Modeling and Predictive Control of Yeast Fermentation Process

By

SOHIBATUL MUIZZAH BT MOHD IZHAR (8980)

Report submitted in partial fulfillment of
the requirements for the
Bachelor of Engineering (Hons)
(Chemical Engineering)

JULY 2010

Universiti Teknologi PETRONAS
Bandar Seri Iskandar
31750 Tronoh
Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

Modeling and Predictive Control of Yeast Fermentation Process

By

Sohibatul Muizzah Bt Mohd Izhar

A project dissertation submitted to the

Chemical Engineering Programme

Universiti Teknologi PETRONAS

In partial fulfillment of the requirement for the

BACHELOR OF ENGINEERING (Hons)

(CHEMICAL ENGINEERING)

Approved by,

____

(Dr. Nooryusmiza Yusoff)

UNIVERSITI TEKNOLOGI PETRONAS

TRONOH, PERAK

DISEMBER 2010

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

SOHIBATUL MUIZZAH BT MOHD IZHAR

ABSTRACT

This work mainly focus on development of advanced process control on the continuous fermentation process using *Saccharomyces cerevisiae*. Today, a lot of research has been done on renewable energy and it has been found that ethanol is one of the best alternatives fuels to substitute petroleum fuels. However, all of this can only be achieved if the production of ethanol is efficient and economical enough. A lot of industry nowadays uses fermentation in batch mode due to the problems occurred in 1970s such as low productivity, low yield, and high level of contamination. Recently, continuous fermentation processes are optimized based on kinetic models to achieve high productivities, high process flexibility and stability and less expensive production cost compared to batch processes. In addition, process control development for continuous fermentation is much better since a lot of research on advanced process is in the continuous mode and almost all kinetic models currently available for continuous fermentation with *Saccharomyces cerevisiae* are in steady state. One of the disadvantages of standard feedback controller is that the action can only be taken after the system has been affected by the disturbance. Thus, an advanced process control (APC) strategy will be developed based on this process. The objective of this work is to optimize the performance of the fermentation process in terms of yield and productivity by using model predictive control (MPC). In this process, the manipulated variable that has been considered is inlet temperature and inlet substrate concentration and the control variable is temperature in the reactor and ethanol concentration. The successful implementation of the controller is greatly affected by the accuracy of the process model.

ACKNOWLEDGMENT

"Praise to Allah, the most Gracious and the most Merciful"

First and foremost, our deepest gratitude goes for God, for He has guided and blessed us during the whole semester in order for us to complete the project. We would also like to take this chance to thank our family & friends, for their full support has kept us going from the start until the end comes.

Our sincerest gratitude and special thanks towards my supervisor, Dr. Nooryusmiza Yusoff for the never ending patience you had to put up , and your determination to guide as much as you can throughout the whole journey to complete this project. With your cooperation and guidance, I have managed to successfully complete my project. Not to forget, FYP coordinator, Dr Khalik Mohamad Sabil for arranging presentation, poster and gave guidance in order to complete this project. Your cooperation is greatly appreciated. Also, to the postgraduate student who has thought me a lot especially on how to deal with Matlab, thank you very much for the time and guidance given. My appreciation also goes to the other lecturers and staff of UTP especially from chemical engineering department for rendering your support with an open hand.

To all my friends especially in Chemical engineering students, thank you all for helping, sharing and learning beside, so that I can complete this project successfully.

Thank you all.

TABLE OF CONTENTS

LIST OF FIGURES

Nomenclature

$C_{heat,ag}$	heat capacity of cooling agent (Jg^{-1} K^{-1})
$C_{heat,\ r}$	heat capacity of mass reaction (Jg^{-1} K^{-1})
c_j	concentration of ion j (j=Na, Ca, Mg, CI, CO_3, etc)
c_{O2}	oxygen concentration in the liquid phase (mg/l)
c_{O*2}	equilibrium concentration of oxygen in the liquid phase (mg/l)
$c_{O*2,\ 0}$	equilibrium concentration of oxygen in distilled water (mg/l)
c_p	product concentration, ethanol (g/l)
c_s	substrate concentration, glucose (g/l)
$c_{s,\ in}$	glucose concentration in the feed flow (g/l)
c_x	biomass, yeast concentration (g/l)
E_{a1}, E_{a2}	apparent activation energy for the growth, respectively, denaturation reaction
F_{ag}	flow of cooling agent (1 h^{-1})
F_e	outlet flow from the reactor (1 h^{-1})
F_i	flow of substrate entering the reactor (1 h^{-1})
H_i	specific ionic constant of ion i (i = Na, Ca, Mg, Cl, CO_3, etc)
I_i	ionic strength of ion i (i = Na, Ca, Mg, Cl, CO_3, etc)
(k_{1a})	product of mass transfer coefficient for oxygen and gas phase specific area (h^{-1})
$(k_{1a})_o$	product of mass transfer coefficient at 20°C for O_2 and gas phase specific area (h^{-1})
K_{O2}	constant of oxygen consumption (g/l)
K_P	constant of growth inhibition by ethanol (g/l)
K_{P1}	constant of fermentation inhibition by ethanol (g/l)
K_S	constant in the substrate term for growth (g/l)
K_{S1}	constant in the substrate term for ethanol production (g/l)
K_T	heat transfer coefficient ($Jh^{-1}m^{-2}K^{-1}$)
m_i	quantity of inorganic salt i (i = NaCl, $CaCO_3$, $MgCl_2$) (g)
r_{O2}	rate of oxygen consumption ($mgl^{-1}h^{-1}$)
R	universal gas constant ($8.31Jmol^{-1}K^{-1}$)
R_{SP}	ratio of ethanol produced per glucose consumed for fermentation

R_{SX}	ratio of cell produced per glucose consumed for growth
T_{ag}	temperature of cooling agent in the jacket (^oC)
T_{in}	temperature of the substrate low entering to the reactor (^oC)
$T_{in, ag}$	temperature of cooling agent entering to the jacket (^oC)
T_r	temperature in the reactor (^oC)
V	volume of the mass reaction (l)
V_j	volume of the jacket (l)
Y_{O2}	yield factor for biomass on oxygen (mg/mg), defined as the amount of oxygen consumed per unit biomass produced
z	ionic charge of ion i
$\boldsymbol{\Delta} H_r$	reaction heat of fermentation (kJ/mol O_2 consumed)
μ_{O2}	maximum specific oxygen consumption rate (h^{-1})
μ_P	maximum specific fermentation rate (h^{-1})
μ_x	maximum specific growth rate (h^{-1})
$\boldsymbol{\rho}_{ag}$	density of cooling agent (g/l)
$\boldsymbol{\rho}_r$	density of the mass reaction (g/l)

CHAPTER 1: INTRODUCTION

1.1 Background Study

1.1.1 Fermentation Process

Recently, the fermentation industry has lagged behind other process industries in implementing control and optimization technology. There are many reasons for the delay. Fermentation processes are much more complex than other industrial processes, involving a large number of complex and dynamic biochemical reactions and transport phenomena, many of which are not well understood. The growing economic pressure to improve the yield, productivity, and quality control of bioreactors to fermentation processes. The primary objectives of control systems are to provide quality assurance and economic incentives.

The purpose of control is to manipulate the control variables to:

i. Maintain the desired outputs at a constant desired value by suppressing the influence of external disturbances or forcing the outputs to follow a desired profile.
ii. Stabilize unstable or potentially unstable processes such as continuous cultures
iii. Optimize the performance as defined by measures such as yield, productivity, or profit.

These objectives are to be achieved under various constraints such as safety, environmental regulations, limited resources, and operational constraints. All of this objective under various constraints can be achieved through advanced process control.

1.1.2 Model Predictive Control Principles

Model Predictive Control (MPC) is a type of an advanced process control. In MPC, the dynamic model and the recent values measurement are used to predict future values of the outputs. By using the input-output relationship, the changes in the individual input variables can be maked. The changes of the input variables can be calculated based on predictions and measurements. In the traditional control loop, the controller input come from the difference between the set point and the recent values. For predictive controller, the input is the difference between future trajectory of the set point and the predicted trajectory of the output.

Model predictive control was developed in 1970s by engineers at Shell Oil to meet control challenges of refineries. Since then, MPC has been a popular controller especially for difficult multivariable control. Early MPC such DMC only provided good control of unconstrained multivariable process. Since then, a lot of improvements have been made to overcome the weakness of the early MPC. By now, a lot of weakness of MPC has been addressed and MPC has become alternative controller for difficult multivariable control problems that include inequality constraints.

The general objectives of MPC in order of importance are (Qin and Badgwell, 2003):

1. Prevent violations of input and output constraints
2. Bring certain output variables to their optimum set point while keep the other output in the specified ranges
3. Bring input variables to their optimum set point
4. Prevent aggressive movement of the input variables
5. Control as many process variables as possible when signal and actuators fail

Set points for the control calculations are calculated from optimization objectives such as maximizing profit function, minimizing cost function, or maximizing production rate. In MPC, the set points are changed frequently and the set points typically calculated at each control calculations are performed. The MPC control calculations are performed to determine a sequence of manipulated input changes so that the predicted response moves in an optimal manner to the set point.

The major differences between feedback controller and MPC controller are (Wojsznis, 2005):

- In feedback controller, the recent error are in the scalar values while MPC predicted error is in the vector form
- The error in a feedback controller is the measurement substracted from the set point value while MPC controller error vector is computed as the corrected model prediction substracted from the future set-point values
- In the MPC, the process output trajectory is bring as near as possible to the set point trajectory and this movement are spread over several moves into the future over the control horizon.
- Disturbances are included in the MPC with proper dynamics based on the identified models from process step response in the prediction of the process output.

MPC controller is suitable for multivariable process since it consider the process interactions. In addition, MPC controller handles constraints for the input and output variables (Wojsznis, 2005). Practical disadvantage of the MPC is the computational cost which tends to limit MPC to linear processes with relatively slow dynamics (Rao et al., 2000)

1.2 Problem Statement

Ethanol is believed to be one of the best alternatives fuels to substitute petroleum fuels. This has led to dramatic increase in its production capacity. However, the ethanol will only substitute petroleum fuels if its production is economically attractive. Thus, it is necessary to make the process of ethanol production more efficient and economical.

By using the standard feedback control on the process, it can show the following disadvantages in the presence of input disturbances or uncertainties (Luyben, 1990; Sthephanopoulos, 1984):

(a) waits until the effect of the disturbance has been felt by the system, before control action is taken

(b) can suffer degradation of the closed-loop performance for slow systems or with significant dead time

(c) can create instability in the closed loop performance.

So, MPC is one of the best methods to control the process in order to achieve the objective function. A lot of research has been done in the implementation of MPC in variety processes. However, most of the research has been done on the batch process, but not on the continuous process.

Fermentation process is greatly get affected by the influence of temperature in the kinetic parameters since it is difficult to maintain a constant temperature in this process. In alcoholic fermentation, a small deviation of temperature can dislocate the process from optimal operating conditions (Costa et al., 2001). In order to obtain optimal process, an efficient control strategy is needed.

1.3 Objective and Scope of Study

This work will mainly focus on the continuous fermentation process using *Saccharomyces cerevisiae*. Ethanol yield and productivity, based on *Zymomonas mobilis* are higher compared to *Saccharomyces cerevisiae* because less biomass is produces and a higher metabolic rate of glucose is maintained through its special Entner–Doudoroff pathway. However, due to *Zymomonas mobilis* specific substrate spectrum as well as the undesirability of its biomass to be used as animal feed, this species cannot readily replace *Saccharomyces cerevisiae* in ethanol production (Bai et al., 2008)

The objective of this work is to study the dynamic behavior of this process. By understanding the dynamic behavior of the process, a more accurate controller can be developed. Advanced process control of the fermentation process is based on the model develop by Z.K Nagy, 2007. There are quite a number of research has been done on this area particularly on linear control. So, this project will used constraint linear model predictive control for an extractive alcoholic fermentation. By using this methodology, dynamic optimization problem is solved online at each control execution in order to optimized yield and productivity of the ethanol.

In this paper, the first section will elaborate on background study, problem statement and objective of this work. In the second section, half of the second section will review on the designing of the fermentation process and half of this section will review on the model predictive control. Section three will discuss briefly on methodology of this project and followed by results and discussion. Last part of this work will be conclusion of this project.

CHAPTER 2: LITERATURE REVIEW

2.1 Challenges of bioprocess control

2.1.1 Bioprocess control

Bioprocess control is defined as providing a conducive environment for microorganisms to grow, multiply, and produce a desired product. This includes providing the right concentration of nutrients to the culture, removing any toxic metabolic products, and controlling important internal cellular parameters such as temperature and pressure.

Fermentation process begin with an inoculation step in which a relatively small number of pure culture cells are transferred to the bioreactor. The cells then grow exponentially until such time there are something limiting or inhibiting the growth. Most bioprocesses become more complicated if an induction or product formation de-repression activity occurs part way through the bioprocess in which the culture is change from ‘growth’ mode to ‘product synthesis’ mode. This induction is often triggered by a programmed shift in temperature or by a chemical addition. In designing of the bioreactor itself, agitator is useful to sparging gas bubbles and to provide homogeneous mixture. However, agitator RPM and types of agitator need to be considered to avoid harmful to the cells (Alford, 2006).

Most bioprocess employs same types of control as in other chemical industries. Over half of most bioprocess control loops can be handled by traditional single input single output feedback PI (proportional + integral) controllers. PID is a controller for linear processes. Microorganism cultures are non-linear in many respects. For example in Bakers Yeast that use *Saccharomyces cerevisiae*, there is an additional non-linear complication in that glucose concentrations that are too high will cause the culture to shift from metabolism of making yeast to making ethanol (Alford, 2006). One of the ways to optimize the process is through minimizing the energy cost. Often, fermentor has the highest energy consumption in a plant due to the high volumes of compressed air and high agitation power required.

2.1.2 Process Dynamics

The first continuous fermentation was invented by Melle-Boinot in the 1970s. However, there are several problems occurred such as high level of contamination, low productivity, low yields, and problems with solid flows. Today's continuous fermentation processes are optimized based on the kinetic models to achieve high productivities, high process flexibility and stability, and low consumption of chemicals and are considered to be less expensive for ethanol production compared to batch processes (Zanin et al., 2000).

There are also critical opinions about continuous process. It is said that batch processes with yeast recycle were shown to be less susceptible to bacterial contamination and corresponding loss in productivity (Godoy et al., 2008). In continuous, the process particularly contaminate by *Lactobacilus*, which are the major factor that can reduce ethanol yield and also impair yeast centrifugation, and greater quantities of antibiotics are needed to address this issue. However, continuous fermentation have the advantages of lower installation cost due to smaller fermentor volumes, less heat exchanger demands, and lower costs due to greater automation (Godoy et al., 2008).

Most industry preferred to do fermentation process in the batch or fed batch mode. However, for this kind of mode, the process never in steady state and the model must consider the process dynamics, at least for the fermentation part. The optimum control strategy is a compromise between the high productivity and yield of the fermentation part and good product quality after down-stream processing.

All kinetic models currently available for the ethanol fermentations with *Saccharomyces cerevisiae* are steady state for continuous fermentations or instantaneous for batch processes. There are only a few reports on the oscillations of sugar, ethanol and biomass in the continuous ethanol fermentations with

Saccharomyces cerevisiae (Borzani, 2001; Bai et al., 2004). For fermentation system composed of 4-6 fermentors, concentrations in the front fermentors do oscillate around the average level but completely attenuated within the last fermentors. (Bai et al., 2008). One of the best ways to minimize product inhibition, increase the fermentation rate and productivity is by in-situ removal of ethanol (Roffler et al., 1984).

2.2 Factorial design and simulation of alcoholic fermentation

2.2.1 Modelling of Fermentation Process

Process modeling of fermentation relies heavily on the kinetics of the reactions involved in the process and simulations experiments would have to be carried out in order to develop a model which accurately describes the dynamics of the fermentation process under consideration. A number of models have been develop for the measurement of microbial growth during fermentation, though the model develop by Monod is the most widely used.

In the fermentation process, different control configurations based on a linear or a non-linear adaptive approach gave satisfactory performances for the required control specifications. In the non-linear multivariable case, the performance and decoupling can be improved by the introduction of a penalty on the input and output control.

2.2.2 Process description

This process involves equation which express heat transfer, the dependence of kinetic parameters on temperature, the mass transfer of oxygen, as well as the influence of temperature and ionic strength on the mass transfer coefficient.

The continuous model of the fermentor is shown in figure below. The fermentor is modeled with continuous stirred tank with constant volumetric mass reaction. In order to get quasi steady-state with regards to biomass, low dilution rate (Fe/V) is necessary, which means that the dilution rate must not exceed the biomass production rate. Thus, the process has a very slow dynamics.

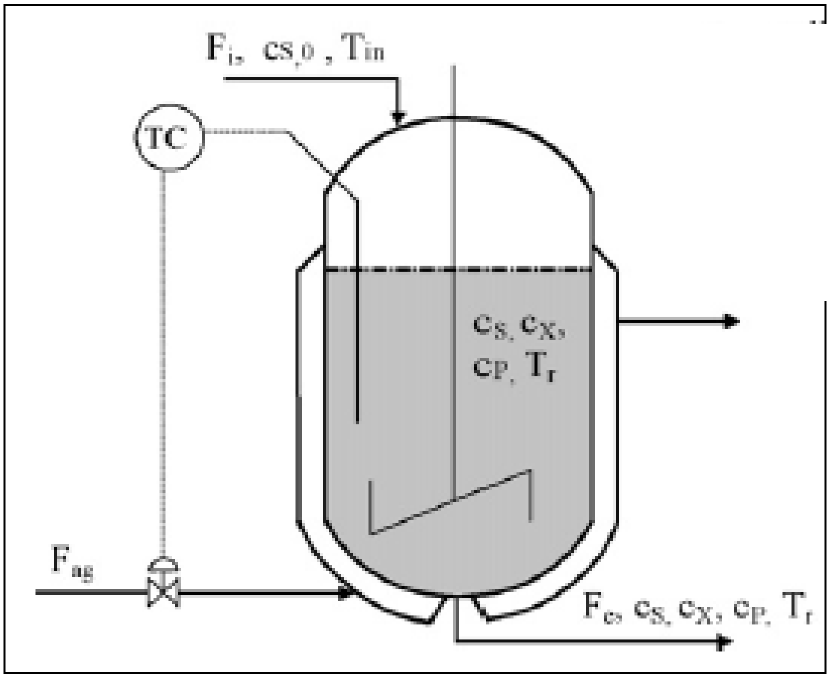

Figure 1: The continuous fermentor (Z. K. Nagy, 2007)

In the feed, yeast is added with inorganic salts to form coenzymes. The inorganic salts have strong influence upon the equilibrium concentration of oxygen in the liquid phase.

The mathematical model of the system is presented below:

Initial data:

m_{NaCl} = 500g	$F_i = F_e = 511h^{-1}$
m_{CaCO3} = 100g	$T_{in} = F_e = 25^oC$
m_{MgCl2} = 100g	C_{Sin} = 60g/l
pH = 6	$T_{in,ag} = 15^oC$

The balance for the total volume of the reaction medium is:

$$\frac{dV}{dt} = F_i - F_e$$

(1)

The mass balances for the biomass and product is:

$$\frac{d_{cx}}{dt} = \mu_x c_x \frac{c_s}{K_s + c_s} e^{-K_p c_p} - \frac{F_e}{V} c_x \quad (2)$$

$$\frac{d_{cp}}{dt} = \mu_p c_x \frac{c_s}{K_{s1} + c_s} e^{-K_{p1} c_p} - \frac{F_e}{V} c_p \quad (3)$$

The first term in Eqs. (2) and (3) represent the quantity of biomass and product, respectively, produce in the fermentor. The last term in the equation represent the amount removal of yeast and ethanol leaving the fermentor.

The mass balance for the substrate is:

$$\frac{dc_s}{dt} = -\frac{1}{R_{sx}} \mu_x c_x \frac{c_s}{K_s + c_s} e^{-K_p c_p} - \frac{1}{R_{sp}} \mu_p c_x \frac{c_s}{K_{s1} + c_s} e^{-K_{p1} c_p} + \frac{F_i}{V} c_{s,in} - \frac{F_e}{V} c_s \quad (4)$$

The first and second term in Eqs.(4) represent the amount of substrate consumed by the biomass for growth and ethanol production. The third term is the quantity of glucose entering the fermentor while the last term represent the quantity of glucose leaving the fermentor.

The first term in equation (5) represent the quantity of oxygen entering in the reaction medium due to the mass transfer and the last term represent the amount of oxygen consumed in the fermentation reaction. The concentration of the dissolved oxygen in the reaction medium is:

$$\frac{dc_{O_2}}{dt} = (k_1 a)(c^*_{O_2} - c_{O_2}) - r_{O_2} \quad (5)$$

The energy balances for the reactor is :

$$\frac{dT_r}{dt} = \frac{F_i}{V}\,(T_{in} + \ 273) - \frac{F_e}{V}\,(T_r + \ 273) + \frac{r_{O_2}\Delta H_r}{32\,\rho_r C_{heat,r}} + \frac{K_T A_T (T_r - T_{ag})}{V\,\rho_r C_{heat,r}} + \frac{K_T A_T (T_r - T_{ag})}{V\,\rho_r C_{heat,r}} \qquad (6)$$

The energy balance for the jacket is:

$$\frac{dT_{ag}}{dt} = \frac{F_{ag}}{V_j}\,\left(T_{in,ag} + \ T_{ag}\right) + \frac{K_T A_T (T_r - T_{ag})}{V_j\,\rho_{ag} C_{heat,ag}} \qquad (7)$$

2.3 Model Predictive Control

Recently, Model Predictive Control (MPC) has been widely used in industry. This algorithm gives several advantages since it consider constraints on input and output in systematic manner and the process model consider dynamic and static interactions between input, output, and disturbance variables.

2.3.1 Difference Between Conventional and MPC

A successful industrial controller for process industries must maintain the system as close as possible to constraints without violating them. Furthermore, process units are typically complex, nonlinear, constrained multivariable systems whose dynamic behavior change with time due to the changes in operating conditions and catalyst aging. This environment has led to the development of a more general model based control methodology in which the dynamic optimization problem is solved online at each control execution.

Process inputs are computed so as to optimize future plant behavior over a time interval known as prediction horizon. Process input and output constraint are included directly in the problem formulation so that future constraint violations are anticipated and prevented. The first input of the optimal input sequence is injected into the plant and the problem is solved again at the next time interval using updated process measurements.

In MPC controller, it has a multi-level hierarchy of control functions as shown in Figure 2.3 (Qin and Badgwell, 2003). Plant-wide optimizer determines optimal steady-state settings for each unit in the plant. The unit optimizer computes an optimal economic steady state and passes this to the dynamic constraint control system for implementation. The dynamic constraint control must move the plant from one constrained steady state to another while minimizing constraint violations along the way. In the conventional controller, this process is achieved by using a combination of

PID algorithms, lead-lag (L/L) blocks and high/low select logic. In the MPC, this combination is replaced by a single MPC controller (Qin and Badgwell, 2003).

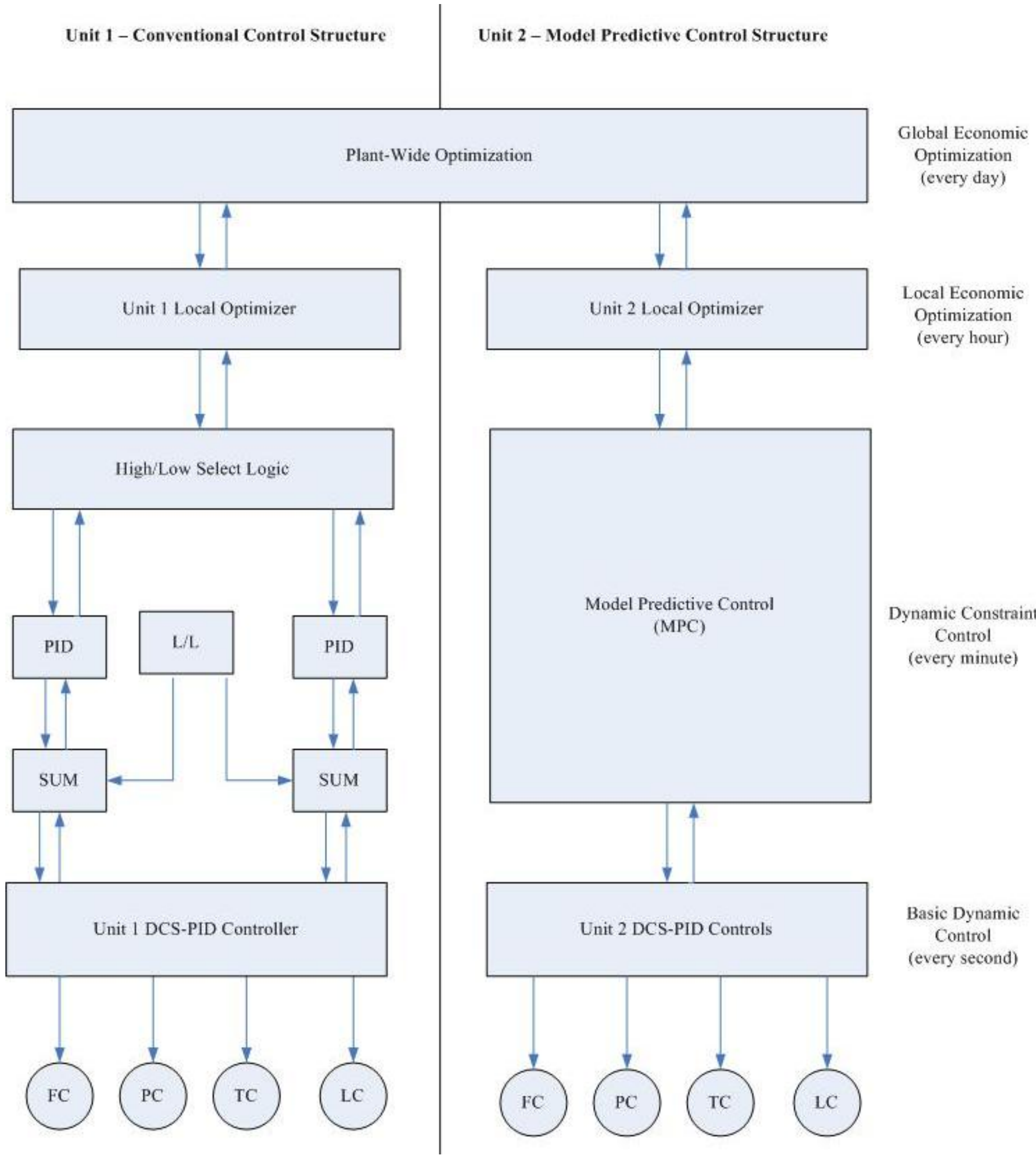

Figure 2: Hierarchy of control system functions in a typical processing plant (Qin and Badgwell, 2003).

2.3.2 Model Predictive Control Calculations

Flowchart in Fig. 2.4 below shows an overview of MPC calculations. This process flow is performed at each control execution time. To simplify the process, we assume that control execution times occur at the same time with the measurement sampling instants. In MPC, the calculated input moves usually implemented as set points for regulatory control loops at the Distribution Control System (DCS) level. If DCS control loop has been disabled or placed in manual, the input variable is no longer available for control.

Before each control execution, it is important to determine relevant output (CVs), input (MVs), and disturbance variables (DVs) based on the control objectives. Variables available for this control calculation can change from one execution time to the next execution due to many reasons and one of the reason probably because failure of the sensor.

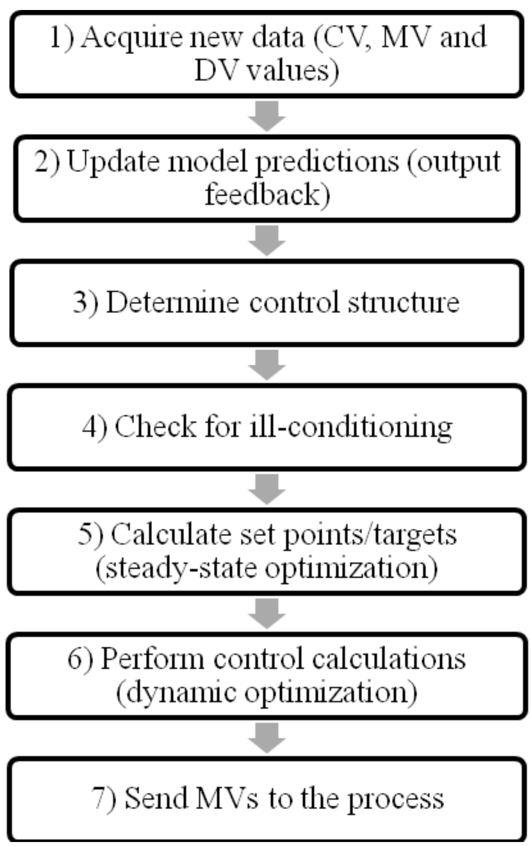

Figure 3: Flow chart for MPC calculation (Qin and Badgwell, 2003)

Output variables can be categorized into critical or noncritical output. If sensor for critical output is not available, the MPC calculations can be stop immediately or after several number of control execution steps. However, for noncritical output, the unavailability of the data can be replaced by model predictions or the output can be removed from the control structure

.

Ill-conditioned occur when inputs have same effect on two or more outputs. Three effective strategies are available to remove the ill-condition (Qin and Badgwell, 2003, Maciejowski, 2002).If ill-conditioning is detected, low priority outputs are sequentially removed from the control structure until ill-conditioning is eliminated. Another solution is based on the singular value analysis (SVA) by removing small singular values. The good side of this approach is that none of the output variables is removed but it depends on how the inputs and outputs are scaled. Ill-condition also can be removed by adjusting MPC design parameter, the move suppression matrix **R**.

2.3.3 MPC with constraints

There are three types of constraints that are commonly used which are hard, soft, and setpoint approximation (Qin and Badgwell, 2003). Hard constraint should not be violated at any time. Soft constraints can be violated but the violation is penalized by modification in the objective function. Setpoint approximation constraint penalizes deviations above and below the constraints.

Setpoints are defined for each soft constraint which will result penalties on both sides of the constraint in the objective function. The output weight is adjusted dynamically so that the weight become significant when the output close to the constraints. Hard output constraints must be used carefully because it can result in infeasible solutions for the optimization problem, especially for large disturbances.

In MPC, the control objective is to keep output variables within upper and lower limit instead forcing them to the set points. This approach is called range control (zone control) and the limits are referred to range limits (zone limits). The limits can be varied with time.

2.3.4 Set-point calculation

In MPC calculation, there are two steps performed at each control execution. Firstly, the optimum set points or targets are determined and then, a set of M control moves are generated by the control calculations. The first move is implemented in the control calculations. The MPC set points are calculated according to the objective function.

Objective function can be defined in three categories which are maximize operating profits, minimize deviations from the reference values and maximize the production rate. The set-point calculations are repeated at each sampling instant because the active constraints can change frequently.

2.3.5 Process model identification

The equations used for process modeling is based on the identification modeling technique. The most common identification technique are Finite Impulse Response and Auto Regressive with eXternal inputs (ARX) (Wojsznis, 2005). The advantage of FIR is that it does not require any preliminary knowledge of the process. However, a shorter horizon with about 60 points is more suitable for FIR since it will results in low confidence levels of identified coefficients value for a large number of coefficients.

For ARX model, it has fewer coefficients, which are defined for higher confidence, provided the process dead are known. So, applying the FIR to define the dead time and then followed by ARX by applying the dead times will give the best identification results (Wojsznis, 2005).

Researcher and USA has put more emphasis on state-space models. This type of model gives an advantage as they extend easily to the multivariable case and there is huge quantity of theoretical results which can be applied to produce controllers/observers and to analyse the models and resulting control laws. In abbreviated form, the model is

$$\mathbf{x}_{k+1} = A\mathbf{x}_k + B\mathbf{u}_k + C\mathbf{w}_k; \qquad \mathbf{y}_k = D\mathbf{x}_k + E\mathbf{u}_k + \mathbf{d}_k$$

x denotes the state vector, **y** denotes the process outputs (or measurements) to be controlled, **d** denotes disturbance and **u** denotes the process inputs (or controller output), **w** denotes state disturbance and *A, B, C, D* are the matrices defining the state-space model. Ordinarily for real processes $E = 0$.

State-space models are used so that the full range such as stable, unstable, and integrating of linear dynamics can be represented. Auto-regressive parametric model form such as a state-space or ARX model is used to overcome problems from the impulse and step response model. Both models can be problematic when controlling a process with widely varying time constant; for this case it is typical to sacrifice dynamic control of the fast process modes in order to keep the model length reasonable. Other significant problem with the impulse and step response models is that they are limited to strictly stable processes. While it is certainly possible to modify the algorithms to accommodate a pure integrator, these modifications may lead to other problems, such as adding the derivative of a noisy output signal into the feedback path. It is not possible, in general, to represent an unstable process using an impulse response model. All of these problems can be solved by using state-space or ARX model (Qin and Badgwell, 2003).

2.3.6 Selection of Design and Tuning Parameters

In order to design MPC, a number of parameter must be specified which are:

- Sampling period Δt and model horizon N

  The sampling period Δt and model horizon N should be chosen so that $N\Delta t = t_s$, where t_s is the settling time for the open-loop response. This choice ensures that the model reflects the full effect of a change in an input variable over time required to reach steady state. A different value of N can be used for each output and also, different model horizons can be used for the inputs and disturbances.

- Control M and prediction P horizons

  MPC controller become aggressive when the value of M increases and the required computational effort increases. However, the computational effort can be reduced by input blocking. A different value of M can be specified for each input. The prediction horizon P is often selected to be P = N + M so that full effect of the last move is taken into account. Decreasing value of P tend to make the controller become more aggressive. A different value of P can be selected for each output if their settling times are different.

- Weighting matrices

  The output weighting matrix allows the output variables to be weighted according to their relative importance. It allows the output variables to be weighted individually, with the most important variables having the largest weights. It can be advantageous to adjust the output weighting over the prediction horizon.

- Reference trajectory, αi

  In MPC, the desired future output behavior can be specified in several different ways: as a set point, high and low limits, a reference trajectory, or a funnel. Both the reference trajectory and the funnel approaches have a tuning factor that can be used to adjust the desired speed of response for each output.

CHAPTER 3: METHODOLOGY

This work consist of four phases which are Plant testing, Design of an APC, Implementation of APC and finally Comparison with the base layer control. All of this phases shown below, in Figure 4.

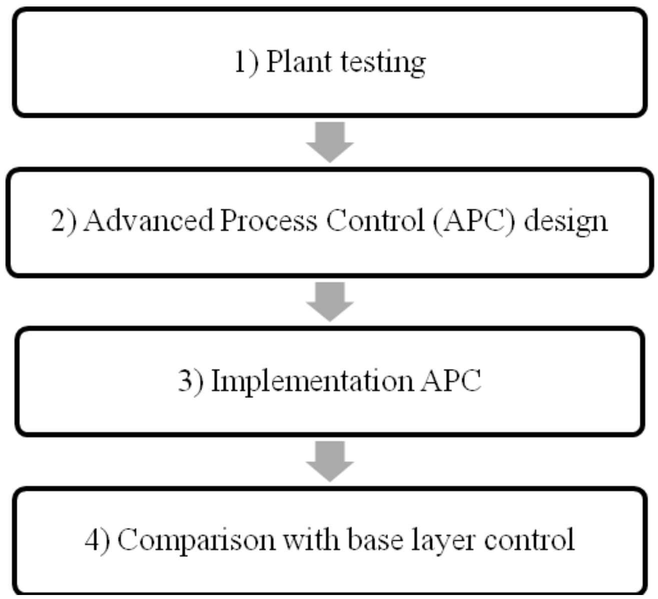

Figure 4: Flow of project activities

The model of this process is based on the Z.K Nagy, 2007. This fermentation process which has been develop using Matlab and Simulink are going to be used as the model to develop the APC.

3.1 Plant Testing

The plant test usually consists of changing an input variable or a disturbance variable from one value to another. The objective is to determine how the output variables change with time influenced by changes in the inputs.

Before doing a formal plant test, a pre-test is needed for three reasons (Qin and Badgwell, 2003). Firstly, step each manipulated variables and adjust existing instruments and PID controllers. Second, obtain time for steady state for each output variables and lastly, obtain data for initial identification.

In the plant tests, the magnitudes of the moves should be carefully chosen because movements which are too small may result in the step responses being obscures by normal process fluctuations and measurement noise. However, if the change is too large, it may result in an output constraint violation or nonlinear process behavior that cannot be accurately described by a linear model.

Each manipulated variables is stepped eight to fifteen times, with the output variables signal to noise ratio at least six. During the test, no tuning changes and synchronizing or correlated moves are allowed. If the lower level PID control tuning changes significantly, it shows the inaccuracy of the process model. It may be necessary to construct a new process model (Qin and Badgwell, 2003).

3.2 APC Design

APC design is the main focus of this work. However, the success of APC depends on the accuracy of the process model. The APC design is based on the control and optimization objectives, process constraints, and the dynamic model of the process. This work will focus more on the linear process control with added constraints.

It is important to verify acceptability of the performance and robustness of the control. Tests are performed to check the regulatory and servo response of each output variables, and system violations of major constraints is verified. Then, final tuning is tested for sensitivity and model mismatch by varying the gain and dynamics of key process models.

3. 3 Implementation of APC and Comparison with Base Layer Control

After finish with the APC design, the next phase will implement the APC to the process model. In this phase, the performance of the process will be observed and compared with the base layer control.

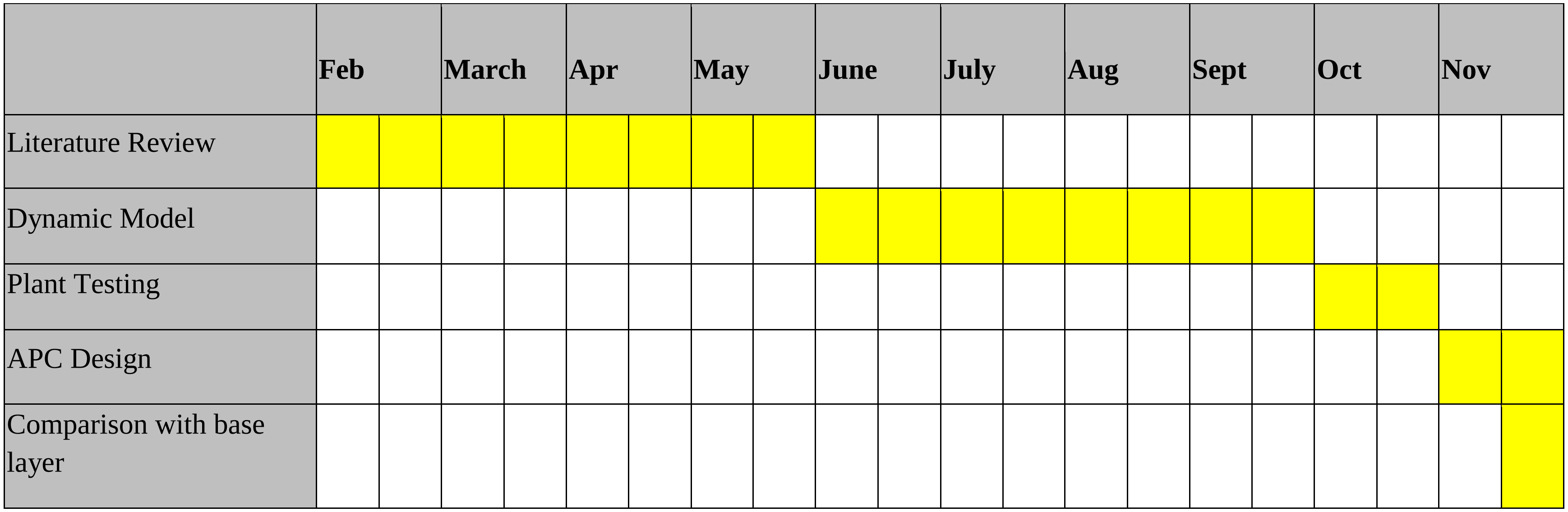

Figure 5: Gantt chart for FYP

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Dynamic Behavior of the Process

To choose the best control structures for a given process, its open-loop dynamic behavior must be investigated. The objective is to determine how the output variables change with time get influenced by changes in the input (manipulated variables and possible disturbances). This can be done by changing the values of the various input variables, one by one and observing the change of the output variables with time.

In this process, the volume of the reaction medium (V) is kept constant. Thus, flow of substrate entering the reactor (Fi) and outlet flow from the reactor (Fe) is not considered in this process. The input variables considered for manipulation are: flow of cooling agent (Fag), glucose concentration in the feed flow (Cs,in) and temperature of the substrate flow entering to the reactor (Tin). The output are: biomass concentration (Cx), product concentration (Cp), substrate concentration (Cs), oxygen concentration in the liquid phase (Co_2), temperature in the reactor (T), and temperature of cooling agent in the jacket (Tr).

The output variables are selected based on variable that seriously interact with other controlled variables and variable that represent a direct measure of the product quality. Based on these criteria, temperature in the reactor (Tr) and product concentration (Cp) are selected as the control variables. Temperature in the reactor is chosen since it effect other variables. Meanwhile, product concentration is chosen since it reflects the product yield.

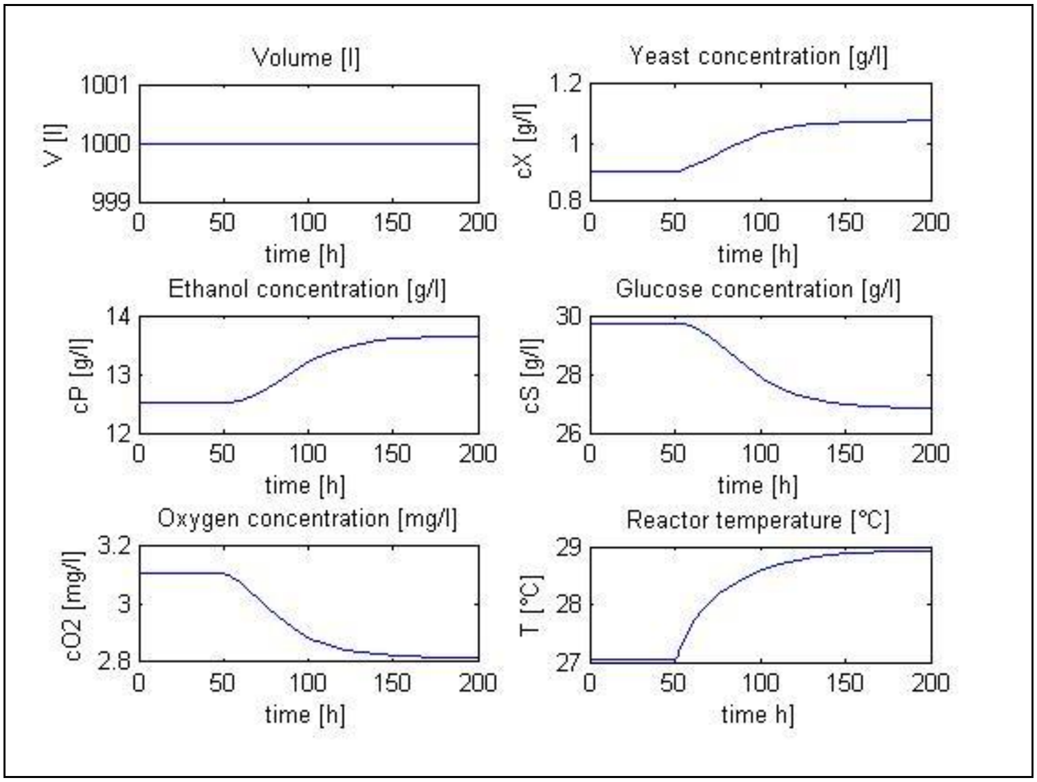

Figure 6: Dynamic behavior of the process with temperature change from 25°C to 27°C

From figure above, it shows that 2°C change in the input temperature affect most of the output especially product concentration (Cp), glucose concentration (Cs) and reactor temperature (Tr).

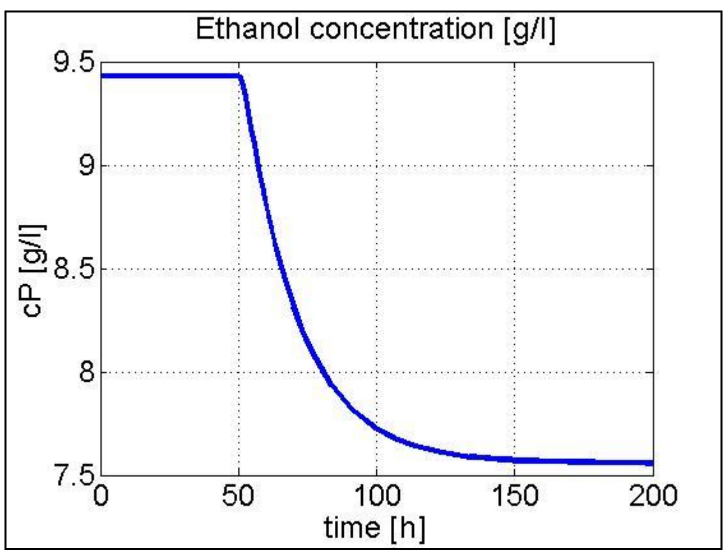

Figure 7: Cp change with changes on Cs,in from 25g/L to 20g/L

From figure 7, it shows that changes from 25g/L to 20g/L concentration of the inlet substrate concentration (Cs,in) change the product concentration (Cp) from 9.4 g/L to 7.6g/L.

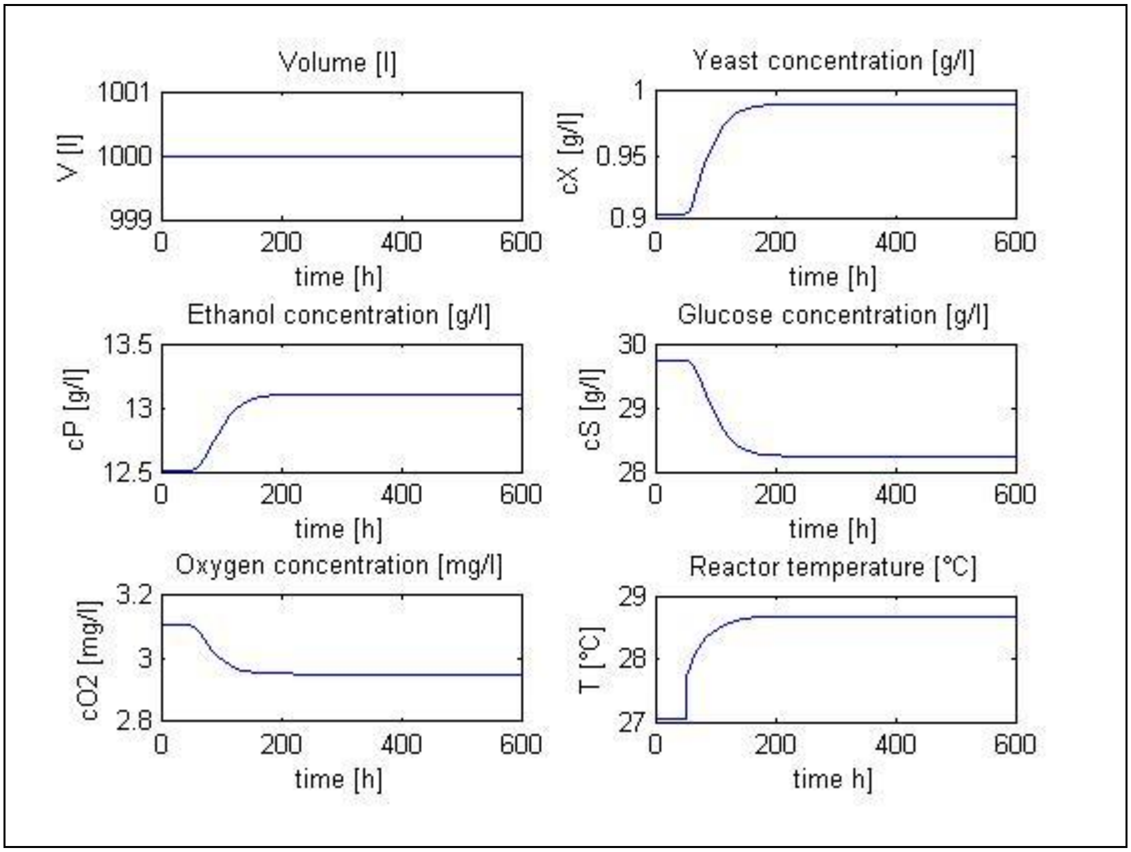

Figure 8: Dynamic behavior of the process with changes in the Fag from 18^{o}C to 13^{o}C

From figure 8, it shows that changing of flowrate of cooling agent (Fag) does affect much on the output especially on the product concentration. Changes on the flowrate of cooling agent mostly affect the glucose concentration (Cs) and temperature in the reactor (Tr).

Manipulated variables are chosen based on the variable that have large effects on controlled variables and variable that rapidly affect the outputs. From the figure shown above, temperature input (Tin) and glucose concentration in the feed flow (Cs,in) are selected. Changing the inlet temperature affect the temperature of the reactor and thus affect other variables. Meanwhile, product concentration mostly affected by inlet glucose concentration.

4.2 Model Predictive Control

The Wood-Berry model is a well-known 2x2 transfer function model. In this process, Wood-Berry model is used. The output variables are the concentration (Cs) and temperature in the reactor (Tr). They are controlled by manipulating the temperature input (Tin) and glucose concentration in the feed flow (Cs,in). The unmeasured disturbance variable is set to 0.
The model is shown below.

$$\begin{bmatrix} \frac{Tr(s)}{Cp(s)} \end{bmatrix} = \begin{bmatrix} \frac{0.9492e^{-4.67s}}{5.452s+1} & \frac{0.3049e^{-19.6s}}{10.3s+1} \\ \frac{0.5769e^{-9.54s}}{3.66s+1} & \frac{0.3963e^{-14.3s}}{8.134s+1} \end{bmatrix} \begin{bmatrix} \frac{Tin(s)}{Cs,in(s)} \end{bmatrix} \tag{8}$$

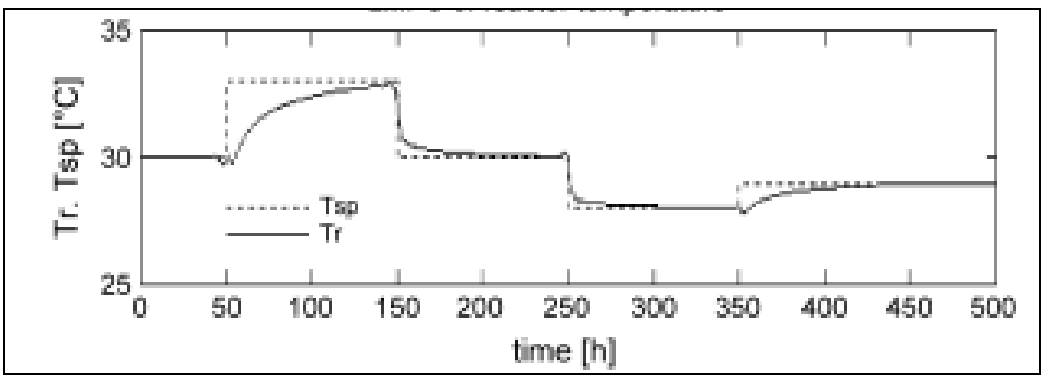

Figure 9: MPC of the reactor temperature (Tr)

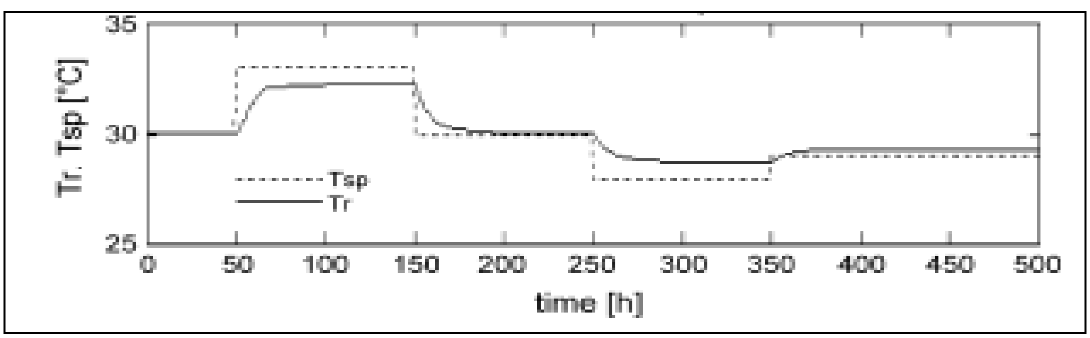

Figure 10: PID control of reactor temperature (Tr)

Figure above shows that MPC give better result compared to the PID controller. MPC give faster control response and thus indicates that the control performance of MPC controller is better than that of the PID controller.

CHAPTER 5: CONCLUSION AND RECOMMENDATION

Ethanol is one of the best alternatives fuels to substitute petroleum fuels. However, all of this can only be achieved if the production of ethanol is efficient and economical enough. Thus, continuous fermentation process gives great advantage especially for high production rate. Process control of the fermentation process using *Saccharomyces cerevisiae* can be develop using advanced process control to improve the productivity of the process. The successful of the controller is greatly affected by the accuracy of the process model.

This work can be improve by considering more disturbances and manipulated variable especially those that affect the reactor temperature since fermentation process sensitive with the change in temperature.

REFERENCES

A.D. Kroumov, A.N. Modenes, M.C. de Araujo Tait, Developmentof new unstructured model for simultaneous saccharification and fermentation of starch to ethanol by recombinant strain, Biochem. Eng. J. 28 (2006) 243–255.

Ashoori, Ahmad, Moshiri, Behzad, Khaki-Sedigh, Ali and Bakhtiari, Mohammad R. Optimal control of a nonlinear fed-batch fermentation process using model predictive approach 2009

Bai FW, Chen LJ, Anderson WA, Moo-Young M. Parameter oscillations in very high gravity medium continuous ethanol fermentation and their attenuation on multi-stage packed column bioreactor system. Biotechnol Bioeng 2004a;88:558–66.

BorzaniW. Variation of the ethanol yield during oscillatory concentrations changes in undisturbed continuous ethanol fermentation of sugar-cane blackstrap molasses. World J Microbiol Biotechnol 2001;17:253–8.

Cervantes, Ania L., Agamennoni, Osvaldo E. and Figueroa, José L. A nonlinear model predictive control system based on Wiener piecewise linear models 2003

5Costa, Aline C., Atala, Daniel I. P., Maugeri, Francisco and Maciel, Rubens. Factorial design and simulation for the optimization and determination of control structures for an extractive alcoholic fermentation 2001

Godoy, A., Amorim, H.V., Lopes, M.L., Oliveira, A.J., 2008. Continuous and batch fermentation processes: advantages and disadvantages of these processes in the Brazilian ethanol production. Int. Sugar J. 110 (1311), 175–182.

Kargupta K, Datta S, Sanyal SK. Analysis of the performance of a continuous membrane bioreactor with cell recycling during ethanol fermentation. Biochem Engng J 1998;1:31–7

Luyben,W.L. (1990). Process modeling. *Simulation and control for chemical engineering* (2nd ed.). New York: McGraw-Hill.

M. Phisalaphong, N. Srirattana,W. Tanthapanichakoon, Mathematical modeling to investigate temperature effect on kinetic parameters of ethanol fermentation, Biochem. Eng. J. 28 (2006) 36–43.

Maciejowski, J.M., Predictive Control with Constraints, Prentice Hall, Upper Saddle River, NJ, 2002.

Nagy, Zoltan K. Model based control of a yeast fermentation bioreactor using optimally designed artificial neural network 2007

Ochoa, Silvia, Repke, Jens-Uwe and Wozny, Günter. Integrating real-time optimization and control for optimal operation: Application to the bio-ethanol process

Qin, S. J., Badgwell, Thomas A. A survey of industrial model predictive control technology 2003

Rao, Christopher V., Rawlings, James B. Linear programming and model predictive control 2000

Roffler SR, Blanch HW, Wilke CR. In situ recovery of fermentation products. Trends Biotechnol 1984;2:129–36.

Seborg, D.E., Edgar, T.F. and Mellichamp, D.A., Process Dynamics and Control, 2nd Ed., John Wiley, 2004

Silva FLH, Rodrigues MI, Maugeri F. Dynamic modelling, simulation and optimization of an extractive continuous alcoholic fermentation. J Chem Tech Biotechnol 1999;74:176–82.

Sthephanopoulos, G. (1984). *Chemical process control: An introduction to theory and practice*. New Jersey: Prentice-Hall.

Zanin, G.M., Santana, C.C., Bon, E.P.S., Giordano, R.C.L., de Moraes, F.F., Andrietta, S.R., Neto, C.C.D., Macedo, I.C., Fo, D.L., Ramos, L.P.and others, 2000. Brazilian bioethanol program. Appl. Biochem. Biotechnol. 84–86, 1147–1161

31