanks has been used to get the water level of the tanks and these values are then used for adjusting the control signals, hence confirming it is a feedback system.

4.1.1 Control Modes of a PID Controller

The PID Controller basically comprises of three operational modes namely; *Proportional, Integral* and the *Derivative* modes respectively. The combinational effect of these three modes is then used in the control signal. And these modes have their specific output forms. It is represented mathematically in the following form;

$$u = u_0 + k_p e + \frac{k_p}{T_i}\int_0^t e d\tau + k_p T_d \frac{de}{dt} \tag{4.1}$$

And the parameters further defined as;

$$u_p = k_p e \tag{4.2}$$

$$u_i = \frac{k_p}{T_i}\int_0^t e d\tau \tag{4.3}$$

$$u_d = k_p T_d \frac{de}{dt} \tag{4.4}$$

Where k_p is the proportional term, $T_i[s]$ is the integral time, and $T_d[s]$ is the derivative time. The norminal value of the control variable is u_0. Furthermore, u_p is the P-term, u_i is the I-term and u_d is the D-term (Haugen, 2004b).

The three operational modes can be combined in the form of P-Proportional, PD-Proportional Derivative, PI-Proportional Integral and the general PID-Proportional Integral Derivative. The P controller usually changes the control signal in proportion to the error between the set point and the process variable. In this case, if the levels in the tanks 1 and 2 are more than the set point, the control error e is negative thereby making the controller gain k_p gives more control variable adjustment, $k_p e$ for a given error e and giving less error in turn. Instances where the proportional gain is very high, it results in the system's instability. And when the proportional gain is low, it may result in very small control action responding to the system disturbance.

For the I-controller, it is mostly used with a P-controller to yield PI-controller. And for PI-controller, its integral part makes the process variable to move faster to the set point. The PI-controller is widely accepted in industries as it does not pose any form of functionality challenge in its application. Finally, the derivative part of the controller is mostly known for its ability to reduce the rate of change of the controller output. Conclusively, the derivative control is used for reducing the magnitude of produced overshoot due to integral action and hence improves the systems stability.

In precise, the P and the PI-controllers are obtained from the PID controllers as follows;

P controller is obtained by setting the $T_i = \infty$ (or setting to a very large value), while setting $T_d = 0$. Also, the PI controller is obtained by setting $T_d = 0$.

4.1.2 Tunning of the PID controller

It is based on the requirements for using the PID controller to control the 4-tank process satisfactorily, that the best values of k_p, T_i and T_d must be selected by controller tunning. There are quite several methods for tunning a PID controller, but the Ziegler-Nichols' closed loop method is used to adjust the PID controller parameters. In using the Ziegler-Nichols' method, the controller parameters are first set by $K_p = 0$ with $T_i = \infty$ and $T_d = 0$. The controller is then set in automatic mode and K_p is increased until the control reaches the critical gain, K_{pu}, where the output signal sustains oscillations. K_{pu} must be the smallest K_p value that would drive the control loop into sustained oscillations. When the system attains the critical gain, the critical period T_u of the sustained oscillations is measured. Ziegler-Nichols' method gives the controller parameters based on just the two values K_{pu} and T_u as in Table 4.1.

Table 4.1: Controller parameters using Ziegler-Nichols' method.(Haugen, 2004b)

	k_p	T_i	T_d
P controller	$0.5k_{pu}$	∞	0
PI controller	$0.45k_{pu}$	$\frac{T_u}{1.2}$	0
PID controller	$0.6k_{pu}$	$\frac{T_u}{2}$	$\frac{T_u}{8}$

In this process, the level of water in the tanks account for the stability of the process. When the water levels in the tanks is lowered, there is little pressure forcing the pumps to keep the levels at the setpoints, hence making the process to be unstable. But when the level in the tanks are reasonably high, there is much pressure given from the pumps to keep the levels at the setpoints and the process becomes stable. The controller is then tunned at low levels where the process is unstable. Here, the three-way valve is set to one (1) resulting in the water flow to the lower tanks (tank 1 and tank 2). But the process involves two regulating systems, as it is a multi-loop control system. According to the reports by (Gøthesen Dan-Krister and Semb, 2009), by applying Ziegler-Nichols tunning, the parameter values results; $K_p = 0.9$ and $T_i = 5$. And also applying thesame procedure for tunning the second controller, the parameter values then becomes; $K_p = 0.8$ and $T_i = 4.1$ The controller parameters are different, and it results from the variation in the outlet pipes causing outflows. Although, the controllers takes some time to turn on, but the performance is quit satisfactory.

4.1.3 Effect of Multivariable transmission zero

The two valves position are set prior to the experiment, these valves position are interpreted using the parameters $\gamma_1, \gamma_2 \in [0, 1]$. If $\gamma_i = 0$ the entire flow goes into the upper tanks and with $\gamma_i = 1$, the flows go into the lower tanks. The four-tank dynamics has an adjustable multivariable transition zero such that its position can be in the Left Half-Plane (LHP) or Right Half-plane (RHP), and this depends on the ratio of the flow rates between the tanks as determined by γ_1 and γ_2. Hence, the position of the multivariable zero is a source of motivation for investigating the performance limitations arising from the right-half plane transmission zeroes[1]. It is also referred to as transmission zeros.

$$detG(s) = \frac{T_1 T_2 k_1 k_2}{a_1 a_2 A_1 A_2 A_3 A_4} \Pi_{i=1}^{4} (1 + sT_i)^{-1} \times [\gamma_1 \gamma_2 a_1 a_2 A_3 A_4 T_3 T_4 s^2 + \gamma_1 \gamma_2 a_1 a_2 A_3 A_4 (T_3 + T_4) s$$

$$+ a_3 a_4 A_1 A_2 (\gamma_1 + \gamma_2 - 1 - \gamma_1 \gamma_2) + a_1 a_2 A_3 A_4 \gamma_1 \gamma_2] \tag{4.5}$$

The transfer matrix G, thus has two finite zeros. One of the zeros lies in the left half-plane, because all the process parameters are positive. The location of the other zero depends on the sign of; $\eta := a_3 a_4 A_1 A_2 (\gamma_1 + \gamma_2 - 1 - \gamma_1 \gamma_2) + a_1 a_2 A_3 A_4 \gamma_1 \gamma_2$ (Johansson, 2000).

The multivariable zero is in the right half-plane if $\eta < 0$ and would be in the left half-plane if $\eta > 0$. For this four-tank process we have $a_3 a_4 A_1 A_2 = a_1 a_2 A_3 A_4$. See Table 3.1, therefore the system is non-minimum phase for the condition;

[1]According to (Johansson, 2000), the multivariable zeros are the zeros of the numerator polynomial of the rational function and are dependent on the transfer function matrix (4.5).

$$0 < \gamma_1 + \gamma_2 < 1 \tag{4.6}$$

And minimum phase for the condition;

$$1 < \gamma_1 + \gamma_2 \leq 2 \tag{4.7}$$

4.1.4 Right half-plane zeros of the four-tank process

In MIMO systems, the undesirable process interactions and the location of the transmission zeros in the right half-plane are very important. This is because they describe the stability as well as the controllability of the entire system. The right half-plane zero impose limitations on the stability and controllability of the system. A zero in the right half-plane also implies inverse transient response and larger response time in the step response(Haugen, 2004a).

In this thesis work (4-tank process) in which the paramount interest is the development and comparison of control strategies implemented ranging from the decentralized PI controller to the advanced controllers, it is already observed that the right half-plane zero results in process instability and difficulties in achieving good control. In section 4.1.3, the condition for non-minimum phase is stated which results in this four-tank process having a right half-plane (RHP) zero. When the valves are adjusted such that, $\gamma_1 + \gamma_2$ is slightly less than one i.e. $(\gamma_1 + \gamma_2 \approx 1)$, the process would then have a RHP zero that is close to the origin and the levels in the lower tanks would be difficult to control. All thesame, a little change in one of the valves could result in $\gamma_1 + \gamma_2$ to be greater than one and there would not be any limitations on the system's achievable control performance. Although in practice, the difficulty in the control of the levels in the four-tank process is not changed unexpectedly sudden with a small variations in one of the valves.

The position of the multivariable transmission zero being either in the LHP or in the RHP is interpreted using physical illustrations as follows; Assuming the flow from the pump i is represented by q_i. And that, $q_1 = q_2$, then the sum of the flows going into the two upper tanks is $(1-\gamma_1)q_1+(1-\gamma_2)q_2 = [2-(\gamma_1+\gamma_2)]q_1$. The total sum of flow going into the two lower tanks is $(\gamma_1 + \gamma_2)$. Therefore, if the system is in minimum phase we have that $1 < \gamma_1 + \gamma_2 \leq 2$, that is the flow to the two lower tanks are more than the flows to the two upper tanks. On the other side, the flow to the two lower tanks is smaller than the flow to the two upper tanks if the system is in non-minimum phase such that $0 < \gamma_1 + \gamma_2 < 1$. It is inherently easier to control y_1 and y_2 (levels of tank 1 and tank 2) with v_1 and v_2 respectively when most or all of the flows from the pumps goes directly into the two lower tanks.

4.2 Model-based Predictive Controller

The Model-based Predictive Controller (MPC) is a more recent control strategy which has been a special case of the optimal control theory developed in the 1960s and later. The concept of Model Predictive Control (MPC) obviously emanated from using process models as sources for developing new multivariable controllers. Although it is not limited to the chemical and Petroleum process industries, but they are widely characterized by being multivariate in nature with many constraints (Luyben and Luyben, 1997).

The technique that is employed by the Model-based Predictive Controller, focuses mainly on constructing controllers that is capable of adjusting the control action in a way before any change in the output occurs. This inherent predictive nature or ability, in combination with the traditional feedback operation enables the controller to make adjustments that are smoother and very close to the optimal control action values.

The method in which the control action is calculated in the MPC differs from the other types of control strategies. Usually, a finite horizon optimal control problem is solved at each sampling time instant. And for the calculated control sequence, the first step is then applied to the process (plant), while the subsequent control sequences are discarded. These calculations are performed at the next sampling time instant. It is a good idea to handle the MIMO plants and their constraints explicitly. Although two important obstacles to be considered are the computation time that is required to solve the optimal control problem at each sampling time instant and the model of the plant which is non-linear.

Model predictive controllers are applied to process plants that are having slow dynamics such that the computation time is negligible when compared to the sampling intervals. An example of this application is the control of petrochemical process plants. Nevertheless, MPCs are been applied to systems with faster dynamics like Aeroplanes and Combustion engines.

In recent times, MPC applications seem to be next to the PID control in the automation industry. The process model to use, could be linear or non-linear in finding most appropriate changes in the manipulated variables for obtaining desired control variables. The controller function is based on a continuous calculation of the optimal sequence or time series of the control variable, u_k as in Figure 4.3. The calculation is based on predicting the future behaviour of the process to be controlled (Haugen, 2009). There exist an optimization problem associated with MPC, which involves the computation of control input vector, u_k, which is to be feed into the system while taking process constraints (System input amplitude constraints) into consideration at the same time.

SOME OF THE ADVANTAGES OF THE MPC

1. The MPC is able to find most economical set-points and operating points.
2. The MPC ensures process and utility system operations to be stable and respond appropriately to changing requirements.
3. There is coordination in control calculation using the calculation of optimum setpoints.
4. The MPC is capable of providing timely warnings, notifications and alarms of the possible future problems in the plant.
5. It also ensures reduced maintenance and longer plant life.

4.2.1 General Overview of the MPC

The wide acceptance of the MPC by many industries is basically for its smart performances in difficult multivariable control conditions. It is designed such a way that it inherently ensures the control of process variables as best possible in the absence of a sensor or actuator in the process. The MPC aims at preventing the violations of input and output constraints, as well as preventing the excesses that could arise in the movement of input variables. The model of the process is used in predicting current values of the output variables. When the actual and predicted outputs are compared, their resulting difference is used as a feedback signal to the prediction block. And the predictions achieved, are used at each sampling time instant for the calculation of the setpoint and the control signal calculations. A simple block that illustrates the MPC is Figure 4.1.

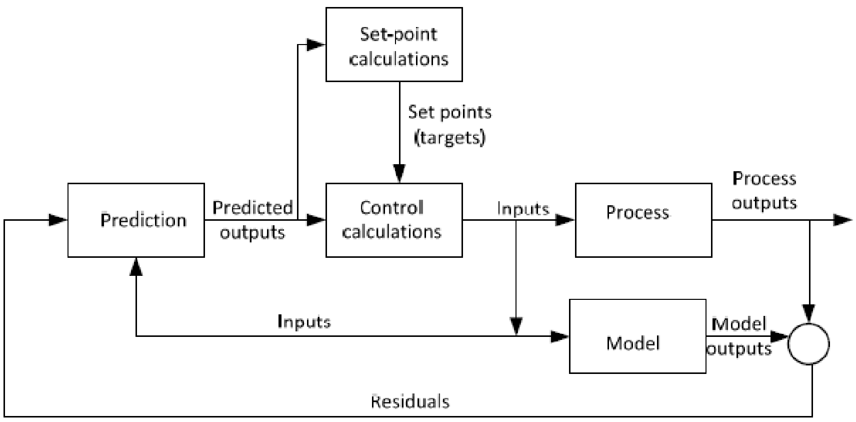

Figure 4.1: Block diagram of the model predictive control(Seborg E. Dale and Mellichamp, 2003).

The inequality constraints on input and output variables, as the upper and lower limits respectively is included in any of the calculations. According to (Seborg E. Dale and Mellichamp, 2003), the objective of the MPC control calculations is for determining a sequence of the so called *control moves* (manipulated input changes) such that the predicted response moves to the setpoint is in an optimal way. In Figure 4.2, the actual output y , the predicted output $\hat{y}$, and the manipulated input u are plotted. Considering the current sampling instant which is denoted as k , the MPC strategy calculates a set of number of input values $\{u(k+i-1), i = 1, 2, ..., M\}$. The calculated control inputs, consists of the current input $u(k)$ and $M-1$ future inputs. However, these inputs are calculated such that the set of P predicted outputs $\{\hat{y}(k+i), i = 1, 2, ..., P\}$ gets to the setpoint in an optimal way. P is the number of predictions which is referred to as Prediction horizon, and M is the number of control moves also referred to as Control horizon. In the sequence of control moves that is being calculated at each sampling time instant, it is the first move that is practically implemented. Another sequence is also calculated at the next sampling time instant, which is based on the available measurements and only the first control move is implemented as well. See Figure 4.2.

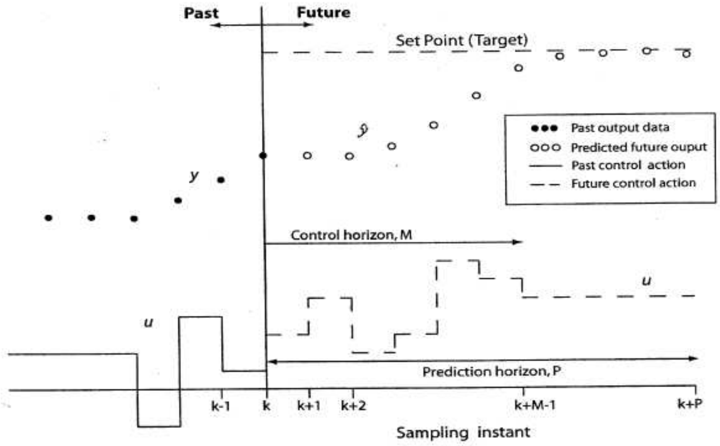

Figure 4.2: Concepts of Prediction and Control horizon in MPC(Seborg E. Dale and Mellichamp, 2003).

4.2.2 Calculation of the control actions

Normally, at each control execution time, the control action which is required by the process is normally calculated based on the available Controlled variables (CVs), inputs (Manipulable Variables, MVs) and the disturbance variables (DVs). These process data are all obtained through the regulatory control system (DCS) that is interfaced to the process. The model of the process is then used to calculate new output predictions in step 2 of Figure 4.3. The structure of the control action could possibly change with respect to the varying execution time instant, thereby making the subsequent control calculations to become ill-conditioned[2]. Although, the ill-conditioning can be removed by adjusting an MPC design parameter such as the *move suspension matrix,* ***R.*** Further readings on this could be found in Seborg et al. (2003). On a general note, applying the MPC give benefits resulting from the determination of the optimal operating condition and the movement of the process to these operation conditions.

[2]Ill-condition: Arises when available inputs have similar effects on two or more outputs

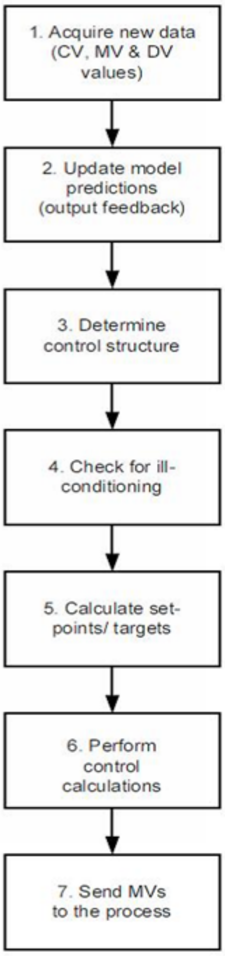

Figure 4.3: Flow chart for MPC calculations

Since the importance of the Model Predictive Controller is to calculate the input signal (which is $u_k = v_1, v_2$ in this project) that most appropriately corresponds to a set of criterium predicting the behaviour of the system on applying the signal. The problem has been made a mathematical programming problem for a given state. The feedback strategy is developed by solving the problem at each sampling time and only the present control action u_k is used. It is often denoted as a Receding horizon problem. It can be summarized in steps as follows:

1. At sampling time k, model Equations (3.6) and (3.7) are used to compute future outputs. i.e. $y_{k+1}, y_{k+2}, ..., y_{k+L}$as a function of future control inputs $u_k, ..., u_{k+L-1}$
2. Minimize the cost function, $J_k$with respect to unknown future and present controls in $u_{k|L}$
3. Apply $u_k$as feed to the process.
4. For next sampling time, $k = k + 1$ and back to step 1, where the optimization problem is done at each new time instant k.

4.2.3 Optimization formulation

The central idea behind formulating an optimization criteria is because of the computation of the new control input vector that is fed to the process, while taking the process constraints into consideration at thesame time. Hence, the MPC optimization criteria consists of terms or components to be treated in next section.

4.2.3.1 Cost function

The cost function which is also known as the control objective, J_k, is a scalar criterion that helps in measuring the process behaviour over a certain prediction horizon, L. The control objective is usually minimized with respect to the future control vectors, $u_{k+1|L}$, and afterall only the first control vector, u_k, is applied in the control implementation. The cost function (control objective) used in connection with MPC is given by the function;

$$J_k = \sum_{i=1}^{L}((y_{k+i} - r_{k+i})^T Q_i (y_{k+i} - r_{k+i}) + u_{k+i-1}^T P_i u_{k+i-1} + \triangle u_{k+i-1}^T R_i \triangle u_{k+i-1}) \tag{4.8}$$

Where L is defined as the prediction horizon, $Q_i \in \mathbb{R}^{m\times m}, P_i \in \mathbb{R}^{r\times r}$and $R_i \in \mathbb{R}^{r\times r}$are symmetric and positive semi-definite weighting matrices that are specified by the user. The weighting matrices Q and R are the parameters that is tunned until a desired performance is achieved. This adjustment is a kind of tradeoff between a fast system and a smooth signal. Usually, if a signal is desired, then the ratio $\frac{Q}{R}$ should be kept minimal. And if on the other hand a faster system is of interest, then the ratio should be increased gradually until the speed is achieved. Since only two (2) states are to be controlled in this work, a more general choice is to specify Q_i, and $R_i$as diagonal weighting matrices having non zero values on the positions coressponding to states 1 and 2. The weighting matrices are usually dependent on the process and must usually be choosen by the trial and error method (DiRuscio, 2009).The control objective is considered as a Quadratic Programming (QP) problem, and the matrix equivalent is given by (4.9);

$$J_k = (y_{k+1|L} - r_{k+1|L})^T Q (y_{k+1|L} - r_{k+1|L}) + u_{k|L}^T P u_k + \triangle u_{k|L}^T R \triangle u_k \tag{4.9}$$

4.2.3.2 Constraints

In MPC implementation, there is good motivation in the sense that constraints like the input amplitude constraints and input rate of change constraints are treated more efficiently than in the conventional PID-controller. It leads to inequality constraints as, $Au_{k+1|L} \leq b$, which is an additive to the optimization problem. The input amplitude constraint is a lower and upper bound on the actuator (pump). The constraints are to a large extent seen as a means for limiting the resources (i.e. water flow) from the pumps in the case of input constraint. And the output constraints are set to limit the amount of water retained in the tanks, as it is set by constraining the tanks height. The minimum is zero $0[cm]$ and maximum is $20[cm]$ for the four tanks.

The amplitude constraints on the input signal to practical control systems is formulated as follows;

$$u_{min} \leq u_{k|L} \leq u_{max} \tag{4.10}$$

It could as well be conviniently formulated in a standard form for Quadratic programming problems as;

$$\begin{bmatrix} I \\ I \end{bmatrix} u_{k|L} \leq \begin{bmatrix} u_{max} \\ -u_{min} \end{bmatrix} \tag{4.11}$$

The system output constraint is also defined mathematically as follows;

$$y_{min} \leq y_{k+1|L} \leq y_{max} \tag{4.12}$$

Since it contains the term of the prediction model, a direct substitution is then made resulting in the Equation (4.13). i.e. $y_{k+1|L} = p_L(k) + F_L u_{k|L}$ which finally yields

$$\begin{bmatrix} F_L \\ -F_L \end{bmatrix} u_{k|L} \leq \begin{bmatrix} y_{max} - p_L(k) \\ -y_{min} + p_L(k) \end{bmatrix} \tag{4.13}$$

4.2.3.3 Prediction Model

This is a model that is constructed from the process model and it is used in describing the relationship existing between the future outputs and the future control inputs to be computed. Hence, making the PM[3] a part of the optimization problem. The Prediction Model is the best tool for forecasting the behaviour of the system in L sampling times ahead into the future. L is the prediction horizon choosen.

Considering a discrete time state-space model as of Equations (4.14) and (4.15), the system dynamics could be computed recursively. However, the states have to be measurable, otherwise a Kalman filter or

[3]PM: Prediction Model.

State observer would be needed. But for the four-tank process in this thesis, the two lower tanks are measurable and only the upper two tanks would need to be estimated.

$$x_{k+1} = Ax_k + Bu_k \tag{4.14}$$

$$y_k = Cx_k \tag{4.15}$$

With a horizon of L, the prediction would be:

$$x_{k+1|L} = \begin{bmatrix} x_{k+1} \\ . \\ . \\ . \\ x_{k+L} \end{bmatrix} = \begin{bmatrix} Ax_k & Bu_k \\ Ax_{k+1} & Bu_{k+1} \\ . & . \\ . & . \\ Ax_{k+L-1} & Bu_{k+L-1} \end{bmatrix} = ...Fx_k + Hu_{k|L} \tag{4.16}$$

Where

$$u_{k|L} = \begin{bmatrix} u_k \\ u_{k+1} \\ . \\ . \\ u_{k+L-1} \end{bmatrix} \tag{4.17}$$

is the control input sequence for $x_{k+1|L}$ (DiRuscio, 2009).

The MPC is quit advantagous, as cross coupling in multiple input amd multiple output(MIMO) systems are been taken into consideration in an optimal way. The MPC method can also be used in computing future optimal controls, $u_{k|L}$. Hence, providing a methodology for computing control suggestions that may be valuable for process operators.

4.3 Parameter Estimation

In attempt to have a stable and robust controlled multivariable system in the absence of some states of the system, there is need for some soft-sensing methods for estimating these parameters or states. The estimates are possibly used as feedforward control signals in the controllers.

4.3.1 The Kalman Filter

The Kalman filter algorithm was developed in the 1960s by Rudolf E. Kalman. It is usually used in the estimation of state variables of dynamic systems that are excited by stochastic disturbances and stochastic measurement noise. The Kalman filter is very much versatile and is used in so many applications. Some of its applications are in fault detection systems, dynamic positioning of ships, soft sensor systems which are used for supervisory and radar applications when someone is interested in target tracking. The Kalman filter produces an optimal estimate such that the mean value of the sum of the estimation errors gets a minimum value (DiRuscio, 2010). In (Haugen, 2009), it is suggested that a discrete Kalman filter be used for implementation on a non-linear state space model. A discrete non-linear model can be written as follows;

$$x_{k+1} = f(x_k, u_k) + Gw_k \tag{4.18}$$

$$y_k = g(x_k, u_k) + Hw_k + v_k \tag{4.19}$$

Where

- x_k is the state vector, including all possible augmented states.
- u_k is the vector of manipulable input.
- w_k is the process noise vector. w has auto-covariance of the form; $R_w(L) = Q\delta(L)$ in which $\delta(L)$ is the unit pulse function. And a standard assumption is that;

$$Q = \begin{bmatrix} Q_{11} & 0 & 0 & 0 \\ 0 & Q_{22} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & Q_{nn} \end{bmatrix} = diag(Q_{11}, Q_{22}, Q_{33}, ...Q_{nn})$$

- G is process noise gain matrix relating the process noise to state variables. And it is commonly assumed that G is a squared matrix. i.e.

$$G = \begin{bmatrix} G_{11} & 0 & 0 & 0 \\ 0 & G_{22} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & G_{nn} \end{bmatrix}$$

  Its elements are set to 1 thereby making it an identity matrix.

- y is the measurement vector of r variables.

- g is the measurement vector function, typically on the form; $g(x) = Cx$. And C is the measurement gain matrix.

- H is a gain matrix relating the disturbances directly to the measurements , and it is commonly assumed that H is a zero matrix of dimension $(r \times q)$ in the form;

$$H = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & H_{rq} \end{bmatrix}$$

- v is a random measurement noise vector. v has auto-covariance of the form; $R_v(L) = R\delta(L)$ in which R is the auto-covariance of v at lag $L = 0$. And a standard assumption is that;

$$R = \begin{bmatrix} R_{11} & 0 & 0 & 0 \\ 0 & R_{22} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & R_{rr} \end{bmatrix} = diag(R_{11}, R_{22}, R_{33}, ...R_{rr})$$

The variances Q and R are usually increased in situations when the strength of the process noise w and measurement noise v are needed to be adjusted respectively. In (Haugen, 2009), the following steps have been presented for calculating the Kalman filter state estimate and its labVIEW implementation is in Figure 4.5;

Step 1 : *Initial step;* Assume the initial guess of the the state to be x_{init}. The initial value $x_p(0)$ of the predicted state estimate $x_p$is set to the intial value.

Initial state estimate:

$$x_p(0) = x_{init} \tag{4.20}$$

Step 2 : *Predicted measurement estimate;* which is derived from the predicted state estimate.

Predicted measurement estimate:

$$y_p(k) = g[x_p(k)] \tag{4.21}$$

The noise terms $Hv(k)$ and $w(k)$ are assumed to be unpredictable , thus they are not used in calculating the predicted measurement estimate.

Step 3 : *Calculating the Innovation process or variable;* This is the difference between the measurement $y(k)$ and predicted measurement $y_p(k)$.

Innovation variable:

$$e(k) = y(k) - y_p(k) \tag{4.22}$$

Step 4 : *Calculating the corrected state estimate, $x_c(k)$;* This is achieved by adding the corrective term $Ke(k)$ to the predicted state estimate $x_p(k)$.

The Corrected state estimate:

$$x_c(k) = x_p(k) + Ke(k) \tag{4.23}$$

Where K is denoted the Kalman Filter gain. The corrected state estimate is also known as *aposteriori* estimate or *measurement-updated* estimate.

Step 5 : *Calculating the next predicted state estimate, $x_p(k+1)$;* This is achieved by using present state estimate $x_c(k)$ and the unknown input $u(k)$ in the process.

Predicted state estimate:

$$x_p(k+1) = f[x_c(k), u(k)] \tag{4.24}$$

In practical applications, 4.23 is used as the state estimate. The predicted state estimate is also known as *apriori* estimate or *time-updated* estimate. The calculation of the *Kalman Filter gain K* as used in (4.23) is further presented as follows;

Step 1 : *Initial step;* The initial value $P_p(0)$ is set to a guessed matrix e.g the identity matrix.

Step 2 : *Calculating the Kalman Gain;*

The Kalman Filter gain:

$$K(k) = P_p(k)C^T[CP_p(k)C^T + R]^{-1} \tag{4.25}$$

Step 3 : *Calculating the auto-covariance of corrected state estimate error;*

Auto-covariance of corrected state estimate error:

$$P_c(k) = [I - K(k)C]P_p(k) \tag{4.26}$$

Step 4 : *Calculating the auto-covariance of next time step of predicted state estimate error;*

Auto-covariance of predicted state estimate error:

$$P_p(k+1) = AP_c(k)A^T + GQG^T \tag{4.27}$$

4.3.1.1 Implementation of the Kalman Filter

Before implementing the Kalman filter estimator to work correctly, it is utmost necessary to test for the observability of the system whose states are being estimated. In this work, the condition of observability of the system is tested on the *KG1.vi, KG2.vi, KG3.vi and KG4.vi* respectively for the four tanks in the system. And these observability tests are all indicated by a Light Emitting Diode (LED) turning on.

The Kalman filter state estimator 's behaviour is assessed by the observation of the physical process, and the physical knowledge about the process. Usually, when there are noises in the estimate, the matrix Q which is a tunning parameter is adjusted inorder to avoid noisy estimates. If the value of Q is made large, it results in larger Kalman Gain K and also stronger updating of the estimates. According to (Haugen, 2009), there would be addition of more measurement noise to the state estimates which is because the measurement noise is a term in the innovation process e that is calculated by K. See Figure 4.4 for illustration. And the number of state estimates is a determining factor for the dimension of the process disturbance (noise) auto-covariance matrix Q.

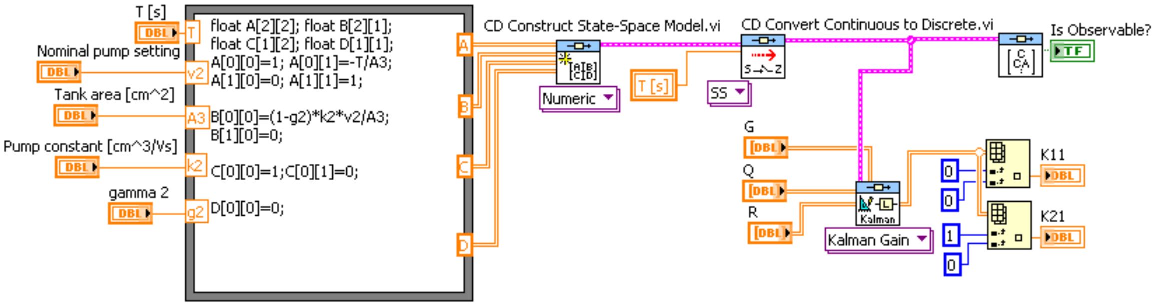

Figure 4.4: Kalman Gain block.

Since the fundamental reason for applying the Kalman filter is for the estimation of the unmeasured water levels in tank 3 and tank 4, different Kalman filters would hence be designed for estimation of the water level and outflow in all the tanks. See part of the program that implements the state estimation in Figure 4.5.

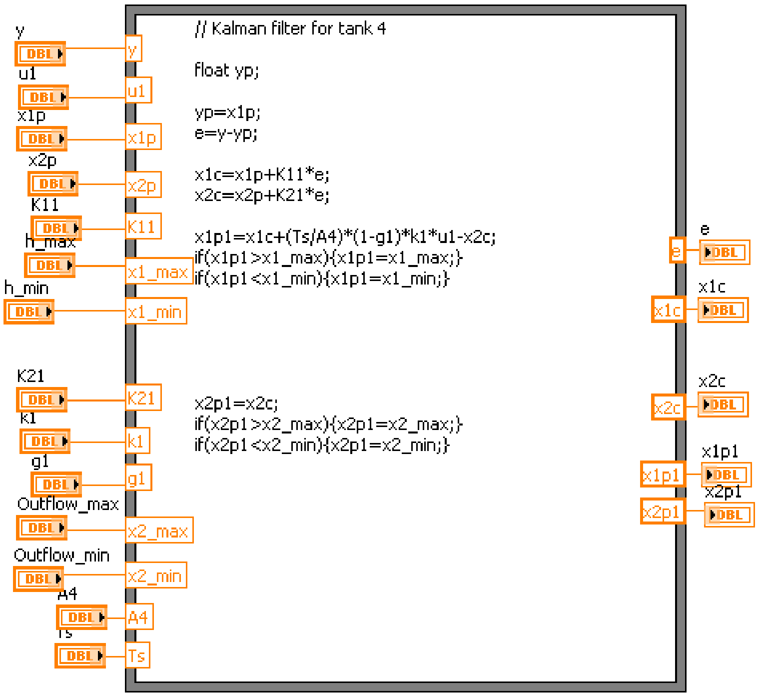

Figure 4.5: Kalman filter LabVIEW program.

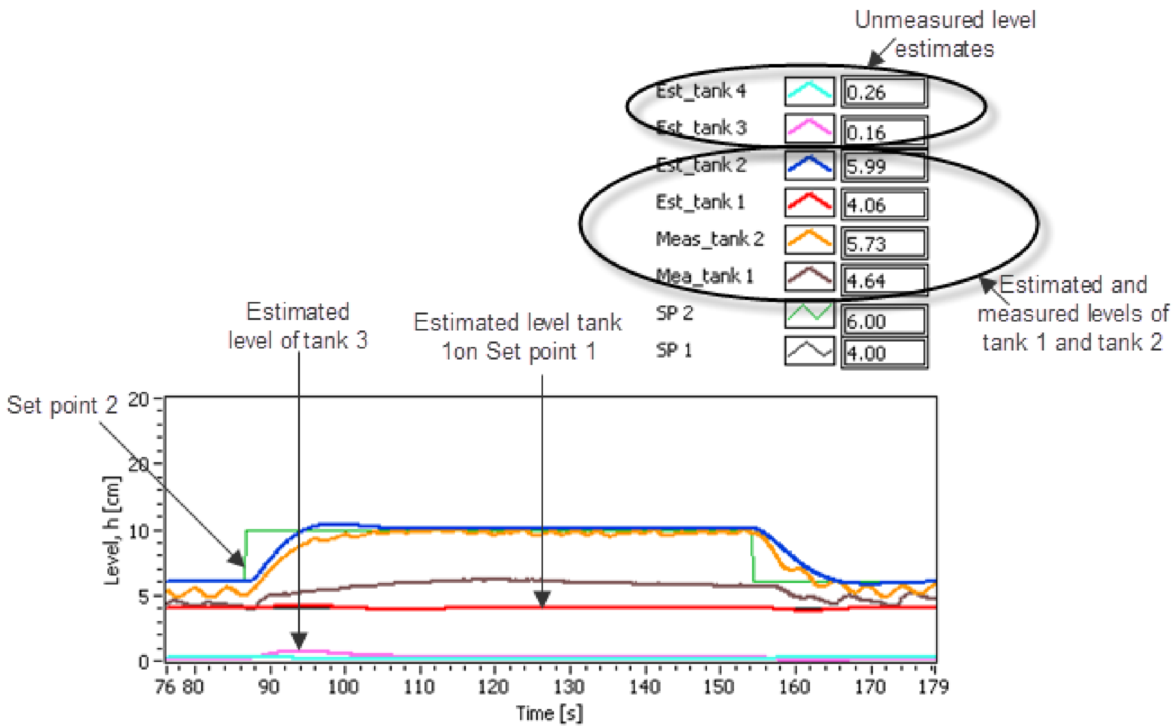

Figure 4.6: Kalman filter Estimation of the 4 levels in the Real process

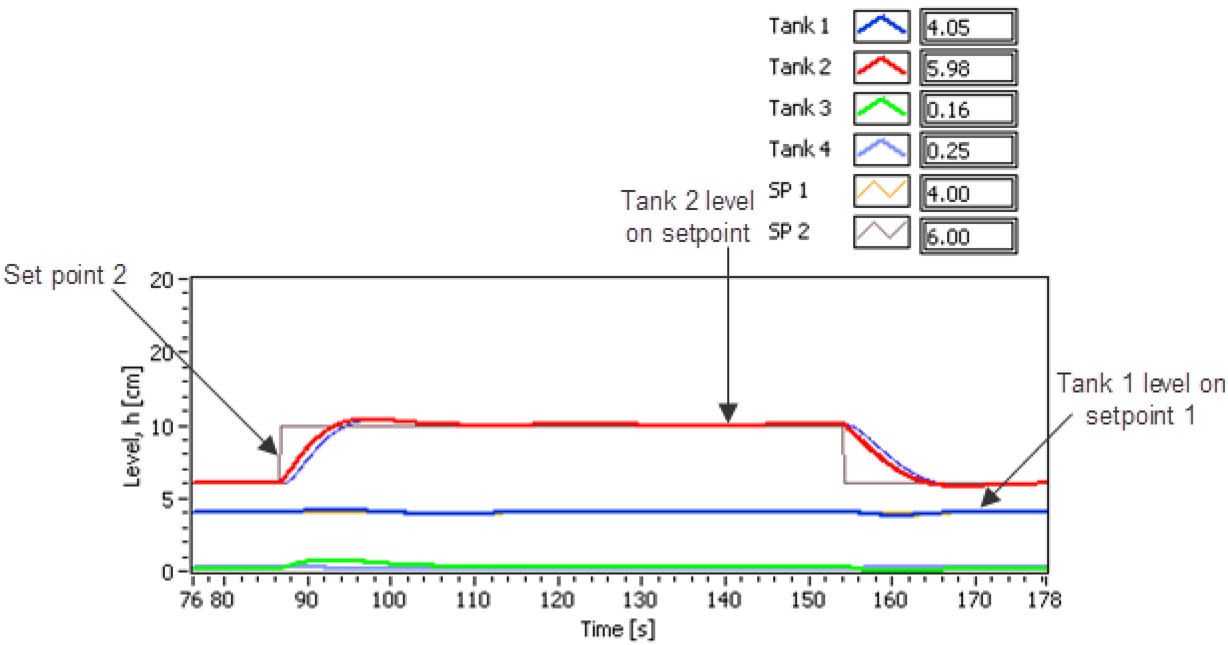

Figure 4.7: Simulator tank levels corresponding to the Estimated and Measured levels of real process

Since the levels in the two upper tanks (tank 3 and tank 4) are not measured, implementing an estimator as in Figure 4.5 is the best alternative to solve such problems of unmeasured states in a multivariable process. Having tested the estimator on the real process and the simulator, there is no significant difference noticed. Although, the system responses as in figure 4.6 is a little noisy; but is surely reliable as substitute in sensor absence or failure. see Figures 4.6 and 4.7 for comparison.

Part II

Implementation of control strategies

Chapter 5

Implementation and results

In this section of the thesis task, a simulator of the model and the real process (Physical equipment of the 4-tank process) in a parallel form are implemented having them side by side to each other. This is aimed at making good assessment, comparison and necessary criticisms based on the respective performances of the processes.

The communication with the real process is achieved using two (2) NI USB-6008 devices, see Figure 3.8. A simple schematic which indicates the data flow from the LabVIEW program to the process is shown in Figure 3.9.

It is considered very useful to show the allocation of the two (2) NI USB-6008 devices amongs the equipments of the process. i.e. the level sensor 1, level sensor 2, valve 1, valve 2, pump 1 and pump 2. This will assist the users and students in confirming that appropriate channels are connected to each and all of the measurement and control devices in the entire process, see Table 5.1 for clarifications.

Table 5.1: NI USB-6008 allocation.

Name	Measurement	NI USB-6008	Channel Number.
Level sensor 1, LT01	$h[cm]$	#1	Analogue Input- AI1
Level sensor 2, LT02	$h[cm]$	#2	Analogue Input- AI1
Valve 1, LCV01	y	#1	Analogue Output -AO0
Valve 2, LCV02	y	#2	Analogue Output -AO0
Pump 1, LCP01	$y[V]$	#1	Analogue Output -AO1
Pump 2, LCP02	$y[V]$	#2	Analogue Output -AO1

The simulated model and the real system is controlled simultaneously with the USB-I/O devices. The LabVIEW program is able to synchronize with the process through the sensors in the physical 4-tank process. The sensors signal generated from tank 1 and tank 2 levels are transmitted to the NI USB-6008 devices, and these signals are further transmitted to LabVIEW through the MAX application. This synchronization of the signals happens very fast, though it is not a real-time system. The sensors used are pressure sensors; one at each bottom of tank 1 and tank 2, and also feedback signals from each of the valves 1 and valve 2 respectively. The valve indicators as shown on the front panel of the main labVIEW program are used to show the values of the two (2) valve positions. Tank level indicators are also used to show the levels in the tanks. For the real process, only the levels in the lower two tanks are being plotted. This is because there is no measurement of the levels in the upper tanks, the levels of the top two tanks are considered as disturbances to the lower two tanks.

On the other side (the model), the levels of all the 4-tanks are plotted accordingly. When the process is controlled (both model and real), only the levels of the two lower tanks (tank 1 and tank 2) are compared except in the case when estimators are included.

The control of the process (real and model) can be chosen to be manual or automatic control of the pumps depending on the interest of the user. In automatic control, the PI controller regulates the pumps (pump 1 and pump 2) with respect to the level of water in the tanks. The user can force the pump manually between 0 to $5V$ (off and maximum flow rates), this is achieved by setting the controller to *"Manual mode"*. The valves are being adjusted such that the pumps influences respective tanks connected to them. The user or student using this equipment is able to make selection of the type of control from the front panel switch labelled "Auto or Manual".

The signals to the pumps here are dependent on the corresponding PI controller's output values which is between $0-100\%$. The pump signal of $0-100\%$ has been scaled to $0-5V$, using the relationship;

$$y = \frac{x}{20} \tag{5.1}$$

Where $x = (0-100\%)$ and $y = (0-5)V$. x is the controller output signal ranging between $0-100\%$. y is the scaled controller output signal in voltage to the pump and ranges between $0-5V$.

The tank levels of the real system as indicated by the two tank indicators which is read from the USB devices into the LabVIEW program is achieved with regards to the scaling relationship as follows;

$$h = (5 \times u) - 10 \tag{5.2}$$

Where $u = (2-6)[V]$, the voltage from the USB device. And $h = (0-20)[cm]$, the level in the tanks.

The position of the valves as shown by the corresponding indicators ranges between $0-1$. These value of valves is determined by the operator or student operating the system, and is feedback from the valve through the USB device. The positional sizing of the valves in LabVIEW is calculted by the relationship as follows;

$$y = \frac{u}{5} \tag{5.3}$$

Where $u = (0-5)[V]$, is the voltage from the USB device. And $y = (0-1)$, which represents the position of the valve to be set by the user. When the value of γ is set to zero (0), all the water will flow into the upper tanks (tank 3 and tank 4). Also, when the value of γ is set to one (1), all the water will flow into the lower tanks only. i.e.(tank 1 and tank 2). And if the operator decides to set the gamma value (γ) between 0 and 1, the water will then flow proportionately into the four (4) tanks depending on the set values. If the valve position (gamma, γ) is set between 0 and 1, its corresponding voltage from the USB device to the valves is calculated by the formular;

$$y = 5 \times u \tag{5.4}$$

Where $x = (0-1)$ in LabVIEW. And $y = (0-5)[V]$, is the output from the USB device to the pumps respectively.

For the devices whose scaling properties have been discussed above, a tabular illustration showing the devices and the type of system is as shown in Table 5.2.

Table 5.2: Devices and Scaling in Systems

Devices	System-LabVIEW	System-Real system
Pumps (P1 and P2)	$(0-100)[\%]$	$(0-5)[V]$
Valves (V1 and V2)	$(0-1)$	$(0-5)[V]$
Level sensors (LT01 and LT02)	$(2-6)[V]$	$(0-20)[cm]$

Chapter 6

Implementation of the PID Controller

The main focus in simulating the system (model and real system) using the centralized PI controller is to enhance good observation of the system's behaviour in response to parameter changes such that would be benchmarked for reference and comparison purposes for other strategy. The simulation of this system is done using four (4) PI controllers in the LabVIEW program such that; two (2) PI controllers will control the real process and the other two (2) PI controllers would be controlling the model simultaneously. Some of the purposes of the simulation are;

1. To observe the behaviour of the system in response to changes in any control function such as, the valve position that results in the minimum and the non-minimum phase operating conditions.
2. The control behaviour in response to set point changes.

RESULTS:

In experimenting the control and stability behaviour of the systsem using the PI controllers for the simulator and the real process, parameter values are choosen to observe the response of the processes both for the case of LHP zeroes and the RHP zeroes respectively. The choosen parameters are as shown in Table 6.1. The parameter values corresponding to the minimum phase operating point, P_L is the case when the processes have minimum phase characteristics. i.e. The process only have LHP zero. Likewise, the parameter values that corresponds to the non-minimum phase operating point , P_R is the case when the processes (real and simulator) have non-minimum phase characteristics. i.e. The processes then only have RHP zero.

Table 6.1: Parameter values for minimum and non-minimum phase operating points.

	P_L	P_R
$(h_1^0, h_2^0$ $[cm]$	$14.99, 14.99$	$14.99, 14.97$
(h_3^0, h_4^0) $[cm]$	$0.24, 0.21$	$3.37, 9.05$
(v_1^0, v_2^0) $[V]$	$3.85, 2.96$	$4.34, 1.33$
(k_1, k_2) $[cm^3/Vs]$	$0.67, 0.74$	$0.67, 0.74$
(γ_1, γ_2)	$0.93, 0.9$	$0.5, 0.5$

The results of the minimum phase and non-minimum phase of the real process and the model as well as their controller actions are shown in Figures 6.1, 6.2, 6.3 and 6.4 respectively.

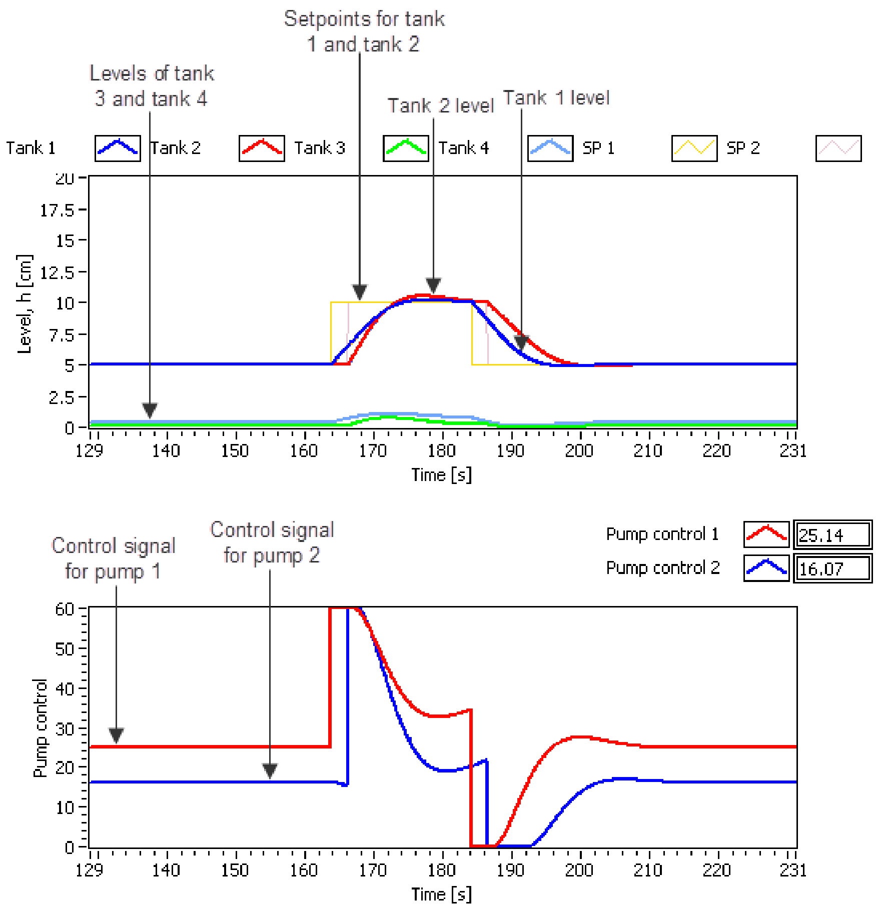

Figure 6.1: Minimum phase process and control signal (Model).

For the non-minimum phase operating condition, set point changes are made and the controller action as well as the process output (level of tanks) signals are plotted in Figure 6.2.

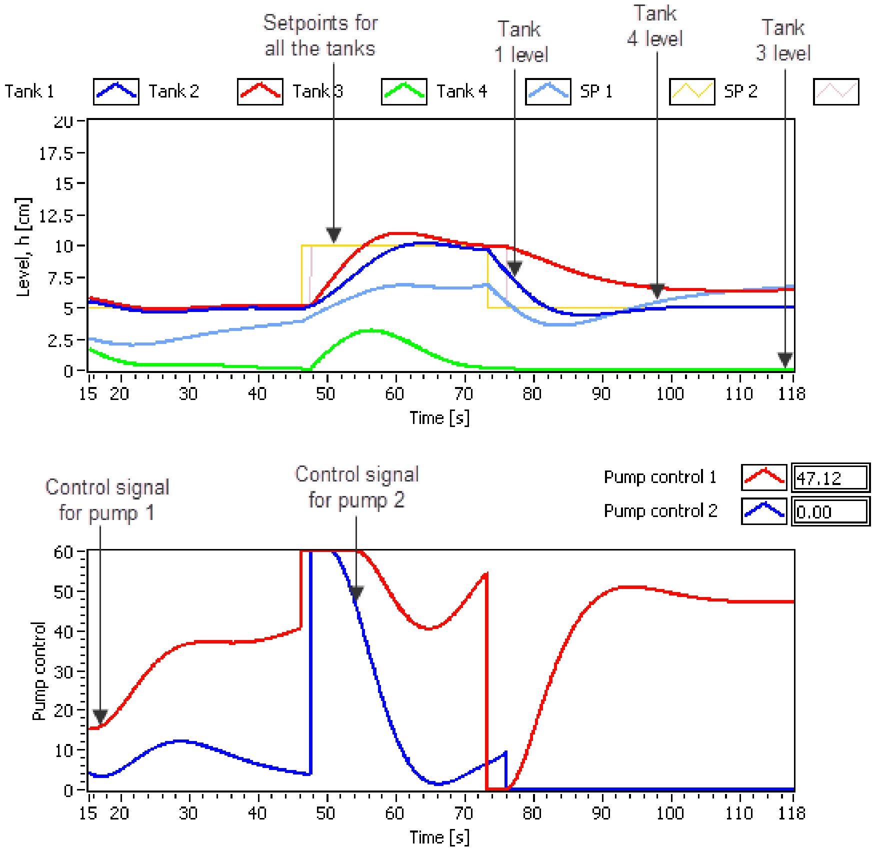

Figure 6.2: Non-minimum phase process (model)

Likewise, the minimum and non-minimum phase operating conditions have been applied to the real process and its responses as well as the controller behaviour is as shown in Figure 6.3 and Figure 6.4 respectively.

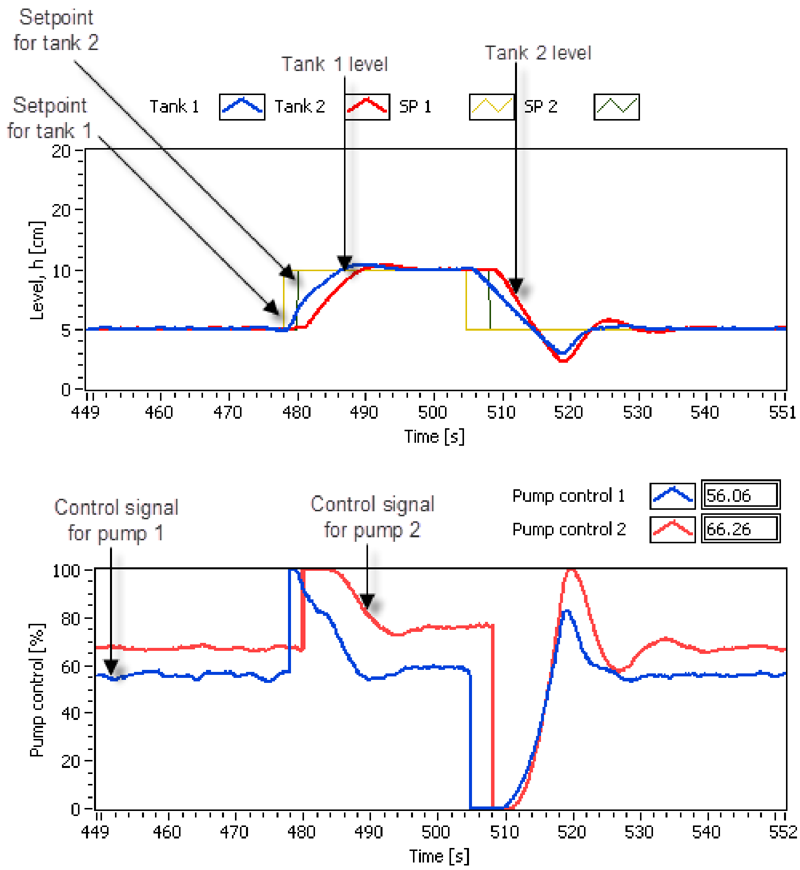

Figure 6.3: Minimum- phase operating condition (Real process)

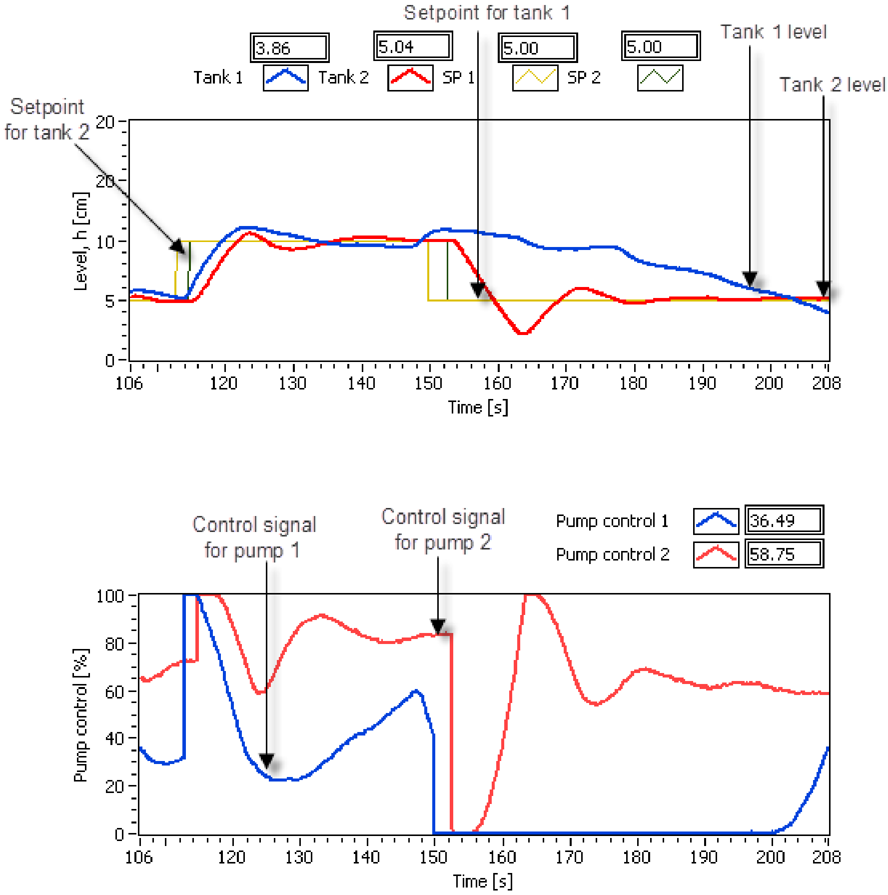

Figure 6.4: Non-minimum phase operating condition (Real process)

Having implemented the control of the process (including the simulator) with consideration on the two operating conditions (positions) of the transmission zero, the control, response time and stability of the process is observed. The responses from the real and the model (simultor) are quite similar. Figure 6.3 and Figure 6.4 shows that the response and settling times for the non-minimum phase process is longer than the minimum phase process. And there is a good difference in the controller behaviour for both conditions, as the controller is more stable making the process to be controlable in the minimum phase. Figures 6.1 and 6.3 shows stable processes, while Figures 6.2 and 6.4 shows unstable and uncontrollable processes.

6.1 Lowpass filter implementation

In the course of testing the controller performance with the real process, it has been noticed that the measurements from the process was quite noisy. And this calls for implementation of a low pass filter that would considerably reduce the noise in the signals. The filter is implemented using a formular node, which is based on the transfer function of a lowpass filter having input variable u and an output variable y . It is written on the form in Equation (6.1).

$$\frac{y(s)}{u(s)} = H(s) = \frac{1}{T_f s + 1} \tag{6.1}$$

$$T_f = \frac{1}{w_b} \tag{6.2}$$

where T_f is the filter time constant, $w_b = 2\pi f$, and f is the signal frequency.

It is very necessary to apply the Euler backward difference on $\dot{y}(t)$ (time domain) of Equation (6.1), which is to help in obtaining a mathematical relationship that is used in deriving a discrete version of the filter. Hence, cross multiplying and taking the inverse laplace transform of Equation (6.1) yields;

$$T_f s \times y(s) + y(s) = u(s) \tag{6.3}$$

$$\mathcal{L}^{-1}\left\{T_f s \times y(s) + y(s)\right\} = \mathcal{L}^{-1}\left\{u(s)\right\} \tag{6.4}$$

$$T_f \times \dot{y}(t) + y(t) = u(t) \tag{6.5}$$

Now applying the Euler backward difference on $\dot{y}(t)$ and knowing that $y(t) = y(k)$ gives;

$$\dot{y}(k) = \frac{y(k) - y(k-1)}{h} \tag{6.6}$$

And then substituting into Equation (6.5) yields;

$$T_f \times \left(\frac{y(k) - y(k-1)}{h}\right) + y(k) = u(k) \tag{6.7}$$

$$y(k) = \frac{T_f}{T_f + h} y(k-1) + \frac{h}{T_f + h} u(k) \tag{6.8}$$

Where $u(k) = y_{input}(k)$, is the filter input.

$$y(k) = \frac{T_f}{T_f + h} y(k-1) + \frac{h}{T_f + h} y_{input}(k) \tag{6.9}$$

We can now define $a = \frac{h}{T_f + h}$, which yields;

$$y(k) = (1 - a) \times y(k-1) + a y_{input}(k) \tag{6.10}$$

It is important to note that $0 \leq a \leq 1$, otherwise the system will be unstable.

Chapter 7

Implementation of the MPC

The performance of an MPC controller depends on the accuracy of the model. Although, it is possible to specify for the MPC controller to incorporate integral action such that it can compensate for the differences between the real plant and the model of the plant. The creation or implementation of the MPC controller is based on a state-space model of the plant. But in the case of transfer function model or a zero-pole-gain model, the model needs to be converted to a state-space model.

7.1 Selection of design and tuning parameters

A good MPC controller is achieved when the required design parameters are specified correctly in the implementation process of the controller. There are quit some design parameters which are used in the tuning of the controller.

7.1.1 Sampling period and model horizon

Sampling period $\triangle t$ and the model horizon N , are parameters that should be chosen such that $N\triangle t = t_s$. Where t_s is denoted the settling time for the open-loop response. This parameter selection ensures the model to reflect the complete effect of a change in an input variable over the time it needs to attain steady state. In (Seborg E. Dale and Mellichamp, 2003), it is pointed that it is very typical that $30 \leq N \leq 120$. Also if the output variables are responding on different time scales, then different values of N could be used for each output.

7.1.2 Control horizon

This is the number of samples within the prediction horizon of which the MPC controller could affect the control action. It is also fixed for the duration of the controller's execution. If the control horizon increases, the MPC controller tries to become aggressive such that there would be increased requirement for the computational effort. It is sometimes denoted as M , and conventionally selected within $5 \leq M \leq 20$. According to (Seborg E. Dale and Mellichamp, 2003), it is possible to specify different values of M for each of the inputs.

7.1.3 Prediction horizon

This is the number of samples into the future during which the MPC controller would predict the plant output. It is denoted as P and selected by $P = N + M$ thereby making the complete effect of the most recent input move to be accounted for. The decrement in its value results in making the controller to be more aggressive. Thus, different values of P can be selected for each output if their settling times are different. For implementation in LabVIEW program, it is denoted as $\mathrm{N_p}$. The desired prediction and control horizon as defined in this task is shown in Figure 7.1

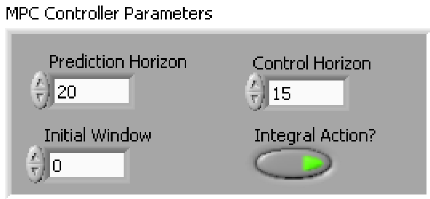

Figure 7.1: Prediction and control horizon

7.1.4 Weighting matrices, Q and R

The weighting matrix Q as in the definition of the cost function in Equation (4.8), allows output variables being weighted according to their relative importance. Note that, an $mP \times mP$ diagonal Q matrix will allow the output variables to be weighted individually while the most important variables will have the largest weights. For example, if the levels in the four (4) tank laboratory process is considered more important than the temperature in the tank, then the tank level in that case will be assigned a larger weighting factor.

Likewise, R is a weighting matrix that allows input variables to be weighted according to their importance. Also note that, an $rM \times rM$ matrix is referred to as an *input weighting matrix*. It is a diagonal matrix whose elements are referred to as *move suppression factors*. Convenient tuning is achieved as a result of increasing the values of the elements and in turn makes the MPC controller to be conservative by the reducing the input moves.

7.1.5 Reference trajectory

The future output behavior in an MPC application are specified in a number of different ways like, the set-point , reference trajectory, high and low limits. But the reference trajectory has a tunning factor that is used in adjusting the desired speed of response for each output. The reference trajectory can be specified by the concept of performance ratio[1].

7.2 Creation of the MPC

According to the National Instruments (NI), the specified value for the control horizon must be less than the value to be specified for the prediction horizon. They also recommends that the length of the prediction horizon be set according to the requirements of the control problem because both the lengths of the prediction or control horizon cannot be changed while the controller is being executed. In (DiRuscio, 2009), it is pointed that a short prediction horizon limits the MPC controller's performance, thereby making it to operate like a feedback controller.

A long prediction horizon increases the ability of the MPC controller to predict more effectively, although this long prediction horizon could as well decrease the performance of the MPC controller as it adds extra calculations to the control algorithm.

As mentioned in section 4.2.2 , the MPC controller calculates a sequence of future control actions in such a way that a cost function is minimized. The weighting matrices in the cost function is been specified in such a way that they help in adjusting the priorities of the control action, rate of change in the control action and the outputs of the plant. Additionally, the constraints on the parameters of the MPC controller in this case have been specified by the dual optimization method. It is much easier for understanding of the target reader and/or student as it clearly indicates the initial and final, as well as minimum and maximum value constraints on the control action, output of the plant and the rate of change in control action. Although, the concept of the constraints is much explained in section 4.2.3.2, but its selection as used in creating the MPC controller is as presented in Figure 7.2 and the block diagram in Appendix 3.

[1]Performance ratio: Is the ratio of the desired closed-loop settling time to that of open-loop settling time

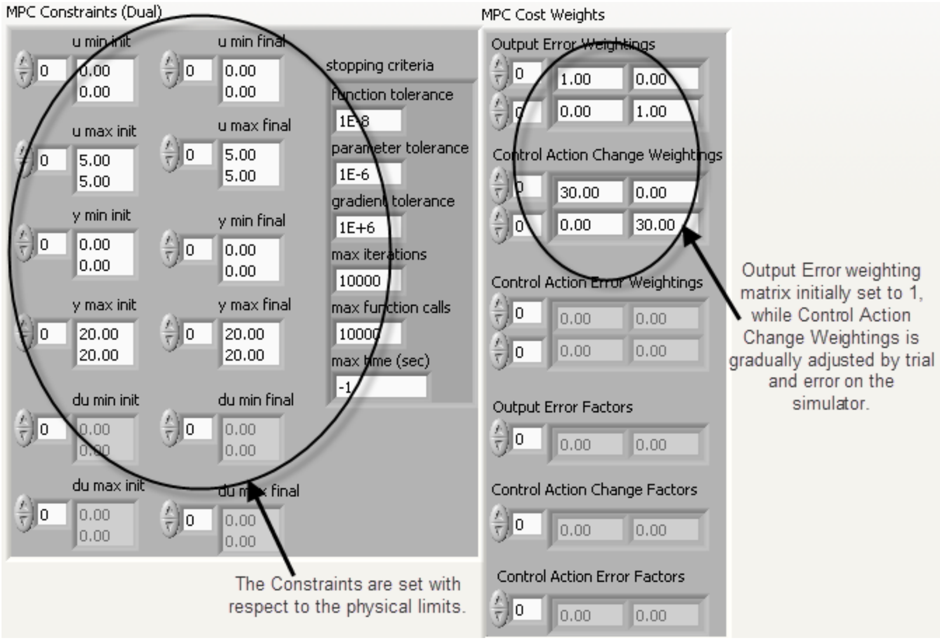

Figure 7.2: Specified MPC constraints.

The requirement for setpoint specification to the MPC controller operates by comparing the plant input and the output values to setpoint profiles. These setpoint profiles contain the predicted values of the control action and plant output setpoints at certain time instants, the profiles are been sent to the MPC controller that calculates the error by comparing the predicted plant inputs and outputs to the setpoint profiles. The MPC controller will then try to reduce the error by minimizing a cost function which takes this error into account.

Now parameter values exactly as used in the implementation of the multivariable control using the PI controller as in Table 6.1 of chapter 6 are chosen and the MPC implemented successfully. The results of the minimum phase and non-minimum phase of the process as well as with the corresponding controller actions are shown in Figures 7.3 and 7.4.

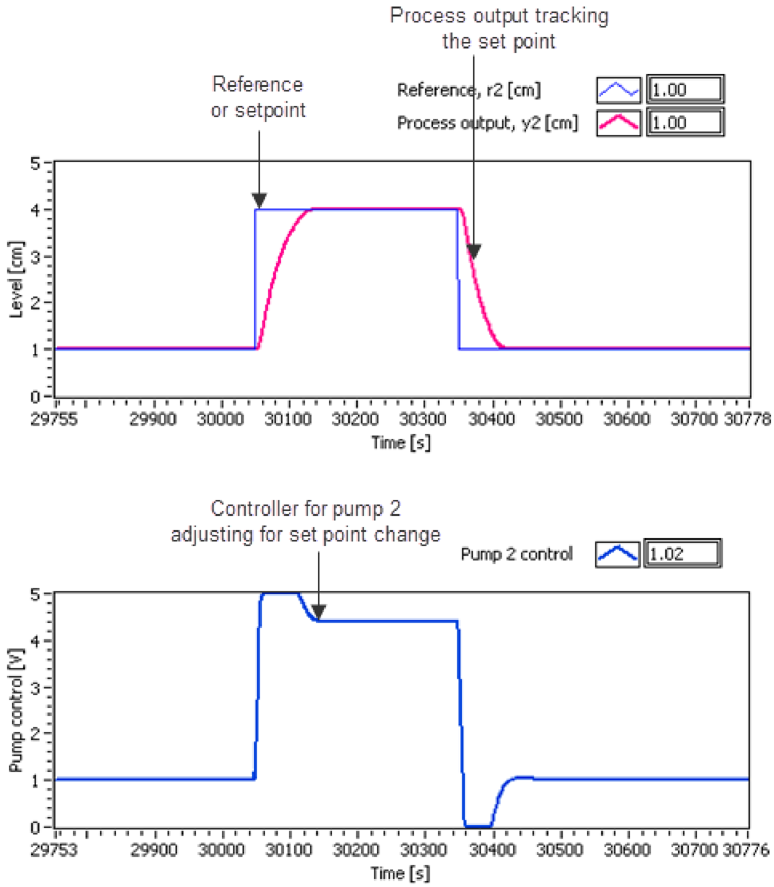

Figure 7.3: Controller action in minimum phase operating condition

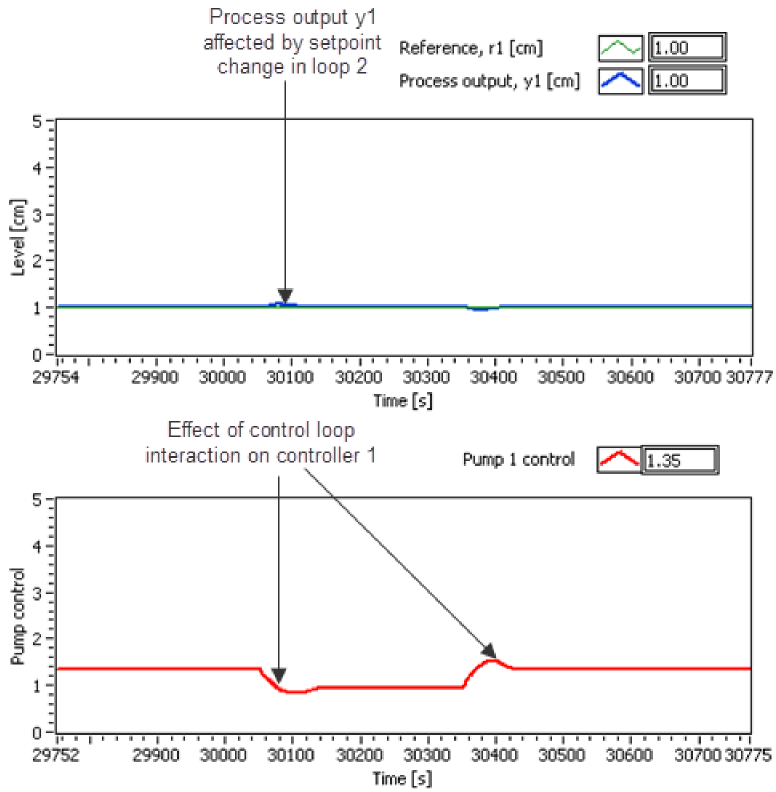

Figure 7.4: Second control loop adjusting for setpoint change in other loop

The controller is set to non-minimum phase operating condition and the results of its performance with the process output are as in figures 7.5 and 7.6.

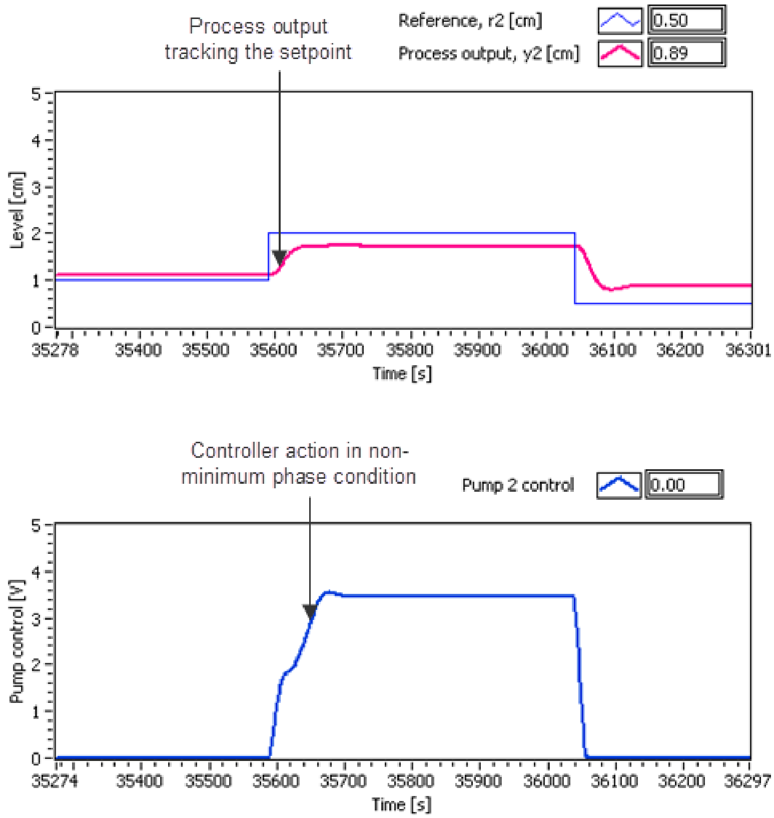

Figure 7.5: Controller action in non-minimum phase operating condition

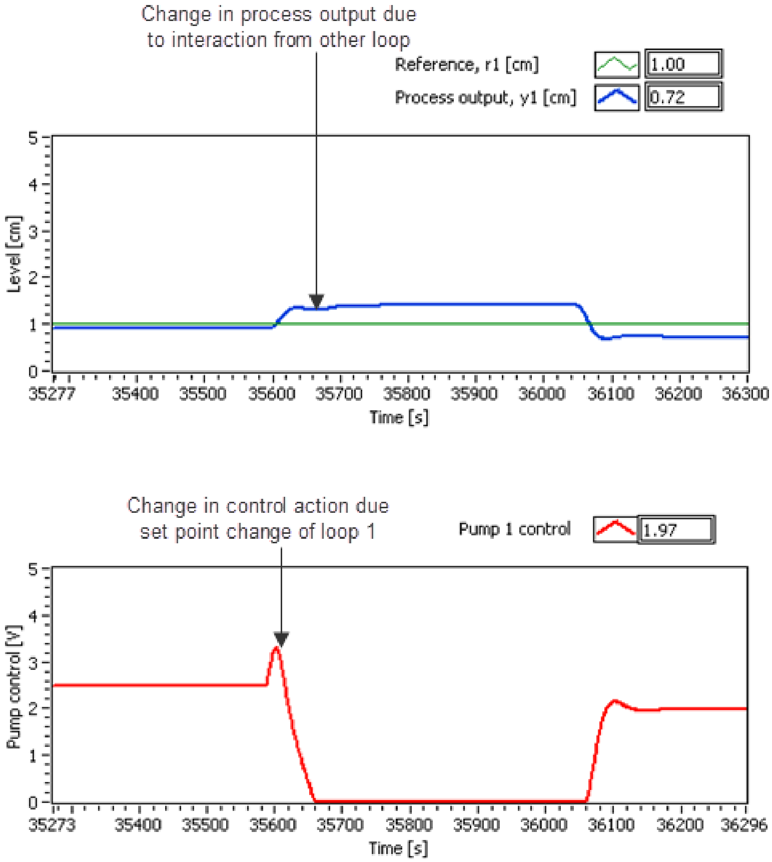

Figure 7.6: Second control loop adjusting for setpoint change in non-minimum phase

Chapter 8

Discussions

In as much as the system is non-linear, complete expurgation of model uncertainties is not wholly guaranteed in control system design. Although the choice of model type might not be so important now. A linearized model of the process is used for control implementation, though not exactly as an original linear model.

Since this thesis is aimed at comparing the performance of control strategies as applied to the four-tank process, the design is for the case of PI (proportional integral) controller and MPC (model predictive controller) as described in Chapter 4.

Considering the PI controller implementation where the levels of the two lower tanks are controlled by the two pumps, it results in using two independent PI controllers. And the multiloop control emerges from these loops. The upper tanks (tank 3 and tank 4) in the system which are supplied proportionately depending on the valve positions, thereby resulting to minimum phase and non-minimum phase operating conditions. For the minimum phase condition, it is easy to obtain controller parameters that gives good performance. The PI parameters obtained in Section 4.1.2 are implemented, resulting in responses as in Figure 6.1 and Figure 6.2 which are the operating conditions of minimum phase and non-minimum phase respectively. The implemented controller was tested on the real process and the noted discrepancies between the simulation and the real life responses are quite small. The process is generically difficult to control in the case of non-minimum phase. When there is high process interaction, with the presence of nonlinear effects, the closed loop responses becomes very oscillatory around the setpoints. And when some random parameters are applied using trial and error, it results in slower responses more than in minimum phase condition. And the settling time is much longer for the non-minimum phase. Some of the strengths of PID controller in control design are;

- Excellent performance without model of the process.
- It has the tendency to perform better when the process model is incorporated in it.

And the basic difficulty with PID controllers is that it is a feedback system, its overall performance is reactive since it has no direct knowledge of the process. When there is non-linearities, it may trade off its regulation for response time.

Having evaluated the performance of the PI controller, it is very important that control loop interaction be eliminated or considerably minimized in a multivariable process.

The MPC which is just dependent on the properties of the model of the system as described in Chapter 7, manipulates the signals to the pumps to control the levels in the lower two tanks. Some of the identified proficiencies of the MPC in the process are;

- The MPC is able to effectively decouple process interaction.
- It implicitly handles constraints on process inputs and outputs systematically, while having smoother control signal.
- It is able to plan control by looking ahead.

Some other advantages of the MPC documented in this thesis are in Section 4.2. While some of the challenges identified with the MPC are;

- Model development, computation as well as implementation.
- Its adaptation and non-linearity handling.

- Lacks more friendly user interface.
- It has been noticed that the tunning of the MPC controller really poses great challenge on its implementation.

The implemented controllers (PI and MPC), have performed satisfactorily, especially in their behaviour resulting from setpoint changes and the position of the multivariable transmission zeros. And the performance of the MPC remains thesame not minding the location of the transmission zero. The control and simulation study of the system which is implemented independently, has shown some of the differences and shortcomings among the controllers.

The four-tank process has two unmeasured states, which are the levels of the upper two tanks (tank 3 and tank 4), and having implemented the Kalman estimator was able to estimate the unmeasured levels respectively. And this estimates as in Figure 4.6 can be used when situations of sensor failure occurs.

8.1 Recommendation

I would like to suggest for onward research in the application of the MPC for controlling the 4-tank process. This strategy really has a promising future since it is able to handle multivariable process interactions. It is also of great importance that the sensors on the physical process be properly calibrated for onward experiments to be carried out on it. It would be very much comfortable if subsequent experiments using the 4-tank process are implemented firstly in the MATLAB/Simulink (especially the MPC strategy) before been transfered to LabVIEW that has better graphical user interface, this is to ensure proper functioning of the process as it would have an alternative test programme.

Chapter 9

Conclusion

The implemented controllers (PI and MPC), have performed satisfactorily in the control of the four-tank process, especially in their behaviour resulting from setpoint changes and the varying position of the multivariable transmission zeros.

The control and simulation study of the system which is implemented independently, has shown some of the differences and shortcomings among the controller types. And developing this control strategies whose performances have been compared, really serve as a means of providing experience in analyzing dynamic features of systems having feedback for evaluating the parameters of the control system. Control system situations that requires compensation for time delays and multivariable interactions are thus better handled with MPC controllers, since it is able to handle multivariable problems naturally. The implemented strategies are kind of stepping stone for readers to gain experience in the setting up of different control algorithms like the PID algorithm, MPC algorithm as well as feedback by the state. The designed control strategies are ensured to enable remote access to documents and LabVIEW programs for undergraduate students in Telemark university college.

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Part III

Appendices

Appendices

Appendix 1: Thesis Topic Description

Telemark University College
Faculty of Technology

FMH606 Master's Thesis

Title: Developing Advanced Control strategies for a 4-Tank Laboratory Process

TUC supervisor: Hans-Petter Halvorsen, M.Sc.

External partner:

Task description:

In this project you will analyze and develop advanced control strategies for a 4-tank Laboratory Process available at TUC. The purpose is to design and test different control strategies on a multivariable system.

The 4-tank Laboratory Process is a small transportable and light-weight system containing of 4 connected water tanks, two pumps, 2 level sensors, 2 valves.

- A mathematical model for the process is developed but could be further investigated and used in control strategies such as design of a state variable feedback system and Observer Design. Because the level in only two of the four water tanks are measured the level in the two other tanks need to be estimated. Techniques such as Kalman filter, etc. should be considered.
- The control strategies shall be implemented in a suitable development tool such as LabVIEW or C#.NET. The control systems should be implemented, analyzed and documented.
- As part of the report the student should discuss the different implementations and find the advantages and disadvantages based on a theoretical and practical study of the process and the control strategies.
- In addition to the project report there should be a "Training Kit" which makes it easy for teachers, laboratory personnel and students to use the system in laboratory work.

Task background:

The laboratory process was development by a Bachelor project group the spring 2009.
The idea is to use the laboratory process and the control systems designed in this project in the students laboratory work in the future.

Adress: Kjølnes ring 56, NO-3918 Porsgrunn, Norway. **Phone:** 35 57 50 00. **Fax:** 35 55 75 47.

The student will learn how to use and design advanced control strategies on a small-scale process system; learn about process equipment such as pumps, sensors, and valves. The student will also learn to use modern development tools, simulation and data acquisition.

Student category: SCE students

Practical arrangements:

Filename: FMH606 Master Thesis - 4-Tank Laboratory Process.docx

Signatures:

Student (date and signature): 01/02/2010 Halemi.

Supervisor (date and signature): 29/1-10 Hans-Petter Halvorsen

Appendix 2: Training Kit

Training Kit for experimenting the 4-Tank laboratory process using the PI and MPC controllers.

Department of Electrical, Information Technology and Cybernetics, HiT, Norway.

June 4, 2010

1 Introduction

This is a laboratory work that is aimed at studying the performances of the PI and MPC controllers by applying them to control the levels of the two lower tanks of the 4-tank laboratory process in Telemark University College, Norway. The four-tank process is a multivariable process that possesses non-minimum phase characteristics depending on the position of the two valves in the process. The performance of these controllers will be assessed and/or evaluated in a simulator and on the real process.

2 Installation/ requirements

In order to be able to carry out this laboratory work either in Telemark University College laboratory (HiT) or on remote sites by connecting through the internet to the college homepage, it is fundamentally required that your (user's) computer (or Laptop) has LabVIEW programme of version 2009 or later version already installed on it. If it is on the University (HiT) laboratory computer, then you are (the user is) required to "log on" using your university account/password. You (the user) now have to download the "zip folder.zip" that contains all the VIs which is organised in a labVIEW project unto your local hard drive. Unzip and extract the downloaded folder.zip carefully and the labVIEW project explorer with the organised VIs is opened as in Figure 1.

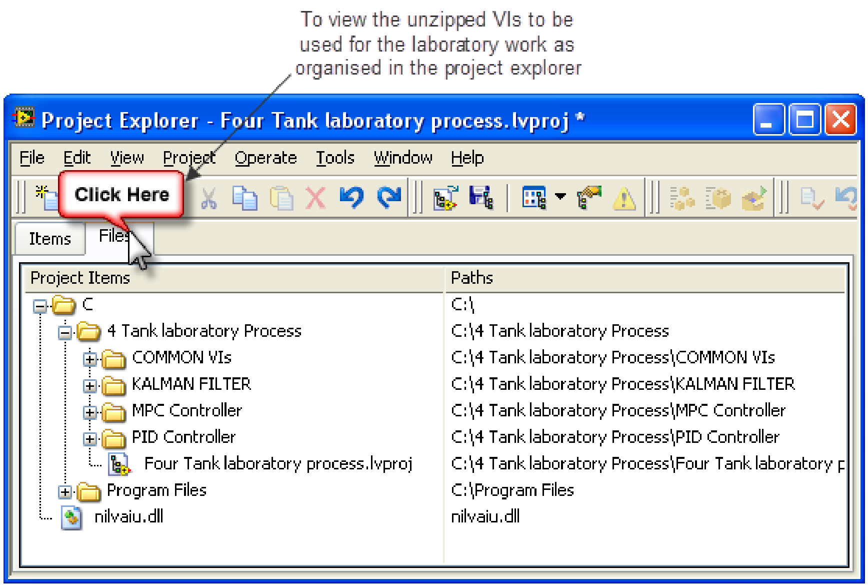


Figure 1: Unzipped project explorer

After having a glimpse at the VIs available and the control strategy of interest is to be run, then take the steps in section 3 accordingly.

3 PI experiment

In this section, it is assumed that you are interested in performing experiment (controlling the levels) on the four-tank process using the PI controller. The experiment is usually advised to be initially carried out on the simulator before advancing to compare and confirm on the real physical process. In selecting the PI controller to use in carrying out experiment, it is done as in Figure 2.

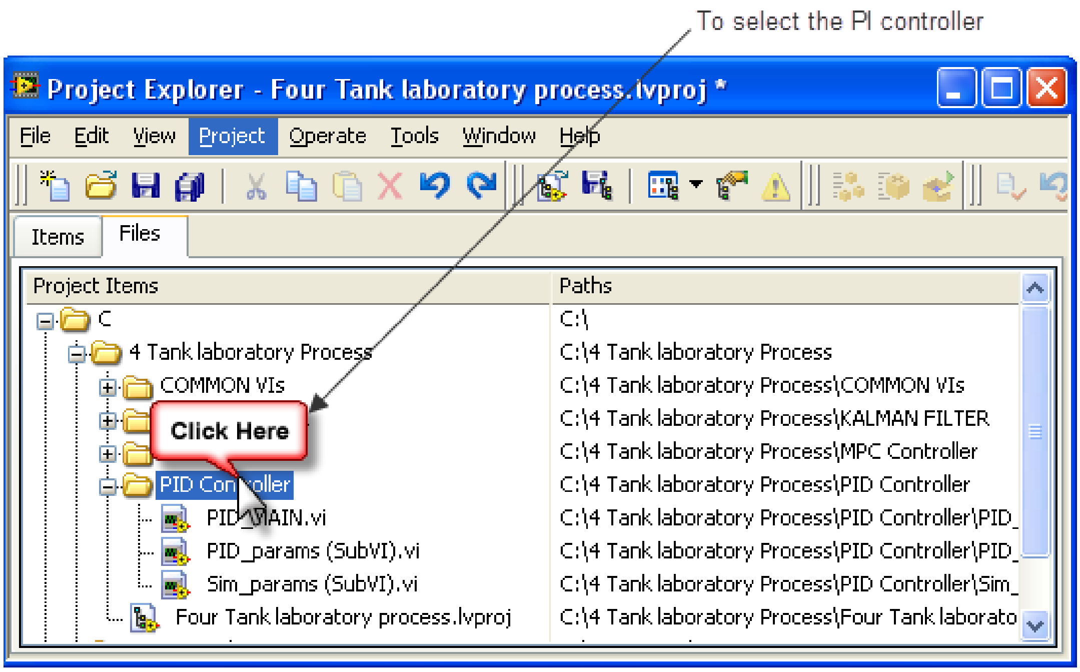


Figure 2: Selecting the PI controller

On selecting the PID controller as in Figure 2, you should now "click on" the main VI that implements the PI controller for the process. See Figure 3 for guidance.

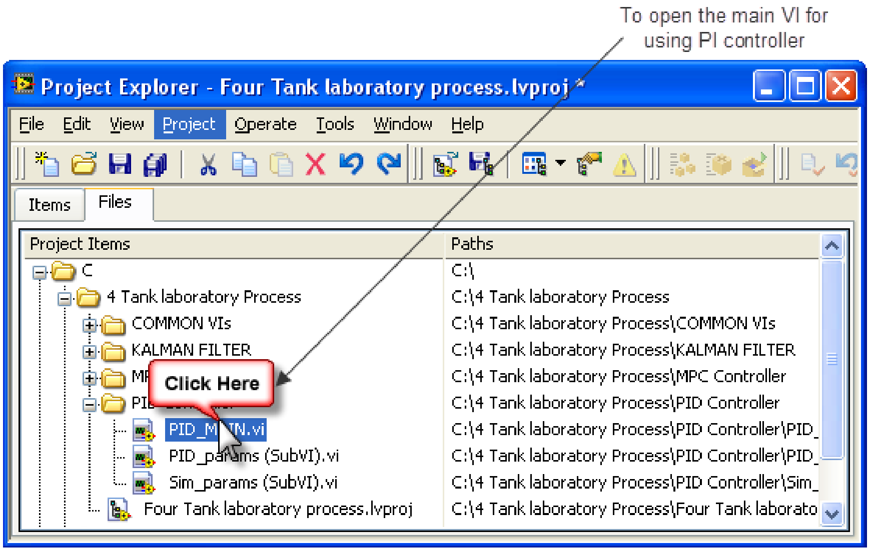


Figure 3: Opening the main PID controller VI

And on loading the VI, PID_MAIN.vi, the front panel appears as in Figure 4. This is now ready to be run.

3.1 Procedure

Prior to running of the PID_MAIN.vi, some parameter values must first be configured;

- You must select the controller mode (Manual or Auto) by pushing the switch labelled "Manual or Auto"
- Then select values for γ_1, γ_2[1]
- You then give values to set point 1 and set point 2.
- Now, "click" the run button to start the program.
- You should now observe the process carefully, and document the results obtained with relevant plots of signals. Several parameter value changes can be possibly done for analysing the system performance.

The Simulator and Real process are running simultaneously, and you can select only simulator by using the Disable structure in the Block diagram.

[1]The values of γ_1 and γ_2 to choose must be within the range of 0 to 1, which is used to determine the proportion of water flow that is been distributed into the lower and the upper tanks respectively. If γ_1 and γ_2 are set to 1 , all the flows from the pump will go into the lower tanks. Also if $\gamma_1$and γ_2 are set to 0, all the flows in this case will go into the upper tanks.

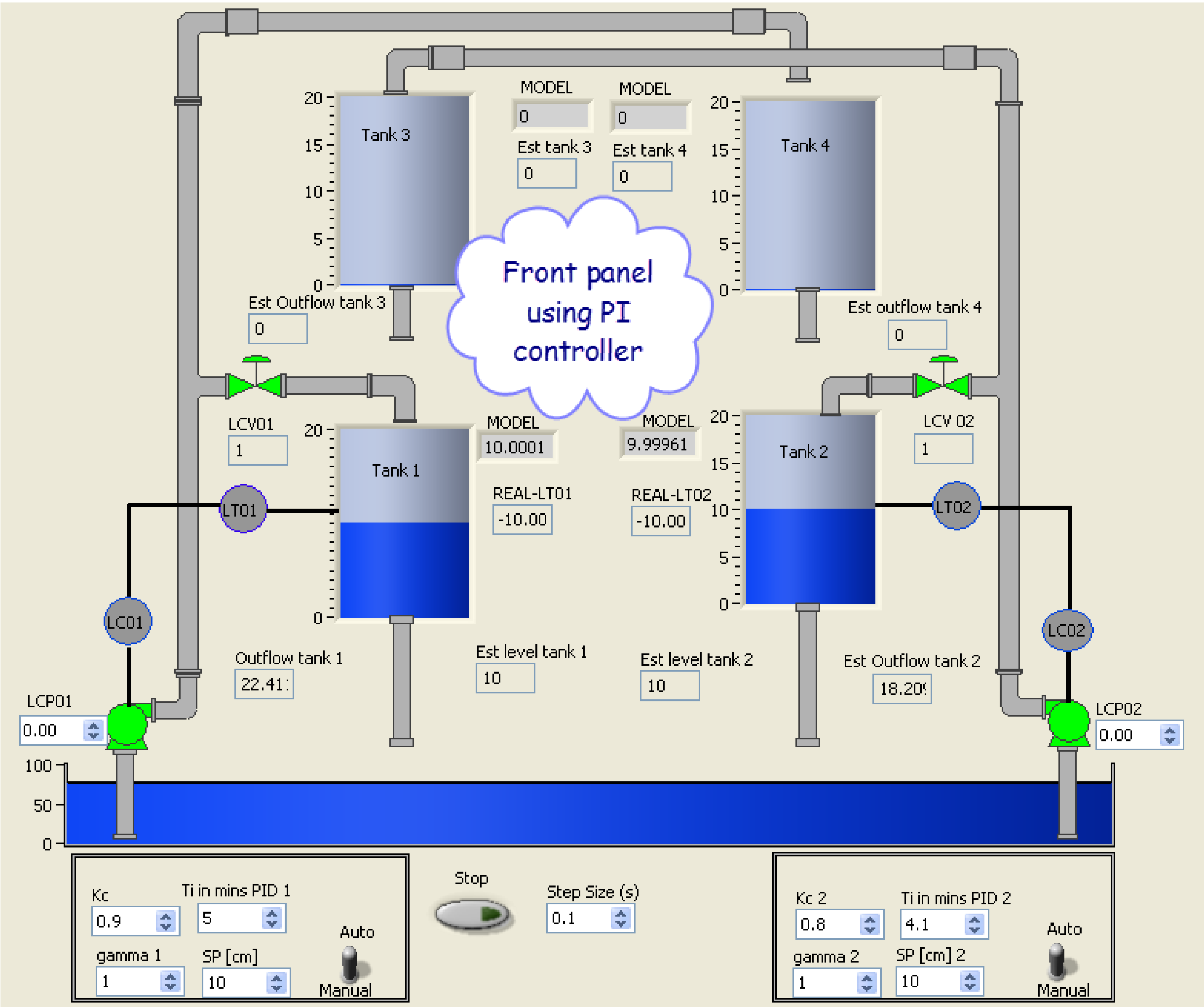


Figure 4: Front panel for using PI controller

4 MPC experiment

Now, you are about selecting the MPC controller for performing the experiment on the laboratory process (to control the levels).

- Go to the “Project explorer” as in Figure 1.
- Then click the folder MPC controller, and then “click on” MPC_MAIN.vi which is the main VI for using the MPC controller.
- Then go to Figure 6 to open MPC program main VI.

See Figures 5 and 6 for guidance, and the MPC_MAIN.vi after loading appears as in Figure 7.

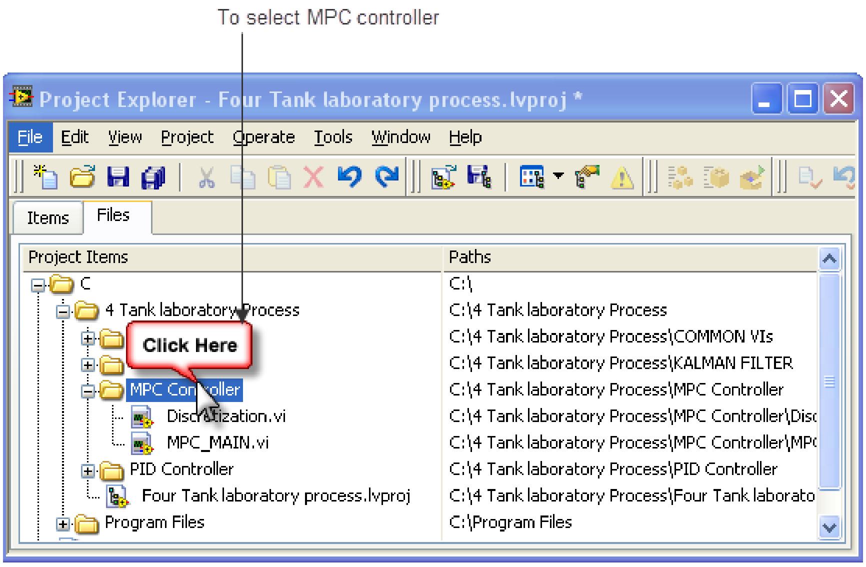


Figure 5: Selecting MPC controller

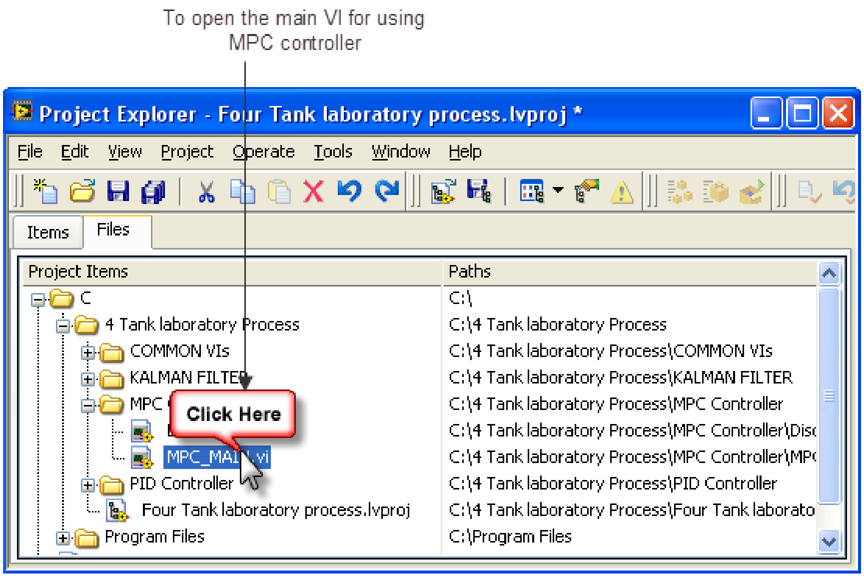


Figure 6: Opening MPC main VI

And on loading the VI, MPC_MAIN.vi, the front panel appears as in Figure 7. This is now ready to be run.

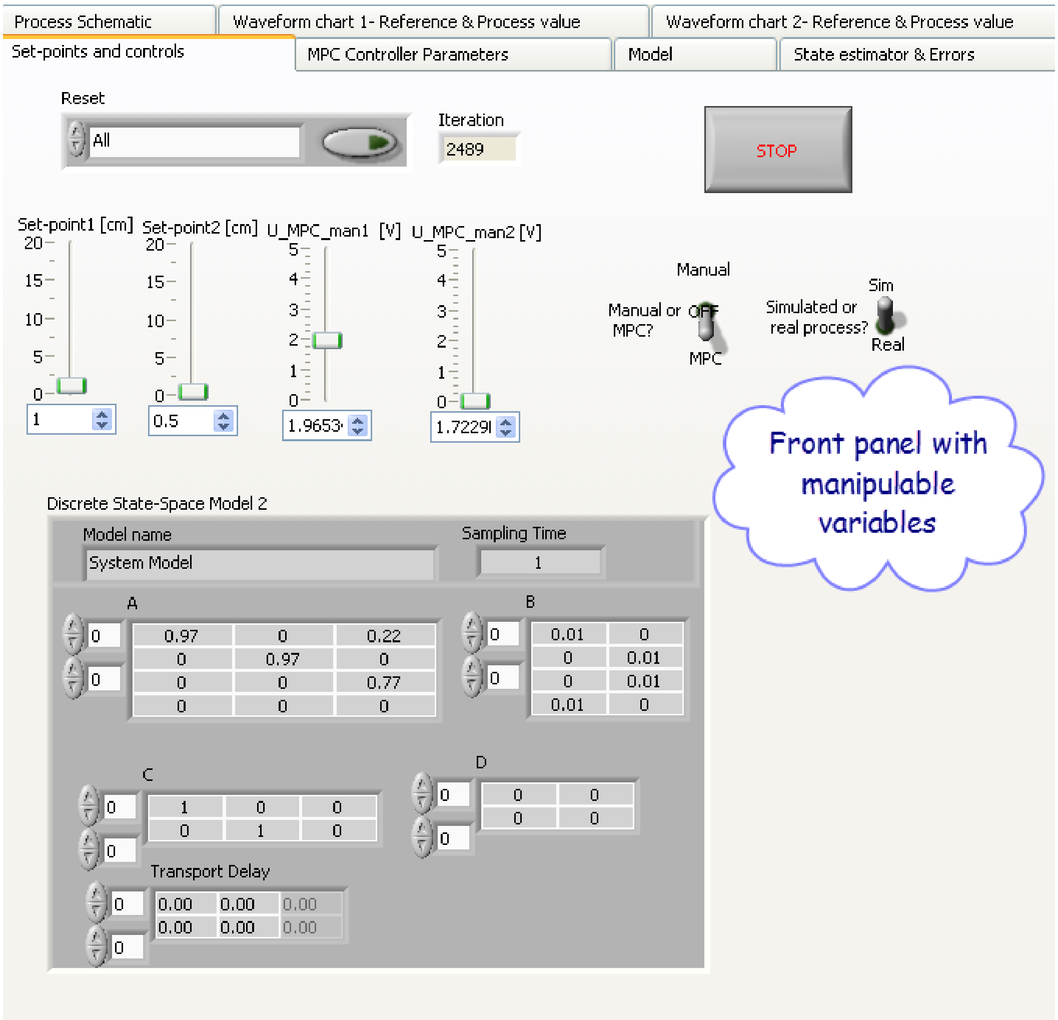


Figure 7: Front panel for using MPC controller

4.1 Procedure

In order to start running the MPC_MAIN.vi,

- You must select the controller mode (Manual or MPC) by pushing the switch labelled "Manual or MPC?"
- Then you should select Simulator or Real process by pushing the switch labelled, "Simulator or Real process?"
- Then give values to set point 1 and set point 2.

- Now, “click” the run button to start the program.
- You should now observe the process carefully, and document the results obtained with relevant plots of signals. Several parameter value changes can be possibly done for analysing the system performance.

5 Kalman filter experiment

Now, you are about using the Kalman filter estimator to determine some of the levels in the process that has not been measured with hard physical sensors. This part of the thesis work is inherently implemented in the PI controller VI named PID_MAIN.vi. Using and observing the performance of the estimator for the PI controller, see Figure 8 and the Kalman filter loads up immediately. On clicking the “run” button, the Kalman estimator starts its estimation.

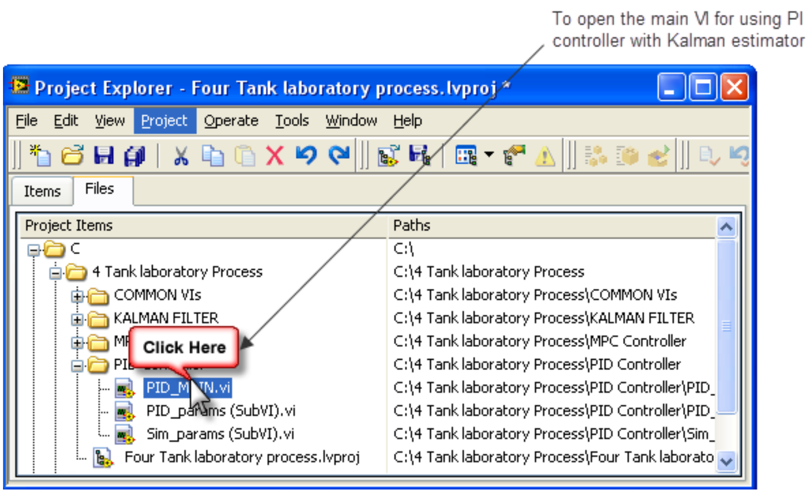


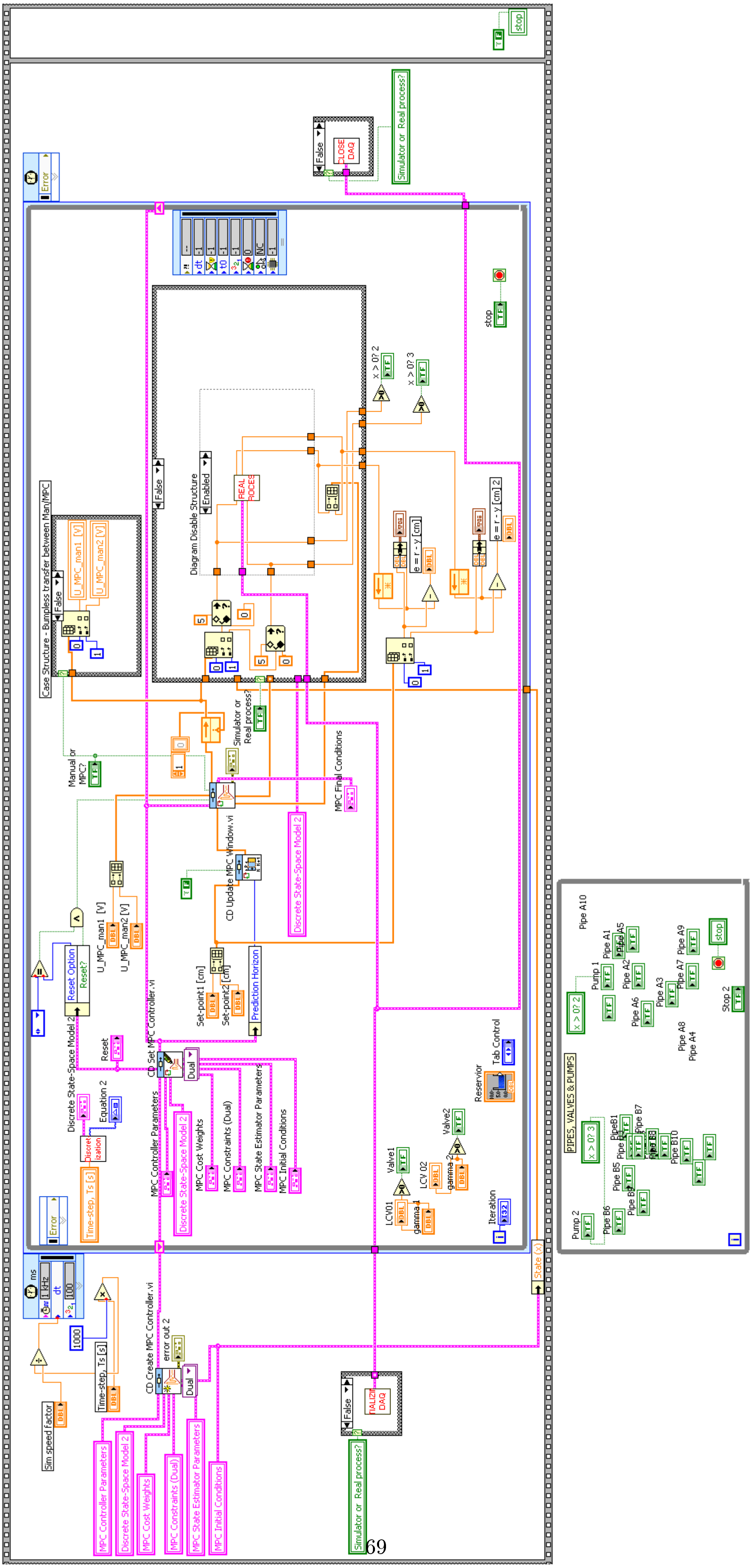
Figure 8: Kalman estimator

For further enquiries or information, see the main thesis report.

6 Reference

Ademu, V.O. (2010). Developing Advanced Control strategies for a 4-tank laboratory process.

Appendix 3: MPC Block diagram



Appendix 4: Discretization Block diagram