การควบคุมแบบโมเดลพรีดิกทีฟ
สำหรับเครื่องแยกแบบเยื่อแผ่นอัลตราฟิลเตรชันที่มีการไหลแบบขวางของของแข็งและของเหลว

นางสาว วีรวรรณ วีรชัยพิเชษฐ์กุล

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิศวกรรมศาสตรมหาบัณฑิต

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MODEL PREDICTIVE CONTROL
FOR LIQUID-SOLID CROSS FLOW ULTRAFILTRATION MEMBRANE SEPARATOR

Miss Weerawun Weerachaipichasgul

A Thesis Submitted in Partial Fulfillment of the Requirements
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By	Miss Weerawun Weerachaipichasgul
Field of Study	Chemical Engineering
Thesis Advisor	Associate Professor Paisan Kittisupakorn, Ph. D.

Accepted by the Faculty of Engineering, Chulalongkorn University in Partial Fulfillment of the Requirements for the Master 's Degree

…………………………………………… Dean of Faculty of Engineering
(Professor Somsak Panyakeow, Dr. Eng.)

THESIS COMMITTEE

…………………………………………… Chairman
(Professor Piyasan Praserthdam, Dr. Ing.)

…………………………………………… Thesis Advisor
(Associate Professor Paisan Kittisupakorn, Ph. D.)

…………………………………………… Member
(Montree Wongsri, D. Sc.)

…………………………………………… Member
(Associate Professor Tawatchai Charinpanitkul, Dr. Ing.)

วีรวรรณ วีรชัยพิเชษฐ์กุล : การควบคุมแบบโมเดลพรีดิกทีฟสำหรับเครื่องแยกแบบเยื่อแผ่นอัลตราฟิลเตรชันที่มีการไหลแบบขวางของของแข็งและของเหลว (MODEL PREDICTIVE CONTROL FOR LIQUID-SOLID CROSS FLOW ULTRAFILTRATION MEMBRANE SEPARATOR) อ. ที่ปรึกษา : รศ.ดร. ไพศาล กิตติศุภกร, 91หน้า. ISBN 974-17-1661-3

การควบคุมโมเดลพรีดิกทีฟ(เอ็มพีซี)เป็นการควบคุมขั้นสูงซึ่งได้นำมาใช้ในกระบวนการเคมีเมื่อไม่นาน อุตสาหกรรมที่เกี่ยวกับปิโตรเคมี โลหะ หรืออุตสาหกรมอื่นๆ ได้เข้มงวดขึ้นในการปล่อยน้ำเสียที่มีน้ำมันปนเปื้อน การแยกน้ำมันออกจากน้ำเสียที่ใช้อย่างแพร่หลายในอุตสาหกรรมคือการแยกโดยใช้เยื่อแผ่นเพราะ ไม่มีการเปลี่ยนเฟสโดยการเติมสารเคมี หรือให้ความร้อน การแยกแบบเยื่อแผ่นชนิดอัลตราฟิลเตรชันที่มีการไหลแบบขวางของของแข็งและของเหลวในการแยกน้ำมันจากน้ำประกอบด้วยแบบจำลองทางคณิตศาสตร์ และการทดลอง แบบจำลองทางคณิตศาสตร์ใช้กลไกที่สารแพร่ผ่านเยื่อแผ่น ส่วนการทดลองมุ่งที่กลไกการเกิดการอุดตัน การควบคุมค่าฟลักซ์ของน้ำใช้ความดันตกคร่อมเยื่อแผ่นเป็นตัวแปรปรับ มีสองกรณีที่ศึกษา กรณีที่หนึ่งคือการควบคุมค่าฟลักซ์สู่ค่าเป้าหมายเป็นค่าคงที่ได้จากออพติไมเซชันทั้งระบบ กรณีที่สองเป็นการควบคุมค่าฟลักซ์สู่ค่าเป้าหมายเป็นค่าคงที่สามช่วงได้จากพลวัตออพติไมเซชัน ผลการจำลอง ตัวควบคุมพีไอดีไม่สามารถควบคุมค่าฟลักซ์ของน้ำให้สู่ค่าเป้าหมายทั้งสองกรณี ตัวควบคุมจีเอ็มซีเหมาะที่จะควบคุมค่าฟลักซ์สู่ค่าเป้าหมายที่มาจากการออพติไมเซชันทั้งระบบ แต่ไม่เหมาะที่จะควบคุมในกรณีที่ค่าเป้าหมายมาจากการพลวัตออพติไมเซชัน ตัวควบคุมเอ็มพีซีสามารถควบคุมค่าฟลักซ์สู่ค่าเป้าหมายที่มาจากการออพติไมเซชันทั้งระบบและจากการพลวัตออพติไมเซชัน ตัวควบคุมเอ็มพีซีมีผลการควบคุมที่ดีที่สุดเมื่อเทียบกับตัวควบคุม จีเอ็มซี และพีไอดี

กรณีแบบจำลองของกระบวนการผิดพลาด ตัวกรองคาลมานจะนำมาใช้ร่วมกับตัวควบคุม เอ็มพีซี และจีเอ็มซี เพื่อที่จะประมานค่าตัวแปรที่ทราบค่าไม่แน่นอน ก็คือความหนืด และค่าคงที่ของแบบจำลองของฟิวด์ ที่มีค่าผิดพลาด50%จากค่าทั่วไป พบว่าตัวควบคุม เอ็มพีซี และจีเอ็มซีร่วมกับตัวกรองคาลมานจะให้การควบคุมค่าฟลักซ์ของน้ำที่เหมาะสม อย่างไรเสียเอ็มพีซีก็มีผลการควบคุมที่ดีกว่าจีเอ็มซี ดังนั้นเอ็มพีซีร่วมกับตัวกรองคาลมานมีความทนทานสูง และควบคุมระบบการแยกแบบเยื่อแผ่นชนิดอัลตราฟิลเตรชันที่มีการไหลแบบขวางของของแข็งและของเหลวในการแยกน้ำมันจากน้ำได้สำเร็จ

ภาควิชา.....วิศวกรรมเคมี..... ลายมือชื่อนิสิต..........

สาขาวิชา.....วิศวกรรมเคมี..... ลายมือชื่ออาจารย์ที่ปรึกษา..........

ปีการศึกษา.....2545.....

##4370643421: MAJOR CHEMICAL ENGINEERING

KEY WORD: OPTIMIZATION / CONTROL / MODEL PREDICTIVE CONTROL / MEMBRANE SEPARATOR / ULTRAFILTRATION MEMBRANE

WEERAWUN WEERACHAIPICHASGUL: MODEL PREDICTIVE CONTROL FOR LIQUID-SOLID CROSS FLOW ULTRAFILTRATION MEMBRANE SEPARATOR THESIS ADVISOR: ASSOC. PROF. PAISAN KITTISUPAKORN, Ph.D., 91 pp. ISBN 974-17-1661-3

Regarding to present state of the art in theory and practice, Model Predictive Control (MPC) is one of most widely implemented advanced process control technology for chemical process recently. The petrochemical, metallurgical and processing industries discharge of oily wastewater into the sea or rivers has been under increasingly careful. A new separation of the oil out of the wastewater technology called membrane technology has been used widely in separation industry because it does not give rise to phase changed by adding chemical and heat. The cross-flow ultrafiltration membrane of an Oily-Water emulsions system combine mathematical and experimental models; the mathematical model is based on solute diffusion through membranes and the experimental model focuses on the fouling mechanisms. The control of permeated flux of water using the transmembrane pressure, a manipulated variable, can be studied in two cases. One is to control the flux at a constant set point obtained from an overall optimization. The other one is to control the flux at three interval constant set points obtained from a dynamic optimization. Simulation results have shown that the PID controller cannot control the permeated flux of water to the set point for both cases. Although the GMC controller is able to control the flux at the set point obtained from the overall optimization, it cannot control the flux at the set points obtained from the dynamic optimization. The MPC controller, on the other hand, can control the flux at the set points obtained from both overall and dynamic optimization. This shows that the MPC controller provides the best control response over the GMC and the PID controllers.

In the presences of plant/model mismatch, the Kalman filter is incorporated into both MPC and GMC controllers to estimate unknown/uncertain parameters. Here, the viscosity and constant's Field model, unknown/uncertain parameters, have been increased 50 % from nominal values. It was found that both MPC and GMC controllers with the Kalman filter are still able to control the flux water at set point obtained from both cases. However, the MPC provides better control response than the GMC controller. Therefore the MPC with the Kalman Filter is the most robust and effective control algorithm for the cross flow ultrafiltration membrane of the oily water emulsion system.

Department Chemical Engineering	Student's signature…………………………
Field of Chemical Engineering	Advisor's signature…………………………
Academic Year 2002	

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NOMENCLATURE

A	=	Membrane area (M^2)
C	=	Solute concentration at point (mg/M^3)
C_0	=	The initial Concentration (mg/M^3)
C_b	=	Bulk solute concentration (mg/M^3)
C_p	=	Concentration of the species in the permeate side of the membrane (mg/M^3)
C_M	=	Solute concentration at the membrane surface (mg/M^3)
C_G	=	The gel concentration (mg/M^3)
d	=	The fluid channel height on top of the membrane (mM)
D_v	=	Solute diffusion Coefficient (M^2/min)
$e(t)$	=	Error
J_w	=	Permeate fluxes (M^3/M^2.min)
J_w^*	=	The steady state flux (M^3/M^2.min)
J_{wsp}	=	Out put trajectory(M^3/M^2.min)
k	=	Mass transfer coefficient (M/min)
K	=	The control gain of MPC controller
K_1	=	Tuning constant of GMC controller
K_2	=	Tuning constant of GMC controller
K_c	=	Proportional gain of PID controller
K_J	=	Constant in Field's model (Kg/Pa^2.min^2.M^3)
K_K	=	The Kalman gain
m_c	=	The accumulate mass of gel
N_m	=	The control horizon steps
N_p	=	The process response steps

NOMENCLATURE (Continue)

P	=	The matrix estimated uncertainly
Q	=	The matrix variable of model
R	=	The matrix variable of measurement
r	=	The rate of recovery (min^{-1})
Re	=	The Reynolds number, $\mathrm{Re} = \dfrac{\rho d v}{\mu}$
R_r	=	The rejection coefficient
R_M	=	Hydraulic resistance created by the membrane (M^{-1})
R_G	=	Hydraulic resistance created by the gel layer (M^{-1})
R_t	=	The total resistance (M^{-1})
Sc	=	The Schmidt number, $Sc = \dfrac{\mu}{D_v \rho}$
Sh	=	The Sherwood number
t_f	=	The future time.
u	=	The manipulated input variable
$U_{\min}$	=	The minimum of constraint
$U_{\max}$	=	The maximum of constraint
V	=	The solution volume in the membrane (M^3)
V_0	=	The initial solution volume (M^3)
W_1	=	The weighting factor of state variable
W_2	=	The weighing factor of manipulated variable
y	=	Output of the process model

Greek Letters

δ	=	Boundary layer thickness (M)
μ	=	The concentration viscosity (Kg/M.min)

NOMENCLATURE (Continue)

Greek Letters (Continue)

λ	=	Largrange Multiplier
ΔPTM	=	The transmembrane pressure (Pa)
ξ	=	Damping constant
ρ	=	The concentration density (Kg/M^3)
τ	=	Time constant
τ_d	=	Derivative time constant
τ_i	=	Integral time constant
Δt	=	The sampling period

Subscript

W	=	water
0	=	initial
sp	=	set point
M	=	the membrane
G	=	the gel layer
T	=	the total
p	=	the permeated
b	=	the bulk
c	=	the accumulate

Chapter 1

Introduction

A membrane is a selective barrier that permits the separation of certain species in a fluid by a combination of sieving and sorption diffusion mechanisms. In terms of energy, membrane separations have an important advantage in that, unlike evaporation and distillation, no change of phase is involved in the process, thus avoiding latent heat requirements. No heat is required with membranes, thus it is possible to produce products with functional properties superior in some respects to those produced by conventional processes. Membrane technology also enables to simultaneously concentrate, fractionate, and purify the products. The membrane separation process enjoys numerous industrial applications with the following advantages:

1. Appreciable energy savings
2. Environmentally benign
3. Clean technology with operational ease
4. Replaces the conventional processes like filtration, distillation, ion-exchange and chemical treatment systems
5. Produces high, quality products
6. Greater flexibility in designing systems.

Almost membrane separation process were found operating condition that could be obtained maximizing permeate flux rate by using good condition experiments. But permeate flux in cross-flow filtration was controlled dynamic process of gel-layer formation and growth. The permeated flux decline is mainly caused by the concentration polarization layer resistance. After a short period of time, the solute concentration at the membrane surface reaches the limiting gel-layer concentration and gel-layer formation commences. The mass of cake increase until the system reaches steady state.

The cross flow filtration is increasingly used in the industry, but remains a complex process. Synthetic solutions have often been used in laboratory to develop models of fouling when a real solution is filtered. Experiments are required for the design of the filtration unit. To date no rigorous methodology has been proposed principally because of the large number of variables that must be controlled simultaneously (type of membrane, cut-off, product and membrane conditioning, yield optimal volumetric reduction factor, temperature, velocity, transmembrane pressure, control and operating time). In addition, the results depend on the way the run is conducted and the operating conditions, which are not always well controlled.

More than 15 years after model predictive control (MPC) appeared in industry as an effective means to deal with multivariable constrained control problems. A theoretical basis for this technology has started to emerge. The issues of feasibility of the on-line optimization, stability and performance are largely understood for system description by linear models. Much progress has been made on these issues for non-linear system but for particle applications many questions remain including the reliability and efficiency of the online computation scheme. Many particle problem likes control objective prioritization and symptom-aided diagnosis can be integrated systematically and effectively into the MPC framework by expanding the problem formulation to include integer variables yielding a mixed-integer quadratic or linear program.

In the past, the models of membrane were mostly based on partial differential equations. The experimental of Field could make ordinary differential equation membrane model. The experimental contribution focuses on the mechanisms and model flux decline. The control system in the most industries is PID control, this controller can handle the process performance but the response is slow and not accurate particular highly nonlinear process. The GMC and MPC based process control has drawn considerable attention in process control because of its good performance characteristics.

In this thesis, we propose a strategy to handle the control of the permeated flux in the cross-flow ultrafiltration membrane of oily water emulsions system. First, the permeated flux control could be studied in two cases. One is overall optimization to specify set point. Another is dynamic optimization. Model Predictive Control (MPC) is applied with Parameter Estimator to control the permeated flux. Finally, MPC with Kalman Filter compared with Generic Model Control (GMC).

1.1 Research Objective

The objectives of research are;

1. To study the separation process with ultrafiltration membrane,
2. To study MPC with and without Kalman filter,
3. To study behavior by simulation of separation process,
4. To study control permeate flux and estimate unknown parameter,
5. To study compare controller PID, GMC, MPC, with and without Kalman filter.

1.2 Scope of Research

The scope of this research can be listed as follows;

1. An inorganic membrane, cross-flow ultrafiltration membrane of oily-water emulsions, is studied in this work.

2. Pressure gradient (transmembranes) is a manipulated variable.

3. Constraints of transmembranes depend on robustness of inorganic membrane is used.

4. A nonlinear model predictive control with and without Kalman filter is used to control the cross-flow ultrafiltration membrane.

5. Matlab language is used to simulation and control the process.

6. Set point has 2 cases that are calculated by optimization of system (overall optimization and dynamic optimization).

7. The PID, GMC and MPC are controller that are used in system

8. The GMC with Kalman filter is compared with MPC with Kalman filter.

1.3 Research Contribution

The research contribution can be listed as follows;

1. Behaviors and parameters of cross-flow ultrafiltration membrane process have been known.

2. MPC with and without Kalman filter would be made comprehension.

3. The Implement of MPC with Kalman filter would decease operating cost and increase product.

1.4 Work Schedule

Activity	Time																				
	2001						2002												2003		
	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3
1.study the separation process with ultrafiltration membrane																					
2.study MPC and MPC with Kalman filter																					
3.control permeated flux and estimated unknown parameter by PID,GMC, MPC with and without Kalman filter																					
4.compare controller PID, GMC, MPC with and without Kalman filter																					
5.discuss and comprehend of simulation process																					
6.write the report																					

Chapter 2

Literature Review

2.1 Separation membrane Process

Sets of mathematical equations based on solute diffusion through membranes were developed. These differential equations were solved simultaneously using a numerical solution technique. The solute adsorption phenomenon, which creates large flux drops for polymer membranes was investigated for the mathematical model, and used in the computer program. The validity of the model was tested for single and multiple component system using experimental data. The systems studied during this project were chlro-and nitrophenals in water. High separations (up to 99%) for some ionized chloro-substituted phenolics were achieved, (Didakar Bhattacharyya, et al, 1988)

Numerical study of the fluid dynamics and mass transfer of an ultrafiltration performance in a tube membrane module, A numerical treatment is presented for the pressure-driven ultrafiltration process of a solution flowing laminarly in a tube membrane module for variable permeation flux, high wall Reynolds numbers and incomplete solute rejection. Both the Navier-Stokes and diffusion equations are solved numerically in terms of finite differences using a boundary condition for the concentration on the membrane obtained from the balance of the rate of the solute arriving at the membrane and the sum of leakage and rate of back diffusion. Plots representing the membrane concentration, permeation velocity and fraction of solvent removed are provided. (Kotzev Tzventan, 1994)

A filtration device included an ultrafiltration having an inlet chamber, an outlet chamber, and an ultrafiltration membrane separating the inlet chamber from the outlet chamber. An inlet flow connected the inlet chamber to a source of dialysis liquid. Pressure sensors determined pressure value on opposite side of membrane and a controller calculated a transmembrane pressure there from and compared the calculated transmembrane pressure with a predetermined threshold value. If the threshold value was reached, the controller emitted a threshold signal to either warn an operator or alternatively to automatically diverted flow to bypass the ultrafilter. (United States Patent, 1995).

Prediction of the rate of cross-flow membrane ultrafiltration: A colloidal interaction approach, A model is developed using simple hydrodynamics for the flow in a rectangular channel with one porous wall, but focusing on a detailed description of the dependence of both osmotic pressure and gradient diffusion coefficient on concentration and physicochemical parameters. The analysis is based on a fundamental calculation of colloidal interactions between particles expressed in terms of osmotic pressure. The osmotic pressure modeling accounts for multiparticle electrostatic interactions, dispersion forces and configurationally entropy effects. The osmotic pressure is further used in the calculation of the gradient diffusion coefficient from the generalized Stokes-Einstein equation. The cross-flow ultrafiltration model yields an a priori prediction (with no adjustable parameters) for the filtration rate of colloids at various operating conditions (applied pressure, cross-flow rate, membrane resistance) as a function of particle size, zeta potential or surface charge, and ionic strength. Model predictions are compared to experimental filtration data for the protein bovine serum albumin (Bowen W. Richard, et al, 1996)

Present separate of oils from wastewater by ceramic ultrafiltration membrane (UF). UF was used separation of emulsified oil by multi-channel monolith ceramic membranes of MWCO 150,000 and 50,000. The experiments were carried out at constant temperature, ranges of operating pressure is 120-500 kPa, cross-flow velocity was 1.5-4.7 m/s and feed concentration was 2,310-154,000 ppm, The optimum operating conditions were found by pressure at 120kPa and velocity at 4.7m/s which provided high flux and rejections. (K. Wongcharee, et al,1996)

The study constrained model predictive control (CMPC) for reverse osmosis (RO) desalination unit had been conducted and comparison purposes PI. The experimental unit used a series of four cellulose acetate membranes. The RO system had 4 output were permeate flow rate, permeate conductivity is indicative of salt content in the product, transmembrane pressure and inlet pH and 2 input are flow rate of permeate and inlet acid flow rate. The result of comparison between CMPC and PI confirmed the excellent potential of CMPC for RO desalination plants. (A. Z. James, et al, 1997)

Flux decline in crossflow ultrafiltration and microfiltration was investigated by perceiving membrane fouling as a dynamic process from non-equilibrium to equilibrium. Under the influence of the boundary condition at the initial section and cross flow, the equilibrium is first reached at the initial section of the crossflow filter and the front of the equilibrium region progresses with time toward the end of the filter. A mathematical model was developed to describe this dynamic process and a closed-form solution of the model was provided. With the model, the time-dependent flux and the time required to reach the steady state in a crossflow filtration can be easily determined. The fouling process under different conditions is simulated as an illustration and demonstration of the newly developed model (Song Lainfa, 1998)

Pilot plant unit for a cross-flow microfiltration and ultrafiltration of fermentation broths, A detailed description of an automated pilot plant unit of our original design is given. The operating parameters such as transmembrane pressure drop, cross-flow velocity, permeate flow rate, temperature and pH can be controlled and continuously monitored during test runs. The pilot plant operation is controlled by an industrial programmable logic controller, connected to a personal computer. An original SCADA application was developed which enables a remote control of the pilot plant and data acquisition. The pilot plant can be run either by static or dynamic counterpressure of the permeate. The dynamic counterpressure of the permeate assures a uniform transmembrane pressure drop (UTP) along the whole filtration element. Three different modes of operation can be selected: a constant transmembrane pressure drop mode, a constant flux mode and a stand-by mode for startup and cleaning operations. The unit is successfully used for the microfiltration and ultrafiltration of various fermentation broths. Some experimental results are shown and discussed, (David Senica, et al1999)

Mechanisms and modeling flux decline of Cross-flow and dead-end microfiltration of oily-water emulsions. The modeling flux declines of cross flow filtration at constant transmembrane pressure were examined. The best-fit data sets examined were obtained with the model developed previously by Field. The general equation is depended upon the fouling mechanism and the steady state flux. This approach to analysis of the flux data has the ability to identify the dominant mechanism, which has been shown to depend upon the membrane used and operating conditions. In order not to give undue emphasis to early or late time, the data were fitted in both flux and resistance from simultaneously. The dominant fouling mechanism was found to be either incomplete pore blocking or cake filtration. Trends in the model parameter are also discussed in relation to operating conditions such as model of filtration, cross flow velocity and transmembrane pressure. For dead –end filtration, the initial rate of flux decline was found to be proportional, as suggested by theory. The two most significant particle observation are (1) the initial rate of fouling is significantly lower for the cross flow velocity of 0.8ms-1 or greater and (2) the transmembrane pressure of 1 bar can lead to excessive fouling, with regard to microfiltration modeling generally, (T.C. Arnot, et al, 1999)

Treatment of wastewater by ultrafiltration, the testing in a lab scale combines of sand filtration and UF producing clear disinfected water, which could be reused. A tubular inorganic membrane CARBOSEP with 50,000 Da MWCO was used for this study. At a cross flow velocity of 4 m/s the polarization phenomena were limited leading to a maximum value of about 100 l/h.m2 for a transmembrane pressure of 1 bar. With an increase of the cross flow velocity up to 6–7 m/s, the relation between the filtrate flux and the transmembrane pressure becomes nearly linear: in these conditions, in a range of transmembrane pressure 0.5–2 bar, the filtrate flux is only 15% lower than the pure water flux, proving a very low level of fouling. The removal efficiency of organics and suspended solids (including acteria) was very good: 1) low values of COD (12 mg/l) BOD (5 mg/l) and absence of indicators of fecal contamination are the main characteristics of the treated water; 2) it can be concluded from these tests that the combination sand filtration/UF is efficient and that a cut-off of 50 Kda is a good choice. (D. Abdessemed, et al 1999)

Experiments on microfiltration of raw cane re-melt with tubular mineral membranes showed that rigorous methodology (Punidadas, et al, 1991). The main variables of ultrafiltration were sugar dilution and the control mode. Optimal sugar dilution was on the basis of the highest dry substance flux criteria. Comparison between the two control modes, with the re melts and tubular mineral membrane, showed that use of constant permeate flux reduced fouling of the mineral membrane without altering selectivity. The optimal flux set point corresponded to the maximal productivity and the lowest cleaning frequency. The permeated flux control mode was favorable in ultrafiltration, but was less influential than in microfiltration. Ultrafiltration of re -melt through spiral organic membrane showed that the control mode was also less important in this case. The results confirmed that the control model is of importance in the particular case of microfiltration through tubular mineral membranes. Few relevant studies have been published, as these membranes are not widely used, (Martine Decloux, 1999)

The mathematics model has been developed that was able to predict experimental data under different operating conditions in copper biosorption system by Arthrobactor separation in a Ultrafiltration/microfiltration membrane (UF/MF) reactor in order to confine cells. The mathematical model based on metal mass balance taking into account the effect of pH on the Langmuir equilibrium adsorption parameter. Experimental results obtained by using this system could be model up to pH=5 without considering cell disruption phenomenon, while at pH=6 possible chemical reactions of biomass constituents could happen (F. Beochini, F. Pagnanell and F. Vegio, 2001)

A method and an apparatus for cross-flow filtration of a fluid utilizing a porous membrane arranged in housing. Approximate the feed inlet and the retentate outlet are the flow of retentate during back washing away and along the membrane. The back washing is achieved by means of a hydrophore, an on/off valve and a constant flow pump such that a positive back washing. The transmembrane pressure maintained during a majority of the period of time in which the intermittent back washing takes place. (PCT, 2001)

Developed a system capable of meeting oily wastewater discharged regulation. This system was used ceramic ultrafiltration membranes. The produce 99 gallons of clean effluent are acceptable for every one hundred gallons in Oil/Water Separator (OWS). The permeated quality averaging is less than 5 ppm and below 15 ppm. 95% of time has been achieved abroad ship. Regeneration studies were underway to reduce cossets by allowing membrane re-use. (K.T. Tompkins, et al, 2002)

2.2 Model-Based Predictive Control

Though the ideas of receding horizon control and model predictive control can be traced back to the 1960s(Garcia, Prett and Morari, 1989), interest in this filed started to surge only in the 1980s after publication of the first papers on IDCOM(Richalet, Rault, Teatus and Papon,1978) and dynamic matrix control(DMC) (Cutler and Ramaker,1979,1980) and the first comprehensive exposition of generalized predictive control(GPC)(Clark, Mohtadi and Tuff,1987).

DMC had tremendous impact on industry. There is probably not single major Oil Company in the world, where DMC (or a functionally similar product with a different trade name) is not employed in most new installations or revamps. For Japan some statistics are available (Ohshima, Ohno and Hashimoto, 1995). The initial research on MPC is characterized by attempts to understand DMC, which seemed to defy a trasitional theoretical analysis because it was formulated in a non-conventional manner. One example was the development of internal mode control (IMC)(Garcia and Morari, 1982), which failed to shed light on the behavior of constrained DMC, but led to some insights on robust control (Morari and Zafiriou, 1989).

This paper discusses Model Predictive Control (MPC), a scheme in which an open-loop performance objective is optimized over a finite moving time horizon. MPC is shown to provide performances superior to conversional feedback control for nonminimum phase systems or systems with input constraints when future set points are known. Stabilizing unstable linear plants and controlling nonlinear plants with multiple steady state are also discussed. (John W. Eaton and James B. Rawlings, 1992)

A packed distillation column separates a mixture of cyclohexane and n-heptane was simplified to a form suitable for use in on-line model predictive control calculations. The packed distillation column was operated at several operating conditions to estimate two unknown model parameters in the rigorous and simplified models. The actual column response to step changes in the feed rate, distillate rate and re-boiler duty agreed well with dynamic model predictions. One unusual characteristic observed was that the packed column exhibited gain-sign changes, which are very difficult to treat using conventional linear feedback control. Nonlinear model predictive control was used to control the distillation column at an operating condition where the process gain changed sign. An on-line, nonlinear model-based scheme was used to estimate unknown/time-varying model parameters, (Patwardhan Ashutosh, et al, 1993)

Proposed a new on-line control algorithm, based on GMC, for improving the automatic startup of a binary distillation column. A series of tests had been performed on an industrial-scale distillation column. The experimental results demonstrated the effectiveness and robustness of the proposed method with respect to process/model mismatch. The implementation of the algorithm was simple and could be accomplished with standard industrial instrumentation and a cheap personal computer. (Barolo, et al., 1993)

Successive linearization in nonlinear model predictive control was used for technique base on local linear approximation of state/ measurement equations computed at each sample time. The prediction equation is made linear with respect to the undecided control input move by making linear approximations dual to those made for the Extended Kalman Filter (EKF). As a result of these approximations, increase in the computational demand over linear MPC is quite mild. The prediction equation can be computed via non-iterative nonlinear integration. Minimization of the weighted 2-norm of the tracking errors with various constraints can be solved via quadratic programming. Connections with previously published successive linearization based approaches of nonlinear quadratic dynamic matrix control are made, (Jay H. Lee, et al, 1994)

Short horizon nonlinear model predictive control that concerns nonlinear model predictive control of the multivariable, open-loop stable processes whose delay-free part is minimum-phase. The control law is derived by using a discrete-time state-space formulation and the shortest 'useful' prediction horizon for each controlled output. This derivation allows to establish the theoretical connections between the derived nonlinear model predictive control law and the discrete-time globally linearizing control, and to deduce the conditions for nominal closed-loop stability under the model predictive control law. Under the nonlinear model predictive controller, the closed-loop system is partially governed by the zero dynamics of the process, which is the nonlinear analog of placing a subset of closed-loop poles at the zeros of a process by a model algorithmic controller. (Sorous et al, 1995)

Nonlinear predictive control of an exothermic CSTR using recursive quadratic state space models, The possibility of using a discrete quadratic perturbation model for approximating nonlinear plant dynamics in the neighborhood of the operating point is explored in this paper. A method is evolved for computing the model coefficients using first and second order sensitivity equations. The proposed model is further used to develop a nonlinear Model Predictive Control algorithm. The performance of the proposed control algorithm is demonstrated by simulating a benchmark CSTR control problem characterized by the change in the sign of the steady state gain in the operating region. (Patwardhan Sanchin C. and Madhavan K.P. ,1995)

The GPC approach is not suitable or, at the very least, awkward for multivariable constrained systems, which are much more commonly encountered in the oil and chemical industries than situation where adaptive control is needed. Essentially all vendors have adopted a DMC like approach (Qin and Badgwell, 1996).

Robust stability conditions for SISO model predictive control algorithms, that presents a new method for deriving robust stability conditions for single-input/single-output (SISO) model predictive-control algorithms, based on an application of Jury's dominant coefficient lemma. Model uncertainty is parameterized by a range of possible plant impulse responses. The method is illustrated by deriving robust stability conditions for the extended-horizon predictive control algorithms EHPC1 and EHPC2, as well as for a prototypical model predictive controller presented originally by Garcia and Morari. (Badgwell Thomas A., et al, 1997)

Predictive control of a glass process, that presents an application of single input single output (SISO) and multi input multi output (MIMO) predictive control laws in the glass industry. Control strategies have been developed on different parts of the process in order to improve the quality of the bottles that are produced. A generalized predictive control (GPC) algorithm with feedforward control has been used after modeling based on the predictive error method. Identification and control algorithms have been implemented for more than one year on B.S.N. plants, providing a significant improvement in the quality of production (Wang Q., et al, 1997)

Model Predictive Control (MPC) is applied to control the temperature of a batch reactor with exothermic reactions and its performance is compared with GMC to that of individually / simultaneously plant / model mismatches in heat transfer coefficient, total mass in the reactor, rate of reaction and heat of reaction. In addition, since both MPC and GMC are the model based controllers; they need the measurement of all states as well as the value of process parameters, in this work, the heat released of chemical reactions is needed but cannot be measured. In this situation, Kalman Filter estimates it and the estimates of heat released is incorporated into the MPC/GMC. Simualtion studies show MPC to be as good as GMC for all cases for which both controllers are well tuned (S. Phupaichitkun, 1998).

The application of Model Predictive Control (MPC) with Kalman filter for the control of the temperature and the concentration of a reversible exothermic, The design MPC with Kalman filter which can give a good control performance and guarantee the stability of closed-loop nonlinear continuous time systems subject to constraints. Several different problems have been considered, such as control performance, disturbance rejection, set point tracking and parametric model/plant mismatch, etc. Simulation results have shown that the MPC with Kalman filter provides better control performances than the conventional PID controller does for the control of the temperature and the concentration of a continuous stirred tank reactor in the cases of disturbance rejection and setpoint tracking. In addition, the MPC is more robust than the PID in presence of model/plant mismatch (P. Ruksawid, 1999)

Predictive control in power generation, Power generation systems are very complex in their nature and are subject to greater constraints on environmental pollution, safety regulations and at the same time, increasing demands for flexibility of operation. These factors together have led to the search for more efficient control techniques for power system applications. Predictive control methods are used for unit level control. State-space algorithms for predictive control are presented and application to a constrained dynamic performance predictive controller are presented on a simulation model of a gas (Ordys Andrzej W. and Grimble Michael, 1999)

Model predictive control algorithms were in continuous fermentor, Model-based control schemes have been developed and implemented for a continuous fermentor. The first method modified the well-known dynamic matrix control (DMC) algorithm by making it adaptive. The other two used nonlinear model predictive control algorithms for calculation of control actions. The NMPCI algorithm, which used orthogonal collocation in finite elements, acted similar to NMPCII, which used equidistant collocation. These algorithms were compared with DMC. The results obtained show the good performance of nonlinear, (Silva R.G., et al, 1999)

The robustness of model predictive control (MPC) with respect to satisfaction of process output constraints by a closed-loop MPC system that employs an uncertain process model. The method relies on formulation output constraints as chance constraints using the uncertainty description of the process model. The resulting on-line optimization problem is convex. (Alexander T. Schwarm and Michael Nikolaou, 1999)

The application of a state feedback controller the control of the pH value of the wastewater of a Cold Roll Mill Plant, Kalman filter is incorporated in the state feedback control formulation to estimate unknown/uncertain parameters. Formulating the state feedback controller as well as the mathematical model of the plant on a Matlab program has done simulation study. Simulation results indicate that the state feedback controller can be used to control multi-outputs and gives a better performance in comparison to a PID controller does, in the presence of disturbances in feed flow rate and feed concentration of waste water and acid. Furthermore, the addition of the Kalman filter in the state feedback controller formulation can improve the performance of the state feedback controller in the presence of random noise in measurements (W. Duangwang, 1999)

Present the application of MPC control the temperature of a batch polymerization reactor. Kalman filter, an estimation technique is included into the MPC algorithm to estimate unmeasurable states as well as unknown/ uncertain parameters used in the formulation of MPC. The performance of MPC with Kalman filter is compared to that of a simple nonlinear control technique named Generic Model Control (GMC). Simulation results have shown that MPC with Kalman filter give a better control performance than GMC with Kalman filter in normal case. And even in the presence of plant/ model mismatch in decrease in heat transfer coefficient and rate of termination reaction and in increase of the monomer concentration and heat of reactions. (S. Tongmeesee, 2000)

Two robust model predictive control (MPC) algorithms for linear integrating plants described by a state-space model. The first formulation focuses on steady-state offset whereas the second minimizes output deviations over the entire prediction horizon. The input matrix parameters of the plant are assumed to lie in a set defined by an ellipsoidal bound. Robustness was achieved through the addition of constraints that prevent the sequence of the optimal controller costs from increasing for the true plant. The resulting optimization problems solved at each time step are convex and highly structured. Simulation example compares the performance of these algorithms with those based on minimizing the worst-case controller cost. (Sameer Ralhan and Thomas A. Badgwell, 2000)

This research presents the implementation of Globally Linearizing Control (GLC) together with an extended Kalman filter to control pH of the wastewater treatment process that is a part of an electroplating plant. The GLC is a model based control technique; it needs measurements and values of states and parameters, which are neither all measurable nor known exactly. Therefore, the extended Kalman filter has been applied to estimate unavailable or unknown states and parameters and these estimates are incorporated in the control action determination in the GLC algorithm. Simulation results have shown that in a nominal case, the GLC is able to control the pH of the system to a desired set point and its control performance is equivalent to the PID one. In the presence of plant/model mismatch, the GLC is still able to handle this mismatch and gives a good control performance whereas the PID gives a poor control response; the GLC is much more robust than the PID (N. Siripun, 2000)

Using the subspace identification method to describe the relationship between the manipulated variables and the important qualities in the process identifies a Wiener model. This process is a continuous polymerization reactor, which is a highly nonlinear MIMO system with input constraints. The WMPC performs better than the LMPC in the sense of better regulation and offset elimination. (Boong-Goon Jeong, et al, 2001)

GMC for relative degree higher than one processes a case study: A concentration control of continuous stirred tank reactor with first-order exothermic reaction, the GMC applies for a concentration control of continuous stirred tank reactor with first-order exothermic reaction, which was the process of relative degree two. This research used an internal controlled variable, the key component that made the control variable to be effected directly like the relative degree one processes. The results showed that the GMC with internal controlled variable could use the techniques that improved the robustness like a conventional GMC. (P. Meethong, 2002)

Optimization and control of peraporative membrane reactor, the maximization of the desired product is considered as an objective function in the optimization problem formulation subject to other process constraints, which is solved by the sequential optimization approach. A generic model control (GMC) coupled with an extended Kalman filter is implemented to track both optimal temperature set point and optimal temperature profile obtained in the off-line optimization. Application of these control strategies to control the pervaporative membrane reactor shows that the proposed control strategy provides good control performances in a nominal case. The GMC coupled with Kalman filter has been found to be effective and robust with respect to changes in process parameters. (O. Moolasartsatorn, 2002)

2.3 Optimization

Present solved optimal control problems that have discontinuous profiles in fed-bath reactor system. This system is nonlinear programming (NLP). The solution based on successive quadratic programming (SQP) and orthogonal collocation on finite elements with continuous profiles approximated by Lagrange polynomials. Two important theoretical are approximation properties were considered through an equivalence between orthogonal collocation on finite elements and fully implicit Runge-Kutta integration points. Results agree well with previously obtained (J.E. Cuthrell and L.T. Biegler, 1988)

Present optimized batch-operating conditions. The optimal control problem is converted into a nonlinear programming (NLP) solved by generalized reduced gradient (GRG). The objective is to optimize different variables and to take into lower and upper bounds on the variables and constraints on variables. The different variables of the problem are lower and upper bounded. The solving differential problems determined two profiles are optimal operation time and /or optimal initial ratio. (V.Garcia, et al, 1995)

Structural design of integrated online process optimization and regulatory control systems base on an economic analysis of different structures is addressed. The regulatory control layer is assumed to implement using model predictive control (MPC) techniques. The analysis of the dynamic economic of MPC is presented with uses the state formulation as the plant model. Out put feedback is performed in the framework of linear quadratic filtering theory using A Kalman filter. Using the unconstrained MPC laws, variance of the constrained variables, the necessary back of from the constrained due to regulatory disturbances is calculated and the dynamic economics are established. The dynamic economics of the model predictive regulatory control system are incorporated into the method of the average deviation from optimum analyzing the economic performance of an online optimization system. Different structures of the integrated system of online optimization and MPC-based regulatory control can be analyzed in term of their economic performance, and the necessary structural design decisions can be taken. (C. Leoblein and J. D. Perkins, 1999)

The design and implement three different types of controllers namely PI, PID (both in DM strategy) and GMC controllers to track the optimal reactor temperature profiles using a complex reaction scheme in a batch reactor. Off-line optimal control problem had been formulated and solved to obtain the optimum temperature profiles (dynamic set point for controllers) to maximize the amount of the desired product while minimizing the waste by-product. Neural network technique was used as the on-line estimator the amount of heat released by the reaction within the GMC algorithm. The GMC controller coupled with a neural network was found to be more effective and robust than the PI and PID controllers in tracking the optimal temperature profiles to obtain the desired products on target (Aziz N., et al., 2000)

Apply an on-line optimal control for the control of batch crytallizers. Algorithms have two steps. The first finds the optimal crystallizer temperature. The second uses a feedback control system in order to achieve the desired final product.

The on-line optimal control provides better than simplified optimal. (G.P. Zhang and S. Rohani, 2001).

2.4 Kalman Filter

Described and illustrated an efficient new algorithm on process examples for solution of the extended Kalman filter equations for a continuous dynamic system with discrete measurements. Implicit simultaneous methods, which were powerful in terms of accuracy and efficiency, were utilized for numerical integration. At the internal integration step level, the new algorithm exploited the decoupled nature of the state estimate and error covariance equations along with the symmetry of the error covariance matrix. The error control strategy included both the state estimates and error covariance. (Myers M. A., and Luecke, R. H., 1991)

Applied two estimation techniques, the extended Kalman filter (EKF) and the iterative extended Kalman filter (IEKF), to a nonlinear time-varying system that had non-measurable state variables. An iterative solution to a fed-batch fermentation process was reported using the EKF based on measurements of the oxygen and carbon dioxide concentrations. The results demonstrated that this estimation technique could be successfully applied to complex biological processes. (Tan L., et al., 1991)

An adaptive control of input-output linearizable systems, together with an extended Kalman filter (EKF), was applied to a simulated batch polymerization reactor to realize the output (monomer conversion) tracking in the presence of model parameter uncertainties. Simulation results showed that this technique was robust and the output tracking performance could be ensured even in the presence of large model parameter errors and disturbances. (Wang Z.L. et al., 1993)

An application of state and parameter estimation techniques in an altering activated sludge process with regard to biological phosphorus removal. A simplified model describing the phosphorus dynamics in an alternating activated sludge process was proposed based on insight into the process with a mechanistic activated sludge model. State and parameter estimation problems relating to the non-measurable dynamics of a most important limiting substrate poly-hydroxy-alkanoate (PHA) were formulated and discussed. Several schemes were presented which involved a state estimator designed with the extended Kalman filter algorithm, two specific parameter estimation procedures and an adaptive scheme for simultaneous state and parameter estimation. (Ahao and Kummel, 1995)

Presented the design and development of a multirate software sensor for use in the chemical process industry. The measurements of process outputs that arrived at different sampling rates were formally accommodated into the estimation strategy by using the multirate formulation of the iterated extended Kalman filter. Measurement delays associated with some of the process outputs were included in the system description by addition of delayed states. Observability issues associated with state and parameter estimation in a multirate framework were discussed and modified measurement equations were proposed for systems with delayed measurements to ensure relatively strong system observability. (Gudi R. D., et al., 1995)

The design and develop a Kalman Filter State and Parameter Estimation (kSTAPEN) software. This program is written in Borland C++ Builder who simplifies the algorithm by dividing into simple steps with each step corresponding to an input window or dialog. And it is tested with a level control system, a batch exothermic reactor and a stirred-tank reactor. Simulation results show that the kSTAPEN can give satisfactorily good estimates for all cases. It can be used for the demonstration of both state and parameter estimation applications (S. Bamrungwongdi, 1998)

Investigated a model-based inferential quality monitoring approach for a class of batch systems. First, an extended Kalman filter based fixed-point smoothing algorithm was presented and compared to a popular approach to estimating the initial conditions. Subsequently, a nonlinear optimization-based approach was introduced and analyzed. A sub-optimal on-line approximation to the optimization problem was developed and shown to be directly related to the extended Kalman filter based results. Finally, some practical implementation aspects were discussed, along with simulation results from and industrially relevant example application. (Russell, et al., 2000).

The design and develop two software programs based on Kalman filter. The first one, named kSTAPEN+, was a software component based on Kalman filter. In kSTAPEN+, users could define their own systems including states and parameters to be estimated. After running the program, estimation results are given. The estimates obtained from the kSTAPEN+ had been compared to those obtained from the program written on Matlab. Furthermore, the program had been tested with a heater, a stirred-tank reactor and a microfeeder. In kSTAPEN-C, the component had been developed by using Component Object Model (COM) technology. The estimates obtained from kSTAPEN-C had been compared to those obtained from kSTAPEN+. Results had shown that both kSTAPEN-C and kSTAPEN+ were equivalent. (V. Lersbamrungsuk, 2000)

Chapter 3

Theory

The purpose of this chapter is to lay theoretical groundwork. Section 3.1 describes a general of ultrafiltration for separation process membrane that based on gel polarization model and important parameter of system. Section 3.2 describes Model Predictive Control (MPC). The MPC can handle both linear and nonlinear model. The algorithm MPC based on dynamic matrix control. The minimum's principle is solved the optimal control by Lagrange Multiplier. Section 3.3 explains discrete Kalman Filter that is a linear system and addresses the general problem of trying to estimate.

3.1 Separation Membrane Process

A membrane is a selective barrier that permits the separation of certain species in a fluid by a combination of sieving and sorption diffusion mechanisms. In terms of energy, membrane separations have an important advantage in that, unlike evaporation and distillation, no change of phase is involved in the process, thus avoiding latent heat requirements. No heat is required with membranes, thus it is possible to produce products with functional properties superior in some respects to those produced by conventional processes. Membrane technology also enables to simultaneously concentrate, fractionate, and purify the products.

Membranes can selectively separate components over a wide range of particle sizes and molecular weights, from macromolecular materials such as starch and protein to monovalent ions. Membrane should be selected such that the size of the pores is smaller than the size of the smallest particle in the feed stream that is to be retained by the membrane.

Membranes are available in several different configurations – tubular, hollow-fiber, plate-and-frame, and spiral-wound. Some of these designs may work better than others for a particular application, depending on such factors as viscosity, concentration of suspended solids, particle size, and temperature.The membrane processes are classified according to the driving force used in the process. The various membrane processes along with the driving force are listed below:

1. Pressure differential across the membrane is the driving force.
    - Reverse osmosis
    - Ultrafiltration
    - Microfiltration
    - Membrane gas and vapor separation
    - Pervaporation

2. Temperature difference across the membrane is the driving force.
    - Membrane distillation

3. Concentration difference across the membrane is the driving force.

- Dialysis
- Membrane extraction

4. Electric potential difference across the membrane is the driving force.

- Electrodialysis

The process of cross-flow pressure-driven membrane filtration is very simple, requiring only the pumping of the feed-stream tangentially across the appropriate membrane, i.e., and parallel to the membrane surface. The membrane splits the feed stream into two streams: one stream is the permeate, consisting of components small enough to pass through the membrane pores; the other stream is the concentrate (retentate) consisting of components large enough to be retained by the membrane. The retentate stream is usually recirculated through the membrane module because one passage through the membrane may not deplete the feed significantly. Important operating variables are applied transmembrane pressure and cross-flow velocity through the membrane module. Cross-flow velocity is the average rate at which the process fluid flows parallel to the membrane surface. Velocity has a major effect on the permeate flux. The permeated flux depends on the applied transmembrane pressure for a given surface area up to a threshold transmembrane pressure. Above this pressure, which has to be experimentally determined for each application, higher pressures have little or no effect. In fact, too high a pressure may aggravate fouling of the membrane.

3.1.1 Ultrafiltration

Ultrafiltration (UF) is a pressure-driven membrane separation technique for dissolved and suspended materials based on molecular size. Substances smaller than the pore size of the filter are driven through with the solvent while larger substances are retained. Ultrafiltration is used for separating particles with molecular weights from 500-300,000 (or 10-100°A). Pressure has exerted on a solution is 1 – 10 bars as a driven force that causes a flow of solutes and water toward the ultrafilter. (Leos J. Z, et all, 1996)

Mass Transfer and Gel Polarization

In Ultrafiltration, the concentration of retained macro solutes will build up at the membrane surface due to the removal of solvent. This causes a concentration gradient with the maximum macro solutes level at the membrane. This phenomenon is known as concentration polarization as a result of the increased concentration at the membrane surfaces there is a tendency for solute to diffuse away from this point. Under steady state condition the connective mass transfer toward the membrane balanced by the diffusive movement in the opposite direction, could be explained by the following equation.

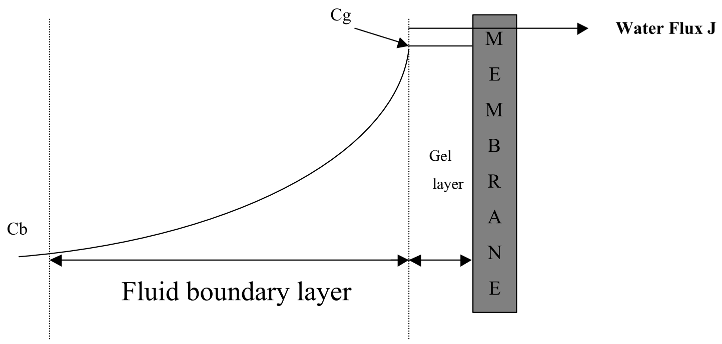


Figure3.1: Concentration gradient during gel polarization

$$JC - D_v \frac{dc}{dx} = JC_p \qquad (3.1)$$

Boundary condition $$X = 0 : C = C_b \qquad (3.2)$$

$$X = \delta : C = C_w \qquad (3.3)$$

J = Permeate fluxes ($M^3/M^2.s$)
C = Solute concentration at point X (mg/M^3)
D_v = Solute diffusion Coefficient (M^2/s)

can be integrated across the solute boundary layer to give

$$J = \left(\frac{D_v}{\delta}\right) \ln\left(\frac{C_M}{C_b}\right) \qquad (3.4)$$

C_M = Solute concentration at the membrane surface (mg/M^3)
C_b = Bulk solute concentration (mg/M^3)
δ = Boundary layer thickness (M)

or

$$J = k \ln\left(\frac{C_M}{C_b}\right) \qquad (3.5)$$

where

$$k = \frac{D_v}{\delta}$$

k = Mass transfer coefficient (M/s)

Under actual operating conditions, the value of C_M can be increased until the point that the retained solute forms a gel layer. This gel concentration C_G is the maximum value of C_M and may be substituted into

$$J = k \ln\left(\frac{C_G}{C_b}\right) \qquad (3.6)$$

C_G is dependent upon operating pressure temperature solubility and pH that C_G is actually the concentration at which osmotic back-pressure is high enough to prevent flux

k is generally not a function of the solute concentration but depend on the driving pressure and any fluid flow across the membrane. k is a function of the fluid velocity across the membrane

$$S_h = \frac{kd}{D_v} = A\,\mathrm{Re}^B\, S_c^{\left(1/3\right)} \qquad (3.7)$$

d = The fluid channel height on top of the membrane

Re = The Reynolds number, $\mathrm{Re} = \dfrac{\rho d v}{\mu}$

Sc = The Schmidt number, $Sc = \dfrac{\mu}{D_v \rho}$

Sh = The Sherwood number

A, B = Constants

B = 0.5 in laminar flow, 1.0 in turbulent flow (Gekas and Hallstrom, 1970)

μ = The concentration viscosity

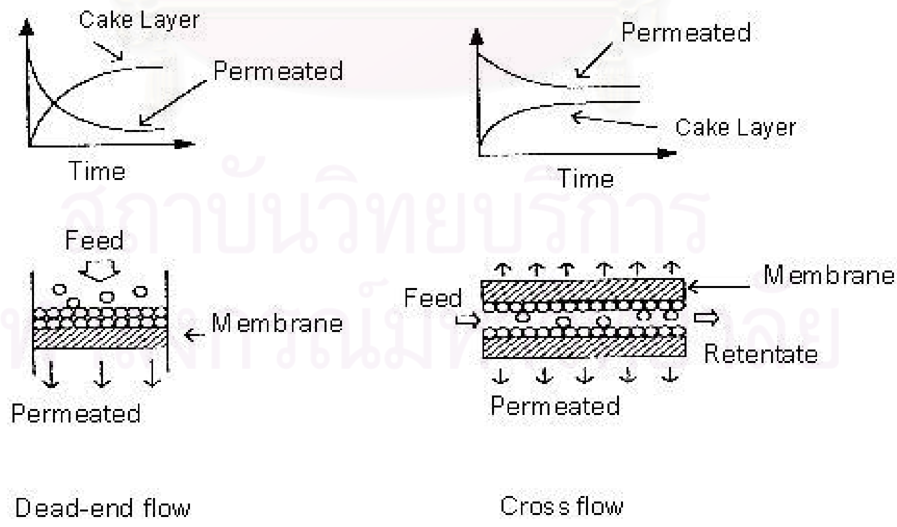


Figure 3. 2: Comparison of cross flow and dead-end filtration

Cross Flow Filtration

The effects of gel polarization can be reduced by cross flow filtration. In cross flow filtration the feed stream flows tangentially across the membrane surface This operation makes the movement of a solute away from the membrane and reduces the thickness of the gel layer so the problem of clotting in filtration process can be reduced.

The driving force through the membrane is also determined by pressure. This transmembrane pressure is the different between the pressure on the feed side and on the filtrate side of the ultrafilter. The differential will be highest at the inlet and reduce to the minimum at the outlet.

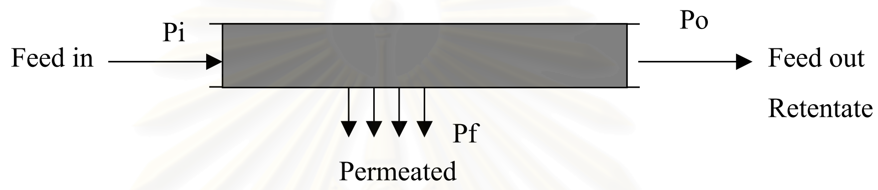


Figure 3. 3: Cross-flow filtration pressure relationships

An average driving force is

$$\Delta PTM = \frac{p_i + p_o}{2} - p_f \qquad \text{(Pa)} \qquad (3.8)$$

Generally the filtrate pressure is negligible and p_f is taken as zero

$$\Delta PTM = \frac{p_i + p_o}{2} \qquad \text{(Pa)} \qquad (3.9)$$

The flux rate will be a function of ΔPTM as defined by

$$J = \frac{\Delta PTM}{\mu\left(R_M + R_G\right)} \qquad (\mathrm{M^3/M^2.s}) \qquad (3.10)$$

R_M = Hydraulic resistance created by the membrane (M^{-1})
R_G = Hydraulic resistance created by the gel layer (M^{-1})

Parameter Flux

1.Pressure

The permeated flux will increase with pressure until the point when gel layer forms and increases overall resistance. Then further increases in pressure will increase the thickness and the resistance of gel layer so the permeate flux will reach a maximum and become relatively constant with pressure.

2.Recirculation Velocity

The mass transfer coefficient will increase with re-circulation velocity moreover an in crease in re-circulation velocity increase the shear force at membrane surface such that the thickness of gel layer and gel resistance decreases. But the average driving force ΔPTM will decrease with the increasing of re-circulation velocity

3.Temperature

The mass transfer coefficient will increase when temperature increases, so the permeate flux increases with the temperature.

4.Concentration of Solution

The permeated flux decreases with the solute concentration.

Membrane Rejection

The ability of an ultrafiltration membrane to retain a given species is defined by the rejection coefficient

$$R_r = 1 - \frac{C_p}{C_b} \qquad (3.11)$$

C_p = Concentration of the species in the permeate side of the membrane (mg/M^3)

Membrane Material used for the membrane cover a wide range, from organic polymeric materials to inorganic materials. Normally they are solid. Membranes are prepared from these materials and used for various separation processes

3.2 Model Predictive Control

The MPC reference to as Receding Control and Moving Horizon Optimal Control, has been widely adopted in industry as an effective means to deal with multivariable constraints control problems

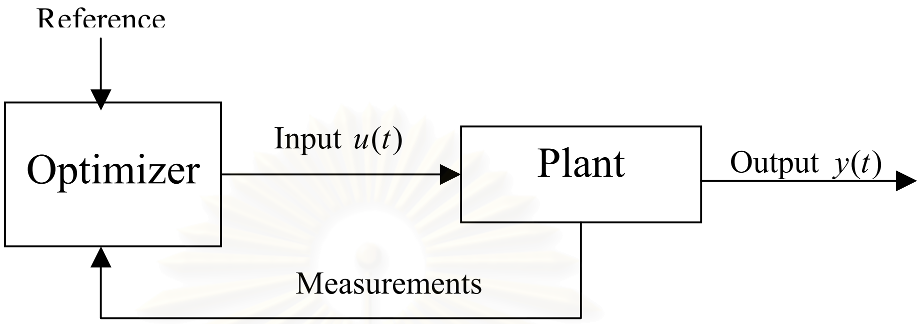


Figure 3.4: Basic structure of MPC

The conceptual structure of MPC is depicted in figure 3.4. The name MPC stems from the ideal of employing an explicit mode of the plant to be controlled which is used to predict the future output behavior. This Prediction capability allows solving optimal control problem on line, where tracking error, namely the difference between the predicted output and the desired reference, is minimized over a future horizon, possibly subject to constraints on the manipulated inputs and outputs. The result of the optimization is applied according to a receding horizon philosophy: At time t only the first input of the optimal command sequence is actually applied to the plant. The remaining optimal inputs and discarded, and a new optimal control problem is solved at time $t+1$. This idea is illustrated in following figure 3.5.

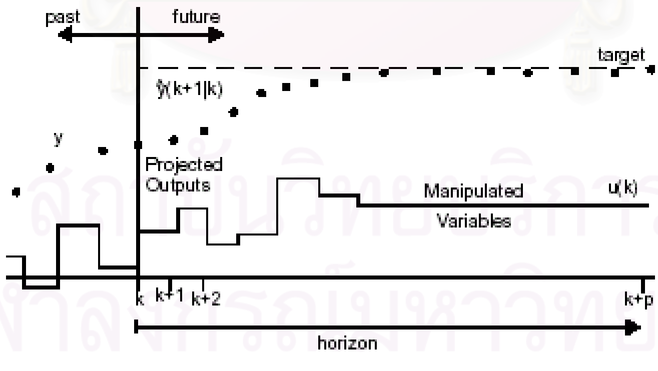


Figure 3.5: Definition of the optimization problem for MPC

For any assumed set of present and future control moves Δu (k), Δu (k + 1) . . ., Δu(k + m – 1) the future behavior of the process outputs y(k + 1|k),y(k + 2|k), . . . , y(k + p|k) can be predicted over a horizon p. The m present and future control moves (m ≤p) are computed to minimize a quadratic objective .Though m control moves are calculated, only the first one (Δu(k)) is implemented. At the next sampling interval, new values of the measured output are obtained, the control horizon is shifted forward by one step, and the same computations are repeated. The resulting control law is referred to as “moving horizon” or “receding horizon.” The predicted process outputs y(k + 1|k), . . . ,y(k + p|k) depend on the current measurement and assumptions we make about the unmeasured disturbances and measurement noise affecting the outputs.

MPC formulation

Objective function $min \int_{t_k}^{t_k+T_p} \left\{ \left(W_1 (X - X_{sp})^2 + W_2 (\Delta U)^2 \right) \right\} dt$

State Space $\dot{X} = f((X(t), U(t))$

Constraint’s manipulated variable $U_{\min} < U(t) < U_{\max}$

Control variable is fix $X(t + t_f) = X_{sp}$

When

W_1 and W_2 are weighting factors.

$U_{\min}$ and $U_{\max}$ are minimum and maximum of constraint is manipulated variable.

t_f is future time.

Model predictive control used a process model to;

1. Estimate and predict the disturbance entering the process. If there is process dead time then disturbance could be estimates by extrapolation forward in time by the amount of dead time.

2. Predict the Process State (including the controlled variable) on dead time into the future based on current measurements, current and past controls, and the extrapolated disturbances.

3. Compute the desired future values of the Process State beyond the dead time starting with the Process State predicted in step 2. Desired future state should evolve as a reference dynamical system whose relative order (Kravaris and Chang-Bock, 1987) is the same or greater than that of the process model. For systems which have no right-half plane transmission zeros the reference dynamical system is usually an n^{th} order linear system (i.e. a lag), where the order n lies between the relative order and (normal) order of the model.

4. Compute the controls which force the model to track the desired future states computed in step.3 at some future time (e.g. the next sample interval beyond the dead time) or as closely as possible over some time horizon into the feature.

Process models used in MPC should have unique trajectories for unique inputs. Future, the process outputs and states should depend continuously on the process inputs at each instant of time.

Process Simulation

$$\begin{aligned} \dot{x} &= f(x,u) \\ y &= g(x,d) \end{aligned} \qquad (3.12)$$

when

f is process dynamic

x is state variable vector

u is manipulated variable vector

y is output variable vector

Continuous equation

$$\begin{aligned} \frac{dx}{dt} &= Ax + Bu \\ y &= Cx \end{aligned} \qquad (3.13)$$

when

A, B and C are constant matrix $n \times n$

$$A = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \cdots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \cdots & \frac{\partial f_2}{\partial x_n} \\ \vdots & \vdots \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} \cdots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} \qquad B = \begin{bmatrix} \frac{\partial f_1}{\partial u_1} & \frac{\partial f_1}{\partial u_2} \cdots & \frac{\partial f_1}{\partial u_n} \\ \frac{\partial f_2}{\partial u_1} & \frac{\partial f_2}{\partial u_2} \cdots & \frac{\partial f_2}{\partial u_n} \\ \vdots & \vdots \ddots & \vdots \\ \frac{\partial f_n}{\partial u_1} & \frac{\partial f_n}{\partial u_2} \cdots & \frac{\partial f_n}{\partial u_n} \end{bmatrix} \qquad C = \begin{bmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \cdots & \frac{\partial g_1}{\partial x_n} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \cdots & \frac{\partial g_2}{\partial x_n} \\ \vdots & \vdots \ddots & \vdots \\ \frac{\partial g_n}{\partial x_1} & \frac{\partial g_n}{\partial x_2} \cdots & \frac{\partial g_n}{\partial x_n} \end{bmatrix}$$

Discrete equation

$$\begin{aligned} x_{(k+1)} &= Gx_k + Hu_k \\ y_k &= Cx_k \end{aligned} \qquad (3.14)$$

when

G, H and C are constant matrix

Constraints are combined inequality constants and equality constraints.

1. Equality constraints

$$h(x,u) = 0$$

2. Inequality constants are Hard Constraint

$$u_{\min} \le u \le u_{\max}$$

3.2.1 Objective function

The Model Predictive Control (MPC) is closely related to linear quadratic optimal control. MPC leads to an optimization problem that is solved on-line in real time at each sampling interval. The optimization problem is formulated to minimize a quadratic objective. The objective function is remainders power two of state variable and manipulated variable. Efficiency objective function is stipulated by optimization. The objective function of Dynamic Matrix Control (DMC) (Prett and Gillette, 1979) is in this form

$$J = \frac{1}{2}\left[(x_{sp} - x)^T W_1 (x_{sp} - x) + (u_k - u_{k-1})^T W_2 (u_k - u_{k-1})\right]$$

or (3.15)

$$J = \frac{1}{2}\left[x^T W_1 x + u^T W_2 u\right]$$

W_1 is weighting factor of state variable and W_2 is weighting factor of manipulated variable. The weighting factor is essential in process tuning.

MPC could control to target into control horizon N_m step and compute resolute of process response N_p step. The objective function can be write index equation

Continuos equation

$$J = \int_t^{t+N_p} \frac{1}{2}\left[x^T W_1 x + u^T W_2 u\right] \qquad (3.16)$$

MPC can be control to target when time is $k + N_m$. Values of manipulated and state variables are zero after time is $k + N_m$. The objective function can be write new index equation

Discrete equation

$$J = \sum_k^{k+N_m} \frac{1}{2}\left[x^T W_1 x + u^T W_2 u\right] \qquad (3.17)$$

3.2.2 Optimization

Manipulated variables of real process have performance limits. The manipulated variable of ultrafiltration membrane is transmembrane pressure. The limit is between 1 to 10 bars because this is robustness of membrane. A method of optimization this process is Largrange Multiplier (White, 1977). The objective function of MPC combines equality constant and inequality constant. The model simulation is state space form are.

$$x_{k+1} = Gx_k + Hu_k$$
$$y_k = Cx_k \qquad (3.18)$$

Equality constant

$$Gx_k + Hu_k - x_{k+1} = 0 \qquad (3.19)$$

Inequality constant

$$u_{k,\min} \le u_k \le u_{k,\max} \qquad (3.20)$$

New objective function is

Continuos equation

$$L(x,u) = \sum_t^{t+N_m} \frac{1}{2}\left[(x^T W_1 x + u^T W_2 u) + \lambda'(Gx + Hu - x')\right] \qquad (3.21)$$

Discrete equation

$$L(x,u) = \sum_k^{k+N_m} \frac{1}{2}\left[(x_k^T W_1 x_k + u_k^T W_2 u_k) + \lambda_{k+1}(Gx_k + Hu_k - x_{k+1})\right] \qquad (3.22)$$

When

$\lambda(t) \in R^n$ is Largrange Multiplier n equation. The minimum optimization has the necessary condition of manipulated variable (u_{k+i}^j) when $i = 0,1,\ldots,N_m$ are

$$\frac{\partial L}{\partial x} = 0$$
$$W_1 x + G^T \lambda - \lambda' = 0 \qquad (3.23)$$

$$\frac{\partial L}{\partial u} = 0$$
$$W_2 u + H^T \lambda = 0 \qquad (3.24)$$

$$\frac{\partial L}{\partial \lambda} = 0$$
$$Gx + Hu - x' = 0 \qquad (3.25)$$

The necessary condition is fixed at $\lambda_k = P_k x_k$. Therefore the equation (3.23)-(3.25) represent in equation (3.26)-(3.28) consequently.

$$W_1 x_k + A^T P_{k+1} x_{k+1} - P_k x_k = 0$$
$$(P_k - W_1) x_k = A^T P_{k+1} x_{k+1} \qquad (3.26)$$

$$\begin{aligned} &W_2 u_k + H^T P_{k+1} x_{k+1} = 0 \\ &u_k = W_2^{-1} H^T P_{k+1} x_{k+1} \end{aligned} \qquad (3.27)$$

$$x_{k+1} = Gx_k + Hu_k \qquad (3.28)$$

u_k of equation (3.27) takes place in equation (3.28). The result is

$$\begin{aligned} &x_{k+1} = Gx_k + HW_2^{-1} H^T P_{k+1} x_{k+1} \\ &x_{k+1}(I - HW_2^{-1} H^T P_{k+1}) = Gx_k \\ &x_{k+1} = (I - HW_2^{-1} H^T P_{k+1})^{-1} Gx_k \end{aligned} \qquad (3.29)$$

x_{k+1} takes place in equation (3.26). The result is

$$\begin{aligned} &(P_k - W_1)x_k = A^T P_{k+1}(I - HW_2^{-1} H^T P_{k+1})^{-1} Gx_k \\ &(P_k - W_1) = A^T P_{k+1}(I - HW_2^{-1} H^T P_{k+1})^{-1} G \end{aligned} \qquad (3.30)$$

From theory of matrix are

$$(A + BDC)^{-1} = A^{-1} - A^{-1} B(D^{-1} + CA^{-1} B)^{-1} CA^{-1}$$

Results are

$$P_k = W_1 + G^T P_{k+1}\{I - HW_2^{-1}[I + H^T P_{k+1} HW_2^{-1}] H^T P_{k+1}\} G \qquad (3.31)$$

$$P_k = W_1 + G^T P_{k+1} G - G^T P_{k+1} H[W_2 + H^T P_{k+1} H] H^T P_{k+1} G \qquad (3.32)$$

Or

$$P_k = W_1 + G^T P_{k+1} G - G^T P_{k+1} H[W_2 + H^T P_{k+1} H] H^T P_{k+1} G \qquad (3.33)$$

In The closed loop

$$\begin{aligned} u_k &= -Kx_k \\ &= -W_2^{-1} H^T P_{k+1} x_{k+1} \\ &= -W_2^{-1} H^T (P_k - W_1) x_k (G^T)^{-1} \end{aligned} \qquad (3.34)$$

When K is the control gain.

$$K = -W_2^{-1} H^T (P_k - W_1)(G^T)^{-1} \qquad (3.35)$$

Algorithm of MPC in this thesis could present in flow chart (see Figure 3.6). Steps of algorithm are

1. Guess manipulated variable u_{k+i}^{j} ($u_{k+i}^{j} = u_k$ when $i = 0,1,...,N_m$)

2. Calculated next step state space $x_{(k+1)} = Gx_k + Hu_k$

3. Set optimize objective function
$$L(x,u) = \sum_{t}^{t+N_m} \frac{1}{2}\left[(x_k^T W_1 x_k + u_k^T W_2 u_k) + \lambda_{k+1}(Gx_k + Hu_k - x_{k+1})\right]$$

4. Used the necessary condition and fixing $\lambda_k = P_k x_k$

5. Calculated gain process of control $K = -W_2^{-1} H^T (P_k - W_1)(G^T)^{-1}$

6. Calculated manipulated variable $u_{k+i} = -Kx_{k+i}$

7. Go to step 1.

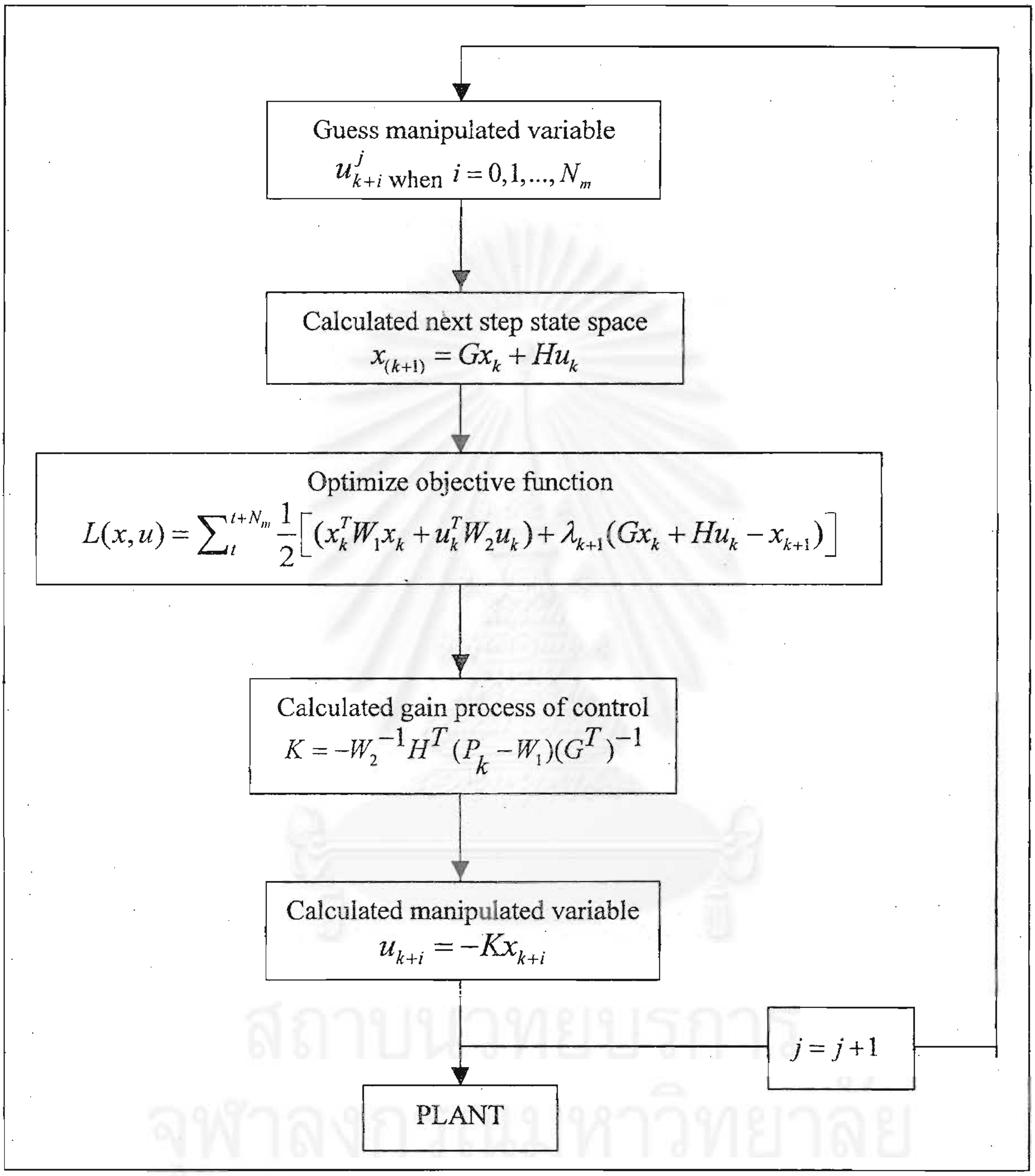


Figure 3.6: Flow chart of MPC algorithm

3.3 Kalman Filter

The purpose is to reset observer state in the presence of modeling error or unmeasured disturbances. Detailed information is on incorporating a Kalman Filter with MPC. The solution of the Kalman filter gain requires the dynamic matrix of linearized model to be stable

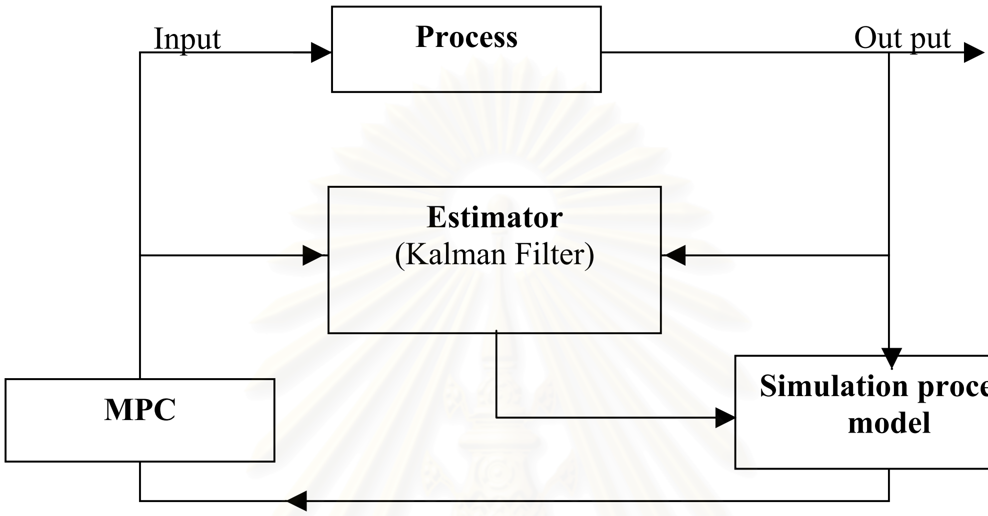


Figure 3.7: MPC with estimator

The Kalman Filter is a set of mathematical equations that provides an efficient computation (recursive) solution of the least-squares method. The filter is very powerful in several aspects: it supports estimation of past, present, and even future state, and it can do so even when the precise nature of the model system is known. The Kalman Filter is a linear system and addresses the general problem of trying to estimate the state $x \in \Re^n$ of a discrete-time controlled process. The linear model of state variation is

$$x_k = Ax_{k-1} + Bu_k + \varepsilon_{k-1} \qquad (3.36)$$

with a measurement $y \in \Re^m$ that is

$$y_k = C_k x_k + \eta_k \qquad (3.37)$$

The random variables ε_k and η_k represent the process and measurement noise (respectively) and assume to be independent (of each other), white, and with normal probability distributions.

$$P(\varepsilon) \approx N(0, Q) \qquad (3.38)$$

$$P(\eta) \approx N(0, R) \qquad (3.39)$$

In particle, the process noise covariance Q and measurement noise covariance R matrices might change with each time step or measurement, however here they are assumed to be constant.

The $n \times n$ matrix A in the difference equation (3.36) relates the state at the previous time step $k-1$ to the state at the current step k, in the absence of either a driving function or process noise. Note that in practice A might change eith each time step, but here it is assume to be constant. The $m \times l$ matrix B relates the optional control input $u \in \Re^l$ to the state x. The $m \times n$ matrix C in the measurement equation (3.37) relates the state to the measurement y_k. In practice C might change with each time step or measurement, but here it is assume to be constant.

The computational origins of the filter

Define $\hat{x}_k^- \in \Re^n$ to be a priori state estimate at step k given knowledge of the process prior to step k, and $\hat{x}_k \in \Re^n$ to be a posteriori state estimate at step k given measurement y_k. A priori and a posteriori estimate errors can be defined as

$$e_k^- \equiv x_k - \hat{x}_k^-$$

and

$$e_k^- \equiv x_k - \hat{x}_k$$

The a priori estimate error covariance is the

$$P_k^- = E[e_k^- e_k^T] \qquad (3.40)$$

and the a posteriori estimate error covariance is

$$P_k^- = E[e_k e_k^T] \qquad (3.41)$$

An a posteriori state estimate $\hat{x}_k$ is computed as a linear combination of an a priori estimate $\hat{x}_k^-$ and weighted difference between an actual measurement y_k and a measurement prediction $C\hat{x}_k^-$ as shown below in equation (3.42). Some justification for equation (3.42) is given in " The Probabilistic Origins of the Filter" found below.

$$\hat{x}_k = \hat{x}_k^- + K(y_k - C\hat{x}_k^-) \qquad (3.42)$$

The difference ($y_k - C\hat{x}_k^-$) in equation (3.42) is called the measurement innovation or the residual that minimizes the a posteriori error covariance equation (3.41). This minimization can be accomplished by first substituting equation (3.42) into the above definition for e_k, substituting that into equation (3.41), performing the indicated expectation, taking the derivative of the trace of the result with respect to

K, setting that result equal to zero and, then solving for K. One from of the resulting K that minimizes equation (3.41) is given by:

$$K_k = P_k^- C^T (CP_k^- C^T + R)^{-1} = \frac{P_k^- C^T}{CP_k^- C^T + R} \qquad (3.43)$$

From equation (3.43) as the measurement error covariance R approach zero, the gain K weights the residual more heavily

$$\lim_{R_k \to 0} K_k = C^{-1} \qquad (3.44)$$

Another way of thinking about the weighting by K is that as the measurement error covariance R approach zero, the actual measurement y_k is trusted more and more, while the predicted measurement $C\hat{x}_k^-$ is trusted less and less. On the anther hand, as the priori estimate error covariance P_k^- approach zero the actual measurement y_k is trusted less and less, while the predicted measurement $C\hat{x}_k^-$ is trusted more and more.

Kalman Filter algorithm

The Kalman Filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman Filter fall in two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the priori estimates for the next time step. The measurement update equations are responsible for the feedback-i.e. for incorporating a new measurement into the priori estimate to obtain an improved a posteriori estimate.

The Kalman Filter algorithm combines the time and measurement updates:

Time Update equation (Predictor equation)
Project the state ahead $\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k$ Project the error covariance ahead $P_k^- = AP_{k-1}A^T + Q$

Measurement Update equation (Corrector equation)

Compute the Kalman gain

$$K_k = P_k^- C^T (C P_k^- C^T + R)^{-1}$$

Update estimate with measurement y_k

$$\hat{x}_k = \hat{x}_k^- + K_k (y_k - C \hat{x}_k^-)$$

Updated the error covariance

$$P_k = (I - K_k C) P_k^-$$

The time update equations can be also thought of as predictor, while the measurement update equations can be thought of as corrector equations. Indeed the final estimation algorithm resembles that of a predictor-corrector algorithm for solving numerical problems as show in figure 3.8

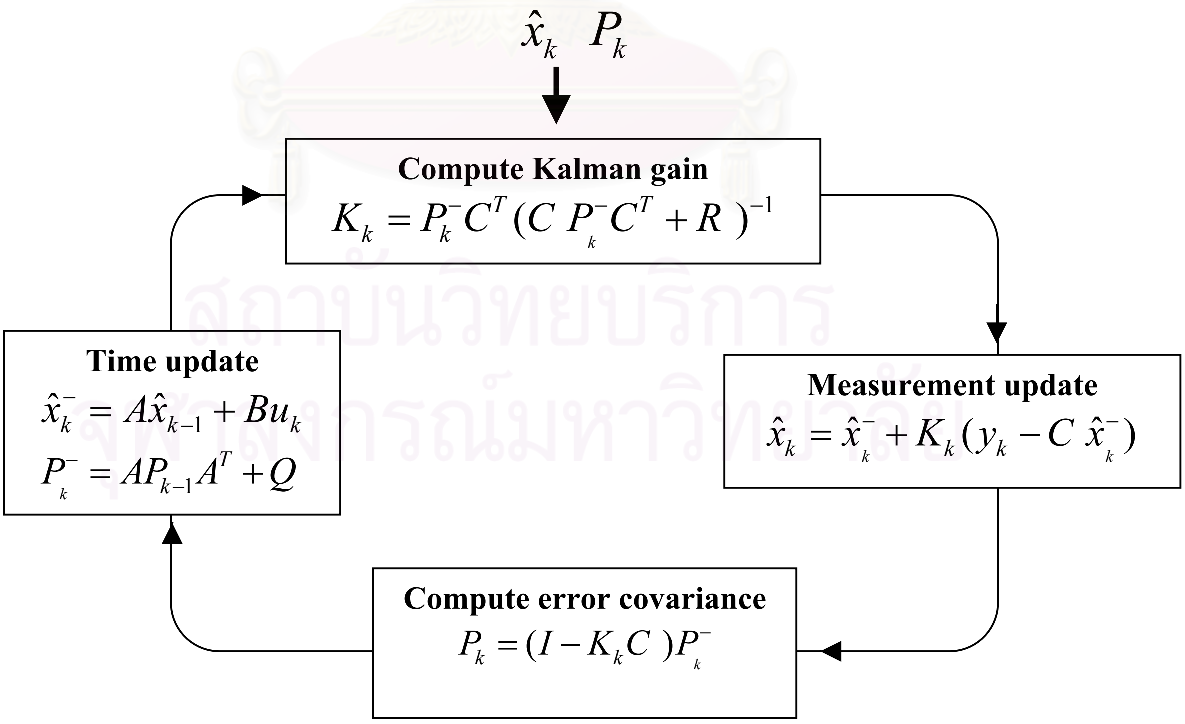


Figure3.8: The Kalman Filter loop

Filter parameter and tuning

In the actual implementation of the filter, the measurement noise covariance R is usually measured prior to operation of the filter. Measuring the measurement error covariance R is generally practical and is supposed to be able to measure the process anyway (while operating the filter).

The determination of the process noise covariance Q is generally more difficult because it does not have the ability to directly observe the estimating process. Sometimes a relatively simple (poor) process model can produce acceptable results if one injects enough uncertainly into the process via the selection of Q.

The tuning of the parameter Q and R is usually performed off-line, frequently with the help of another Kalman Filter in the process generally referred to as system identification. In the fact constraints, the parameter Q and R estimate error covariance P_k and the Kalman gain K_k.

Chapter 4

The Cross-Flow Ultrafiltration Membrane of Oily Water Emulsion System

The discharge of crude oily wastewater into the sea or rivers has been under increasingly careful scrutiny in recent years. In addition to oily wastes from the petrochemical, metallurgical and processing industries, it should be remembered that the production of crude oil is often accompanied, on average, by an equal volume of water. A production separator that separates most of the oil from the water is usually used to give an initial separation of oil and water. The small quantity of remaining oil in the water must be reduce to an acceptable limit before the water can be discharged into sea or rivers or re-injected of water flooding. The separation can be done by the use of large gravity settling vessel, because large hold-up volumes are acceptable. In the part separation was done with air induced flotation tank based system, where a fine mist of air is injected in conjunction with surfactants to float oil droplets to surface. This method and other conventional technologies including parallel plate coalesces and granular media filtration, do not produce effluent that consistently meets the discharge limits and re-injection requirements. The oil industry has been increasingly using liquid-liquid hydro-cyclone to separate the oily water to cut down the operating cost as well as solving the problem of space and weight. However, hydro-cyclones are more efficient at high operating pressure and large oil drop alternative technologies. The extent to which this is necessary can be gauged to use centrifuges for some duties.

Thus the membrane technology and other new technology is an opportunity that can meet current limits across a variety of old fields, as well as further lower limits. The membrane technology has been used widely in separation industry because it does not give rise to phase changed by adding chemical and heat. Also membrane-operating cost is compared with another process, it will have the less operating cost. The membrane separation technology is good way to select.

In the past, The models of membrane were mostly based on partial differential equations. The experimental of Field could make ordinary differential equation membrane model. The experimental contribution focuses on the fouling mechanisms. The control system in the most industries is PID control, this controller can handle the process performance but the response is slow and not accurate particular highly nonlinear process. The GMC and MPC based process control has drawn considerable attention in process control because of its good performance characteristics.

4.1 Process and Mathematical Modeling

The treatments of oily wastewater system have pre-treated to the OWS before membrane separation. The cross-flow ultrafiltration membrane of oily-water emulsions system (OWS) was designed. The system incorporated a feed pump, a re-circulation pump, and membranes

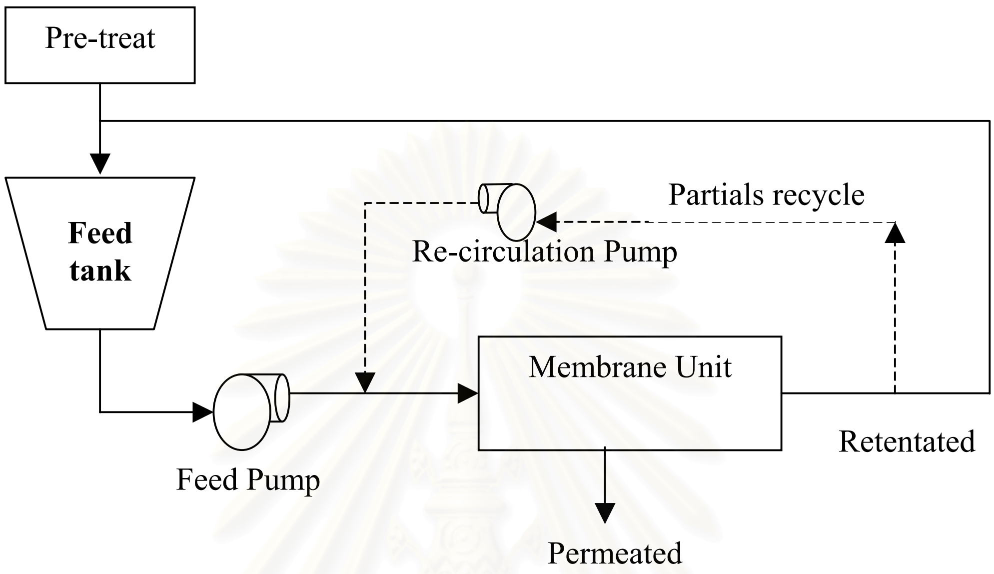


Figure 4.1: Batch Ultrafiltration membrane

In this thesis the process model for Ultrafiltration membrane involves a material balance and experimental.

Assumptions are;

1. Bath filtration process
2. Constant pressure
3. Cross-flow filtration
4. The fouling mechanism

Mathematical model (Appendix A)

$$\frac{dC_b}{dt} = \frac{C_b R_r A J_w}{V_0 (1-r)} \qquad (4.1)$$

$$\frac{dr}{dt} = \frac{A}{V_0} J_w \qquad (4.2)$$

$$\frac{dm_c}{dt} = A\left(J_w - J_w^*\right) C_b \qquad (4.3)$$

From experimental model (Field, 1995) used equation. The differential equation of the permeated flux could present

$$\frac{dJ_w}{dt} = -K_J \left(J_w - J_w^*\right) J_w^2 \qquad (4.4)$$

$$\frac{dR_t}{dt} = K_J \Delta PTM^2 \left(\frac{J_w^*}{\Delta PTM} - \frac{1}{R_t}\right) \qquad (4.5)$$

when

$$J_w^* = \frac{\Delta PTM}{\mu R_t} \qquad (4.6)$$

The batch ultrafiltration membrane could present the controller system (see Figure 4.2). The system has feed pump, pressure sensor and permeated flux sensor. They transformed data input and output to the controller. The controller transformed data to feed pump.

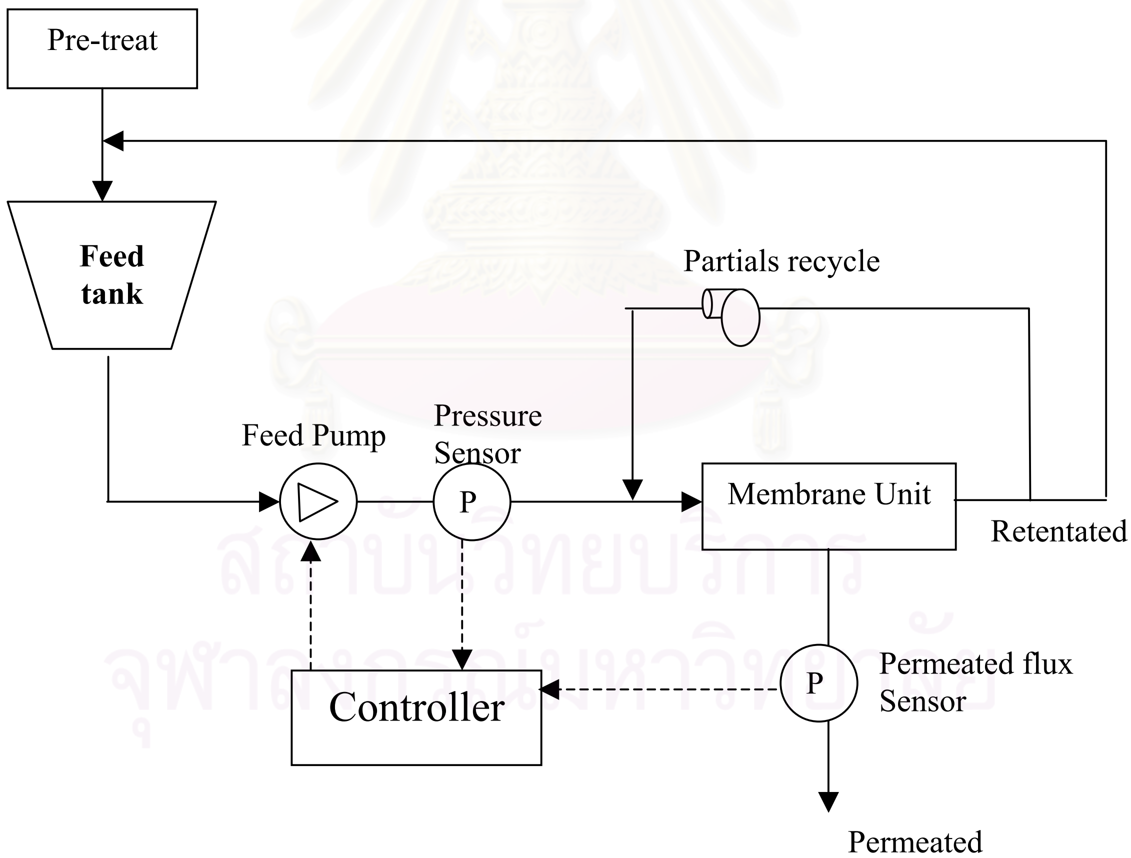


Figure 4.2: Control system of Batch Ultrafiltration membrane

4.2 Process Parameter

In the past, The models of membrane were mostly based on partial differential equations. But the experimental of Field 1995 made ordinary differential equation membrane model. This thesis referred operating condition of experimental model (Field, 1995).

Table 4.1: Parameter in membrane separation of experimental model (Field, 1995).

Parameter	Value	Unit
A	$1.40*10^{-3}$	(M^2)
R_m	$1.69*10^{11}$	(M^{-1})
K_J	$7.51*10^{8}$	$(Kg/Pa^2.min^2.M^3)$
V_0	$1.50*10^{-4}$	(M^3)
μ	$5.48*10^{-2}$	(Kg/M.min)

Table 4.2: Operating initial condition in membrane separation of experimental model (Field, 1995).

Parameter	Initial	Unit
C_0	10^3	(mg/M^3)
C_b	10^3	(mg/M^3)
J_w	$7.54*10^{-5}$	$(M^3/M^2.min)$
R_t	$1.69*10^{11}$	(M^{-1})
m_c	0	(mg/min)
r	0	(min^{-1})
ΔPTM	$1.20*10^{5}$	(Pa)

4.3 Optimization

In this work, An off-line optimal control is solved with fixed time to calculate the maximum the permeated flux of water for the cross flow ultrafiltration membrane of oily water emulsion system to its set point. The operating time of system is 150 minutes. The manipulated variable of ultrafiltration membrane is transmembrane pressure. The limit robustness membrane was between 1 to 10 bars. A method of optimization was Largrange Multiplier (White, 1977).

The result of flux control could be studied in two cases. One is overall optimization to specify set point. Another is dynamic optimization. The optimization problem computed to minimize a quadratic objective therefore the objective function is.

$$J = -J_w \tag{4.7}$$

or

$$J = -x$$

Equality constant

$$Gx_k + Hu_k - x_{k+1} = 0 \tag{3.19}$$

Inequality constant

$$10^5 \le u_k \le 10^6 \tag{3.20}$$

The objective function is

$$L(x,u) = -x_k + \lambda_{k+1}(Gx_k + Hu_k - x_{k+1}) \tag{4.8}$$

The optimization used fmincon function in Matlab program. The function fmincon was function optimization in toolbox. This solved problem Sequential Quadratic Programming (SQP Appendix B).

Algorithm of optimization could present in flow chart (see Figure 4.3). Steps of algorithm are

1. Guessed manipulated variable u_{k+i} ($u_{k+i} = u_k$ when $i = 0,1,\ldots,t$)
2. Calculated next step state space equation are $x_{(k+1)} = Gx_k + Hu_k$
3. Set optimize objective function follow equation (4.8) was $L(x,u) = -x_k + \lambda_{k+1}(Gx_k + Hu_k - x_{k+1})$
4. Used Necessary condition calculated Largrange in the past time.
5. Used function fmincon in matlab calculates optimization. It was function optimization in toolbox of Matlab Program.
6. Go to step 1.

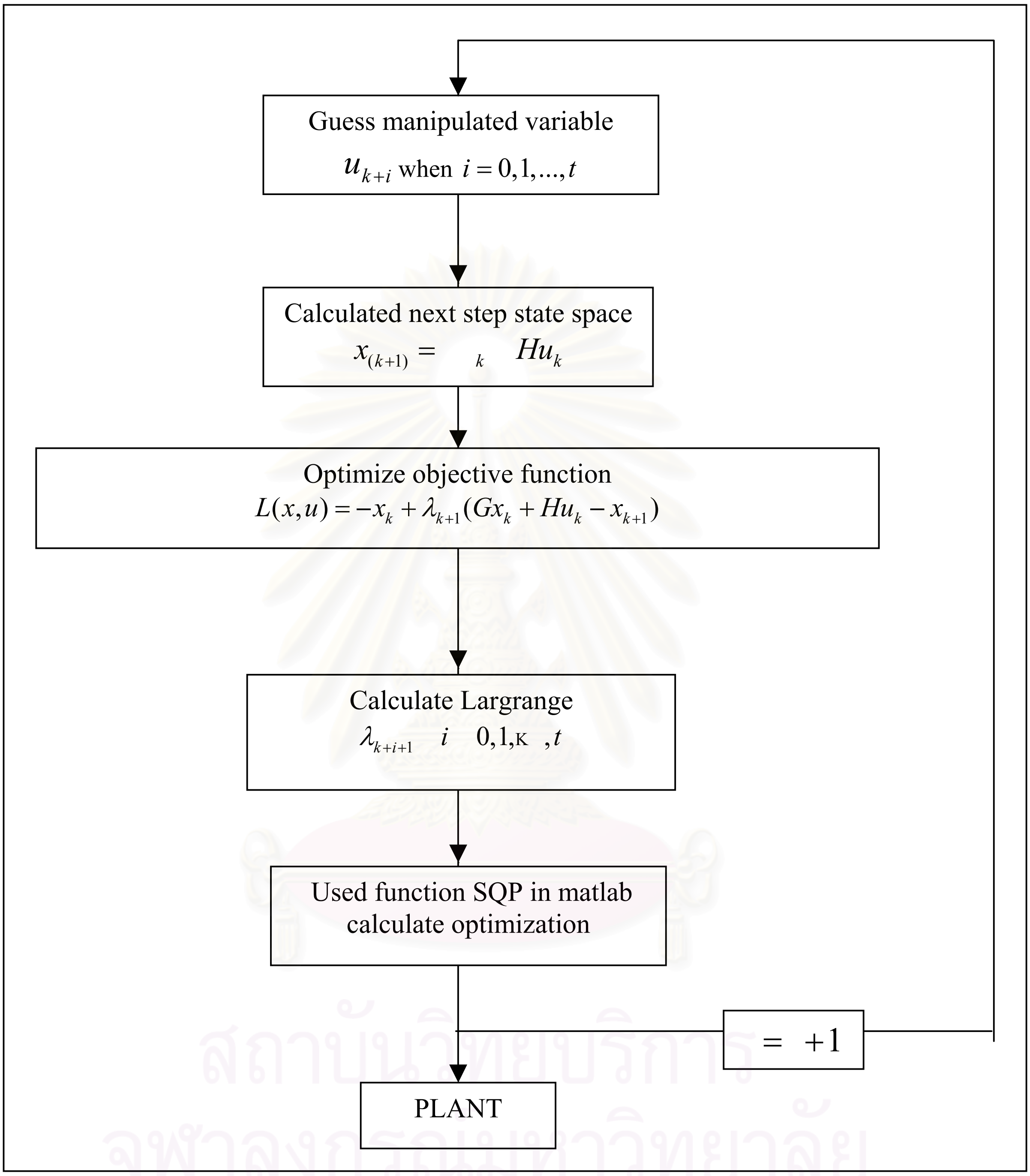


Figure 4.3: Flow chart of optimization algorithm

4.4 MPC in Cross-Flow Ultafiltration Membrane

The permeated flux is controlled by transmembrane pressure (ΔPTM). It is value of calculated. It could not measure. It was changed to volumetric out put. Because of this thesis referred experimental model (Field, 1995). The process model presented in permeated flux equation. The permeated flux equation is

$$\frac{dJ_w}{dt} = -K_J\left(J_w - J_w^*\right) J_w^2 \quad (4.4)$$

$$\frac{dR_t}{dt} = K_J \Delta PTM^2 \left(\frac{J_w^*}{\Delta PTM} - \frac{1}{R_t}\right) \quad (4.5)$$

This equation can handle state space formation.

$$\frac{dx}{dt} = Gx + Hu \quad (4.9)$$

where

$$x = \begin{bmatrix} J_w \\ R_t \end{bmatrix}$$

$$G = \begin{bmatrix} -3K_J J_w^2 + \dfrac{2K_J(\Delta PTM)J_w}{\mu R_t} & 0 \\ \dfrac{-K_J(\Delta PTM)J_w^2}{\mu R_t^2} & \dfrac{K_J(\Delta PTM)^2}{R_t^2}\left(1-\dfrac{1}{\mu}\right) \end{bmatrix}$$

$$H = \begin{bmatrix} \dfrac{K_J J_w^2}{\mu R_t} \\ \dfrac{-2K_J(\Delta PTM)}{R_t}(1-\dfrac{1}{\mu}) \end{bmatrix}$$

$$y = J_w$$

The controlled variables (x) are J_w, the manipulated variables (u) are ΔPTM and the measured output (y) are J_w

The permeated flux could not measure. It was changed to volumetric out put is

$$V_{out} = J_w * A \quad (4.10)$$

The MPC used optimal method to control the water permeated flux. The manipulated variable of ultrafiltration membrane is transmembrane pressure. The objective function of MPC combines equality constant and inequality constant.

Objective function

$$J = \frac{1}{2}\left[x^T W_1 x + u^T W_2 u\right] \tag{3.15}$$

Equality constant

$$Gx_k + Hu_k - x_{k+1} = 0 \tag{3.19}$$

Inequality constant

$$u_{k,\min} \le u_k \le u_{k,\max} \tag{3.20}$$

New objective function is

$$L(x,u) = \sum_{t}^{t+N_m} \frac{1}{2}\left[(x_k^T W_1 x_k + u_k^T W_2 u_k) + \lambda_{k+1}(Gx_k + Hu_k - x_{k+1})\right] \tag{3.22}$$

When

$\lambda(t) \in R^n$ is Largrange Multiplier n equation. The minimum optimization has the necessary condition of manipulated variable (u_{k+i}^j) when $i = 0,1,\ldots,N_m$ and fixing necessary condition at $\lambda_k = P_k x_k$. The manipulated variable and the control gain in optimal control are presented

$$u_k = -Kx_k \tag{3.34}$$

$$K = -W_2^{-1} H^T (P_k - W_1)(G^T)^{-1} \tag{3.35}$$

The MPC could control to target into control horizon N_m steps and compute resolute of process response N_p steps. In this research, N_p steps are assigned to equals N_m steps. The MPC weighting give importance; W_1 is weighting factor of error and W_2 is weighting factor of manipulated variable that W_1 is 1×10^{15} and W_2 is 1. The first transmembrane pressure is in the calculated manipulated variable set that is selected to apply in system. The current of transmembrane pressure shows in figure 4.4 at time j

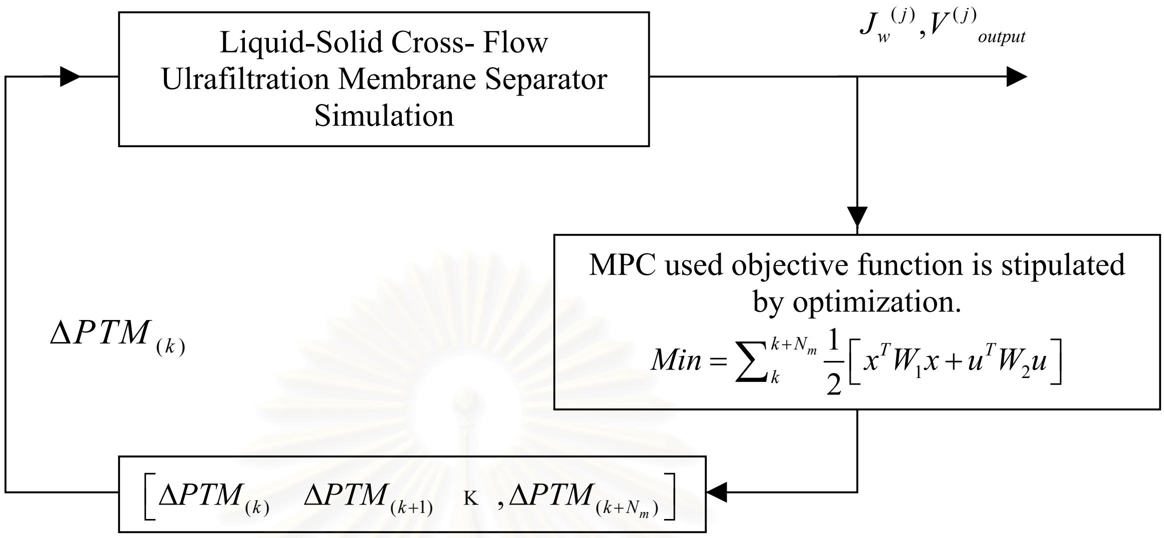


Figure 4.4: MPC in Liquid-Solid Cross-Flow Ulrafiltration Membrane Separator Process at time j

4.5 Kalman Filter in Cross-Flow Ultafiltration Membrane

The Kalman Filter was used to estimate two parameters (μ, K_J). The models of Kalman Filter are state space form

$$\frac{dx}{dt} = Ax + Bu \qquad (4.11)$$

$$Y = Cx \qquad (4.12)$$

The Kalman Filter model was checked observability. Checking observability is said to be observable if measurement of the output y contains sufficient information to enable us to completely identify the state x. The observability was checked by determinant observability matrix.

$$Observability \quad matrix = \left[C^T \quad AC^T \quad \ldots \; , \quad (A^T)^{n-1} C^T \right]$$

Where fixed the matrix x is.

$$x = \left[J_w \quad R_t \quad K_J \quad \mu \right]^T$$

$$A = \begin{bmatrix} (-3K_J J_w^{\ 2} + \dfrac{2K_J J_w \Delta PTM}{\mu R_t}) & \dfrac{-K_J \Delta PTM J_w^{\ 2}}{\mu R_t^2} & -(J_w - \dfrac{\Delta PTM}{\mu R_t^2}) J_w^{\ 2} & -K_J (J_w - \dfrac{\Delta PTM}{\mu^2 R_t}) J_w^{\ 2} \\ 0 & K_J (1 - \dfrac{1}{\mu}) \dfrac{\Delta PTM^2}{R_t^2} & -(1 - \dfrac{1}{\mu}) \dfrac{\Delta PTM^2}{R_t} & -K_J \dfrac{\Delta PTM^2}{R_t \mu^2} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} \dfrac{K_J J_w^{\ 2}}{\mu R_t} \\ \dfrac{-2K_J \Delta PTM}{R_t}(1 - \dfrac{1}{\mu}) \\ 0 \\ 0 \end{bmatrix} \quad \text{and } C = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$$

The determinant of observability matrix is not zero. Hence the Kalman Filter model could observe. P is matrix estimated uncertainly, Q is matrix variable of model and R is matrix variable of measurement. The initial value of Kalman Filter parameter is

$$P = \begin{bmatrix} 1\times10^{50} & 0 & 0 & 0 \\ 0 & 1\times10^{10} & 0 & 0 \\ 0 & 0 & 1\times10^{4} & 0 \\ 0 & 0 & 0 & 4\times10^{20} \end{bmatrix}$$

$$Q = \begin{bmatrix} 4.3\times10^{59} & 0 & 0 & 0 \\ 0 & 1\times10^{30} & 0 & 0 \\ 0 & 0 & 1\times10^{10} & 0 \\ 0 & 0 & 0 & 600 \end{bmatrix} \quad \text{and} \quad R = 1\times10^{69}$$

The Kalman Filter measures the volumetric output that transfers to the permeated flux of process. It circulates loop follow step of Kalman (See Figure 4.5) for estimated. The estimated value was sent to process simulation that compared process and simulation process.

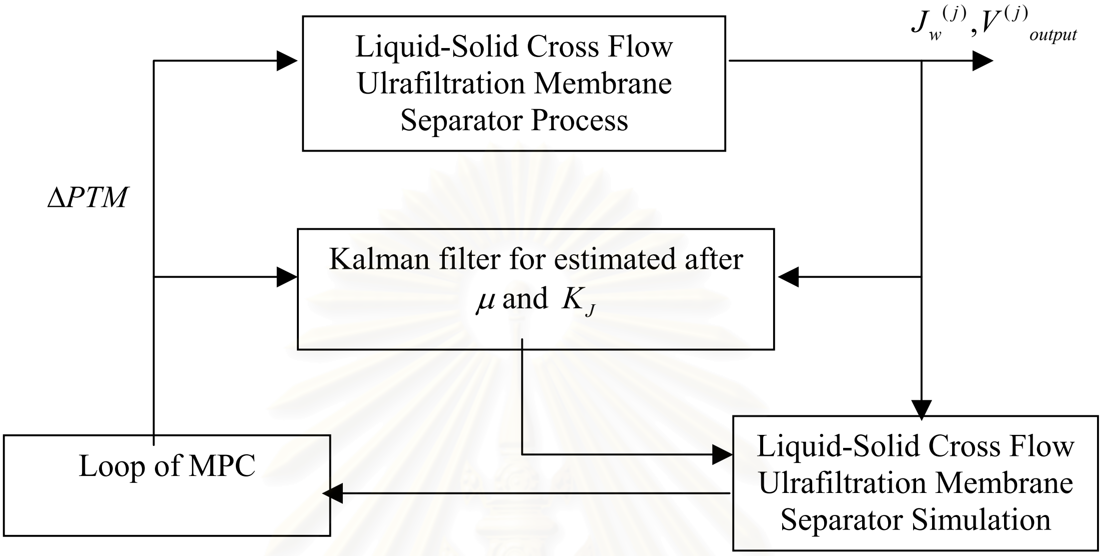


Figure 4.5:MPC with kalman filter control Liquid-Solid Cross Flow Ulrafiltration Membrane Separator Process

Chapter 5

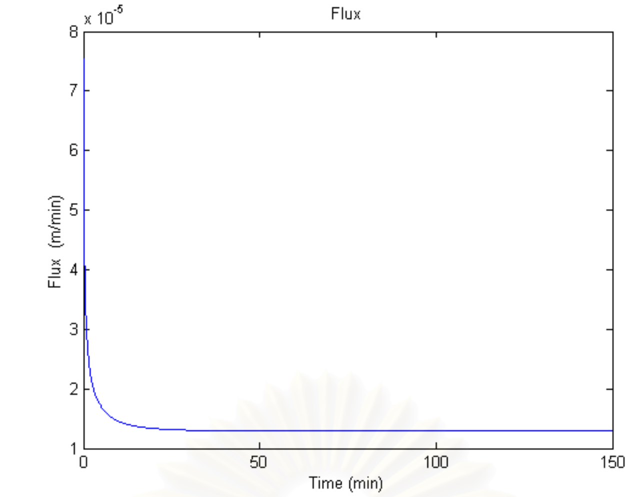
Simulation Result

This chapter presents the controlled result of the permeated flux of water in the oily water emulsion system. The simulation system is cross-flow ultrafiltration membrane of oily water emulsion. Title 5.1 presents open-loop behavior of system on observed time. The result of the desired set point to control the permeated flux is shown in title 5.2. The result in this title is studied in two cases that consist of overall optimization and dynamic optimization. The parameter tuning and the performance of controller that consist of PID, GMC and MPC controller are presented in title 5.3. Title 5.4 shows the result of closed-loop behavior. Title 5.5 presents results of flux control of the system under parameters mismatch and unknown parameters with Kalman Filter. Comparisons of the control performance index for PID, GMC and MPC controller under similar operating conditions are summarized in table 5.2-5.3.

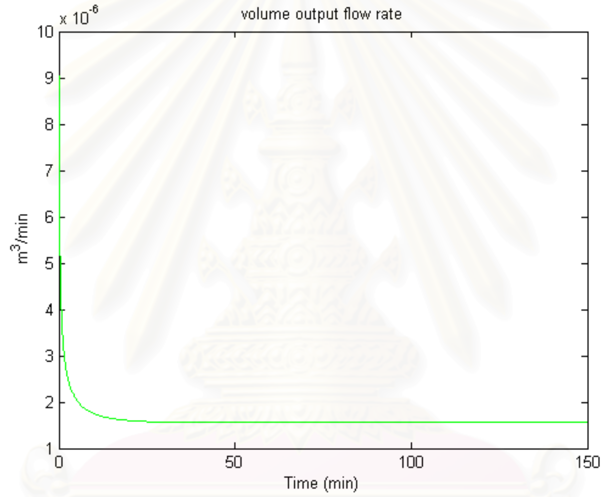
5.1 Open-Loop Behavior

The investigation of the uncontrolled (open-loop) cross-flow ultrafiltration membrane of oily-water emulsions presents the permeated flux of water, the total resistance, the bulk solute concentrations, the out put flow rate and the mass of cake. The analysis open loop refers the operating condition in table 4.1 and table 4.2. The operating initial condition is membrane separation of experimental model of Field, 1995. The simulation process uses equations in chapter 4. The open loop shows behavior of system. The permeated flux of water in the oily water emulsion system and the total resistance are important in this work. The bulk solute concentrations, out put flow rate and mass of cake are supported in the simulation process. Figure 5.1(a) though figure 5.1(e) shows the simulation results of open loop behavior such as the permeated flux decline, increasing of the mass of cake and increasing of the total resistance.

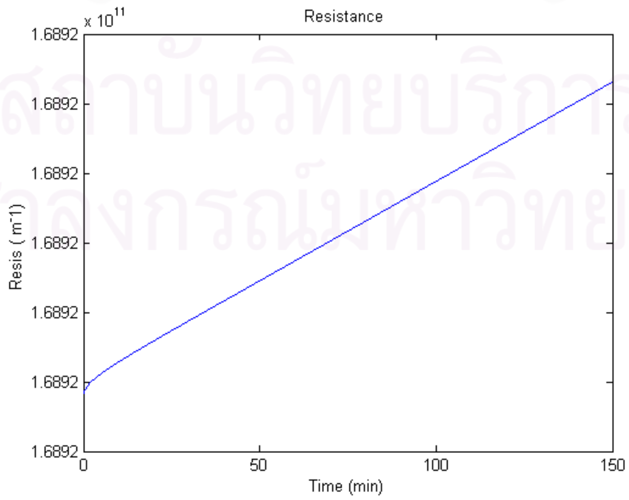
The permeated flux decline is mainly caused by the concentration polarization layer resistance. After a short period of time, the solute concentration at the membrane surface reaches the limiting gel-layer concentration and gel-layer formation commences. The mass of cake increase until the system reaches steady state. In this thesis, the concentration polarization layer resistance is proposed in the total resistance that is combined the concentration polarization layer resistance and membrane resistance.



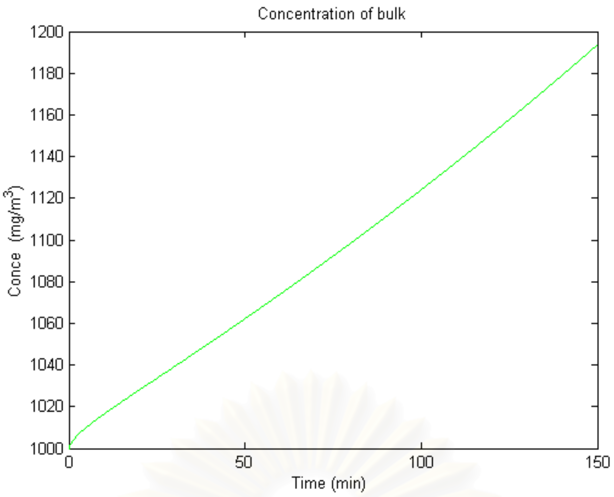
(a.) Permeated flux



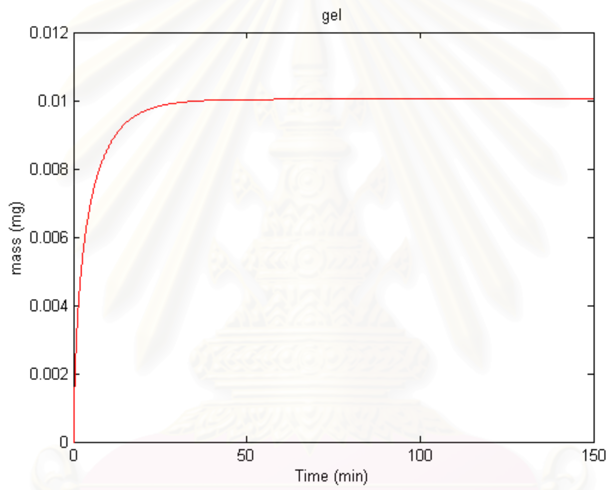
(b.) Out put flow rate



(c.) Total resistance



(d.) Bulk solute concentration



(e.) Mass of gel

Figure 5.1: Present behavior of cross-flow ultrafiltration membrane of oily-water emulsions (a.) Permeated flux (b.) Volumetric out put (c.) total resistance (d.) Bulk solute concentration (e.) Mass of gel

5.2. Optimization

The permeated flux control of water in this work can be studied in two cases that are found the desired set point. The desired set point is defined by optimization on observation time. Case 1 is studied in overall optimization and Case 2 is studied in dynamic optimization.

Figure 5.2 shows the comparison result of the permeated flux of water in open loop, the desired set point in overall optimization and dynamic optimization. The permeated flux of water in open loop declines. The desired set point in overall optimization is constant that is calculated in all operating time. The desired set point in dynamic optimization is found to the three interval constant set points. The interval of operating time is 50 minutes. The summation of water-permeated flux on observes time in open loop is $2.33*10^{-2}$ m/min.

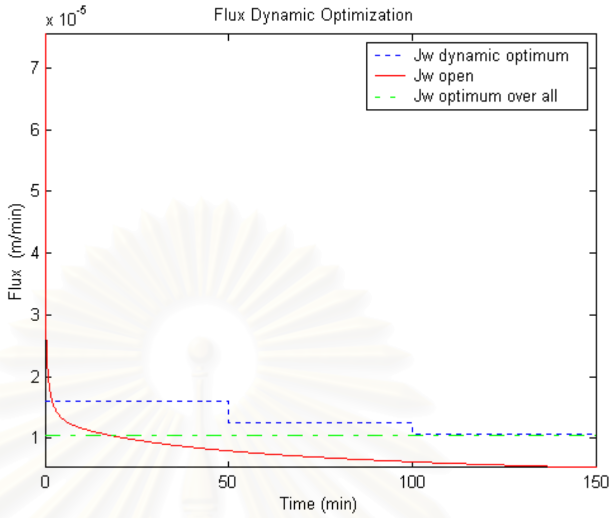


Figure 5.2: Present permeated flux in open loop compared with permeated flux optimization in overall optimization and dynamic optimization

Table 5.1: the optimal result

Case	Off- line optimal permeated flux of water			The summation of water permeated flux	The comparisons of saving permeated flux from open loop
	Switching time				
	50(min)	100(min)	150(min)		
1.Overall optimization	-	-	$1.06*10^{-5}$ M/min	$3.17*10^{-2}$ M/min	36.05%
2.Dynamic optimization	$1.60*10^{-5}$ M/min	$1.25*10^{-5}$ M/min	$1.06*10^{-5}$ M/min	$3.92*10^{-2}$ M/min	68.24%

5.3 Controller

The investigations of the control (closed-loop) cross-flow ultrafiltration membrane of oily water emulsions are PID, GMC and MPC controller. The permeated flux of water is control variable. The transmembrane pressure is manipulated variable. The permeated flux is adjusted by transmembrane pressure.

The permeated flux of water control in this system use Integrated Absolute Error (IAE) and Integral Square Error (ISE) are the control performance index.

$$ISE = \int_0^\infty e^2(t)dt \qquad (5.1)$$

$$IAE = \int_0^\infty |e(t)|dt \qquad (5.2)$$

Comparisons of the control performance index for PID, GMC and MPC controller under similar operating conditions of nominal case are summerized in table 5.2-5.3 and the control performance index of controller with Kalman Filter for GMC and MPC controller are summerized in table 5.8-5.19.

5.3.1 PID Controller

The digital PID controller in the form of difference equation

Continuous from

$$p(t) = \bar{p} + K_c[e(t) + \frac{1}{\tau_i}\int_0^t e(t')dt' + \tau_d \frac{de(t)}{dt}] \qquad (5.3)$$

Discrete from

$$p_n = p_{n-1} + K_c\left[\left(e_n - e_{n-1}\right) + \frac{\Delta t}{\tau_i}e_n + \frac{\tau_d}{\Delta t}\left(e_n - 2e_{n-1} + e_{n-2}\right)\right] \qquad (5.4)$$

where

p = controller out put is ΔPTM

Δt = the sampling period is 0.05 minutes

K_c =controller gain is $6*10^{10}$, τ_i = 30 and τ_d = 0.00001

5.3.2 GMC Controller

GMC Algorithms (Lee and Sullivan, 1988)

$$\frac{dx}{dt} = F(x,u,t) \tag{5.5}$$

$$Y = H(x) \tag{5.6}$$

The control law of GMC is derived as follow. Propose a reference trajectory

$$\dot{Y} = K_1(\overset{*}{Y} - Y) + K_2\int_0^t (\overset{*}{Y} - Y)dt \tag{5.7}$$

Differential equation (5.6)

$$\dot{Y} = \frac{\partial H(x)}{\partial x}.\frac{\partial x}{\partial t} \tag{5.8}$$

$$\dot{Y} = \frac{\partial H(x)}{\partial x}.F(x,u,t) \tag{5.9}$$

$$K_1(\overset{*}{Y} - Y) + K_2\int_0^t (\overset{*}{Y} - Y)dt = \frac{\partial H(x)}{\partial x}.F(x,u,t) \tag{5.10}$$

$$K_1(\overset{*}{Y} - Y) + K_2\int_0^t (\overset{*}{Y} - Y)dt = \frac{\partial H(x)}{\partial x}.[F'(x) + G(x)U] \tag{5.11}$$

Majority equation is $$\frac{\partial H}{\partial x} = 1 \tag{5.12}$$

Continuous from $$U = \frac{K_1(\overset{*}{Y} - Y) + K_2\int_0^t (\overset{*}{Y} - Y)dt - F(x)}{G(x)} \tag{5.13}$$

Discrete from $$U_{(k)} = \frac{K_1(\overset{*}{Y} - Y_{(k)}) + K_2\sum_{k=0}^{k} (\overset{*}{Y} - Y_{(k)})\Delta t - F_{(k)}}{G_{(k)}} \tag{5.14}$$

where

$\overset{*}{Y}$ is out put trajectory (J_{wsp}).Parameter tuning of GMC controller is $K_1 = {}^{2\xi}\!/_{\tau}$ and $K_2 = {}^{1}\!/_{\tau^2}$. ξ and τ have explicit effects on the closed-loop response of output. The parameter ξ determines the shape of the closed-loop response (ξ = 4) while τ determines the speed of the response (τ = 25) (large τ means slow response).

GMC Algorithms of this thesis is

$$\Delta PTM_{(k)} = \mu R_{t(k)} \left[J_{w(k)} + \left(\frac{K_1(J_{wsp} - J_{w(k)}) + \sum_{0}^{k} K_2(J_{wsp} - J_{w(k)}) * \Delta t}{K_J(J_{w(k)}^2)} \right) \right] \quad (5.15)$$

5.3.3 MPC Controller

MPC Algorithm use the objective function of Dynamic Matrix Control (DMC) (Prett and Gillette, 1979) is in this form

$$J = \frac{1}{2}\left[(x_{sp} - x)^T W_1 (x_{sp} - x) + (u_k - u_{k-1})^T W_2 (u_k - u_{k-1})\right] \quad (3.15)$$

W_1 is weighting factor of state variable($W_1 = 1\times10^{15}$) and W_2 is weighting factor of manipulated variable($W_2 = 1$).

5.4 Closed-Loop Behavior

The simulation cases to study are nominal case, robustness test and unknown parameter case. Nominal case is studied the performance of PID, GMC and MPC controller. Robustness tests are evaluated the performance of GMC and MPC controller in the presence of plant/model mismatch. The Kalman Filter for GMC and MPC controller is used to estimate and control the parameter mismatch and the unknown parameter.

5.4.1 Nominal case

5.4.1.1 Overall optimization

Figure 5.3 shows the control response of the PID controller for the oily water emulsion system. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The PID controller cannot control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises. IAE and ISE of this case are $1.70*10^{-4}$ and $4.84*10^{-9}$ consequently.

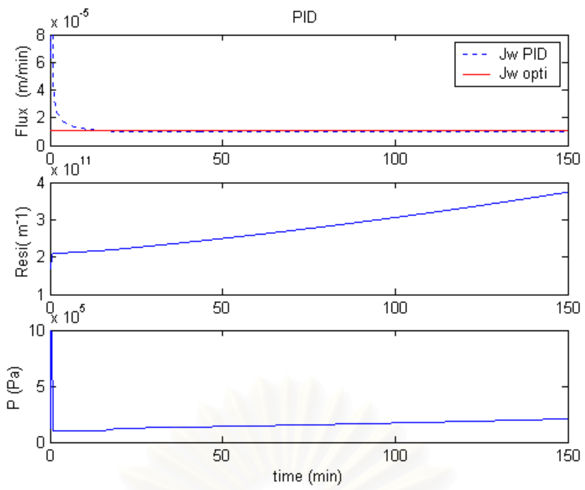


Figure 5.3: The permeated flux control and the total resistance of PID controller for the ultrafiltration membrane of oily water emulsion system in overall optimization

Figure 5.4 shows the control response of the GMC controller for the oily water emulsion system. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The GMC controller can control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises. The permeated flux of water takes long time to reach the set point. This case, IAE is$3.23*10^{-4}$ and ISE is $3.90*10^{-9}$.

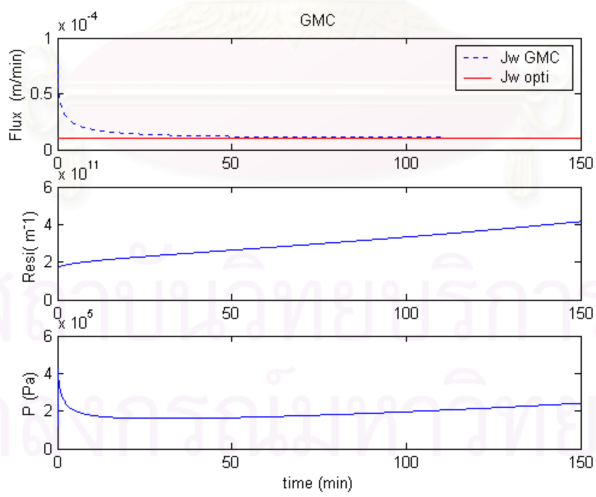


Figure 5.4: The permeated flux control and the total resistance of GMC controller for the ultrafiltration membrane of oily water emulsion system in overall optimization

Figure 5.5 shows the control response of the MPC controller for the oily water emulsion system. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The MPC controller can control the permeated flux of water to the set point. The total resistance increases because the bulk concentration rises. The permeated flux takes short time to reach the set point. This case, IAE is $1.47*10^{-4}$ and ISE is $2.29*10^{-9}$.

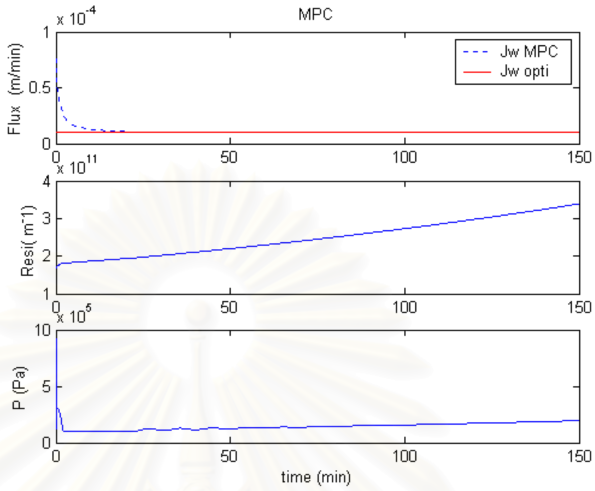


Figure 5.5: The permeated flux control and the total resistance of MPC controller for the ultrafiltration membrane of oily water emulsion system in overall optimization.

5.4.1.2 Dynamic optimization

Figure 5.6 shows the control response of the PID controller for the oily water emulsion system. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The PID controller cannot control the permeated flux of water to the set points. The total resistance increases because the bulk concentration rises. IAE of this case is $4.0*10^{-4}$ and ISE is $7.34*10^{-9}$.

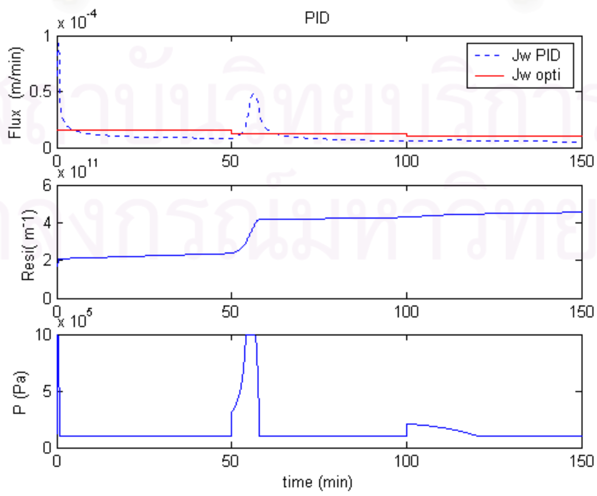


Figure 5.6: The permeated flux control and the total resistance of PID controller for the ultrafiltration membrane of oily water emulsion system in dynamic optimization.

Figure 5.7 shows the control response of the GMC controller for the oily water emulsion system. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The GMC controller cannot control the permeated flux of water to the set points. The total resistance increases because bulk concentration rises. IAE of this case is $3.15*10^{-4}$ and ISE is $2.97*10^{-9}$.

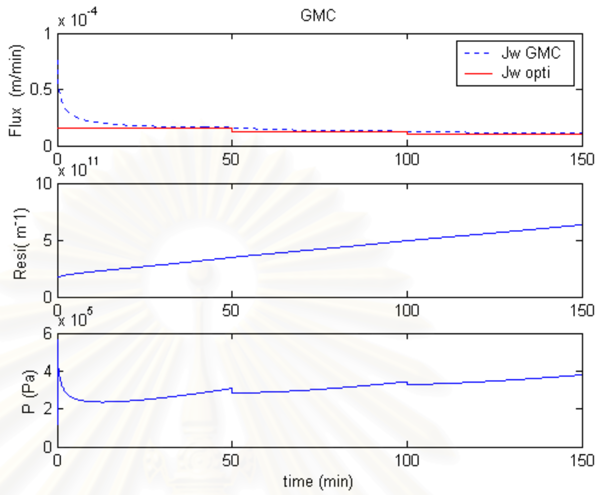


Figure 5.7: The permeated flux control and the total resistance of GMC controller for the ultrafiltration membrane of oily water emulsion system in dynamic optimization.

Figure 5.8 shows the control response of the MPC controller for the oily water emulsion system. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The MPC controller can control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises. IAE of this case is $1.14*10^{-4}$ and ISE is $1.49*10^{-9}$.

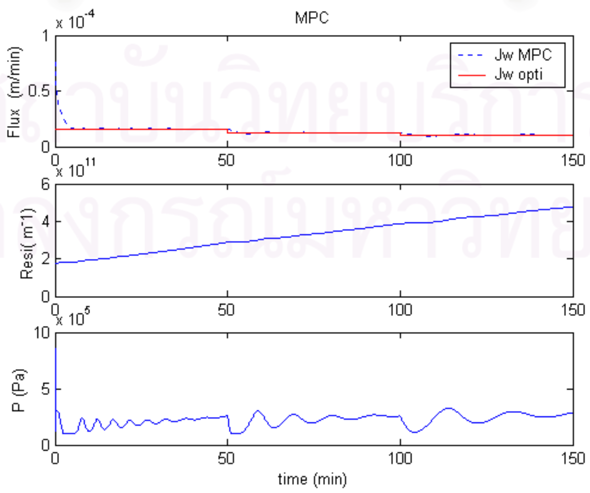


Figure 5.8: The permeated flux control and the total resistance of MPC controller for the ultrafiltration membrane of oily water emulsion system in dynamic optimization.

The nominal case presents the control performance index (IAE and ISE) of PID, GMC and MPC controller in table 5.1-5.2. Table 5.1 presents the control performance index for overall optimization and table 5.2 presents the control performance index for dynamic optimization.

Table 5.2: Control Performance index for Overall optimization

	Controller		
	PID	GMC	MPC
IAE	$4.96*10^{-4*}$	$3.23*10^{-4}$	$1.47*10^{-4}$
ISE	$5.95*10^{-9*}$	$3.90*10^{-9}$	$2.29*10^{-9}$

Table 5.3: Control Performance index for Dynamic optimization

	Controller		
	PID	GMC	MPC
IAE	$9.12*10^{-4*}$	$3.15*10^{-4*}$	$1.14*10^{-4}$
ISE	$1.12*10^{-8*}$	$2.97*10^{-9*}$	$1.49*10^{-9}$

The mark (*) shows on the control performance index of the controllers that cannot control the permeated flux of water to the set point.

In the simulation, the performance of PID controller is poor in the presence for the ultrafiltration membrane of oily water emulsion system because the PID controller cannot control the permeated flux of water to the set point. The GMC and MPC controller is the controller based on math model then the control result give better than the PID controller. The MPC and GMC controller has highly nonlinear behavior while the PID can not handle highly nonlinear behavior. The MPC and GMC is a nonlinear controller with external linear control. They use process models of the plant to determine control action.

The GMC and MPC controller can control the permeated flux of water to the set point for the overall optimization but the GMC controller cannot control the permeated flux of water to the set points in the dynamic optimization. The dynamic optimization is found the set point that is separated to 3 parts. Time to reach the set point of the MPC controller takes shorter than the GMC controller and the control performance index of MPC controller is the better than GMC controller. The MPC controller is the best control in the oily water emulsion system.

5.5 Controller with Kalman Filter

The process parameters are not all known. The essential parameters for the ultrafiltration membrane of the oily water emulsion system are the viscosity (μ) and the constant in Field's model (K_J). The estimate of the parameters is in the parameter mismatch case and the unknown parameter case. The Kalman Filter needs to estimate the parameters in the parameter mismatch and the unknown parameters that can be true the process parameter. The GMC with Kalman Filter and MPC with Kalman Filter are used to control the permeated flux of water to the set point and the Kalman Filter can cater for the parameters in the parameter mismatch and the unknown parameters.

5.5.1 Parameter mismatch

The parameters mismatch, The GMC and MPC controller cannot control the permeated flux of water to the set point and the performance of the MPC and GMC controller is poor. Therefor the GMC and MPC controller are needed to add the evaluated performance by Kalman Filter for the estimate parameter. The control response of controller with Kalman Filter for the parameter mismatch is similar the control response of controller for nominal case because the Kalman Filter can cater for the parameter mismatch as seen in this simulation result.

5.5.1.1 Overall optimization

Figure 5.9 shows the control response of GMC with Kalman Filter for the oily water emulsion system with variation viscosity mismatch 50%. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The GMC with Kalman Filter can control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises.

In this case, Figure 5.10 shows the estimate of the Kalman Filter for the viscosity that is 0.054736 Kg/M.min. IAE and ISE are $3.23*10^{-4}$and $3.90*10^{-9}$ consequently.

The control response of GMC with Kalman Filter takes as well as the GMC controller in the nominal case.

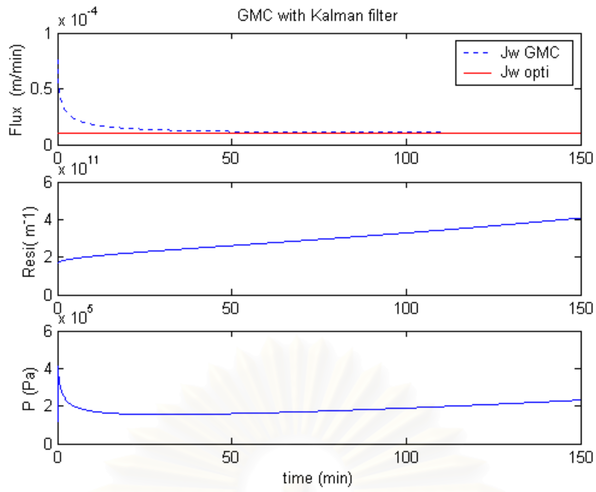


Figure 5.9: The permeated flux control and the total resistance of GMC with Kalman Filter for the ultrafiltration membrane of the oily water emulsion system with variation viscosity mismatch 50 % in overall optimization

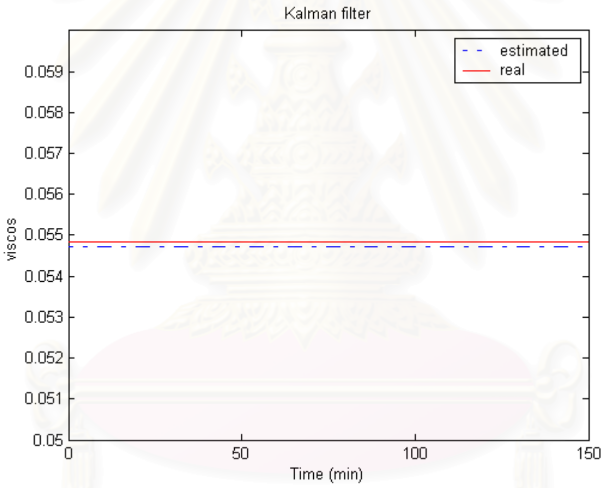


Figure 5.10: The Kalman Filter of GMC controller for the ultrafiltration membrane of the oily water emulsion system with viscosity mismatch 50 % in overall optimization

Figure 5.11 shows the control response of MPC with Kalman Filter for the oily water emulsion system with variation viscosity mismatch 50%. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The MPC with Kalman Filter can control permeated flux of water to the set point. The total resistance increases because bulk concentration rises.

In this case, Figure 5.12 shows the estimate of Kalman Filter for the viscosity that is 0.054756 Kg/M.min. IAE and ISE are $2.73*10^{-4}$and $9.33*10^{-8}$ consequently.

The control response of MPC with Kalman Filter takes as well as the MPC controller in the nominal case.

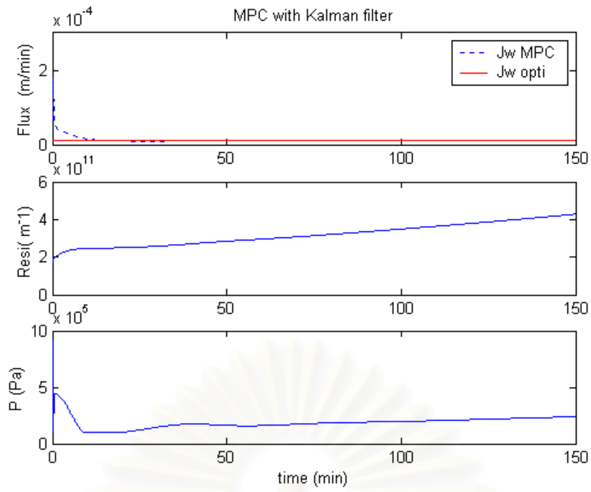


Figure 5.11: The permeated flux control and the total resistance of MPC with Kalman Filter for the ultrafiltration membrane of the oily water emulsion system with variation viscosity mismatch 50 % in overall optimization

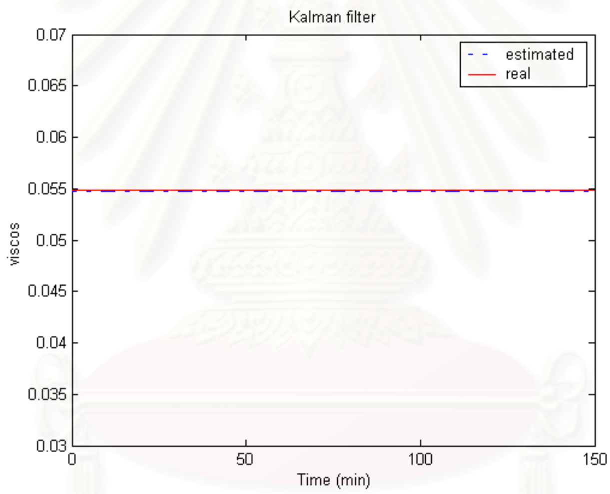


Figure 5.12: The Kalman Filter of MPC controller for the ultrafiltration membrane of oily water emulsion system with viscosity mismatch 50% in overall optimization

Figure5.13 shows the control response of GMC with Kalman Filter for the oily water emulsion system with variation constant in Field's model mismatch 50 %. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The GMC with Kalman Filter can control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises.

In this case, Figure 5.14 shows the estimate of Kalman Filter for the constant in Field's model is $7.50616*10^{8}$ Kg/Pa^{2}.min^{2}.M^{3}. IAE and ISE are $3.23*10^{-4}$ and $3.90*10^{-9}$ consequently.

The control response of GMC with Kalman Filter takes as well as the GMC controller in the nominal case.

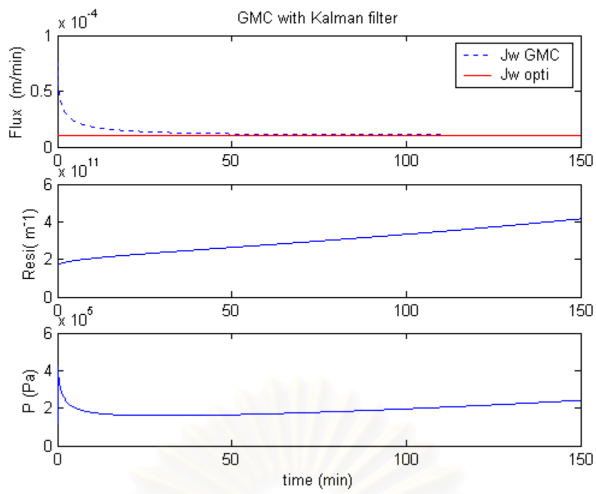


Figure 5.13: The permeated flux control and the total resistance of GMC with Kalman Filter for the ultrafiltration membrane of oily water emulsion system with variation constant in Field's model mismatch 50% in overall optimization

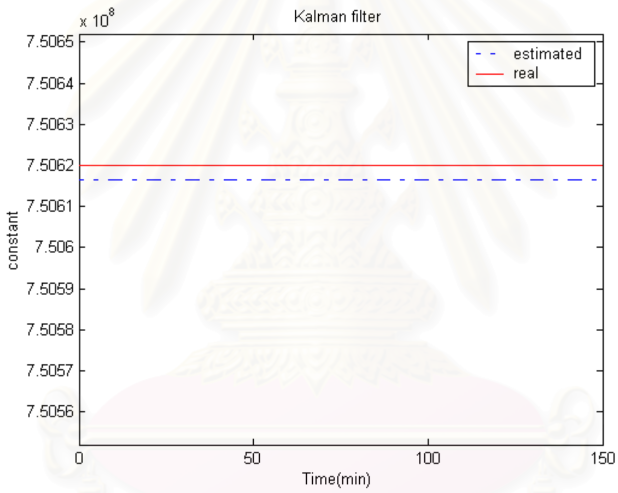


Figure 5.14: The Kalman Filter of GMC controller for the ultrafiltration membrane of oily water emulsion system with constant in Field's model mismatch 50% in overall optimization

Figure 5.15 shows the control response of MPC with Kalman Filter for the oily water emulsion system with variation constant in Field's model mismatch 50% . The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The MPC with Kalman Filter can control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises.

In this case, Figure 5.16 shows the estimate of Kalman Filter for constant in Field's model is $7.50616*10^8$ $Kg/Pa^2.min^2.M^3$. IAE and ISE are$1.52*10^{-4}$and $2.52*10^{-9}$ consequently.

The control response of MPC with Kalman Filter takes as well as the MPC controller in the nominal case.

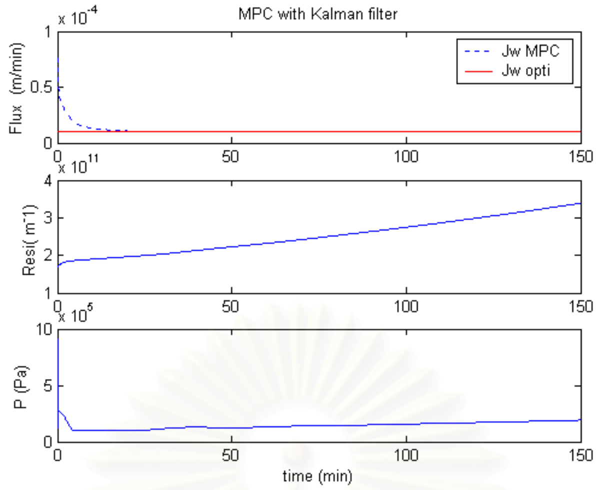


Figure 5.15: The permeated flux control and the total resistance of MPC with Kalman Filter for the ultrafiltration membrane of the oily water emulsion with variation constant in Field's model mismatch 50%in overall optimization

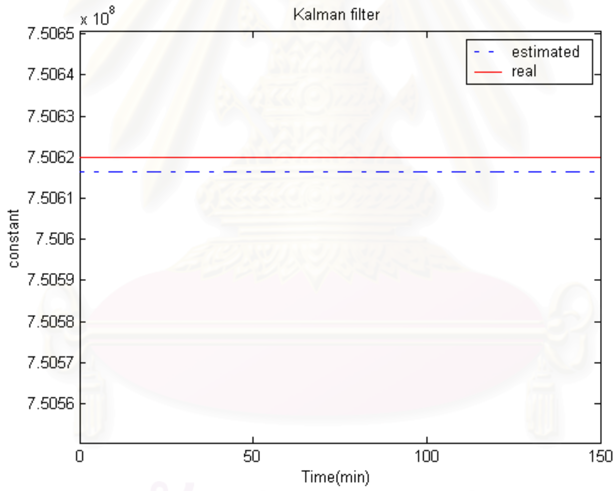


Figure 5.16: The Kalman Filter of MPC controller for ultrafiltration membrane of the oily water emulsion system with constant in Field's model mismatch 50% in overall optimization

5.5.1.2 Dynamic optimization

Figure 5.17 shows the control response of GMC with Kalman Filter for the oily water emulsion system with variation viscosity mismatch 50%. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The GMC with Kalman Filter cannot control to the permeated flux of water to the set points. The total resistance increases because bulk concentration rises.

In this case, Figure 5.18 shows the estimate of Kalman Filter for the viscosity is 0.054736 Kg/M.min. IAE and ISE are $3.15*10^{-4}$ and $2.97*10^{-9}$ consequently.

The control response of GMC with Kalman Filter takes as well as the GMC controller in the nominal case.

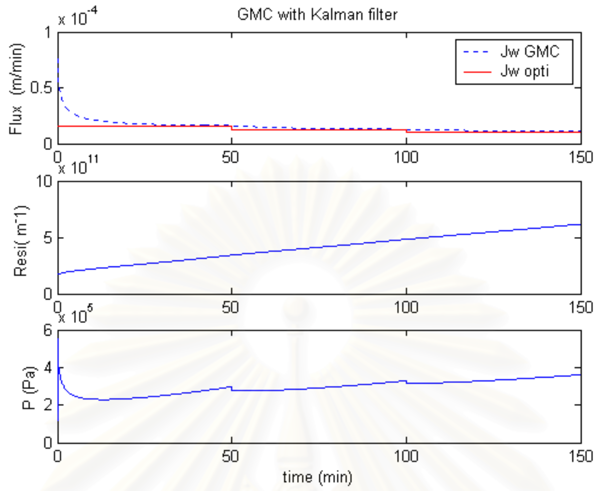


Figure5.17: The permeated flux control and the total resistance of GMC with Kalman Filter for the ultrafiltration membrane of the oily water emulsion system with viscosity mismatch 50 %in dynamic optimization

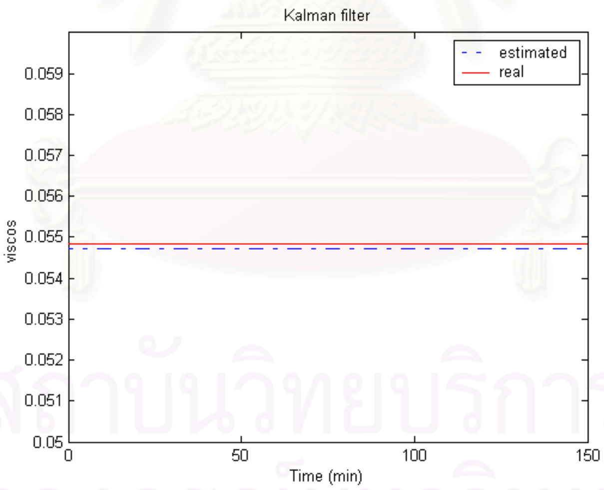


Figure 5.18: The Kalman Filter of GMC controller for the ultrafiltration membrane of oily water emulsion system with viscosity mismatch 50%in dynamic optimization

Figure 5.19 shows the control response of MPC with Kalman Filter for the oily water emulsion system with variation viscosity mismatch 50%. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The MPC with Kalman Filter can control the permeated flux of water to the set points. The total resistance increases because bulk concentration rises.

In this case, Figure 5.20 shows the estimate of Kalman Filter for the viscosity is 0.054756 Kg/M.min. IAE is $1.07*10^{-4}$and ISE is $1.30*10^{-9}$.

The control response of MPC with Kalman Filter takes as well as the MPC controller in the nominal case.

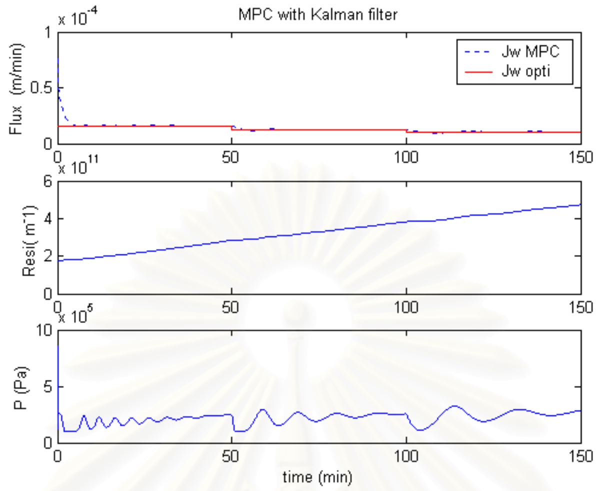


Figure 5.19: The permeated flux control and the total resistance of MPC with Kalman Filter for the ultrafiltration membrane of the oily water emulsion with viscosity mismatch 50 %in dynamic optimization

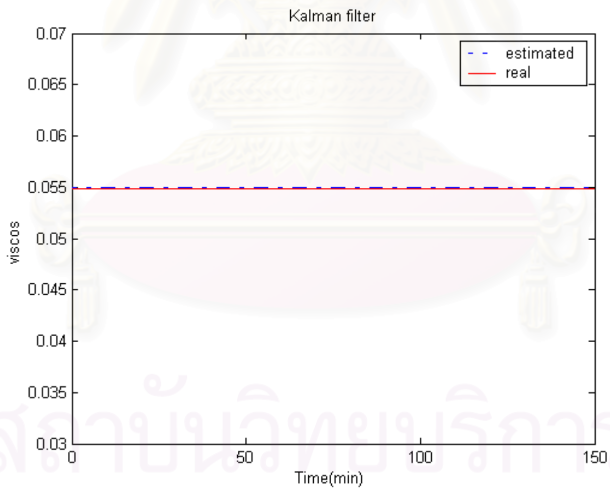


Figure 5.20: The Kalman Filter of MPC controller for the ultrafiltration membrane of oily water emulsion estimated system with the viscosity mismatch 50% in dynamic optimization

Figure 5.21 shows the control response of GMC with Kalman Filter for the oily water emulsion system with variation constant in Field's model mismatch 50%. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The GMC with Kalman Filter cannot control the permeated flux of water to the set points. The total resistance increases because bulk concentration rises.

In this case, Figure 5.22 shows the estimate of Kalman Filter for the constant in Field's model is $7.50616*10^8$ Kg/Pa^2.min^2.M^3. IAE is $3.15*10^{-4}$and ISE is $2.97*10^{-9}$.

The control response of GMC with Kalman Filter takes as well as the GMC controller in the nominal case.

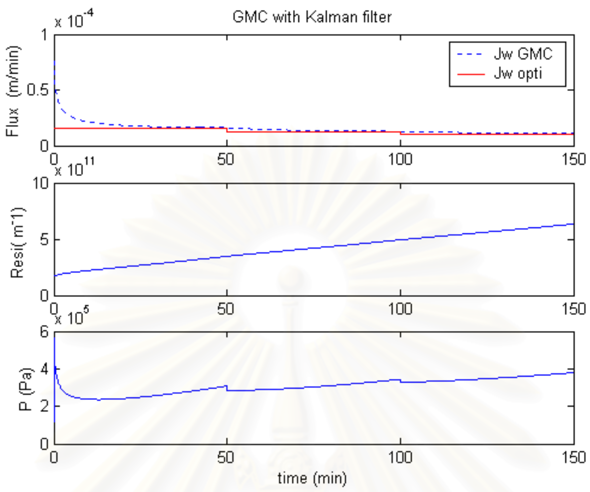


Figure 5.21: The permeated flux control and the total resistance of GMC with Kalman Filter for the ultrafiltration membrane of oily water emulsion system with the constant in Field's model mismatch 50%in dynamic optimization

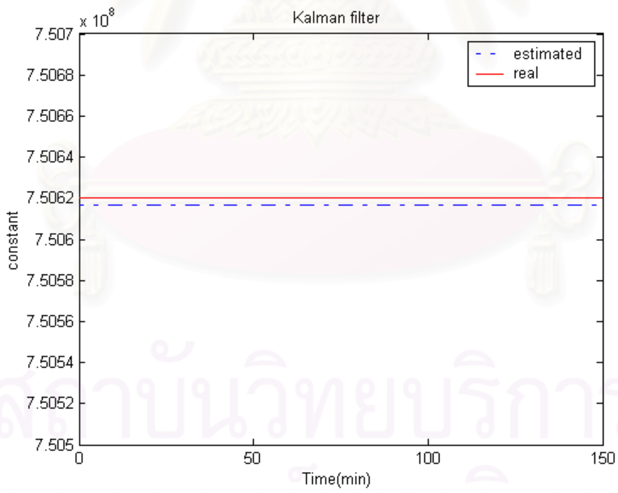


Figure 5.22: The Kalman Filter of GMC controller in the ultrafiltration membrane for oily water emulsion estimated system with the constant in Field's model mismatch 50% in dynamic optimization

Figure5.23 shows the control response of MPC with Kalman Filter for the oily water emulsion with variation constant in Field's model mismatch 50%. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The MPC with Kalman Filter can control the permeated flux of water to the set points. The total resistance increases because bulk concentration rises.

In this case, Figure 5.24 shows the estimate of Kalman Filter for the constant in Field's model is $7.50616*10^{8}$ $Kg/Pa^{2}.min^{2}.M^{3}$. IAE is $1.15*10^{-4}$ and ISE is $1.50*10^{-9}$.

The control response of MPC with Kalman Filter takes as well as the MPC controller in the nominal case.

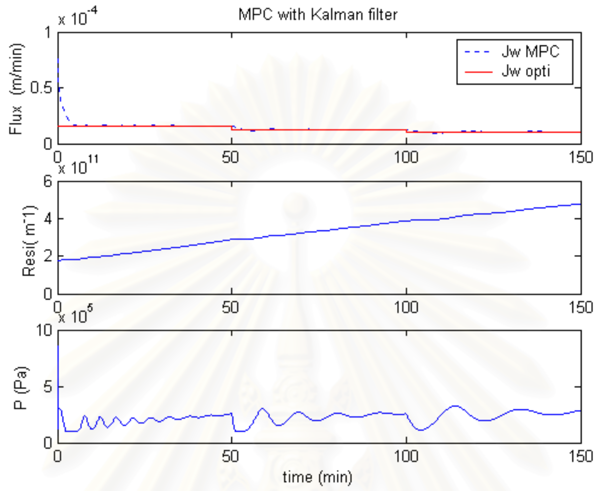


Figure 5.23: The permeated flux control and the total resistance of MPC with Kalman Filter for the ultrafiltration membrane of oily water emulsion system with the constant in Field's model mismatch 50%in dynamic optimization

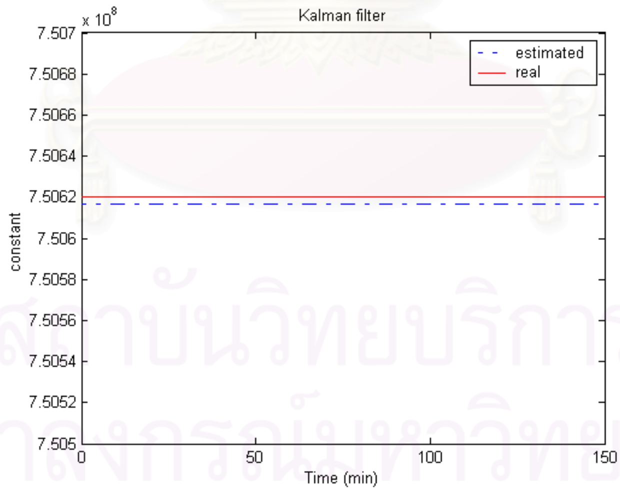


Figure 5.24: The Kalman Filter of MPC controller for the ultrafiltration membrane of oily water emulsion estimated system with the constant in Field's model mismatch 50% in dynamic optimization

The control performance index of controller with Kalman Filter and the parameter estimation presents in table 5.4 –5.11. Table 5.4-5.7 presents control performance in parameter mismatch and parameter estimation in overall optimization. Table 5.8-5.11 presents control performance in parameter mismatch and parameter estimation in dynamic optimization.

Table 5.4: Control performance index for parameter mismatch in the oily water emulsion viscosity (μ) by 50 % Overall optimization

	Controller	
	GMC with Kalman Filter	MPC with Kalman Filter
IAE	$3.23*10^{-4}$	$2.73*10^{-4}$
ISE	$9.33*10^{-8}$	$3.90*10^{-9}$

Table 5.5: Estimated parameter mismatch in the oily water emulsion viscosity (μ) by 50 %, Overall optimization

Controller with Kalman Filter	μ (Kg/m.min)	error
GMC	0.054736	0.19 %
MPC	0.054756	0.16%

Table 5.6: Parameter mismatch in the oily water emulsion constant in Field's model (K_J) by 50 % Overall optimization

	Controller	
	GMC with Kalman Filter	MPC with Kalman Filter
IAE	$3.23*10^{-4}$	$1.52*10^{-4}$
ISE	$3.90*10^{-9}$	$2.52*10^{-9}$

Table 5.7: Estimated parameter mismatch in the oily water emulsion constant in Field's model (K_J) by 50 % Overall optimization

Controller with Kalman Filter	K_J (Kg/Pa^2.min^2.M^3)	error
GMC	$7.50616*10^8$	0.04%
MPC	$7.50616*10^8$	0.04%

Table 5.8: Parameter mismatch in the oily water emulsion viscosity (μ) by 50 % Dynamic optimization

	Controller	
	GMC with Kalman Filter	MPC with Kalman Filter
IAE	$3.15*10^{-4*}$	$1.07*10^{-4}$
ISE	$2.97*10^{-9*}$	$1.30*10^{-9}$

Table 5.9: Estimated parameter mismatch in the oily water emulsion viscosity (μ) by 50 %, Dynamic optimization

Controller with Kalman Filter	μ (Kg/M.min)	error
GMC	0.054736	0.19 %
MPC	0.054756	0.16%

Table 5.10: Parameter mismatch in the oily water emulsion constant in Field's model (K_J) by 50 % Dynamic optimization

	Controller	
	GMC with Kalman Filter	MPC with Kalman Filter
IAE	$3.15*10^{-4*}$	$1.15*10^{-4}$
ISE	$2.97*10^{-9*}$	$1.50*10^{-9}$

Table 5.11: Estimated parameter Parameter mismatch in the oily water emulsion constant in Field's model (K_J) by 50 % Dynamic optimization

Controller with Kalman Filter	K_J (Kg/Pa^2.min^2.M^3)	error
GMC	$7.50616*10^{8}$	0.04%
MPC	$7.50616*10^{8}$	0.04%

The mark (*) shows on the control performance index of the controllers that cannot control the permeated flux of water to the set point.

The inclusion of the Kalman Filter can cater for the parameter mismatch. The GMC and MPC with Kalman Filter can control the permeated flux of water to the set point in the overall optimization. The GMC with Kalman Filter cannot control the permeated flux of water to the set points but the MPC with Kalman Filter can control the permeated flux of water to the set points in the dynamic optimization.

The control result of controller with Kalman Filter and the permeated flux of water to control in nominal case are alike. The control results of GMC and MPC with Kalman Filter for the oily water emulsion system with variation viscosity mismatch and constant in Field's model mismatch are alike. Time to reach the set point of MPC with Kalman Filter takes shorter than the GMC with Kalman Filter. The control performance index of MPC with Kalman Filter is the better than GMC controller. The MPC with Kalman Filter is the best to control the oily water emulsion system.

The Kalman Filter for the oily water emulsion system estimated the viscosity and the constant in Field's model their can be estimated to real process.

5.5.2Unknown parameter

In the system, the process parameters are not all known. The essential parameters are the unknown parameters for the ultrafiltration membrane of the oily water emulsion system that are the viscosity and the constant in Field's model. The Kalman Filter needs to estimate the unknown parameters that can be true the process parameter. The GMC with Kalman Filter and MPC with Kalman Filter are used to control the permeated flux of water to the set point. The control response of controller with Kalman Filter for the unknown parameter is similar the control response of controller for nominal case because the Kalman Filter can cater for the unknown parameter as seen in this simulation result.

5.5.2.1 Overall optimization

Figure 5.25 shows the control response of GMC with Kalman Filter for the oily water emulsion system with viscosity and constant in Field's model are the unknown parameters. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The GMC with Kalman Filter can control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises.

In this case, Figure 5.26 shows the estimate of Kalman Filter for the viscosity is 0.0548572 Kg/M.min and the constant in Field's model is $7.50616*10^{8}$ $Kg/Pa^{2}.min^{2}.M^{3}$. IAE is $3.23*10^{-4}$and ISE is $3.90*10^{-9}$.

The control response of GMC with Kalman Filter takes as well as the GMC controller in the nominal case.

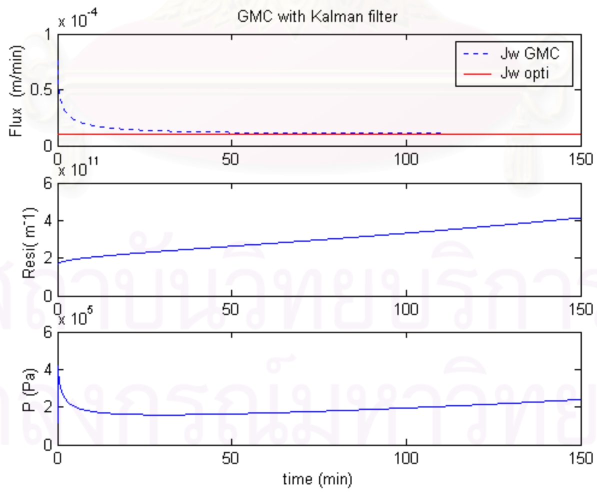


Figure 5.25: The permeated flux control and the total resistance of GMC with Kalman Filter for the ultrafiltration membrane of oily water emulsion system with the unknown parameters in overall optimization

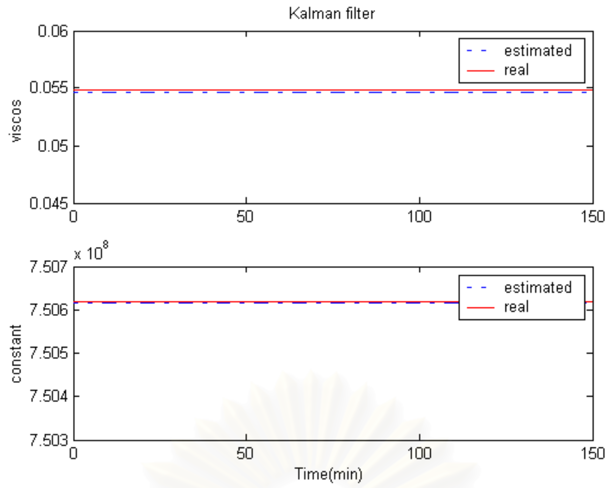


Figure 5.26: The Kalman Filter of GMC controller for the ultrafiltration membrane of oily water emulsion estimated the viscosity and the constant in Field's model that are the unknown parameters in overall optimization

Figure 5.27 shows the control response of MPC with Kalman Filter for the oily water emulsion system with viscosity and constant in Field's model are the unknown parameters. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The MPC with Kalman Filter can control the permeated flux of water to the set point. The total resistance increases because bulk concentration rises.

In this case, Figure 5.28 shows the estimate of Kalman Filter for the viscosity is 0.054897 Kg/M.min and the constant in Field's model is $7.50616*10^{8}$ $Kg/Pa^{2}.min^{2}.M^{3}$. IAE is $.47*10^{-4}$and ISE is $2.29*10^{-9}$.

The control response of MPC with Kalman Filter takes as well as the GMC controller in the nominal case.

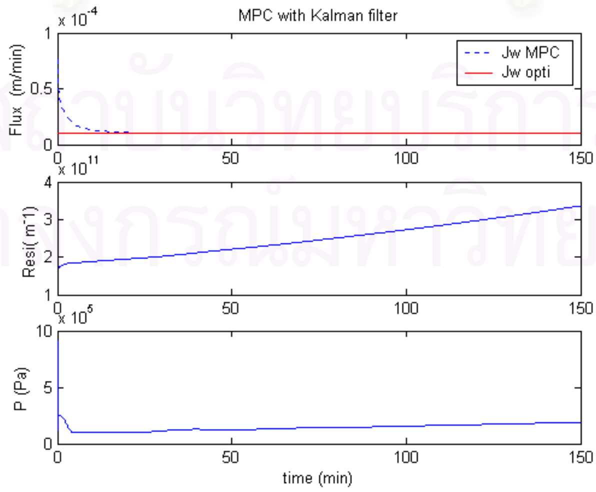


Figure 5.27: The permeated flux control and the total resistance of MPC with Kalman Filter for the ultrafiltration membrane of oily water emulsion system with the unknown parameters in overall optimization

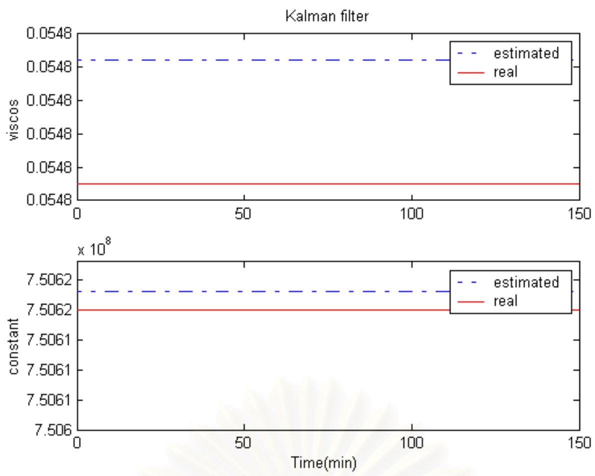


Figure 5.28: The Kalman Filter of MPC controller for the ultrafiltration membrane of oily water emulsion system estimated the viscosity and the constant in Field's model that are the unknown parameters in overall optimization

5.5.2.2 Dynamic optimization

Figure 5.29 shows the control response of GMC with Kalman Filter for the oily water emulsion system with viscosity and constant in Field's model are the unknown parameters. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The GMC with Kalman Filter cannot control the permeated flux of water to the set points. The total resistance increases because bulk concentration rises.

In this case, Figure 5.30 shows the estimate of Kalman Filter for the viscosity is 0.0548572 Kg/M.min and the constant in Field's model is $7.50616*10^{8}$ $Kg/Pa^{2}.min^{2}.M^{3}$. IAE is$1.69*10^{-4}$and ISE is $1.54*10^{-9}$.

The control response of GMC with Kalman Filter takes as well as the GMC controller in the nominal case.

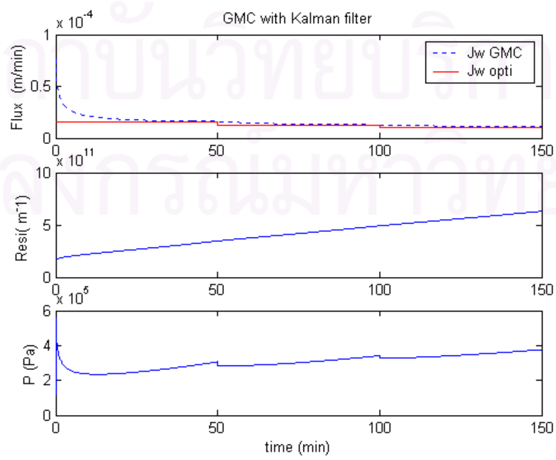


Figure 5.29: The permeated flux control and the total resistance of GMC with Kalman Filter for the ultrafiltration membrane of oily water emulsion system with the unknown parameters in dynamic optimization

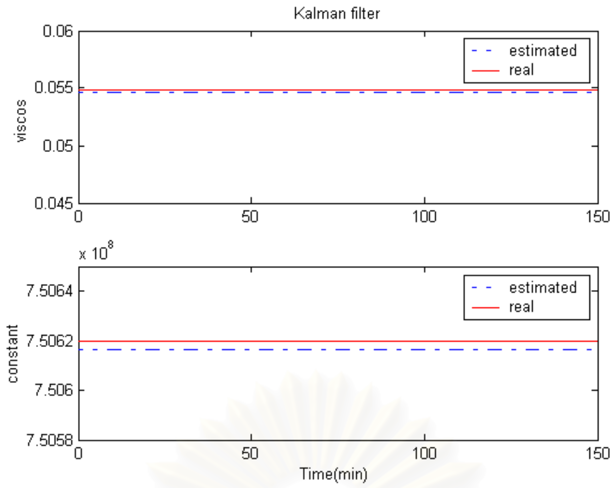


Figure 5.30: The Kalman Filter of GMC controller for the ultrafiltration membrane of oily water emulsion system estimated the viscosity and the constant in Field's model that are the unknown parameters in dynamic optimization

Figure 5.31 shows the control response of MPC with Kalman Filter for the oily water emulsion system with viscosity and constant in Field's model are the unknown parameters. The permeated flux (control variable) is adjusted by transmembrane pressure (manipulated variable). The set point is separated to 3 parts. The MPC with Kalman Filter can control the permeated flux of water to the set points. The total resistance increases because bulk concentration rises.

In this case, Figure 5.32 shows the estimate of Kalman Filter for the viscosity is 0.0548790Kg/M.min and the constant in Field's model is $7.50616*10^{8}$ $Kg/Pa^{2}.min^{2}.M^{3}$. IAE is $1.14*10^{-4}$and ISE is $1.49*10^{-9}$.

The control response of MPC with Kalman Filter takes as well as the MPC controller in the nominal case.

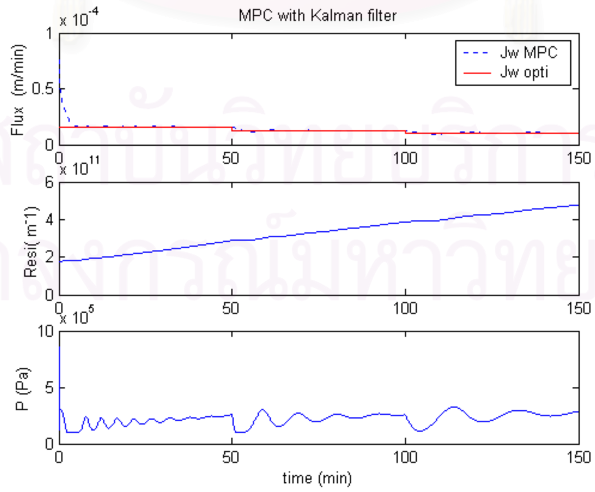


Figure 5.31: The permeated flux control and the total resistance MPC with Kalman Filter for the ultrafiltration membrane of oily water emulsion system with the unknown parameters in dynamic optimization

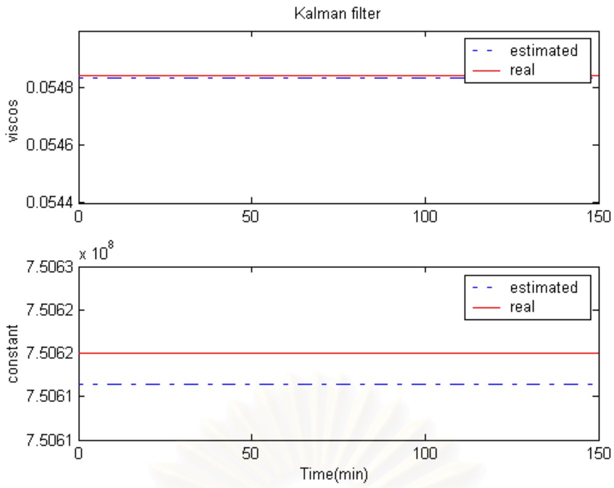


Figure 5.32: The Kalman Filter of MPC controller for the ultrafiltration membrane of oily water emulsion system estimated the viscosity and the constant in Field's model that are the unknown parameters in dynamic optimization

The control performance index of controller with Kalman Filter and the parameter estimation presents table 5.12 –5.15. Table 5.12-5.13 presents control performance in parameter mismatch and parameter estimation in overall optimization. Table 5.14-5.15 presents control performance in parameter mismatch and parameter estimation in dynamic optimization.

Table 5.12: Unknown parameter in the water emulsion Overall optimization

	Controller	
	GMC with Kalman Filter	MPC with Kalman Filter
IAE	$3.23*10^{-4}$	$1.47*10^{-4}$
ISE	$3.90*10^{-9}$	$2.29*10^{-9}$

Table 5.13: Estimated unknown parameter Overall optimization

Controller with Kalman Filter	Parameter			
	μ (Kg/M.min)	error	K_J (Kg/Pa^2.min^2.M^3)	error
GMC	0.0548572	0.05%	$7.50616*10^8$	0.04%
MPC	0.0548790	0.06%	$7.50616*10^8$	0.04%

Table 5.14: Unknown parameter in the water emulsion Dynamic optimization

	Controller	
	GMC with Kalman Filter	MPC with Kalman Filter
IAE	$3.15*10^{-4*}$	$1.14*10^{-4}$
ISE	$2.97*10^{-9*}$	$1.49*10^{-9}$

Table 5.15: Estimated unknown parameter Dynamic optimization

Controller with Kalman Filter	Parameter			
	μ (Kg/M.min)	error	K_J (Kg/Pa^2.min^2.M^3)	error
GMC	0.0548572	0.05%	7.50616*10^8	0.04%
MPC	0.0548790	0.06%	7.50616*10^8	0.04%

The mark (*) shows on the control performance index of the controllers that cannot control the permeated flux of water to the set point.

The inclusion of the Kalman Filter can cater for the unknown parameters. The control result of MPC with Kalman Filter and GMC with Kalman Filter in the unknown parameter can control the permeated flux to its desired set point. As, the control response of MPC with Kalman Filter in unknown parameter case takes as well as the MPC controller in nominal case and the control response of GMC with Kalman Filter in unknown parameter case takes as well as the GMC controller in nominal case.

The Kalman Filter has estimated the oily water emulsion viscosity and the oily water emulsion constant in Field's model. The oily water emulsion viscosity and the oily water emulsion constant in Field's model have been estimated to their real process. Time to reach the set point of MPC with Kalman Filter takes shorter than GMC with Kalman Filter.

The control performance index of controller with Kalman Filter in the unknown parameter takes as well as the control performance index of controller in nominal case. The control performance of MPC with Kalman Filter is the better than GMC controller. The MPC with Kalman Filter is the best control in the oily water emulsion system.

Chapter 6

Conclusion and Recommendation

In this thesis, the cross flow ultrafiltration membrane separator has been studied to control the permeated flux of water for the oily water emulsion system. The achievement of the water permeated flux control depends on the integration of process control, an optimal set point and a choice suitable controller such PID, GMC and MPC controller.

The optimization to control the permeated flux of water is separated in two procedures. The first procedure, an off-line optimal is solved with fixed time to calculate the maximum the permeated flux of water to the set point by SQP (Sequential Quadratic Programming) method that has function fmincon in optimization toolbox of Matlab language (Appendix D). The second procedure, the MPC controller is formulated to minimize a quadratic objective that controls the permeated flux of water to the set point. The MPC leads to an optimization problem that is solved on-line in real time at each sampling interval. The optimization problem is formulated to minimize a quadratic objective.

6.1 Conclusion

In this research, the permeated flux control of water can be studied in two cases. One is to control the flux at a constant set point obtained from an overall optimization. The other one is to control the flux at three interval constant set points obtained from a dynamic optimization.

The control system in the most industries is PID control that is a linear feedback control and the control performance is tuned at an operating condition. Thus, the PID controller can handle the process performance but the response is slow and not accurate particular highly nonlinear process. The PID controller normally cannot handle the nonlinear system such as the performance of PID controller is poor in the presence for the cross flow ultrafiltration membrane of oily water emulsion system because the PID controller cannot control the permeated flux of water to the set point for both cases. The GMC and MPC controller is the controller based on math model then the control result gives better than the PID controller. In the overall optimization case, the GMC and MPC controller can control the permeated flux of water to the set point. Time to reach the set point of the MPC controller takes shorter than that of the GMC controller and the control performance index of MPC controller is the better than that of the GMC controller. In the dynamic optimization, the MPC can control the permeated flux of water to the set points. However, the GMC controller cannot control the permeated flux of water to the set points. The MPC controller provides the best control response over the GMC and the PID controllers.

The essential parameters are viscosity and constant in Field's model that depend on a temperature. The water-permeated flux is sensitive to the parameters change. From mentioned above, the Kalman filter is incorporated into both MPC and GMC controllers to estimate unknown/uncertain parameters. Here, the viscosity and constant's Field model, unknown/uncertain parameters, have been increased 50 % from nominal values. The Kalman Filter could cater to estimate the viscosity and constant in Field' model to approach nominal value. The estimation of Kalman Filter of MPC controller is better than that of GMC controller

The MPC with Kalman Filter and the GMC with Kalman Filter are still able to handle the parameters mismatch, handle the unknown parameters and give a good control performance as well as in the nominal case. In the overall optimization case, The MPC with Kalman Filter and the GMC with Kalman Filter can control the permeated flux to the set points. In dynamic optimization cases, The MPC with Kalman Filter can control the water-permeated flux to the set points whereas the GMC with Kalman Filter cannot because its control response produce offset.

The simulation results were found that both MPC and GMC controllers with the Kalman filter are still able to control the flux water at set point obtained from both cases. However, the MPC provides better control response than the GMC controller. Therefore the MPC with the Kalman Filter is the most robust and effective control algorithm for the cross flow ultrafiltration membrane of the oily water emulsion system.

6.2 Recommendation

In this thesis, the off-line optimal calculate the maximum the permeated flux of water to the set point that separate the calculated set point and the control process. A discrete Kalman Filter is a linear system. The discrete Kalman Filter can estimate the parameter of the nonlinear process because the process is linerized.

In the future, the on-line optimal calculate the flux maximum to the set point that is solved on-line in real time at sampling operating time. The Extended Kalman Filter is the nonlinear system. The Extended Kalman Filter can estimate the parameter of the nonlinear that is not linerization.

Reference

A.V. Balakrishnan, Kalman filter theory, optimization software Inc., New York, 1987.

A.Z. James, W. C. James, D.B. Pradeep and A.M. Imad, Advance control of reverse osmosis desalination unit, Journal Process control, v.7, no.4, 1997, pp.283-289.

Alexander T. Schwarm and Michael Nikolaou, Chance-constrained model predictive control, AIChE Journal, v.45, no8, 1999, 1743-1752.

Arnot T.C., Field R.W. and Koltuniewicz A.B., Cross-flow and dead-end microfiltration of oily-water emulsion Part II. Mechanisms and modelling of flug decline, J. Membrane Sci., 169, 2000, pp.1-15.

Aziz N., Hussain M. A., and Mujtaba I. M., Performance of different types of controllers in tracking optimal temperature profiles in batch reactors, Comp. Chem. Eng., 24, 2000, pp.1069-1075.

Badgwell Thomas A., Robust stability conditions for SISO model predictive control algorithms,Automatica, v.33, no.7, 1997, pp1357-1361.

Barolo M., Guarise G. B., Rienzi S. and Trotta A., On-line startup of a distillation column using generic model control, Comp. Chem. Eng., no.17, 1993, pp.349-354.

Becerra, V. M., Roberts, P. D., and Griffiths, G. W., Applying the extended Kalman filter to systems described by nonlinear differential-algebraic equations. Control Engineering Practice, no.9, 2001, pp. 267-281.

Boong-Goon Jeong, Kee-Youn Yoo, and Hyun-Ku Rhee, Nonlinear model predictive control using a wiener model of a continuous methyl methacrylate polymerization reactor, Ind. Eng. Chem. Res., 2001, 40, 5968-5977.

Bowen W. Richard, Moqruel Anne and Williams Paul M., Prediction of the rate of cross-flow membrane ultrafiltration: A colloidal interaction approach, Chemical Engineering Science, v. 51, no. 18, 1996, pp.4321-4333.

C. Leoblein and J.D. Perkins, Structural Design for On-line process optimization: I. Dynamic economics of MPC, AIChE Journal, v. 45, no.5, May1999, pp. 1018-1029.

Cacik F., Dondo R. G., and Marques D., Optimal control of a batch bioreactor for the production of xanthan gum. Comp. Chem. Eng. no. 25, 2001, pp. 409-418.

Carrasco E. F., and Banga, J. R. Dynamic optimization of batch reactors using adaptive stochastic algorithms, Ind. Eng. Chem. Res., no.36, 1997, pp. 2252-2261.

Cherkasov A.N., Selective ultrafiltration, Journal of Membrane Science, v 50, n 2, 1990, pp. 109-130.

D. Abdessemed, G. Nezzal and R. Ben Aïmb, Treatment of wastewater by ultrafiltration, Institute de Chimie Industrielle, University des Sciences et de la Technologie Houari Boumediene, Algiers, 1999.

David Clarke and M. Morari, Model predictive control: multivariable control technique of choice in the 1990s, Advance in Model-Based Predictive Control, Oxford university press, 1994.

David Senica, Stojan Koge and Aleksander Pavko,LEK, Pilot plant unit for a cross-flow microfiltration and ultrafiltration of fermentation broths, Pharmaceutical and Chemical Company, Faculty of Chemistry and Chemical Technology, University of Ljubljana, Ljubljana, Slovenia, 1999.

Dibakar B. and M. Rasoul M., Separation of phenolic compounds by low-pressure composite membranes: Mathematical model and experimental results, AIChE Symposium series, 1988, pp.139-157.

F. Beochini, F. Pagnanell and F. Vegio/, Modeling of copper Biosorption by Arhrobacter in UF/MF membrane reactor, Environ. Sci. Technol., 2001, 35, pp.3048-3054.

G.P. Zhang, Dynamic optimization of batch crystallization process, 6th World Congress of Chemical Engineering Melbourne, Australia 23-27 September 2001.

Gudi R. D., Shah S. L., and Gray M. R., Adaptive multirate state and parameter estimation strategies with application to a bioreactor, AIChE J., 41, 1995, pp. 2451-2464.

J.E. Cuthrell and L.T. Biegler, Simultaneous optimization and solution method for batch reactor control profiles, Computers chem. Eng., v.13, (1989) 49-62.

Jay H. Lee, Extended Kalman filter based nonlinear model predictive control, Ind. Eng. Chem. Res., v 33, 1994, pp. 1530-1541.

John W.Eaton and James B. Rawling, Model-Predictive Control of chemical process, Chemical Engineering Science, v.47, no. 4, 1992, pp. 705-720.

K. Wongcharee , R. Jiraratananon and D. Uttapap , Separation of oils from Wastewater by ceramic ultrafiltration membrane, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, 1996.

K.T. Tompkins, L.P. Murphy, B.L. Owsenek P.R. Pignataro and A.T. Rodriguez, Ultrafiltration membrane polishing system for shipboard treatment of oily wastewater, http://navyseic.dt.navy.mil/documents/asnemem.pdf, 2002.

Kittisupakorn P., Associate Professor doctor, Advanced Automatic Process Control, 2000.

Kotzev, Tzvetan, Numerical study of the fluid dynamics and mass transfer of an ultrafiltration performance in a tube membrane module, International Journal of Engineering Science, v. 32, no. 2, 1994, pp.359-368.

Leos J. Z, Andrew L Z., Microfiltration and ultrafiltration: principles and applications, Dekker, New York, 1996.

Moutzouris K.C., Gilmour S.G., and Rastall R.A.,Modeling of oligodextran production in an ultrafiltration stirred-cell membrane reactor, Enzyme and Microbial Technology, v 24, no. 1-2, 1999, pp. 75-85.

Myers M. A., and Luecke, R. H., Process control applications of an extended Kalman filter algorithm. Comp. Chem. Eng., 15, 1991, pp.853-857.

N. Siripun, Globally linearizing control for pH control of the wastewater treatment process, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 2000.

O. Moolasartsatorn, Optimization and control of peraporative membrane reactor. Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 2003.

Ordys Andrzej W. and Grimble Michael, Predictive control in power generation, Computing and Control Engineering Journal, v. 10, no. 5, 1999, pp 214-220.

P. Meethong, GMC for relative degree higher than one processes a case study: A concentration control of continuous stirred tank reactor with first-order exothermic reaction. Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 2002.

P. Ruksawid, Application of model predictive control with kalman filter for continuous stirred tank reactor with first order reaction, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 1999.

Patwardhan Sachin C. and Madhavan, K.P., Nonlinear predictive control of an exothermic CSTR using recursive quadratic state space models, IEEE Conference on Control Applications - Proceedings, 1995, pp. 967-972.

Patwardhan, Ashutosh A., Edgar and Thomas F., Nonlinear model predictive control of a packed distillation column, Ind. Eng. Chem. Res., v. 32, no. 10, 1993, pp. 2345-2356.

Paul D. and Ohlrogge K., Membrane separation processes for clean production, Environmental Progress, v. 17, no. 3, 1998, pp 137-141.

PCT., A method of cross-flow filtration and a cross-flow filtration installation, International application published under the patent cooperation treaty (PCT), Patent Number: WO0110540, 2001.

PerKins T.W., Saksena S., and Van Reis R., Dynamic film model for ultrafiltration, Journal of Membrane Science, v. 158, no. 1, 1999,pp. 243-256.

Phani B. S. and Bequette B. W., Nonlinear Predictive Control of Uncertain Processes: Application to a CSTR, AIChE Journal, v.37, no. 11, 1991, pp. 1711-1723.

R. Jiraratananon, D. Uttapap and C. Klun-ngern, Research and Development of KMITT Journal, King Mongkut's University of Technology Thonburi, 1998.

Richard W. B., Membrane technology and applications, McGraw-Hill, New York, 2000.

S. Bamrungwongdi, Software design and development for the Kalman filter algorithm with borland C++, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 1998.

S. Phupaichitkun, Application of model predictive control on the matlab for control of a batch reactor with exothermic reactions, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 1998.

S. Tongmeesee, Model-Based control and estimation for free radical polymerization reactor, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 2000.

Sameer Ralhan and Thomas A. Badgwell, Robust Model predictive control for integrating linear systems with bounded parameters, Ind. Eng. Chem. Res., v.39, 2000,pp. 2981-2991.

Silva R.G., Anastacio C.S. and Kwong W.H., Model predictive control algorithm and their application to a continuous fermenter, J. Chem. Engineering, v.16, no. 2, 1999, pp. 155-161.

Song Lainfa, Flux decline in crossflow microfiltration and ultrafiltration: Mechanisms and modeling of membrane fouling, Journal of Membrane Science, v.139, no.2,1998,pp.183-200.

Soriush Masoud, Kravaris and Costas, Short horizon nonlinear model predictive control, IEEE Conference on Control Applications - Proceedings, 1995, pp. 943-948.

Tan, L., Dowling, J., McCorkell, C., and McCabe H., State estimation for optimal control of a nonlinear system. IECON Proceedings (Industrial Electronics Conference), 3, 1991, pp. 2235-2240.

Tomas F. Edgar,David M. Himmelblau and Leon S. Lasdon, Optimization of chemical Process, second edition, McGraw-Hill, New York, 2001.

United States Patent, Artificial kidney with device for filtering dialysis, United States Patent, Patent number 5, 11 Jul.1995, pp.431-811.

V. Lersbamrungsuk, Kalman filter algorithm software design and development for chemical processes, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 2000.

V.Garcia, M. Cabassud, M.V. Le Lann,L.Pibouleau, G. Cassamatta ,Constrained optimization for fine chemical production in batch, The chemical Engineering Journal, no.59, 1995, pp. 229-241.

W. Duangwang, State feedback controller application for the wastewater ph-control process, Master of Engineering Thesis, Department of Chemical Engineering, Faculty of Engineering, Chulalongkorn University, 1999.

Wang Q. G., Thomad G., and Gilles G., Predictive control of a glass process, Control Engineering Practice, v. 5, no. 2, 1997, pp 167-173.

Wang, Z. L., Corriou J. P., and Pla F., Nonlinear control of a batch polymerization reactor with on-line parameter and state estimations, Proceedings of the IEEE Conference on Decision and Control, 4, 1993, pp.3858-3863.

Yeh Ho-Ming, Decline of permeated flux for ultrafiltration along membrane tubes, Desalination, v. 145, no. 1-3, 2002, pp. 153-157.

APPENDICES

Appendix A
Concerned Mathematical Model

In this thesis the process model for Ultrafiltration membrane involves a material balance and experimental.

Mathematical model

Accumulation = {Input} - {output} + {Generation} - {Consumption}

$$\frac{d(C_b V)}{dt} = -AJ_w C_p \qquad \text{(A.1)}$$

$$V\frac{dC_b}{dt} + C_b\frac{dV}{dt} = -AJC_p \qquad \text{(A.2)}$$

$$\frac{dC_b}{dt} = \frac{-AJ_w C_p - C_b\left(\frac{dV}{dt}\right)}{V} \qquad \text{(A.3)}$$

$$V = V_0\left(1 - r\right) \qquad \text{(A.4)}$$

$$\frac{dr}{dt} = \frac{A}{V_0} J_w \qquad \text{(A.5)}$$

$$\frac{dC_b}{dt} = \frac{-AJ_w C_p + C_b A J_w}{V_0(1-r)} \qquad \text{(A.6)}$$

When

$$R_r = 1 - \frac{C_p}{C_b} \qquad \text{(A.7)}$$

Can Present

$$\frac{dC_b}{dt} = \frac{C_b R_r A J_w}{V_0\left(1 - r\right)} \qquad \text{(A.8)}$$

The membrane used inorganic membrane in liquid-solid cross flow ultrafiltration membrane separator. The rate of solute diffusion in x direction has been assume to be negligible relative to the rate of solute convection in the tangential direction the equation (A.11) is solved subject to the follow boundary condition at membrane surface

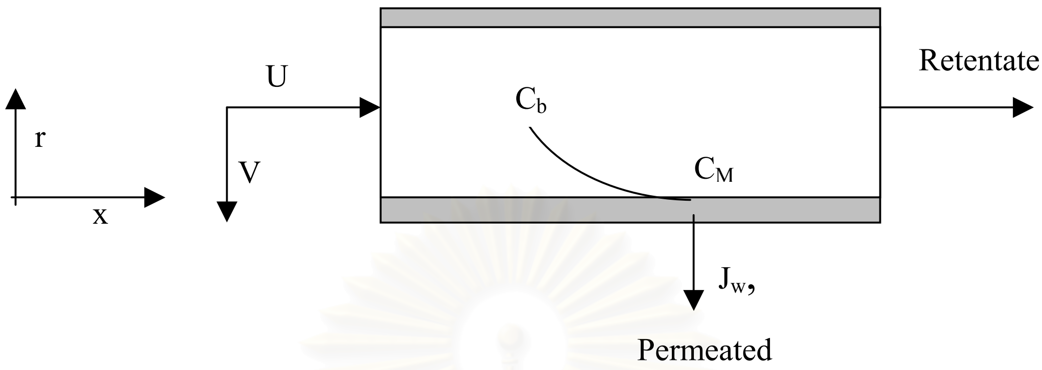


Figure A.2 the mass transfer of the permeated flux in tubular membrane

$$\frac{\partial C}{\partial t}+\frac{\partial}{\partial x}(UC)+\frac{\partial}{\partial r}(VC)=\frac{\partial}{\partial r}\left(D\frac{\partial C}{\partial r}\right) \qquad (A.10)$$

$$V=-J_w \qquad (A.11)$$

$$VC_M-D(\frac{\partial C}{\partial r})=-N_s \qquad (A.12)$$

The solute mass transfer coefficient

$$k=\frac{-D(\frac{\partial C}{\partial r})_M}{C_M-C_b} \qquad (A.13)$$

$$-J_wC_M+k(C_M-C_b)=-N_s=-J_wC_p \qquad (A.14)$$

$$J_w=k\frac{\left(C_M-C_b\right)}{\left(C_M-C_p\right)} \qquad (A.15)$$

The rate of solute diffusion in x direction has been assume to be negligible relative to the rate of solute convection in the tangential direction the equation (A.11) is solved subject to the follow boundary condition at membrane surface

$$JC-D(\frac{\partial C}{\partial r})=J_vC_p \qquad (A.16)$$

$$J_w=\frac{D}{\delta}\ln\frac{\left(C_M-C_p\right)}{\left(C_b-C_p\right)} \qquad (A.17)$$

if $C_p = 0$

$$C_M = C_b \exp(J_w / k) \qquad \text{(A.18)}$$

Take equation (A.19) in equation (A.16)

$$J_w = k \frac{\left(C_b \exp(J_w / k) - C_b \right)}{\left(C_b \exp(J_w / k) \right)} \qquad \text{(A.19)}$$

From experimental model (Field, 1995) used equation (A.19). The differential equation of the permeated flux could present

$$\frac{dJ_w}{dt} = -K_J \left(J_w - J_w^* \right) J_w^2 \qquad \text{(A.20)}$$

The resistant model of permeated flux

$$J_w = \frac{\Delta PTM}{\mu R_t} \qquad \text{(A.21)}$$

Take equation (A.21) in equation (A.20)

$$\frac{dR_t}{dt} = K_J \Delta PTM^2 \left(\frac{J_w^*}{\Delta PTM} - \frac{1}{R_t} \right) \qquad \text{(A.22)}$$

Appendix B
Successive Quadratic Programming (SQP)

Successive quadratic programming (SQP) method solved a sequence of quadratic programming approximation to nonlinear programming problem. Quadratic programs (QPs) have a quadratic objective function and linear constraints, and there exist efficient procedures for solving them

Problem formulation with equality constraints

To derive SQP, we again consider a general NLP

$$\begin{aligned} &Minimize: f(x) \\ &Subjectto: g(x) = b \end{aligned} \qquad \text{(B.1)}$$

The Lagrangian function for this problem is

$$L(x,\lambda) = f(x) + \lambda^T (g(x) - b) \qquad \text{(B.2)}$$

and the KTC are

$$\nabla_x L = \nabla f(x) + \sum_{i=1}^{m} \lambda_i \nabla g_i(x) = 0 \qquad \text{(B.3)}$$

and $$g(x) = b \qquad (3.46)$$

The equation (B.1)-(B.2) is a set of ($n+m$) nonlinear equations in the n unknowns x and m unknown multipliers λ. Linearization of (B.2) and (B.3) with respect to x and λ

$$\nabla_x L - \nabla_x^2 L \Delta x + \nabla g^T \Delta\lambda = 0 \qquad \text{(B.4)}$$

$$g + \nabla g \Delta x = 0 \qquad \text{(B.5)}$$

For problem with only equality constraints, we could simply solve the linear equations (B.2)-(B.3). To accommodate both equalities and inequality, an alternative viewpoint is useful. Consider the quadratic programming problem

$$\begin{aligned} &\min imize: \nabla L^T \Delta x + \frac{1}{2} \Delta x^T \nabla_x^2 L \Delta x \\ &Subject\ to: g + \nabla g \Delta x = 0 \end{aligned} \qquad \text{(B.6)}$$

If we call the Lagrange mutipliers for (B.6) $\Delta\lambda$, the Lagrangian for the QP is

$$L_1(\Delta x, \Delta\lambda) = \nabla L^T \Delta x + \frac{1}{2} \Delta x^T \nabla_x^2 L \Delta x + \Delta\lambda^T (g + \nabla g \Delta x) \qquad \text{(B.7)}$$

Inclusion of the both equality and inequality constraints

When the original problem has a mixture of equalities and inequalities, it can be transformed into a problem with equalities and simple bounds by adding slacks, so the problem has an objective function f , equalities (B.1), and bounds

$$I \le x \le u \qquad \text{(B.8)}$$

This system is the KTC for the QP in (B.6) with the additional bound constraints

$$I \le \bar{x} + \Delta x \le u \qquad \text{(B.9)}$$

Here the QP sub problem now has both equality constraints and must be solved by some iterative QP algorithm.

The approximate Hessian

Solving a QP with a positive-definite Hessian is fairly easy. Several good algorithm all converge in finite number of iterations. However, the Hessian of the QP presented in (B.6) and (B.9) is $\nabla_x^2 L(\bar{x}, \bar{\lambda})$, and this matrix need not be positive-definite, even if $(\bar{x}, \bar{\lambda})$ is an optimal point. In addition, to compute $\nabla_x^2 L$, one must compute second derivative of all problem functions. Both difficulties are eliminate by replacing $\nabla_x^2 L$ by positive-definite quasi-Newton approximate B, which is updated using only values of L and $\nabla_x L$. Most SQP algorithms use Powell's modification of BFGS update. Hence the QP subproblem becomes

$QP(\bar{x}, B)$

$$\min imize: \nabla L^T \Delta x + \frac{1}{2} \Delta x^T B \Delta x$$
$$Subject\ to: \nabla g \Delta x = -g, \quad I \le \bar{x} + \Delta x \le u \qquad \text{(B.10)}$$

The SQP line search

TO arrive at a reliable algorithm, one more difficulty must be over come. Newton and quasi-Newton method may not converge if a step of 1.0 is used at each step. Both trust region and time search versions of SQP have been developed that converge reliability. A widely used line search strategy is to use the L_1 exact penalty function $P(x, w)$. In a line search SQP algorithm, $P(x, w)$ is used only to determine the step size along the direction determined by the QP subproblem $QP(\bar{x}, B)$. The L_1 exact penalty function for the NLP problem is

$$P(x, w) = f(x) + \sum_{i=1}^{m} w_i \mid g_i(x) - b_i \mid \qquad \text{(B.11)}$$

where a separate penalty weight w_i is used for each constraint. The SQP line search chooses a positive step size α to find an approximate minimum of

$$r(\alpha) = P(\bar{x} + \alpha\Delta x, w) \qquad \text{(B.12)}$$

A typical line search algorithm, which uses the derivative of $r(\alpha)$ evaluated at $\alpha = 0$ denote by $r'(0)$, is

1. $\alpha \leftarrow 1$

2. if $r(\alpha) < r(0) - 0.1\alpha r'(0)$ (B.13)

stop and return the current α value

3. Let α_1 be the unique minimum of the convex quadratic function that passes through $r(0)$, $r'(0)$ and $r(\alpha)$. Take the new estimate of α as

$$\alpha \leftarrow \max(0.1\alpha, \alpha_1) \qquad \text{(B.14)}$$

4. Go to step 2.

SQP algorithm

Base on this line search and the QP subproblem $QP(\bar{x}, B)$

1. Initialize: $B^0 \leftarrow I$, $x^0 \leftarrow x$, $k \leftarrow 0$
2. Solved the QP subproblem $QP(\bar{x}, B)$, yieldiging a solution Δx^k and Langrange multiplier estimates λ^k
3. Update the penalty weights in penalty function
4. Apply the line search algorithm, yielding a positive step size α^k
5. $x^{k+1} = x^k + \alpha^k \Delta x^k$, $\lambda^{k+1} = \lambda^k$
6. Evaluated all problem function and their gradients at new point. Update matrix B^k
7. Replace k by k+1, and go to step 2

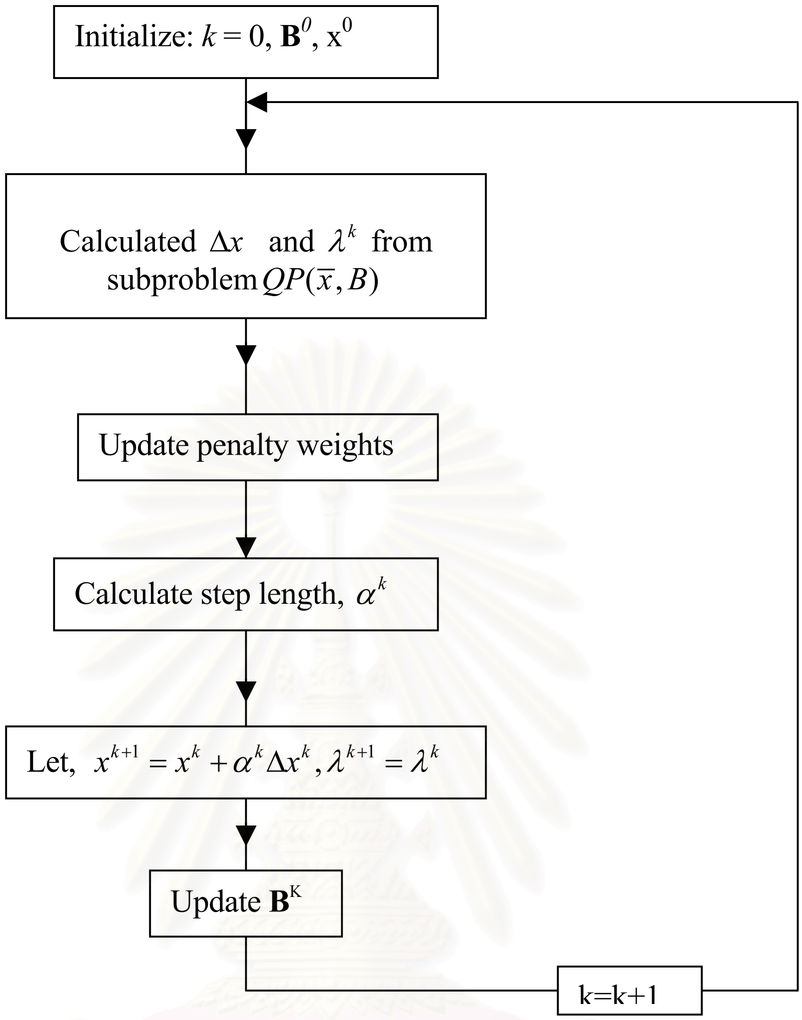


Figure B.1: Flowchart of SQP algorithm

Appendix C
System Checking

State space equation is linearlization of system

$$\frac{dx}{dt} = Ax + Bu \qquad (3.13)$$
$$y = Cx$$

State equation

$$x_{n+1} = Ax_n + Bu_n \qquad (C.1)$$

$$Y_n = Cx_n + Du_n \qquad (C.2)$$

Controllability

A system is said to be controable if it is possible to bring a state variable to any arbitrary value in finite period of time using the manipulated variable that are available.

$$Controllability\ Matrix = [B\ \ AB\ \ A^2B\ldots\ ,A^{n-1}B] \qquad (C.3)$$

n is number of state variable

A necessary and sufficient condition for controllability is that the [compound] " controllability matrix" has full rank. The square controllability matrix, the matrix rang can be calculated by determinate of controllability. The determinate of controllability not equal zero, the system has controllability

Observability

A system is said to be observable if measurement of output Y contain sufficient information to enable us to completely identify the state x.

$$Observability\ Matrix = [C^T\ \ A^TC^T\ldots\ ,(A^T)^{(n-1)}C^T] \qquad (C.4)$$

The discusser of observability and the discusser controllability are alike.

System stability

A necessary and sufficient condition for a system to be stable is that the eigenvalues of A be all (strictly) less than 1 in magnitude

Appendix D
Fmincon Toolbox

Most of these optimization routines require the definition of an M-file containing the function to be minimized, i.e., the objective function. Alternatively, an inline object created from a MATLAB expression can be used. Maximization is achieved by supplying the routines with -f, where f is the function being optimized

Medium-Scale Algorithms

The Optimization Toolbox routines offer a choice of algorithms and line search strategies. The principal algorithms for unconstrained minimization are the Nelder-Mead simplex search method and the BFGS (Broyden, Fletcher, Goldfarb, and Shanno) quasi-Newton method. For constrained minimization, minimax, goal attainment, and semi-infinite optimization, variations of *sequential quadratic programming* (SQP) are used. Nonlinear least squares problems use the Gauss-Newton and Levenberg-Marquardt methods.

A choice of line search strategy is given for unconstrained minimization and nonlinear least squares problems. The line search strategies use safeguarded cubic and quadratic interpolation and extrapolation methods.

fmincon

Find the minimum of a constrained nonlinear multivariable function

$$\min_x f(x) \qquad \text{(D.1)}$$

subject to

$$\begin{aligned} &c(x) \le 0 \\ &ceq(x) = 0 \\ &A \cdot x \le b \qquad\qquad \text{(D.2)} \\ &Aeq \cdot x = beq \\ &lb \le x \le ub \end{aligned}$$

where *x, b, beq, lb,* and *ub* are vectors, *A* and *Aeq* are matrices, *c(x)* and *ceq(x)* are functions that return vectors, and *f(x)* is a function that returns a scalar. *f(x)*, *c(x)*, and *ceq(x)* can be nonlinear functions.

Syntax

```
x = fmincon(fun,x0,A,b)
x = fmincon(fun,x0,A,b,Aeq,beq)
x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub)
x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon)
x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon,options)
x = fmincon(fun,x0,A,b,Aeq,beq,lb,ub,nonlcon,options,P1,P2, ...)
[x,fval] = fmincon(...)
```

```
[x,fval,exitflag] = fmincon(...)
[x,fval,exitflag,output] = fmincon(...)
[x,fval,exitflag,output,lambda] = fmincon(...)
[x,fval,exitflag,output,lambda,grad] = fmincon(...)
[x,fval,exitflag,output,lambda,grad,hessian] = fmincon(...)
```

fmincon finds the constrained minimum of a scalar function of several variables starting at an initial estimate. This is generally referred to as *constrained nonlinear optimization* or *nonlinear programming*. The optimization options parameters used by `fmincon`. Some parameters apply to all algorithms, some are only relevant when using the large-scale algorithm, and others are only relevant when using the medium-scale algorithm.

Examples: Find values of x that minimize $f(x) = -x_1 x_2 x_3$, starting at the point x = [10; 10; 10] and subject to the constraints $0 \le x_1 + 2x_2 + 2x_3 \le 72$

First, write an M-file that returns a scalar value `f` of the function evaluated at `x`.

```
function f = myfun(x)
f = -x(1) * x(2) * x(3);
```

Then rewrite the constraints as both less than or equal to a constant,

$$-x_1 - 2x_2 - 2x_3 \le 0$$
$$x_1 + 2x_2 + 2x_3 \le 72$$

Since both constraints are linear, formulate them as the matrix inequality

$A \cdot x \le b$ where $A = \begin{bmatrix} -1 & -2 & -2 \\ 1 & 2 & 2 \end{bmatrix}$, $b = \begin{bmatrix} 0 \\ 72 \end{bmatrix}$

Next, supply a starting point and invoke an optimization routine.

```
x0 = [10; 10; 10];    % Starting guess at the solution
[x, fval] = fmincon(@myfun,x0,A,b)
```

The solution is x = [24; 12; 12]

Where the function value is

fval = -3.4560e+03

and linear inequality constraints evaluate to be <= 0

A*x-b = [-72; 0]

VITA

Miss Weerawun Weerachaipichasgul was born in Surath-thany on 31 March 1977. Education levels are high school in 1993-1996 from Nawamintrachinutid Treumudomsuksa Nomkrao School, Bangkok, and Bachelor Degree in Chemical Engineering from Srinakharinwirot University, Bangkok in 1996-2000. The last education is studying in Master Degree in Chemical Engineering, Chulalongkorn University that began in 2000.