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CONTROL OF A CONTINUOUS FABRIC PREPARATION PROCESS
BY MPC CONTROLLER

Mr.Ekachai Saechua

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กระบวนการผลิตสิ่งทอประกอบด้วยการเก็บเกี่ยวผลผลิต เพื่อนำมาทำเป็นเส้นใย เปลี่ยนเส้นใยเป็นเส้นด้าย และนำไปทอเป็นผืนผ้า หรือทำเป็นผลิตภัณฑ์อื่นๆ ที่เกี่ยวข้องต่อไป ขั้นตอนต่อมา จะนำผลิตภัณฑ์ที่ได้ไปย้อม หรือการพิมพ์ลาย และตกแต่งวัสดุในขั้นสุดท้าย เพื่อให้ได้เป็นผลิตภัณฑ์สุดท้ายต่อไป โดยส่วนใหญ่ก่อนจะนำผ้าไปย้อม หรือพิมพ์ลายผ้า ต้องมีการเตรียมผ้าก่อน โดยทั่วไปการเตรียมผ้าประกอบด้วยการกำจัดสารลงแป้ง, กำจัดสิ่งสกปรก และการฟอกขาว ซึ่งสมรรถนะของขั้นตอนเหล่านี้ ขึ้นอยู่กับความเข้มข้นของสารเคมีที่ใช้ และอุณหภูมิ ในงานวิจัยนี้ได้ทำการศึกษาการเตรียมผ้าในขั้นตอนเดียว รวมถึงขั้นตอนการล้างที่ผ้าและน้ำไหลสวนทางกัน แบบจำลองทางคณิตศาสตร์ของระบบนี้ได้รับการพัฒนาขึ้นบนพื้นฐานของการดุลมวลสาร และการดุลพลังงาน และใช้การควบคุมแบบโมเดลพรีดิกทีฟร่วมกับตัวกรองคาลมานต์เป็นเพื่อช่วยควบคุมอุณหภูมิให้เข้าสู่ค่าเป้าหมายที่ต้องการ จากผลการจำลองพบว่า การควบคุมแบบโมเดลพรีดิกทีฟร่วมกับตัวกรองคาลมานต์ให้ผลการควบคุมที่ดี และมีความทนทานในสภาวะที่ค่าพารามิเตอร์ของกระบวนการมีความผิดพลาด

ภาควิชาวิศวกรรมเคมี	ลายมือชื่อนิสิต...
สาขาวิชาวิศวกรรมเคมี	ลายมือชื่ออาจารย์ที่ปรึกษา..................................
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##4370634821 : MAJOR CHEMICAL ENGINEERING
KEY WORD: TEXTILE INDUSTRY PROCESS / FABRIC PREPARATION / MODEL PREDICTIVE CONTROL / KALMAN FILTER

EKACHAI SAECHUA : CONTROL OF A CONTINUOUS FABRIC PREPARATION PROCESS BY MPC CONTROLLER.. THESIS ADVISOR : ASSOC. PROF. PAISAN KITTISUPAKORN, Ph.D., 96 pp. ISBN 974-17-4437-4

Textile manufacturing is comprised of preparing of fibers, transforming fibers into yarn, converting the yarn into fabric or related products, dyeing or printing and finishing these materials at various stages of production. Most fabric that is dyed, or printed must first be prepared. Typical preparation includes desizing, scouring and bleaching steps; performance of this step depends upon the chemical concentration as well as temperature. In this research, the single-step of fabric preparation is implemented to accommodate the steps is studied. Rinsing step is counter flow of the fabric and fresh water. The mathematical model of this system is developed based on material and energy balances. A model predictive control (MPC) coupled with Kalman filter is implemented to control the temperature in preparation process at a desired set point. The control results of the MPC coupled with Kalman filter have been found good performance and robust characteristics with respect in process parameters mismatch.

Department Chemical Engineering	Student's signature..............................
Field of study Chemical Engineering	Advisor's signature.............................
Academic Year 2003	

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CONTENTS

Page

CONTENTS (Continued)

Page

CONTENTS (Continued)

Page

LIST OF TABLES

Table **Page**

LIST OF FIGURES

Figure **Page**

LIST OF FIGURES (Continued)

Figure **Page**

LIST OF FIGURES (Continued)

Figure **Page**

NOMENCLATURES

Fabric preparation process

A_i	Heat transfer area of the ith tank $\left(m^2\right)$
A_t	Cross-section area of tank $\left(m^2\right)$
C_P	Specific heat capacity of liquid $\left(kJ/kg \cdot K\right)$
$C_{P,C}$	Specific heat capacity of fabric $\left(kJ/kg \cdot K\right)$
E	Activation energy $\left(kJ/mol\right)$
F_0	Hydrogen peroxide flow rate $\left(m^3/h\right)$
F_4	Water flow rate $\left(m^3/h\right)$
F_5	Sodium hydroxide flow rate $\left(m^3/h\right)$
F_i	Liquid output flow rate from the ith tank $\left(m^3/h\right)$
$-\Delta H$	Heat of reaction $\left(kJ/kmol\right)$
h_i	Liquid level of the ith tank $\left(m\right)$
K_a	Hydrogen peroxide constant
k_0	Pre exponential $\left(1/h\right)$
$P_{u,i}$	Percent pick up $\left(\%\right)$
pH	Acid-base value
R	Gas constant $\left(kJ/mol \cdot K\right)$
r_i	Reaction rate in the ith tank $\left(kmol/m^3 \cdot h\right)$
S_i	Steam flow rate input to the ith tank $\left(kg/h\right)$
T_o	Ambient temperature $\left(K\right)$
T_b	Steam Temperature $\left(K\right)$
T_i	Temperature in the ith tank $\left(K\right)$
U_i	Overall heat transfer coefficient of the ith tank $\left(kJ/h \cdot m^2 \cdot K\right)$
V_i	Liquid volume of the ith tank $\left(m^3\right)$
v_C	Fabric velocity $\left(kg/h\right)$

NOMENCLATURES (Continued)

W_0	Weight per length of fabric input to the first tank (kg/m)
W_i	Weight per length of fabric output from the ith tank (kg/m)
X_0	Hydrogen peroxide concentration input to the first tank $(kmol/m^3)$
X_i	Hydrogen peroxide concentration of the ith tank $(kmol/m^3)$
Y	Sodium hydroxide concentration input to the first tank $(kmol/m^3)$

Controller

A	Incidence matrix with respect to x
B	Incidence matrix with respect to u
C	Incidence matrix with respect to y
e	Error
K	MPC controller gain
K_1	Tuning parameter of GMC controller
K_2	Tuning parameter of GMC controller
K_c	PID controller gain
N_m	Number step of control horizontal
N_p	Number step of prediction horizontal
$\overline{p}$	Bias value
$p(t)$	Controller output
Q	Weighting factor of state variable
R	Weighting factor of manipulated variable
u	Manipulated input vector
u_{max}	Maximize of constraint
$u_{\min}$	Minimize of constraint
x	State variable

NOMENCLATURES (Continued)

y	Output vector
t	Time (h)

Kalman filter

A_K	Incidence matrix with respect to x in Kalman filter
B_K	Incidence matrix with respect to u in Kalman filter
C_K	Incidence matrix with respect to y in Kalman filter
K_K	Kalman filter gain
P_K	Estimation error covariance matrix
Q_K	Process noise covariance matrix
R_K	Measurement noise covariance matrix

Greek letters

ρ	Liquid density $\left(kg/m^3\right)$
λ	Latent heat of vaporization $\left(kJ/kg\right)$
τ	Time constant
τ_I	Integral time
τ_D	Derivative time
ξ	Damping constant

Superscript

T	Transposed matrix

Subscript

i	Number of tank for $i = 1,2,3$
k	At time instant k
n	At sampling instant n
sp	Set point

CHAPTER I

INTRODUCTION

The textile industry is comprised of a diverse, fragmented group of establishments that produce and/or process textile-related products (fiber, yarn, and fabric) for further processing into apparel, home furnishings, and industrial goods. Textile manufacturing begins with the production or harvest of raw fiber. Fiber used in textiles can be harvested from natural sources or manufactured from regenerative cellulosic materials or it can be entirely synthetic. Then the raw natural or manufactured fibers pass through several stages to change these fibers to the various stages of production. The stages can be divided in four main stages as follow:

1. Yarn formation,
2. Fabric formation,
3. Wet processing,
4. Fabrication.

Woven and knit fabrics, product from fabric formation, cannot be processed into apparel and other finished goods until the fabrics have passed through several water-intensive wet processing stages. Wet processing enhances the appearance, durability, and serviceability of fabrics by converting undyed and unfinished goods, known as gray or greige goods, into finished consumers' goods. Also collectively known as finishing, wet processing has been broken down into four stages in this section for simplification: fabric preparation, dyeing, printing, and finishing.

Most fabric that is dyed, printed, or finished must first be prepared, with the exception of denim and certain knit styles. Fabric preparation, also known as pretreatment, consists of a series of various treatment and rinsing steps critical to obtaining good results in subsequent textile finishing processes. In preparation, the mill removes natural impurities or processing chemicals that interfere with dyeing, printing, and finishing. Improper preparation is often the cause of problems encountered in the dyeing, printing and finishing steps. Therefore the fabric preparation is one of the important and influences to the next processes in the wet processing.

In the fabric preparation, many fabrics go through a three-section range where each section is dedicated to desizing, scouring and bleaching. Preparation steps can also include processes, such as singeing and mercerizing, designed to chemically or physically alter the fabric. However, some fabrics may only require one or two steps to complete the preparation process. The fabric preparation process can be carried out as either batch or continuous processes. In batch processing, the entire load of fabric is immersed in the total amount of liquid needed for that process. In continuous preparation, the fabric moves continuously through stages and compartments, which provide the chemical concentration, time, and temperature to improve the performance of cleaning fabric. Due to the effect of the operating temperature, which influences the chemical activity through the water solubility of sizing, it is necessary to control the temperature in preparation process.

In this work, a continuous fabric preparation process is considered. The single-step of fabric preparation is implemented to accommodate the steps is studied. Rinsing step is counter flow of the fabric and fresh water. The mathematical model of this process is developed based on material and energy balances. A steam flow rate is to manipulate the temperature. Model Predictive Control (MPC) coupled with Kalman filter is implemented to control the temperature in this process.

1.1 Objectives of Research

The objectives of this research are:

1. To develop a mathematical model of a continuous fabric preparation process based on material balance and energy balance,
2. To design a control configuration for a continuous fabric preparation process to control the temperature.

1.2 Scope of Research

The scope of this research can be listed as follows.

1. Model of a continuous fabric preparation process is developed based on material balance and energy balance.
2. A continuous fabric preparation process is considered. The study is aimed the single-step of fabric preparation in the first tank and the counter flow washing of rising step in the second and the third tanks.
3. A Kalman filter is used to estimate the uncertain parameters in the model.
4. A model predictive control (MPC) coupled with the Kalman filter is implemented to control the temperature of a continuous fabric preparation process.
5. Programs written to simulate and control the reactor are based on Matlab Program.

1.3 Contribution of Research

The expected contribution of this research can be enumerated as follows.

1. Mathematical model of a continuous fabric preparation process has been developed.
2. A computer program simulation has been developed to study the behavior of a continuous fabric preparation process.
3. Uncertain parameters of a continuous fabric preparation process have been estimated.

1.4 Activity Plan

Activity plan of this research can be enumerated as follows.

1. Relevant information regarding fabric preparation process and is reviewed.
2. Mathematical model of a continuous fabric preparation process is developed.
3. Relevant information regarding a model predictive control (MPC) is studied.

4. MPC coupled with the Kalman filter is implemented to control the temperature of a continuous fabric preparation process.
5. Simulation results are collected and summarized.

This thesis is divided into five chapters.

Chapter I is an introduction to this research. This chapter consists of research objectives, scope of research, contribution of research, and activity plan.

Chapter II reviews the work carried out on fabric preparation process, model predictive control, and Kalman filter.

Chapter III covers some background information of textile industry processes, fabric preparation process, model predictive control, and Kalman filter.

Chapter IV describes process and mathematical model of a continuous fabric preparation, and control configuration.

Chapter V presents the control simulation results that obtained by simulating the process under the proposed strategy.

Chapter VI presents the conclusions of this research and makes the recommendations for future work.

This is followed by:

References

Appendix A: System test
Appendix B: Tuning of GMC controller
Appendix C: Integral error criteria

CHAPTER II

LITERATURE REVIEW

2.1 Fabric Preparation Process

The term "Preparation" has two implications in textile processing. In greige manufacturing, it is used to describe the processes, which prepare yarns for weaving and knitting. Mostly, it is used to describe slashing operations that ready warp yarns for weaving. In wet processing, the term is used to describe those processes that ready fabric for the steps that follow, coloration and finishing. Fabric preparation is the first of the wet processing steps where greige fabric is converted into finished fabric. Improper preparation is often the cause of problems encountered in the dyeing and finishing steps. There are many different fabrics, many different plant set-ups and many different machines used in wet processing. There is no universally accepted best method for each of the wet processing steps. Nonetheless every set-up is expected to, and more often than not, accomplish the same goals. To deal with this seemingly infinite number of permutations, a fundamental understanding of what happens at each step and how to control the chemical and physical parameters becomes paramount.

Anon (1990) presented the single-stage of fabric preparation process. Preparation of 100% cotton woven fabrics is normally done in three separate stages. It would save time, energy and labor costs if a chemical system could be designed to desize, causticize and bleach in one operation. For this study, a medium weight 100% cotton twill fabric sized with starch and PVA was prepared by the conventional three-stage procedure for comparison purposes. Several single-stage chemical formulations were evaluated to determine an acceptable oxidative desize procedure for the fabric. The study showed that selected 100% cotton fabrics can be prepared in a single stage and plant trials noted a 40% reduction in preparation costs using the new procedure.

El-Rafie et al., (1991) proposed the fast desizing/scouring/bleaching system for cotton-based textiles. Treatment of loomstate all-cotton or cotton/polyester blended fabrics with $NaClO_2/KMnO_4$ oxidizing system results in (a) conversion of the starch size to oxidized easily removable products, (b) destruction and disintegration of impurities such as natural fats, pectins, and residual motes, and (c) breaking down the coloring matter without seriously degrading the fiber substance. Owing to this, the system is adequate for effecting desizing, scouring, and bleaching in a one-step process.

Abou-iiana (1998) studied the effect of scouring parameters (pH, temperature), and the scouring method on the dimensional changes of cotton interlock fabrics. As an initial study, scouring processes were performed where a complete range of pH and temperature were examined. The relaxation procedures recommended by the International Institute for Cotton were followed to relax the samples. It was found that in the case of scouring in pots, the temperature variation affected the fabric dimensions. No significant effect of the pH was indicated on the fabric dimensions. The relaxation treatment indicated that most of the dimensional changes occur in the initial wetting processes, and the dimensional changes due to further relaxations were relatively limited.

Csiszar et al., (1998) studied bioscouring of cotton fabrics with cellulase enzyme. When traditional alkaline scouring of desized cotton fabrics was preceded by cellulase enzymatic treatment, two benefits were observed. Beside significant increase in whiteness of fabrics, enhanced removal and alkaline degradation of seed-coat fragments were achieved. Enzyme treatment alone resulted in 14-21% increase in Berger-whiteness. When consecutive cellulase treatment and conventional alkaline scouring were combined, the increase in whiteness was even more significant. Applying cellulase enzyme in concentrations of 1, 5 and 10 g/l, respectively, in biotreatment followed by conventional caustic scouring, a maximum of 18, 25, and 29% increase in whiteness was observed. Cellulase pretreatment also allowed the reduction of the hydrogen-peroxide consumption in the chemical bleaching step.

Hartzell and Hsieh (1998) applied pectinase enzymes to scouring the cotton fabric. A pectinase was found to improve the surface wetting properties of greige cotton fabrics following a water pretreatment at 100 ^{o}C. This study further evaluated seven pectin-degrading enzymes, i.e., four pectinases, two pectinesterases, and a pectin lyase, for scouring raw cotton fabrics. Three of the pectinases significantly improved the wettability of cotton fabrics following a 100 ^{o}C water pretreatment to the same extent as alkaline scouring. The other pectinase, pectinesterases and pectin lyase had no beneficial effects on improving the wettability of raw cotton fabrics. Reaction conditions for the three pectinase treatments were optimized in respect to temperature, concentration, pH, and time. The pectinase treated fabrics did not exhibit additional shrinkage, color change, nor significant strength loss from the fabrics pretreated in water at 100 ^{o}C.

Min and Huang (1998) proposed the possibility of desizing, scouring and dyeing cotton fabrics with no alkaline agent and in a single bath. Based on the results, the color of the treated fabrics is 3-5% lighter than that of the conventionally treated fabrics, but this method will actually save time, energy and water by over one third.

Durden et al., (2001) reviewed progress in bio-friendly textile chemistry and information supplied on early cotton processes. Alkaline scouring of cotton is still the most widely used commercial technique, with sodium hydroxide replacing potash and acetic acid replacing buttermilk. Pollution is a key issue, and a bio-friendly enzymatic preparation eliminating traditional alkaline is desirable. Cotton fiber structure is explained and factors which cause wet processing problems. Pectinase use is reported with improved absorbency from mixed pectinase and cellulase. The composition of alkaline pectinase is recounted, and uses and required storage conditions. Enzymatic scouring produced savings in dyeing time, electricity, water and steam.

Tzanov et al., (2001) introduced the bio-processes in the conventional scouring and bleaching preparation of cotton. The scouring with two types of pectinases and acting under acidic, and alkaline conditions respectively, were as efficient as the chemical process in terms of obtained adequate water absorbency of the fabrics. The necessity of surfactants application in scouring was outlined.

Bleaching of the fabrics was performed with hydrogen peroxide, which was enzymatically produced by glucose oxidase during oxidation of glucose. The aeration plays an important role in the enhancement of the enzyme reaction, so that the quantity of generated peroxide is sufficient to overcome the stabilizing effect of the glucose and protein in the subsequent bleaching. A closed-loop process reusing starch containing desizing baths in a single step scouring/bleaching operation with enzyme-generated peroxide was performed.

Yachmenev et al., (2001) studied effect of sonication on cotton preparation with alkaline pectinase. This research has shown that at the laboratory scale, introducing ultrasonic energy into the reaction chamber during enzymatic scouring of the greige cotton fabric significantly improves pectinase efficiency, but does not decrease the tensile strength of cotton fabric. That alkaline pectinase appears to be a more efficient agent for biopreparation of greige cotton than acidic pectinase, resulting in better wettability and whiteness. Also establish that the combination of pectinase bioscouring with desizing and after-washing insures sufficient fabric wettability with adequate uniformity. The results are comparable to or better than those for fabric after traditional alkaline scouring. Introducing ultrasonic energy could help overcome the major disadvantage of pectinase scouring-a longer processing time compared to conventional alkaline scouring.

Waddell (2002) studied bioscouring of cotton with pectinase enzyme. The role of enzymes in the processing of natural fabrics is reviewed with alkaline stable pectinase a recent addition. Alkaline scouring and its attendant effects are described, followed similarly by bioscouring. Three factors determine pectinase activity and efficiency: time, temperature and pH. Batch processed cotton and poly/cotton knits were selected for study. Three treatments of cotton woven fabrics were covered: pad batch, batch or continuous preparation with the adaptation of the bioscour procedure to each of those covered. It was shown that many advantages surfaced: similar cost comparisons with chemical processes; reduced scouring time; improves scouring efficiency; smoother dyeing among others.

2.2 Model Predictive Control

The idea of model predictive control (MPC) appears to have been proposed long before MPC came to the forefront (Propoi, 1963). MPC was the first implemented in industry under various guises and names long before a thorough understanding of its theoretical properties was available. The first MPC techniques were developed on the 1970s because conventional single-loop controllers were unable to satisfy increasingly stringent performance requirements (Qin and Badgwell, 1977). In the late 1970s Richalet et al. described a successful application of a technique that called Model Heuristic Predictive Control (MHPC) or Model Algorithmic Control (MAC). In 1979 Shell engineers describe the Dynamic Matrix Control (DMC) technique and the results of its application. MPC has established itself over the past decade as an industrially important form of advanced control.

Ricker (1990) developed a state space formulation of the multivariable model-predictive controller with provisions for state estimation. Hard constraints on the manipulated variables and outputs were accommodated, as in Quadratic Dynamic Matrix Control (QDMC) and related algorithms. For unconstrained problems, a low-order analytical form of the controller is obtained. The potential benefits of MPC with state estimation are demonstrated for the case of dual-composition, LV control of the high-purity distillation column problem studied previously by Skogestad and Morari, which is an especially challenging problem for MPC-type algorithms. It is shown that the use of the state estimator with a single tuning parameter (beyond that required for standard MPC) provides robust performance equivalent to the best p-optimal controller designed by Skogestad and Morari.

Eaton and Rawlings (1992) purposed 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.

Sistu et al., (1993) discussed the implementation of different nonlinear strategies in a MPC framework to control an exothermic continuous stirred tank reactor. The computational efficiency of an MPC strategy depends on the method used to predict model outputs within the optimization loop. The computational requirements of collocation and numerical-based methods to solve nonlinear differential modeling equations are compared with the nonlinear quadratic dynamic matrix control (NLQDMC) formulation. The convolution coefficients for NLQDMC are obtained using analytical and numerical methods and their computational time requirements are compared.

Patwardhant and Madhavan (1993) presented the development of an approximate second-order perturbation model, which can be used for single step and multistep predictive control. The algorithm has been successfully implemented on two continuously stirred tank reactors (CSTRs) control problem where the control objective is to operate the reactor at an extremum point. The control problem is associated with the singular nature of the operating point has been successful tackled by the purposed algorithm. The MPC algorithm based on the proposed second-order model is shown to improve the closed loop performance when compared to other nonlinear MPC algorithms. The proposed algorithm has been found to be robust for moderate variations in the kinetic parameters.

Masoud et al., (1995) used the 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.

Phupaichitkun (1998) applied model predictive control (MPC) to control the temperature of a batch reactor with exothermic reactions and its performance is compared with generic model control (GMC) to that of individually/simultaneously plant/model mismatches. In addition, Kalman Filter that used to estimate the heat released of chemical reactions is incorporated into the MPC and GMC. Simulation studies are shown that MPC to be as good as GMC for all cases for which both controllers are well tuned.

Ruksawid (1999) used 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. 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 set point tracking. In addition, the MPC is more robust than the PID in presence of model/plant mismatch.

Ralhan and Badgwell (2000) presented two robust model predictive control algorithms for linear integrating plants described by a state space model. The first formulation focused 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 is 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 compared the performance of these algorithms with those based on minimizing the worst-case controller cost.

Tongmeesee (2000) presented the application of MPC to control the temperature of a batch polymerization reactor. 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 in normal case and presence of plant/model mismatch (decrease in heat transfer coefficient and rate of termination reaction and increase of the monomer concentration and heat of reactions), MPC with Kalman filter give a better control performance than GMC with Kalman filter.

Brempt et al. (2001) presented the advanced model predictive control technology based on rigorous dynamic models. Key requirements of the new technology are the realization of a flexible process operation, a large bandwidth control enabling tight quality control and low application costs. The flexible operation is realized by the combination of a dynamic optimizer over a rigorous model together with a model predictive controller in delta-mode. A large bandwidth control is enabled by the use of high frequent prediction models. Ultimately, reuse of large parts of rigorous models for different applications together with low frequency testing on these rigorous models reduces the application cost. The application of the before mentioned technology is shown successfully on a polyethylene gasphase reactor simulator. A considerable economic benefit can be obtained optimizing the transition trajectory as well as the throughput at that time.

Weerachaipichasgul (2003) applied MPC to control the flux of liquid-solid cross flow ultrafiltration membrane separator. This process used the transmembrane pressure is manipulated to control the permeated flux of water in two cases; to control the flux at a constant set point obtained from an overall optimization and 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 in the first case but it cannot control the flux in the second case. For MPC controller, it can control the flux at the set points obtained from both overall and dynamic optimization.

2.3 Kalman Filter

In most industrial processes, the process parameters and state variables are not all measurable or, not with sufficient accuracy for control purposes. Furthermore, measurements that are available often contain significant amounts of random noise and systematic errors.

State variables of a process determine uniquely the state of the process and are either measured directly or estimated using a state estimator. On the other hand, process parameters provide a mathematical model with flexibility to fit process measurements, are often of great physical importance, and are usually not measured directly. Information on unknown process parameters can be obtained indirectly by means of a parameter estimator. In 1960, Kalman published a famous paper describing a recursive solution to the discrete data linear filtering problem. The Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation.

Tan et al. (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.

Wang et al. (1993) presented 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.

Sargantanis and Karim (1994) applied adaptive control with an iterative extended Kalman filter (IEKF) to control the solid substrate fermentation process. In solid substrate fermentation (SSF), the online measurements of the states of the fermentation like biomass content, dry matter content, and moisture content are not possible. Also, the control of the temperature and the moisture content is critical for optimization of the process. A multivariable adaptive control structure along with state estimation using an iterative extended Kalman filter (IEKF) is proposed for the control. The IEKF uses the measurements of total wet weight and $C0_2$ evolution rate to estimate the states. The simulation results show that a better control of the moisture content can be achieved when compared to the single input-single output (SISO) control strategy.

Gudi et al. (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.

Sirohi and Choi (1996) persented two different on-line parameter estimation methods applied to estimate key kinetic parameters of transition-metal-catalyzed in a continuous fluidized bed olefin copolymerization process. The extended Kalman filter and the nonlinear dynamic parameter estimation technique have been used. Simulation results show that both methods yield quite acceptable performance. Parameter estimation using an extended Kalman filter is shown to perform robustly even in the presence of substantial measurement noise because of greater flexibility in tuning parameters. The nonlinear dynamic parameter estimation technique which utilizes nonlinear programming (NLP) can be made robust to measurement noise by taking frequent samples of the polymer properties.

Tatiraju and Soroush (1997) applied the nonlinear reduced order observer design method to a continuous polymerization reactor where free-radical solution polymerization of methyl methacrylate takes place. Initiator and solvent concentrations and the leading moments of the molecular weight distribution of the polymer are estimated in three measurement cases. In each case, the implementation and performance of the nonlinear observer are compared with those of a deterministic extended Kalman filter.

Bamrungwongdi (1998) presented 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.

Ahn et al. (1999) used the extended Kalman filter (EKF) based nonlinear model predictive controller (NLMPC) that implemented experimentally to control the conversion and the weight-average molecular weight of the polymer product in a continuous methyl methacrylate (MMA) polymerization reactor. To measure the properties of the polymer on line, the densitometer and the viscometer were utilized in such a way that the measured values of density were used to calculate the conversion and the viscosity measurement along with conversion data was used to determine the weight-average molecular weight. On the basis of the experimental results, EKF based NLMPC performed quite satisfactorily for the property control of the continuous polymerization reactor.

Lersbamrungsuk (2000) designed and developed 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. The other one is kSTAPEN-C, the component is developed by technology of Component Object Model (COM). 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.

Moolasartsatorn (2002) used an extented Kalman filter to estimate the heat release of pervaporative membrane reactor. 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.

CHAPTER III

THEORY

The textile industry is one of the oldest in the world. Broadly defined, the textile industry consists of establishments engaged in spinning natural and manmade fibers into yarns and threads. These are then converted into fabrics. Finally, the fabrics and in some cases the yarns and threads used to make them, are dyed, printed, and finished. Product development and innovation in this industry are vital. Success in the industry has always hinged on the ability of producers to innovate.

This chapter provides a brief overview of the textile industry process in Section 3.1 and fabric preparation in Section 3.2. Some background information necessary for understanding Model Predictive Control (MPC) and Kalman filter are presented in Section 3.3 and 3.4, respectively.

3.1 Textile Industry Process

The textile industry is comprised of a diverse, fragmented group of establishments that produce and/or process textile-related products (fiber, yarn, and fabric) for further processing into apparel, home furnishings, and industrial goods. Textile manufacturing begins with the production or harvest of raw fiber. Fiber used in textiles can be harvested from natural sources (wool, cotton) or manufactured from regenerative cellulosic materials (rayon, acetate), or it can be entirely synthetic (polyester, nylon). Then the raw natural or manufactured fibers pass through several stages to change these fibers to the various stages of production. The stages can be divided in four main stages as follow:

1. Yarn formation
2. Fabric formation
3. Wet processing
4. Fabrication

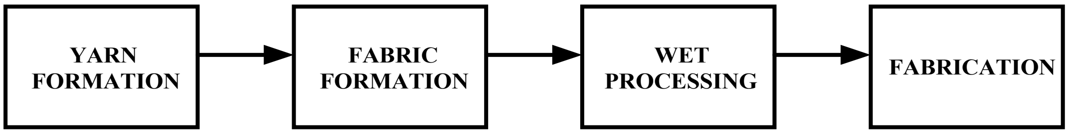

Figure 3.1 Production stages of textile industry process.

In its broadest sense, the textile industry includes the production of yarn, fabric, and finished goods. These sections below focuses on the following four production stages, with a brief discussion of the fabrication of non-apparel goods.

3.1.1 Yarn Formation

Yarn formation is preparing and spinning raw materials (natural and synthetic) or texturizing man-made filament fibers. Textile fibers are converted into yarn by grouping and twisting operations used to bind them together. Although most textile fibers are processed using spinning operations, the processes leading to spinning vary depending on whether the fibers are natural or manmade. Natural fibers need to go through different preparation steps before being spun into yarn but for manmade fibers, just one step of texturizing is needed before spinning (the process used resembles the manufacture of silk).

3.1.2 Fabric Formation

The major methods for convert yarn to fabric are weaving and knitting. Weaving, or interlacing yarns, is the most common process used to create fabrics, while knitting is the second most frequently used method of fabric formation.

Fabrics are formed from weaving by interlacing one set of yarns with another set oriented crosswise. The length-wise yarns that form the basic structure of the fabric are called the warp and the crosswise yarns are called the filling or weft. While the knitted fabrics may be constructed by using hooked needles to interlock one or more sets of yarns through a set of loops. The loops may be either loosely or closely constructed, depending on the purpose of the fabric.

Yarn can be processed directly through knitting operations but typically requires preparation before weaving operations because while the filling yarns undergo little strain in the weaving process, warp yarns undergo much strain during weaving and must be processed to prepare them to withstand the strain. Preparation for weaving includes warping and slashing (sizing).

3.1.3 Wet Processing

Woven and knit fabrics cannot be processed into apparel and other finished goods until the fabrics have passed through several water-intensive wet processing stages. Wet processing enhances appearance, durability, and serviceability of the fabrics by converting undyed and unfinished goods, known as gray or greige goods, into finished consumers' goods. Also collectively known as finishing, wet processing has been broken down into four main stages in this section for simplification: fabric preparation, dyeing and/or printing, and finishing. These stages involve treating gray goods with chemical baths and often require additional washing, rinsing, and drying steps. Note that some of these steps may be optional depending on the style of fabric being manufactured.

3.1.4 Fabrication

The fabrication step includes cutting and sewing of the fabric to form the finished product that a variety of apparel, household and industrial products. The cutting trades usually fabricate apparel and more complex housewares. Before cutting, fabrics must be carefully laid out. Accuracy in cutting the lay fabric is important since any defects created at this point may be carried through other operations and end up in the final product. For simple household and industrial products, sewing is relatively straightforward. The product may then be pressed to flatten the fabric and create crisp edges.

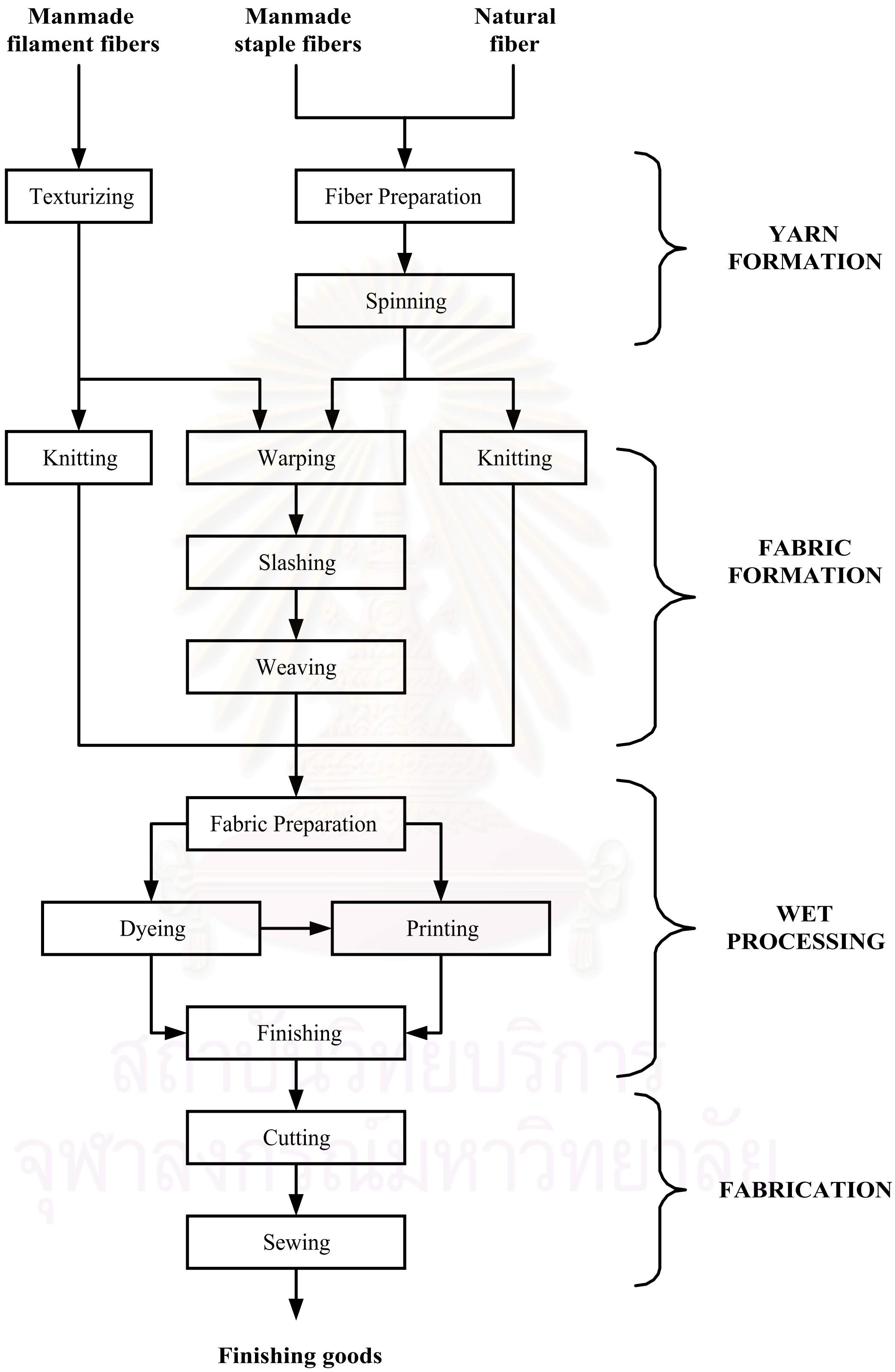

Figure 3.2 Textiles processing flow chart

3.2 Fabric Preparation Process

Wet processing includes several steps that involve preparation step, imparting colors or patterns to the fabric, along with a variety of finishing steps that provide certain desired characteristics to the end product. Fabric preparation or pretreatment step is greatly influenced with the next steps (dyeing and/or printing, and finishing). Improper preparation is often the cause of problems encountered in the dyeing and finishing steps. Most fabric must be prepared before dyeing, printing or finishing.

Fabric preparation is the first of the wet processing that may be taken to removes impurities or processing chemical that interfere with dyeing, printing, and finishing from the fabric. It consists of a series of various preliminary cleaning treatments and rinsing steps. The main steps can be listed as follows.

1. Desizing
2. Scouring
3. Bleaching

There are many different fabric types in the textile industry. Perhaps, fabric preparation can also include processes, such as singeing and mercerizing, designed to chemically or physically depend on the fabric and the fiber type.

3.2.1 Desizing

Desizing is an important preparation step used to remove sizing materials applied to warp yarns prior to weaving. Different removal methods are used, based on the type of size that was applied to the yarn. It is therefore necessary to know what type of size is on the fabric before desizing.

Size materials are applied to warp yarns to improve their strength before they are woven into cloth in the weaving process. The sizing materials form a protective coating over the yarns and prevent chafing or break-age during weaving. Chemicals used as sizing agents may be divided into two categories:

1. Water-soluble sizes, such as PVA and CMC.
2. Water-insoluble sizes, such as starch.

Other additives such as oils and waxes are often used in conjunction with sizing agents to increase the softness and pliability of the yarns. The material coated the yarns can act as a dye and chemical resist in textile wet processing. It must therefore be removed before any subsequent wet processing of the fabric.

Manmade fibers are generally sized with water-soluble sizes that are easily removed by a hot-water wash or in the scouring process. On the other hand, natural fibers such as cotton are most often sized with water-insoluble starches or mixtures of starch and other size materials.

3.2.1.1 Desizing Starch

Starch is the most difficult size to remove. It does not readily dissolve in water and must be broken down chemically into water-soluble compounds by enzymes, or oxidizing agents, or acids. Enzymes breakdown starch into water soluble sugars and dextrines, oxidizing agents oxidize starch into compounds that are soluble in alkaline solution, while acids hydrolyze starch into water soluble compounds. Enzymes are specific in their action in that they do not attack cotton, while oxidizing agents and acids can degrade cotton in addition to starch. Starch is therefore usually desized with enzymes.

3.2.1.2 Desizing PVA

Synthetic polymer sizes such as polyvinyl alcohol (PVA) and carboxy-methyl cellulose (CMC) are very popular because in most cases they are very easy to remove compared to starch. Care must be taken in desizing these sizes because they are available in many grades with varying solubility properties.

PVA is desized with a hot water and rinsing in hot water to complete the removal. The optimum wash temperature is a function of the grade used to size the warp yarns. Lower molecular weight, partially hydrolyzed grades require lower temperatures than fully hydrolyzed, high molecular weight ones. Temperatures near the boil are required for the fully hydrolyzed grades.

After desizing, the fabric should be systematically analyzed by 'Iodine spot test' to determine the uniformity and thoroughness of the treatment. It should first be weighed to determine the percent size removed. The results should be compared to those obtained in the lab.

3.2.2 Scouring

Natural fibers contain oils, fats, waxes, minerals, leafy matter and motes as impurities. Synthetic fibers contain producer spin finishes, coning oils and/or knitting oils. Mill grease used to lubricate processing equipment mill dirt, temporary fabric markings and the like may contaminate fabrics as they are being produced. These impurities coat fibers and inhibit rapid wetting, absorbency and absorption of dye and chemical solutions.

Scouring is a cleaning process that removes impurities from fibers, yarns, or cloth through washing. Oils and fats are removed by saponification with hot sodium hydroxide solution. This process breaks the compounds down into water-soluble glycerol and soaps and is the same process traditionally used in the home to make soaps from animal fat. Unsaponifiable materials such as waxes and dirt are removed by emulsification. This process requires the use of surfactants to disperse the water insoluble material into fine droplets or particles in the aqueous medium. The specific scouring procedures, chemicals, temperature, and time vary with the type of fiber, yarn, and cloth construction.

Properly scoured fabric should wet out faster and be more water absorbent. After scouring, the fabric should be checked for thoroughness of scouring. 'AATCC Test Method No.79' is used to measure fabric wetting. This method is using a clean eyedropper place a drop of water on the fabric and measure the time required for the drop to penetrate the fabric. The faster the wetting time, the more absorbent the fabric.

3.2.3 Bleaching

The whiteness of fiber is an important market color so the whitest white has commercial value. Yellow is a component of derived shades. For example, when yellow is mixed with blue, the shade turns green. A consistent white base fabric has real value when dyeing light to medium shades because it is much easier to reproduce shade matches on a consistent white background than on one that varies in amount of yellow.

Bleaching is a chemical process that eliminates unwanted colored matter from fibers, yarns, or cloth to produce the whitened fabric. Bleaching can be decolorizes colored impurities, which are not removed by scouring, and prepares the cloth for further the next processes. Several different types of chemicals are used as bleaching agents, and selection depends on the type of fiber present in the yarn, cloth, or finished product and the subsequent finishing that the product will receive.

The major bleaching agents used in textile preparation are sodium hypochlorite, hydrogen peroxide and sodium chlorite. All of these are oxidative bleaches. Oxidative bleaches are also known to degrade cellulose so the objective in bleaching is to optimize whitening and minimize fiber damage.

3.2.3.1 Sodium Hypochlorite

Hypochlorite bleaching agent $\left(OCl^-\right)$ is the oldest industrial method of bleaching cotton. Originally, calcium hypochlorite $Ca(OCl)_2$ was used. Sodium hypochlorite $\left(NaOCl\right)$ is the strongest oxidative bleach used in textile processing. Prior to bleaching with hypochlorite, it is necessary to thoroughly scour fabrics to remove fats, waxes and pectin impurities. These impurities will deplete the available hypochlorite, reducing its effectiveness for whitening fabric.

This agent is used mainly to bleach cellulosic fabrics. It cannot be used on wool, polyamide (nylon), acrylics or polyurethane (spandex). These fibers will yellow from the formation of chloramides. Bleaching with hypochlorite is performed in batch equipment. It is not used in continuous operations because chlorine is liberated into the atmosphere. Over time, the pad bath decreases in active chlorine causing non-uniform bleaching from beginning to end of the run.

3.2.3.2 Hydrogen Peroxide

Hydrogen peroxide $\left(H_2O_2\right)$ was first used to bleach cotton in the 1920's. It is the bleach most widely used for cellulosic fibers and well as wool, silk, nylon and acrylics. Today, it is estimated that 90 to 95% of all cotton and cotton/synthetic blends are bleached with hydrogen peroxide. Unlike hypochlorites, peroxide bleaching does not require a full scour. Residual fats, oils, waxes and pectines do not reduce the bleaching effectiveness of hydrogen peroxide. Additionally it can be used on continuous equipment.

Hydrogen peroxide is an extremely weak acid and ionizes in water to form a hydrogen ion $\left(H^+\right)$ and perhydroxyl ion $\left(HOO^-\right)$. The perhydroxyl ion is the active bleaching agent.

$$H_2O_2+H_2O \leftrightarrow H^+ + HOO^- \tag{3.1}$$

On the other hand, the reaction below is not desired in bleaching because it is an ineffective use of hydrogen peroxide and causes fiber damage.

$$H_2O_2 \rightarrow H_2O+\frac{1}{2}O_2 \tag{3.2}$$

Neutral hydrogen peroxide is not an effective bleaching agent. It must be activated by adding alkali, such as sodium hydroxide $\left(NaOH\right)$, to increase pH and generate the perhydroxyl ion that shown in equation (3.3) and (3.4), respectively.

$$H_2O_2+NaOH \leftrightarrow NaHO_2+H_2O \tag{3.3}$$

$$NaHO_2 \leftrightarrow Na^+ + HOO^- \tag{3.4}$$

Sodium hydroxide is used to obtain the proper pH. At pH higher than 11, there is a rapid generation of perhydroxyl ions. When the pH reaches 11.8, all of the hydrogen peroxide is converted to perhydroxyl ions and bleaching is out of control.

After bleaching, the fabric should be measured the whiteness and fluidity. AATCC Test Method 110 measures the amount of blue light reflected by the goods, against a white standard (usually a ceramic tile). This gives a measure of how well the yellow impurities were removed by bleaching. Whiteness is measured by reflectance of green light and by the removal of yellow impurities.

While the fluidity is measured the damaged cellulose that has a lower molecular weight than undamaged cellulose. Fluidity is measured by dissolving cotton in cupriethylene diamine and determining the solutions's viscosity. Viscosity of polymer solutions is directly related to the polymer's molecular weight so a fluidity measurement, in reality, is a viscosity measurement. The difference between viscosity and fluidity is the units used to express the results. Viscosity measurements use water as the reference standard, setting it equal to 1 centipoise. Therefore the higher the polymer molecular weight, the higher the viscosity number. The fluidity scale (Rhes) is just the opposite of the viscosity scale. Low numbers are used to describe high viscosity solutions while high numbers describe low viscosity (more fluid) ones. Undamaged cellulose will have low fluidity numbers and damaged cellulose will have high ones.

3.3 Model Predictive Control

Model Predictive Control (MPC) refers to a class of control algorithms in which a dynamic process model is used to predict and optimize process performance. The first MPC techniques were developed in the 1970s because conventional single-loop controllers were unable to satisfy increasingly stringent performance requirements (Qin and Badgwell, 1997).

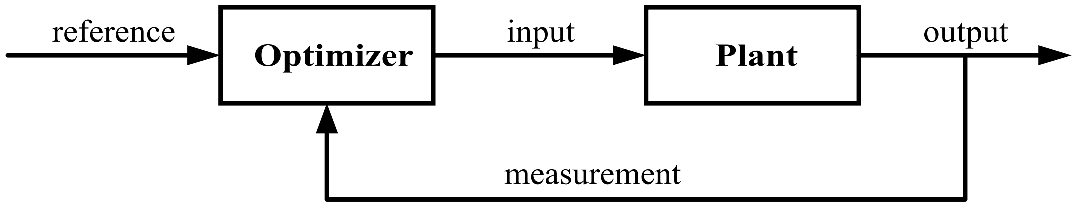

Figure 3.3 Basic structure of MPC

From the diagram that shown in figure 3.3, the came MPC originates from the idea of employing an explicit model of the plant to be controlled to predict the future output behavior. The prediction is used to determine optimal control moves that will bring the plant to a desired condition. The current control action is obtained by solving an on-line finite horizon open loop optimal control problem, using the current state of the plant as the initial state. The optimization problem is solved subject to constraints imposed by the model equations as well as in put and output constraints, and yields an optimal control sequence. However, only the first control in this sequence is applied to the plant. Once some feedback information is available, the optimization is then repeated for the next sampling time interval. Figure 3.3 illustrates the basic idea of MPC that called "receding horizon implementation".

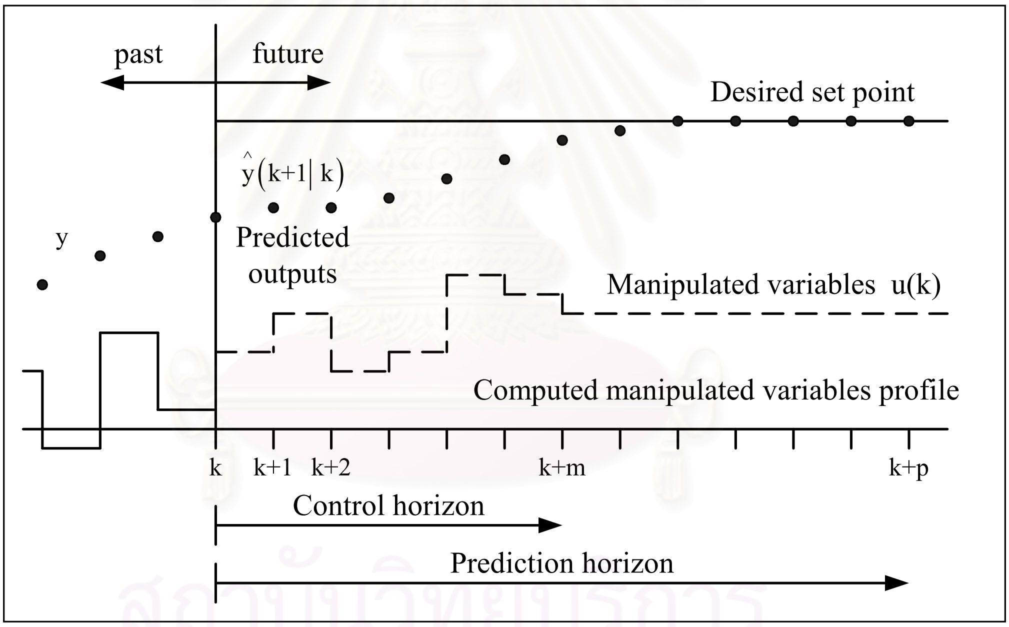

Figure 3.4 Receding horizon strategy

Figure 3.4 depicts the basic idea receding horizon behind model predictive control. Predict the future dynamic behavior of the system or the predicted output values over a prediction horizon (p), and determines a set of future control input minimizing a predetermined objective function (performance index). It has been known that if there were no disturbance and no plant-model mismatch, and if the optimization problem could be solved for infinite horizons, ones could apply the sequence of the control input profile calculated at time k to the system. However, in the presence of unknown disturbance and/or plant-model mismatch, the dynamic system behavior is different from the predicted behavior. To make use some feedback information e.g. measurement and estimation, only the initial value of the control profile computed is applied to the system and then, after obtaining new information at the next sampling time, the optimization procedure is repeated to find a new control input with the control and prediction horizons shifting ahead one sampling time step. This results in a feedback control law; closed loop inputs are computed by solving on-line the optimization problem at each sampling time based on new feedback information from the system.

It is noted that as the MPC determines the manipulated variables by solving the optimization problem, it can naturally take into account constraints on state and control variables in the MPC formulation. This makes the MPC controller very attractive for real industrial application.

3.3.1 MPC Formulation

State space: $\dot{x} = f\left[x(t), u(t)\right]$ (3.5)

Objective function: $\min \int_0^{t_f} \left\{ w_1 \left(x - x_p \right)^2 + w_2 \left(\Delta u \right)^2 \right\} dt$ (3.6)

Constraint’s manipulated variable: $u_{\min} < u\left(t\right) < u_{\max}$ (3.7)

Fix’s control variable: $x\left(t + t_f\right) = x_{sp}$ (3.8)

where w_1, w_2 is weighting factors, t_f is end time, and $u_{\min}, u_{\max}$ are minimum and maximum of constraint’s manipulated variable, respectively.

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3.3.2 Process Model

General form of process model for representing the real process can be written as below.

$$\dot{x} = f(x, u) \tag{3.9}$$

$$y = g(x, d) \tag{3.10}$$

where f is process dynamic, x is state variable vector, u is manipulated variable vector, and y is output variable vector.

State equation in this research is in state space form, which is a linear model. In case the process model is a nonlinear type, after linearization, state equation of the model both continuous and discrete form can be written as below.

Continuous equation

$$\dot{x} = Ax + Bu \tag{3.11}$$

$$y = Cx \tag{3.12}$$

where A, B and C are constant matrixes.

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

Discrete equation

$$x_{k+1} = Gx_k + Hu_k \tag{3.13}$$

$$y_k = Cx_k \tag{3.14}$$

when G, H and C are constant matrixes.

3.3.3 Process Constraint

An important characteristic of process control problems is the presence of constraint on input and output variables. Input constraints arise due to actuator limitations such as saturation and rate of change restrictions. Output constraints usually are associated with operational limitations such as equipment specifications and safety considerations.

There are many different methods to classify constraints. One possible method is categorized to equality constraint and inequality constraint. The inequality constraint can be divided to hard constraint and soft constraint. Hard constraints has no dynamic violations of the bounds are allowed at any time, while soft constraints, violations of the bounds are temporarily permitted on order to satisfy other heavily weighted criteria.

Control constraints generally appear in the MPC problem because, in real application, an ability to manipulate the control variables in always limited. Path constraints are included in the MPC formulation if some of state variables cannot exceed a given limit during the course of process operation. From equation (3.13) and (3.14), model predictive control system can be cooperated with equality constraint and inequality constraint as shown below.

Equality constraint: $$Gx_k + Hu_k - x_{k+1} = 0 \tag{3.15}$$

Inequality constraint: $$u_{k,\min} \leq u_k \leq u_{k,\max} \tag{3.16}$$

3.3.4 Objective Function

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

$$J = \frac{1}{2}\left[(x_{sp} - x)^T Q (x_{sp} - x) + (u_k - u_{k-1})^T R (u_k - u_{k-1})\right] \tag{3.17}$$

or $$J = \frac{1}{2}\left[x^T Q x + u^T R u\right] \tag{3.18}$$

where Q and R are weighting factor matrix of state variable and manipulated variable, respectively. These two matrixes are 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 form as follow.

Continuos equation: $$J = \int_{t}^{t+N_p} \frac{1}{2}\left[x^T Qx + u^T Ru\right]dt \tag{3.19}$$

MPC can be control the controlled variables to be their set point within time $k+N_m$. The movement of manipulated variables and state variables change is zero after time is $k+N_m$. From equation (3.17), the objective function can be rewritten in form below.

Discrete equation: $$J = \sum_{k}^{k+N_m} \frac{1}{2}\left[x^T Qx + u^T R_2 u\right] \tag{3.20}$$

3.3.5 Process Optimization

When applying method of optimization, Lagrange Multiplier's principle, then the objective function can be written as follow.

Continuos equation: $$L(x,u) = \sum_{t}^{t+N_m} \frac{1}{2}\left[(x^T Qx + u^T Ru) + \dot{\lambda}(Gx + Hu - x)\right] \tag{3.21}$$

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

where $\lambda(t) \in R^n$ is Largrange Multiplier n equation.

After solving the equation by fixed $\lambda_k = P_k x_k$, we obtained Ricatti equation in equation (3.23).

$$P_k = Q + G^T P_{k+1} G - G^T P_{k+1} H[R + H^T P_{k+1} H] H^T P_{k+1} G \tag{3.23}$$

From close loop, $$u_k = -Kx_k \tag{3.24}$$

Then the controller gain (K) is $$K = -R^{-1} H^T (G^T)^{-1} (P_k - Q) \tag{3.25}$$

3.3.6 MPC Algorithm

In this thesis, the model predictive control algorithm can be written as follow.

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

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

3. Set optimize objective function

$$L(x,u)=\sum_{k}^{k+N_m}\frac{1}{2}\left[(x_k^T Q x_k + u_k^T R u_k)+\lambda_{k+1}(Gx_k + Hu_k - x_{k+1})\right].$$

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

5. Calculated the controller gain $K=-R^{-1}H^T\left(G^T\right)^{-1}\left(P_k - Q\right)$.

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

7. Go to step 1.

3.4 Kalman Filter

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

$$x_k = A_K x_{k\text{-}1} + B_K u_k + w_{k\text{-}1} \tag{3.26}$$

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

$$y_k = C_{K,k} x_k + \eta_k \tag{3.27}$$

The random variables w_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

$$P_K\left(w\right) \approx N\left(0, Q_K\right) \tag{3.28}$$

$$P_K\left(\eta\right) \approx N\left(0, R_K\right) \tag{3.29}$$

In practice, the process noise covariance $\left(Q_K\right)$ and measurement noise covariance $\left(R_K\right)$ matrix might change with each time step or measurement, however here they are assumed to be constant.

The $n \times n$ matrix A_K in the difference equation (3.26) 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_K might change with each time step, but here it is assumed to be constant. The $n \times 1$ matrix B_K relates the optional control input $u \in \Re^1$ to the state x. The $m \times n$ matrix C_K in the measurement equation (3.27) relates the state to the measurement y_k. In practice C_K might change with each time step or measurement, but here it is assumed to be constant.

3.4.1 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 then

$$P_{K,k}^- = E[e_k^- e_k^{-T}] \tag{3.30}$$

and the a posteriori estimate error covariance is

$$P_{K,k} = E[e_k e_k^T] \tag{3.31}$$

An a posteriori state estimate $\hat{x}_k$ is computed as a linear combination of an a priori estimate $\hat{x}_k^-$ and a weighted difference between an actual measurement y_k and a measurement prediction $C_K \hat{x}_k^-$ as shown below in equation (3.32). Some justification for equation (3.32) is given in the probabilistic origins of the filter found below.

$$\hat{x}_k = \hat{x}_k^- + K(y_k - C_K \hat{x}_k^-) \tag{3.32}$$

The difference $y_k - C_K \hat{x}_k^-$ in equation (3.32) is called the measurement innovation, or the residual. The residual reflects the discrepancy between the predicted measurement $C_K \hat{x}_k^-$ and the actual measurement y_k. A residual of zero means that the two are in complete agreement.

The $n \times m$ matrix K_K in equation (3.32) is chosen to be the gain or blending factor that minimizes the a posteriori error covariance equation (3.31). This minimization can be accomplished by first substituting equation (3.32) into the above definition for e_k, substituting that into equation (3.31), performing the indicated expectations, taking the derivative of the trace of the result with respect to K_K, setting that result equal to zero, and then solving for K_K. One form of the resulting K_K that minimizes equation (3.31) is given by:

$$K_{K,k} = P_{K,k}^{-} C_K^T (C_K P_{K,k}^{-} C_K^T + R_K)^{-1} \tag{3.33}$$

From equation (3.33) as the measurement error covariance R_K approaches zero, the gain K_K weights the residual more heavily.

$$\lim_{R_{K,k} \to 0} K_{K,k} = C_K^{-1} \tag{3.34}$$

Another way of thinking about the weighting by K_K is that as the measurement error covariance R_K approaches zero, the actual measurement y_k is trusted more and more, while the predicted measurement $C_K \hat{x}_k^{-}$ is trusted less and less. On the other hand, as the a priori estimate error covariance $P_{K,k}^{-}$ approaches zero the actual measurement y_k is trusted less and less, while the predicted measurement $C_K \hat{x}_k^{-}$ is trusted more and more.

3.4.2 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 into 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 a 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 a priori estimate to obtain an improved a posteriori estimate. The specific equations for the time and measurement updates are presented as follow.

1. Time update equations (predict equations).

Project the state ahead: $$\hat{x}_k^- = A_K \hat{x}_{k-1} + B_K u_k \qquad (3.35)$$

Project the error covariance ahead: $$P_{K,k}^- = A_K P_{K,k-1} A_K^T + Q_K \qquad (3.36)$$

2. Measurement update equations (correct equations).

Compute the Kalman gain: $$K_{K,k} = P_{K,k}^- C_K^T (C_K P_{K,k}^- C_K^T + R_K)^{-1} \qquad (3.37)$$

Update estimate with measurement y_k: $$\hat{x}_k = \hat{x}_k^- + K_{K,k}(y_k - C_K \hat{x}_k^-) \qquad (3.38)$$

Update the error covariance: $$P_{K,k} = (I - K_{K,k} C_K) P_{K,k}^- \qquad (3.39)$$

The time update equations can also be thought of as predictor equations, 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 shown in Figure 3.5

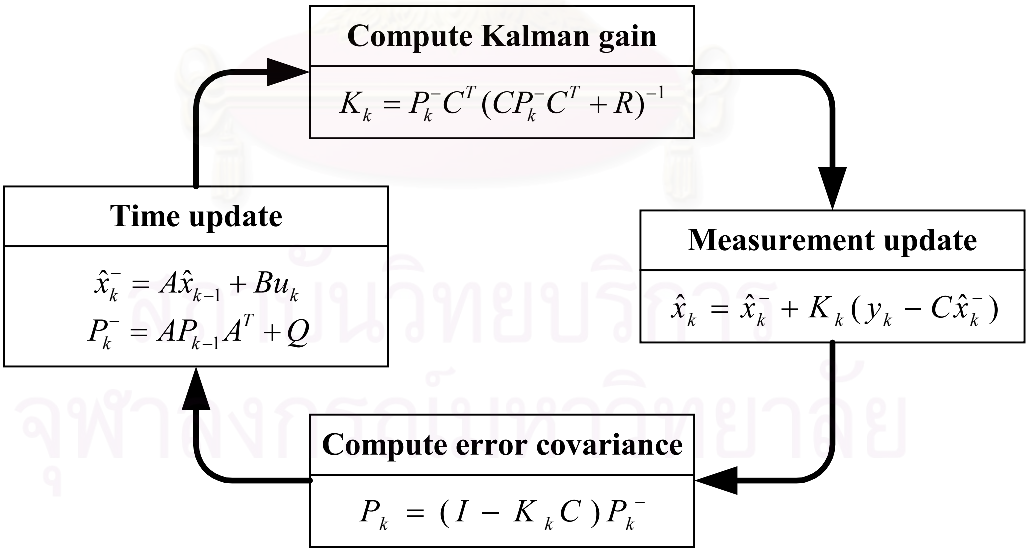


Figure 3.5 Kalman filter loop

3.4.3 Kalman Filter Parameters 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_K 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 uncertainty into the process via the selection of Q_K.

The tuning of the parameters Q_K and R_K is usually performed off-line, frequently with the help of another (distinct) Kalman filter in a process generally referred to as system identification. Under conditions where Q_K and R_K are in fact constant, both the estimation error covariance $P_{K,k}$ and the Kalman gain $K_{K,k}$ will stabilize quickly and then remain constant.

CHAPTER IV

A CONTINUOUS FABRIC PREPARATION PROCESS

Fabric preparation consists of a series of various preliminary cleaning treatments and rinsing steps critical to obtaining good results in subsequent textile finishing processes. Typical preparation treatments include desizing, scouring, and bleaching. Preparation steps can also include processes, such as singeing and mercerizing, designed to chemically or physically alter the fabric. However, some fabric may only require one or two steps to complete the preparation process.

The preparation steps can be carried out as either batch or continuous processes. In batch processing, the entire load of fabric is immersed in the total amount of liquid needed for that process. The fabric is moving through the liquor or both the liquid and the fabric move in relation to each other. This method is limited for total volume of fabric that used in each time. While continuous preparation, the fabric passes non-stop through compartments or stages. It increases the rate of interchange between the liquid and fabric therefore it can be receive larger volume of fabric than the batch processing.

4.1 Process Description

In this work, a continuous fabric preparation process is considered. The study is aimed the single-step fabric preparation in the first tank and the counter flow washing of rising step in the second and the third tanks. The fabric fed through each tank as a continuous rope or as an open width sheet. An open width range has the stacked rollers to handle the fabric where the lower rollers are submerged in the wash water and the upper rollers used to remove the liquid from the fabric. In the first tank, the fabric is impregnated with chemicals solution that reacted the sizing and impurities in the fabric. Hydrogen peroxide $\left(H_2O_2\right)$ and sodium hydroxide $\left(NaOH\right)$, which feed in the first tank, are reacted to form perhydroxyl ion $\left(HOO^-\right)$ as follow in equation (4.1) and (4.2). The perhydroxyl ion is the active agent to react with the impurities in fabric.

$$H_2O_2 + NaOH \leftrightarrow NaHO_2 + H_2O \tag{4.1}$$

$$NaHO_2 \leftrightarrow Na^+ + HOO^- \tag{4.2}$$

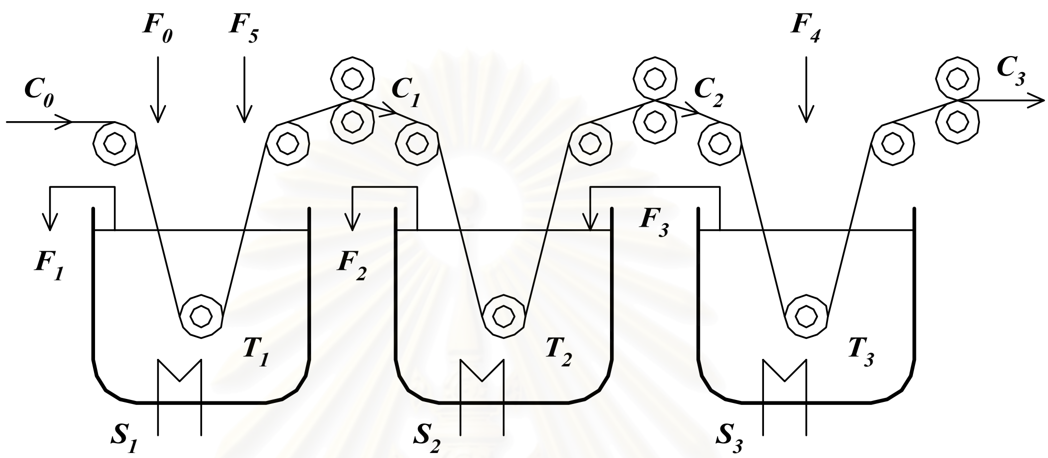


Figure 4.1 Flow sheet of a continuous fabric preparation process.

The rinsing step in the second and the third tank is the counter flow washing. The water flow and fabric flow is countercurrent. Technically, the use of multiple cascade rinse tanks is very effective in reducing the volume of the rinse water used. According to present by Tomasino (1992), one way to reduce water consumption is by counter flow washing. Water flow through the wash boxes counter to the flow of the fabric. Fresh water is fed to the exit compartment to insure that the fabric exits through the cleanest water. The water from the last box is pumped to the preceding wash box, which in turn is pumped to the one preceding it. The water from the entry box is dumped into the drain since it is the most heavily contaminated wash water.

In continuous preparation, the fabric moves continuously through stages and compartments, which provide the chemical concentration, time, and temperature to improve the performance of cleaning fabric. Chemical activity increases with temperature up to maximum and then decreases. Due to the effect of the operating temperature, which influences the chemical activity through the water solubility of sizing, it is necessary to control the temperature in preparation process.

4.2 Mathematical Model

Several key assumption are made for the purpose of this study:

1. The system is supposed to be perfectly mixed.
2. All state variables are measured directly.
3. Density, latent heat of vaporization of steam, and specific heat capacity are supposed to be constant.
4. The fabric flow is supposed to be constant through the process.

4.2.1 Material Balance

The material balance of a continuous fabric preparation process as illustrated in figure 4.1 can be derived in term of liquid level as follow:

1st tank: $$\frac{dh_1}{dt} = \frac{1}{\rho A_t}\left[v_C\left(W_0 - W_1\right) + \rho\left(F_0 + F_5 - F_1\right)\right] \tag{4.3}$$

2nd tank: $$\frac{dh_2}{dt} = \frac{1}{\rho A_t}\left[v_C\left(W_1 - W_2\right) + \rho\left(F_3 - F_2\right)\right] \tag{4.4}$$

3rd tank: $$\frac{dh_3}{dt} = \frac{1}{\rho A_t}\left[v_C\left(W_2 - W_3\right) + \rho\left(F_4 - F_3\right)\right] \tag{4.5}$$

Liquid in each tank is overflow. Then left-hand side of equation (4.3), (4.4), and (4.5) are equal to zero then the flow rate of liquid output in each tank is calculated as following equation.

1st tank: $$F_1 = \frac{v_C}{\rho}\left(W_0 - W_1\right) + \left(F_0 + F_5\right) \tag{4.6}$$

2nd tank: $$F_2 = \frac{v_C}{\rho}\left(W_1 - W_2\right) + F_3 \tag{4.7}$$

3rd tank: $$F_3 = \frac{v_C}{\rho}\left(W_2 - W_3\right) + F_4 \tag{4.8}$$

4.2.2 Component Balance

The component balance of concentration hydrogen peroxide is shown as follow.

1st tank: $$\frac{dX_1}{dt} = \frac{1}{V_1}\left(X_0F_0 - YF_5\right) - r_1 - \frac{X_1}{V_1}\left(F_1 + \frac{v_C}{\rho}W_1P_{u,1}\right) \tag{4.9}$$

2nd tank: $$\frac{dX_2}{dt} = \frac{1}{V_2}\left(X_3F_3 + X_1\frac{v_C}{\rho}W_1P_{u,1}\right) - r_2 - \frac{X_2}{V_2}\left(F_2 + \frac{v_C}{\rho}W_2P_{u,2}\right) \tag{4.10}$$

3rd tank: $$\frac{dX_3}{dt} = \frac{1}{V_3}\left(X_2v_CW_2P_{u,2}\right) - r_3 - \frac{X_3}{V_3}\left(F_3 + \frac{v_C}{\rho}W_3P_{u,3}\right) \tag{4.11}$$

where V_1, V_2, and V_3 are liquid volume in each tank and determined by $V_i = h_iA_t$.

And the equation of the reaction rate in each tank is based on the oxidation reaction of polyvinyl alcohol (PVA) (Oji, n.d.) that used to be sizing. According to the Arrhenius's equation, the rate of reaction depends on the temperature and it can be written by the following equation.

$$r_i = k_0e^{-E/RT}X_i \tag{4.12}$$

Hydrogen peroxide is weak acid. Then the concentration in equation (4.9), (4.10), and (4.11) are derived in terms of H^+ based on equilibrium acid then converted in term of pH by following equation:

$$\mathrm{pH} = -\log\left[H^+\right] \tag{4.13}$$

4.2.3 Energy Balance

For the temperature control in this process, the energy balance around each tank is given by the following equations:

$$\frac{dT_1}{dt} = \frac{1}{V_1}\left[\left(F_0 + F_5\right)T_0 - F_1T_1\right] + \frac{v_CC_{P,C}}{\rho C_PV_1}\left(W_0T_0 - W_1T_1\right)$$
$$+ \frac{1}{\rho C_PV_1}\left[\left(-\Delta H\right)r_1V_1 - U_1A_1\left(T_1 - T_0\right)\right] + \frac{S_1}{\rho C_PV_1}\left[\lambda + C_P\left(T_b - T_1\right)\right] \tag{4.14}$$

$$\frac{dT_2}{dt} = \frac{1}{V_2}\left(F_3T_3 - F_2T_2\right) + \frac{v_CC_{P,C}}{\rho C_PV_2}\left(W_1T_1 - W_2T_2\right)$$
$$+ \frac{1}{\rho C_PV_2}\left[\left(-\Delta H\right)r_2V_2 - U_2A_2\left(T_2 - T_0\right)\right] + \frac{S_2}{\rho C_PV_2}\left[\lambda + C_P\left(T_b - T_2\right)\right] \tag{4.15}$$

$$\frac{dT_3}{dt} = \frac{1}{V_3}\left(F_4T_0 - F_3T_3\right) + \frac{v_C C_{P,C}}{\rho C_P V_1}\left(W_2T_2 - W_3T_3\right)$$
$$+ \frac{1}{\rho C_P V_3}\left[\left(-\Delta H\right) r_3 V_3 - U_3 A_3 \left(T_3 - T_0\right)\right] + \frac{S_3}{\rho C_P V_3}\left[\lambda + C_P\left(T_b - T_3\right)\right] \quad (4.16)$$

All the parameters, constant values and initial condition (Anon, 1990) used in the model are given in Table 4.1 and 4.2.

Table 4.1 Parameters and constant values in model

Parameter	Value	Parameter	Value
A_1	$4.565\ m^2$	F_5	$0.040\ m^3/h$
A_2	$4.565\ m^2$	$-\Delta H$	$1174\ kJ/kmol$
A_3	$4.565\ m^2$	k_0	$1.056\ 1/h$
A_t	$1.87\ m^2$	K_a	1.5×10^{-12}
C_P	$4.208\ kJ/kg\cdot K$	L	$2114.3\ kJ/kg$
$C_{P,C}$	$1.15\ kJ/kg\cdot K$	$P_{u,1}$	0.8 %
E	$3138\ kJ/mol$	$P_{u,2}$	0.6 %
F_o	$0.035\ m^3/h$	$P_{u,3}$	0.4 %
F_4	$0.040\ m^3/h$	R	$8.314\ kJ/mol\cdot K$
T_0	$303\ K$	W_1	$0.09\ kg/m$
T_b	$418\ K$	W_2	$0.07\ kg/m$
U_2	$103.02\ kJ/h\cdot m^2$	X_o	$0.1\ kmol/m^3$
U_3	$103.02\ kJ/h\cdot m^2$	Y	$0.05\ kmol/m^3$
v_C	$840\ m/h$	ρ	$965.34\ kg/m^3$
W_o	$0.05\ kg/m$		

Table 4.2 Initial condition in model

Parameter	Value	Parameter	Value
h_1	$0.5\ m$	S_1	$8\ kg/h$
h_2	$0.5\ m$	S_2	$20\ kg/h$
h_3	$0.5\ m$	S_3	$20\ kg/h$
X_1	$0\ kmol/m^3$	T_1	$343\ K$
X_2	$0\ kmol/m^3$	T_2	$343\ K$
X_3	$0\ kmol/m^3$	T_3	$343\ K$

4.3 Control Configuration

In this work, the manipulated variable is the liquid temperature in each tank (T_1, T_2, and T_3). It is controlled by the steam flow rate (S_1, S_2, and S_3). The overall heat transfer coefficient and heat transfer area (U_1A_1, U_2A_2, and U_3A_3) are uncertainty parameter that used the Kalman filter to estimate. The parameters mismatch that used to test robustness of controller are the heat of reaction $(-\Delta H)$ and the velocity of fabric (v_C).

4.3.1 PID Configuration

The digital PID controller in the continuous and discrete form as shown as follows.

Continuous form: $$p(t) = \overline{p} + K_c\left[e(t) + \frac{1}{\tau_i}\int_0^t e(t^*)dt^* + \tau_d \frac{d\left[e(t)\right]}{dt}\right] \qquad (4.17)$$

Discrete form: $$p_n = p_{n-1} + K_c\left[\left(e_n - e_{n-1}\right) + \frac{\Delta t}{\tau_I}\left(e_n\right) + \frac{\tau_D}{\Delta t}\left(e_n - 2e_{n-1} + e_{n-2}\right)\right] \qquad (4.18)$$

Then the manipulated equations can be rearranged in discrete form as follow:

1st tank: $$S_{1,n} = S_{1,n-1} + K_{c,1}\left[\left(e_{1,n} - e_{1,n-1}\right) + \frac{\Delta t}{\tau_{I,1}}\left(e_{1,n}\right) + \frac{\tau_{D,i}}{\Delta t}\left(e_{1,n} - 2e_{1,n-1} + e_{1,n-2}\right)\right] \tag{4.19}$$

2nd tank: $$S_{2,n} = S_{2,n-1} + K_{c,2}\left[\left(e_{2,n} - e_{2,n-1}\right) + \frac{\Delta t}{\tau_{I,2}}\left(e_{2,n}\right) + \frac{\tau_{D,2}}{\Delta t}\left(e_{2,n} - 2e_{2,n-1} + e_{2,n-2}\right)\right] \tag{4.20}$$

3rd tank: $$S_{3,n} = S_{3,n-1} + K_{c,3}\left[\left(e_{3,n} - e_{3,n-1}\right) + \frac{\Delta t}{\tau_{I,3}}\left(e_{3,n}\right) + \frac{\tau_{D,3}}{\Delta t}\left(e_{3,n} - 2e_{3,n-1} + e_{3,n-2}\right)\right] \tag{4.21}$$

The tuning parameters of PID controller are comprised of the controller gain $\left(K_c\right)$, the integral time $\left(\tau_I\right)$, and the derivative time $\left(\tau_D\right)$.

4.3.2 GMC Configuration

The general form of the GMC control algorithm can be written as:

$$\frac{dy}{dt} = K_1(y_{sp} - y) + K_2\int(y_{sp} - y)dt \tag{4.22}$$

Substituting T_1, T_2, and T_3 for y and $T_{sp,1}$, $T_{sp,2}$, and $T_{sp,3}$ for y_{sp} in equation (4.22) to give the following:

1st tank $$\frac{dT_1}{dt} = K_{1,1}(T_{sp,1} - T) + K_{2,1}\int(T_{sp,1} - T)dt \tag{4.23}$$

2nd tank $$\frac{dT_2}{dt} = K_{1,2}(T_{sp,2} - T) + K_{2,2}\int(T_{sp,2} - T)dt \tag{4.24}$$

3rd tank $$\frac{dT_3}{dt} = K_{1,3}(T_{sp,3} - T) + K_{2,3}\int(T_{sp,3} - T)dt \tag{4.25}$$

Then solving equation (4.23), (4.24), and (4.25) for the manipulated equations in discrete form.

$$\text{1st tank} \quad S_{1,k} = \frac{1}{L + C_P\left(T_b - T_1\right)} \left[\begin{array}{l} \rho V_1 C_P \left(K_{1,1}(T_{sp,1} - T) + \sum_{k=0}^{k} K_{2,1}(T_{sp,1} - T)\Delta t \right) \\ -\rho C_P \left(\left(F_0 + F_5\right) T_0 - F_1 T_{1,k} \right) - C_{P,C} v_C \left(W_0 T_0 - W_1 T_{1,k} \right) \\ -\left(-\Delta H\right) r_{1,k} V_1 + U_1 A_1 * \left(T_{1,k} - T_0\right) \end{array} \right] \tag{4.26}$$

$$\text{2nd tank} \quad S_{2,k} = \frac{1}{L + C_P\left(T_b - T_2\right)} \left[\begin{array}{l} \rho V_2 C_P \left(K_{1,2}(T_{sp,2} - T) + \sum_{k=0}^{k} K_{2,2}(T_{sp,2} - T)\Delta t \right) \\ -\rho C_P \left(F_3 T_{3,k} - F_2 T_{2,k} \right) - C_{P,C} v_C \left(W_1 T_{1,k} - W_2 T_{2,k} \right) \\ -\left(-\Delta H\right) r_{2,k} V_2 + U_2 A_2 * \left(T_{2,k} - T_0\right) \end{array} \right] \tag{4.27}$$

$$\text{3rd tank} \quad S_{3,k} = \frac{1}{L + C_P\left(T_b - T_3\right)} \left[\begin{array}{l} \rho V_2 C_P \left(K_{1,3}(T_{sp,3} - T) + \sum_{k=0}^{k} K_{2,3}(T_{sp,3} - T)\Delta t \right) \\ -\rho C_P \left(F_4 T_0 - F_3 T_{3,k} \right) - C_{P,C} v_C \left(W_2 T_{2,k} - W_3 T_{3,k} \right) \\ -\left(-\Delta H\right) r_{3,k} V_3 + U_3 A_3 * \left(T_{3,k} - T_0\right) \end{array} \right] \tag{4.28}$$

where Δt is the sampling time of the controller.

Choose parameters ξ and τ from figure B.1 (see in Appendix B) to determined GMC parameters using the equations (B.9) and (B.10).

$$K_1 = \frac{2\xi}{\tau} \tag{B.9}$$

$$K_2 = \frac{1}{\tau^2} \tag{B.10}$$

4.3.3 MPC Configuration

State equation in state space form as shown below

$$\dot{x} = Ax + Bu \tag{3.11}$$

$$y = Cx \tag{3.12}$$

Define $\dot{x}$, x, u, y, and C as the following equations:

$$\dot{x} = \begin{bmatrix} \frac{dX_1}{dt} & \frac{dX_2}{dt} & \frac{dX_3}{dt} & \frac{dT_1}{dt} & \frac{dT_2}{dt} & \frac{dT_3}{dt} \end{bmatrix}^T \tag{4.29}$$

$$x = \begin{bmatrix} X_1 & X_2 & X_3 & T_1 & T_2 & T_3 \end{bmatrix}^T \tag{4.30}$$

$$u = \begin{bmatrix} S_1 & S_2 & S_3 \end{bmatrix}^T \tag{4.31}$$

$$y = \begin{bmatrix} T_1 & T_2 & T_3 \end{bmatrix}^T \tag{4.32}$$

$$C = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4.33}$$

Convert equation (4.9) to (4.11) and (4.14) to (4.16) in state space form to given matrix A and B as follow.

$$A = \begin{bmatrix} -1.056e^{-377/T_1} - 0.1169, 0, 0, \frac{-398.57}{T_1^2} e^{-377/T_1} x_1, 0, 0 \\ 0.0712, -1.056e^{-377/T_2} - 0.1166, 0.0553, 0, \frac{-398.57}{T_2^2} e^{-377/T_2} x_2, 0 \\ 0, 4.1530, -1.056e^{-377/T_2} - 0.0791, 0, 0, \frac{-398.57}{T_3^2} e^{-377/T_3} x_3 \\ -0.3052e^{-377/T_1}, 0, 0, -0.2016 - 0.0012S_1 - \frac{115.19}{T_1^2} e^{-377/T_1} x_1, 0, 0 \\ 0, -0.3052e^{-377/T_2}, 0, 0.0243, -0.2256 - 0.0012S_2 - \frac{115.19}{T_2^2} e^{-377/T_2} x_2, 0.0553 \\ 0, 0, -0.3052e^{-377/T_3}, 0, 1.8916\times 10^{-2}, -0.2031 - 0.0012S_3 - \frac{115.19}{T_3^2} e^{-377/T_3} x_3 \end{bmatrix} \tag{4.34}$$

$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1.0835 - 0.0012T_1 & 0 & 0 \\ 0 & 1.0835 - 0.0012T_2 & 0 \\ 0 & 0 & 1.0835 - 0.0012T_3 \end{bmatrix} \tag{4.35}$$

Substituting $\dot{x}$, u, y, A, B, and C in equation (3.11) and (3.12), then rearranged in discrete form as equation (3.13) and (3.14).

When applying method of optimization, Lagrange Multiplier's principle, and then the new objective function can be written as follow.

Discrete equation:

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

where $\lambda(t) \in R^n$ is Largrange Multiplier n equation..

Selecting the number prediction horizontal $\left(N_p\right)$ and the number control horizontal $\left(N_m\right)$, then tuning parameters of Q and R, square matrix dimension 6×6 and 3×3 respectively.

After solving the equation by fixed $\lambda_k = P_k x_k$, the manipulated variable and controller gain are obtained as equation (3.24) and (3.25).

$$u_k = -Kx_k \tag{3.24}$$

$$K = -R^{-1}H^T(G^T)^{-1}(P_k - Q) \tag{3.25}$$

Calculating through MPC algorithm. Finally, the first manipulated variable that is in calculated manipulated set is selected to apply in system.

4.3.4 Kalman Filter Configuration

In this work, the Kalman filter is used to estimate U_1A_1, U_2A_2, and U_3A_3. The Kalman Filter model is state space form. In addition, the state variable is raised as follow.

$$\frac{d\left(U_1A_1\right)}{dt} = 0 \tag{4.36}$$

$$\frac{d\left(U_2A_2\right)}{dt} = 0 \tag{4.37}$$

$$\frac{d\left(U_3A_3\right)}{dt} = 0 \tag{4.38}$$

$$C_K = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{4.39}$$

Convert equation of state variables (equations (4.9) to (4.11), (4.14) to (4.16), and (4.38) to (4.40)) in state space form to given matrix A_K and B_K. Then checking the observability of Kalman filter model (see in appendix A), the determinant of observability matrix is not zero. Hence the Kalman Filter model could observe. Tuning parameters of Kalman filter are P_K, Q_K, and R_K that is the estimation error covariance matrix, process noise covariance matrix, and measurement noise covariance matrix, respectively.

CHAPTER V

SIMULATION RESULTS

This chapter presents the control results of the liquid temperature of a continuous fabric preparation process. The open loop behavior and close loop behavior of system are shown in section 5.1 and 5.2, respectively. The simulation results in section 5.2 are studied in two case, nominal case and parameter mismatch case. The performance of PID, GMC, and MPC controller to control the liquid temperature are simulated in nominal case. The performance of GMC with Kalman filter and MPC with Kalman filter are illustrated in case of parameter mismatch

5.1 Open Loop Behavior

The simulation as shown in figure 5.1 to 5.3 illustrates the open loop behavior of the liquid level, pH, and the liquid temperature in a continuous fabric preparation process where all parameters and constant values used to simulate are given in table 4.1 and 4.2.

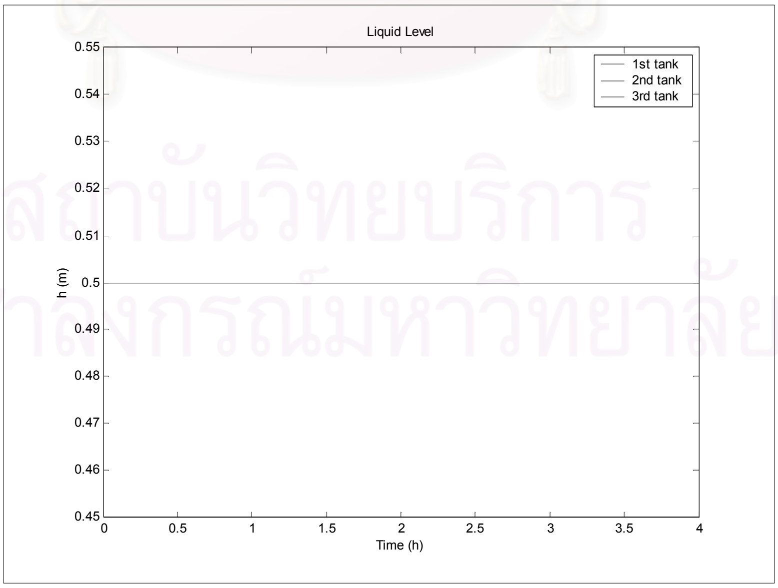


Figure 5.1 Open loop behavior of liquid level in each tank

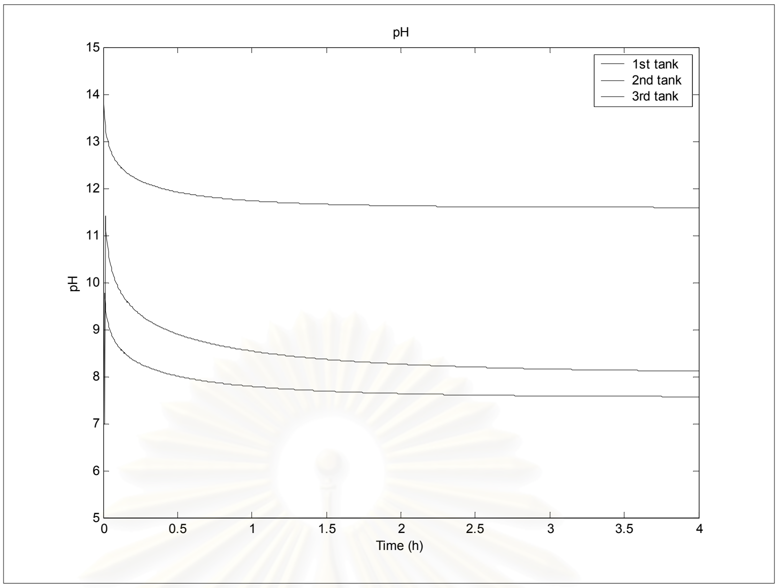


Figure 5.2 Open loop behavior of pH in each tank

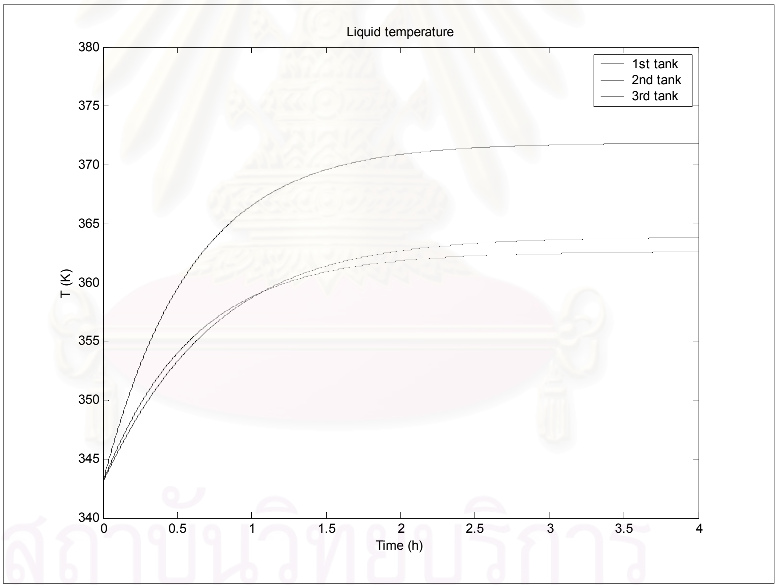


Figure 5.3 Open loop behavior of liquid temperature in each tank

In figure 5.1, due to effect of liquid output flow rate in each tank is overflow, liquid level in each tank is equal to 0.5 m . The pH value of liquid in each tank shown in figure 5.2. Sodium hydroxide that is strong base is fed to the first, the pH value in this tank is higher than the other tank. In the third tank, due to the concentration of hydrogen peroxide is lower than the other tank and the water is fed to this tank, the pH value is lowest In figure 5.3, the liquid temperature convert to the constant value but this value is not a desired set point.

5.2 Control Study

Product quality from fabric preparation process depends on the activity of chemical that used to cleans and rid of impurities in the process. Higher chemical activity is higher performance to clean the fabric. Due to the effect of the operating temperature, which influences the chemical activity through the water solubility of sizing, it is necessary to control the temperature in fabric preparation process.

The purpose of this study is to design a control configuration to control the liquid temperature in a continuous fabric preparation process at desired set point. The set point of liquid temperature of the first tank is $85^{\circ}C$ or $378\,K$ and the other tanks are $80^{\circ}C$ or $373\,K$. Due to the difference of the initial temperature and the desired set point in each tank, which influences the control performance index in each tank is not equivalent, the control performance index must be divided by the difference of the initial temperature and the desired set point in each tank. The integral of the absolute value of error (IAE) and integral of the square of error (ISE) are given as follow.

$$\text{IAE} = \frac{sum\left(\left|T_{sp,i} - T_i\right|_{\text{at time } t}\right)}{\left|T_{sp,i-}\left(T_i\right)_{\text{initial}}\right|} \tag{5.1}$$

$$\text{ISE} = \frac{sum\left(\left|T_{sp,i} - T_i\right|^2_{\text{at time } t}\right)}{\left|T_{sp,i-}\left(T_i\right)_{\text{initial}}\right|} \tag{5.2}$$

5.2.1 Nominal Case

In this case, PID controller, a generic model control (GMC) and a model predictive control (MPC) are implemented to control the liquid temperature.

For PID controller, the manipulated equations can be rearranged in discrete form as given in equation (4.19) to (4.21) and the appropriate values of the tuning parameter of PID controller are shown in table 5.1.

Table 5.1 Parameter of PID controller

PID parameter	1st tank	2nd tank	3rd tank
K_c	22	27	20
τ_I	50	70	100
τ_D	0.005	0.01	0.006

For GMC controller, after choose ξ to give desired shape of response and choose τ to give appropriate timing of response, then it can be calculated the GMC parameter tuning (K_1 and K_2) by using equations (B.9) and (B.10) and substituting in the manipulated equations as shown in equations (4.26) to (4.28).

Table 5.2 GMC parameter tuning

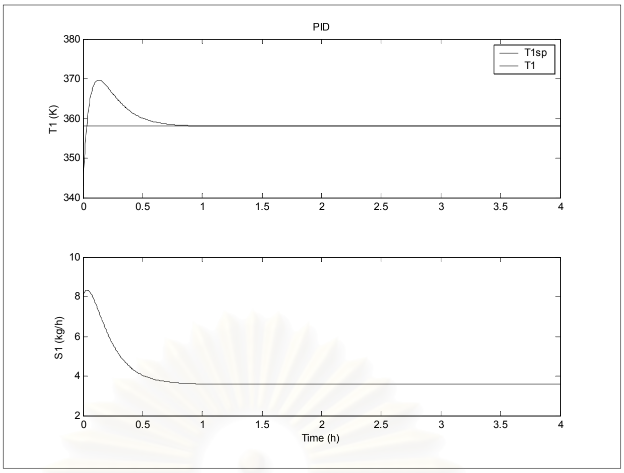
Parameter	1st tank	2nd tank	3rd tank
K_1	0.428	0.345	0.414
K_2	2.27×10^{-3}	1.19×10^{-3}	4.76×10^{-3}

For MPC controller, weighting factors of the state variables and manipulated variables matrix (Q and R), dimension 6×6 and 3×3 respectively, are given as follow.

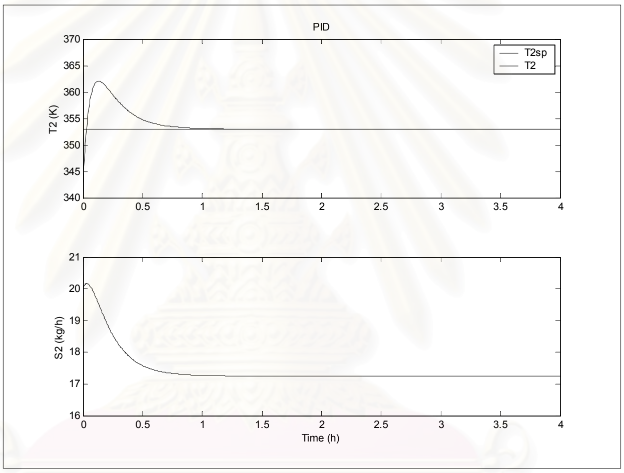
$$Q = \mathrm{diag}\begin{bmatrix}5\times10^5 & 1\times10^4 & 2\times10^4 & 1.6\times10^5 & 3\times10^6 & 8\times10^6\end{bmatrix} \tag{5.3}$$

$$R = \mathrm{diag}\begin{bmatrix}1 & 1 & 1\end{bmatrix} \tag{5.4}$$

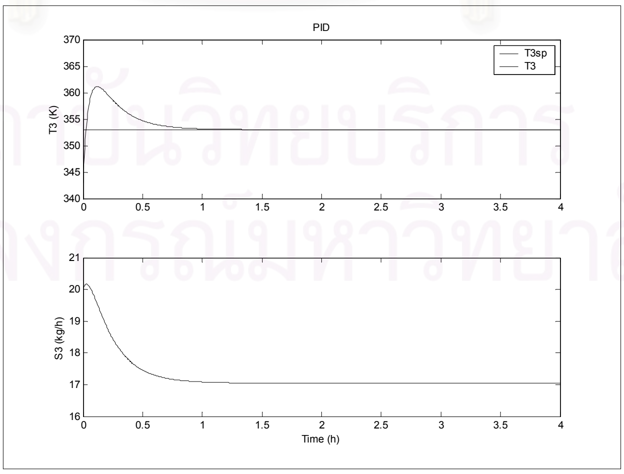
Control response of PID, GMC, and MPC controllers in nominal case are shown in figures 5.4, 5.5, and 5.6, respectively.



(a) 1st tank

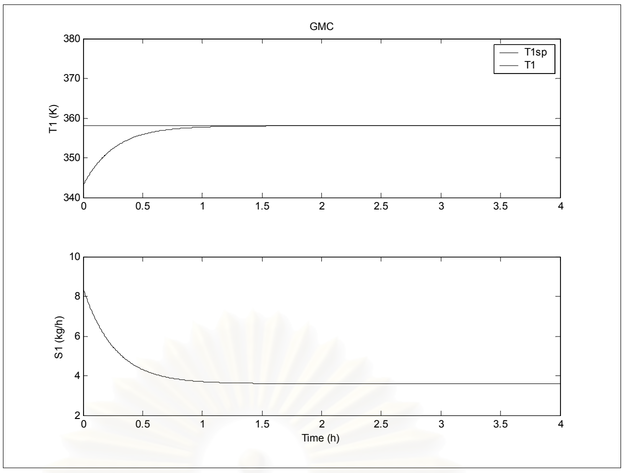


(b) 2nd tank

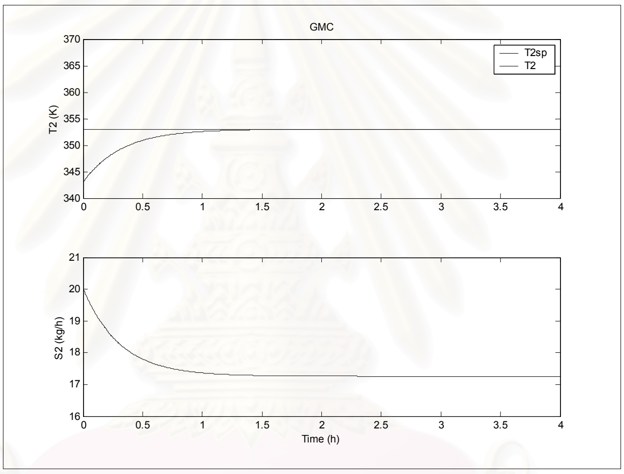


(c) 3rd tank

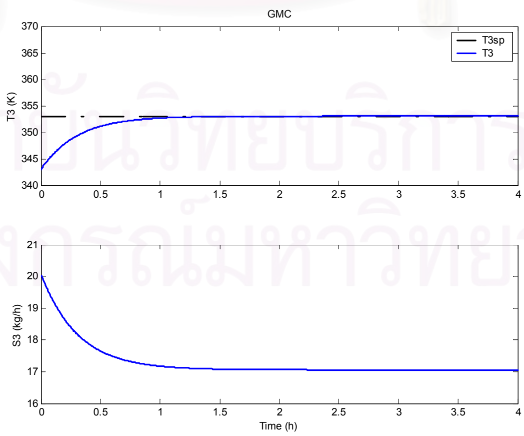
Figure 5.4 Control response of PID controller (nominal case)



(a) 1st tank

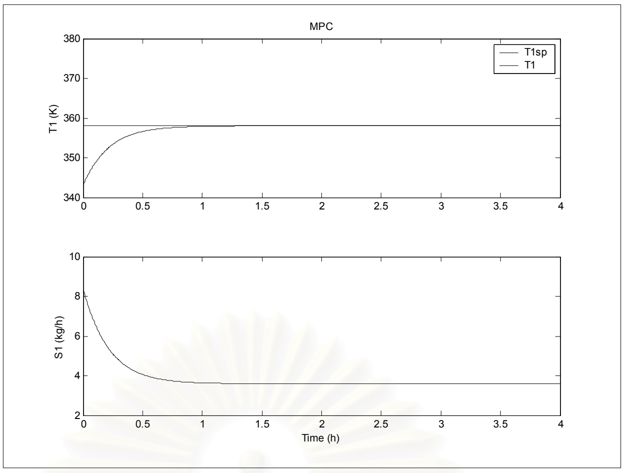


(b) 2nd tank

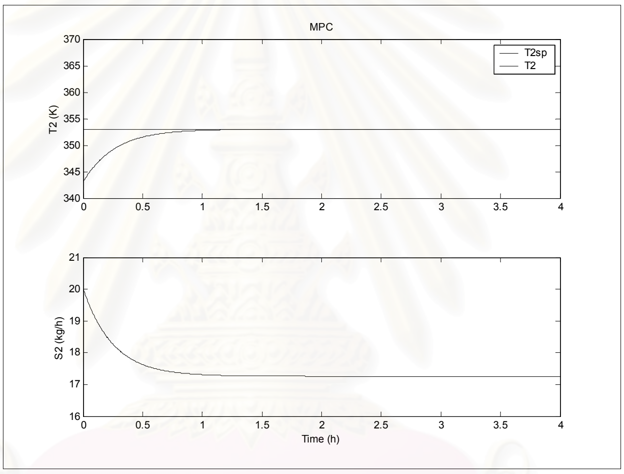


(c) 3rd tank

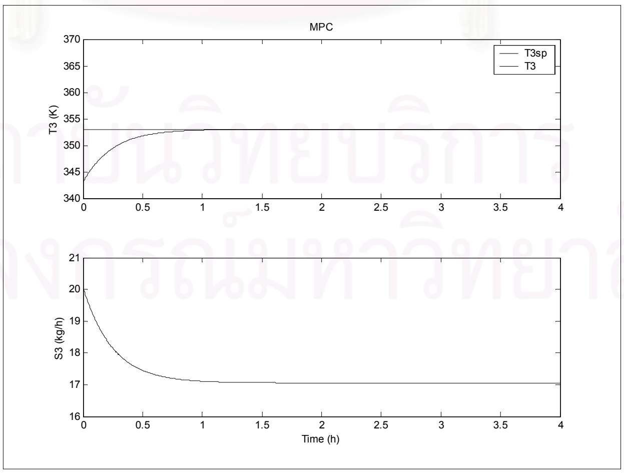
Figure 5.5 Control response of GMC controller (nominal case)



(a) 1st tank



(b) 2nd tank



(c) 3rd tank

Figure 5.6 Control response of MPC controller (nominal case)

5.2.2 Parameter Mismatch Case

The process parameters are not all known. The UA term is the unmeasured term. Then the Kalman filter is implemented to estimate term U_1A_1, U_2A_2, and U_3A_3. The GMC with Kalman filter and the MPC with Kalman filter are implemented to control the temperature. The Kalman filter tuning parameters are given as follow.

$$P_K = \text{diag}\begin{bmatrix}1 & 1 & 1 & 1 & 1 & 1 & 1\times10^5 & 5\times10^5 & 4\times10^5\end{bmatrix} \tag{5.5}$$

$$Q_K = \text{diag}\begin{bmatrix}1 & 1 & 1 & 1 & 1 & 1 & 1\times10^6 & 6\times10^6 & 5\times10^6\end{bmatrix} \tag{5.6}$$

$$R_K = \text{diag}\begin{bmatrix}1 & 1 & 1\end{bmatrix} \tag{5.7}$$

where the matrixes P_K, Q_K, and R_K have dimension 9×9, 9×9, and 3×3 respectively.

Table 5.3 Conditions of parameter mismatch

Case	Condition
I	$+30\%\ U_1$
II	$+30\%\ (U_1 \text{ and } U_2)$
III	$+30\%\ (U_1 \text{ and } U_3)$
IV	$+30\%\ (U_1, U_2, \text{and } U_3)$
V	$+30\%\ (U_1, U_2, U_3)$ and $+30\%\ (-\Delta H)$
VI	$+30\%\ (U_1, U_2, U_3)$ and $+30\%\ (v_C)$
VII	$+30\%\ (U_1, U_2, U_3)$ and $-30\%\ (v_C)$

Table 5.3 shown the conditions of parameter mismatch. Parameter mismatch consists of the overall heat transfer coefficient in each tank (U_i), the heat of reaction $(-\Delta H)$, and the fabric velocity (v_C).

The Estimate of U_iA_i and the control response of GMC with Kalman filter and MPC with Kalman filter are shown in figures 5.7 to 5.34.

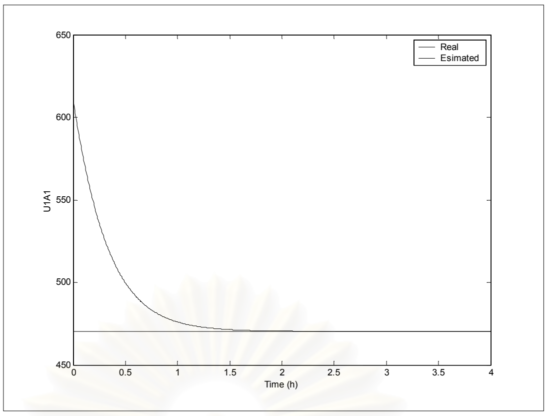
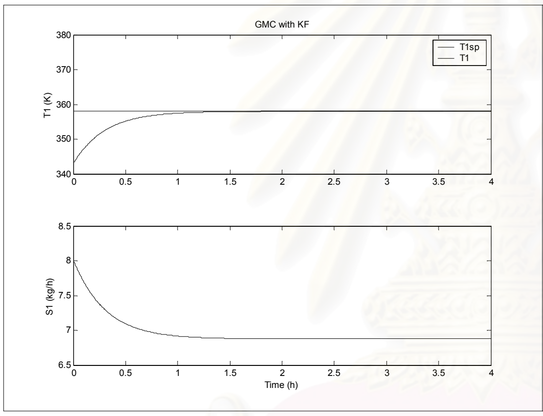
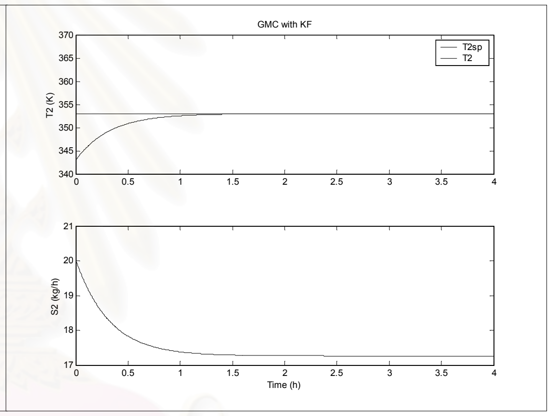


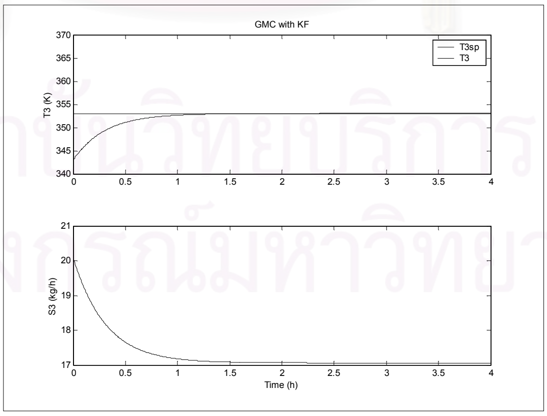
Figure 5.7 Estimate of U_1A_1 for +30% U_1 change



(a) 1st tank



(b) 2nd tank



(c) 3rd tank

Figure 5.8 Control response of GMC with Kalman filter for +30% U_1 change

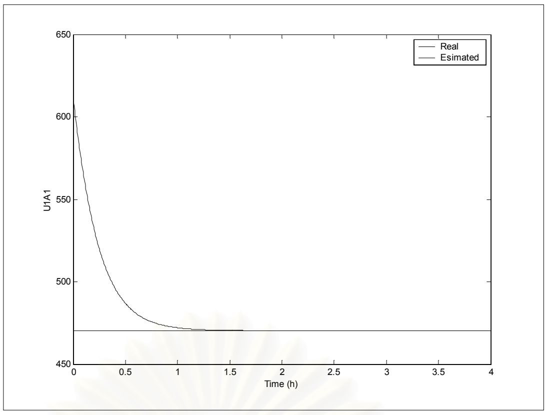
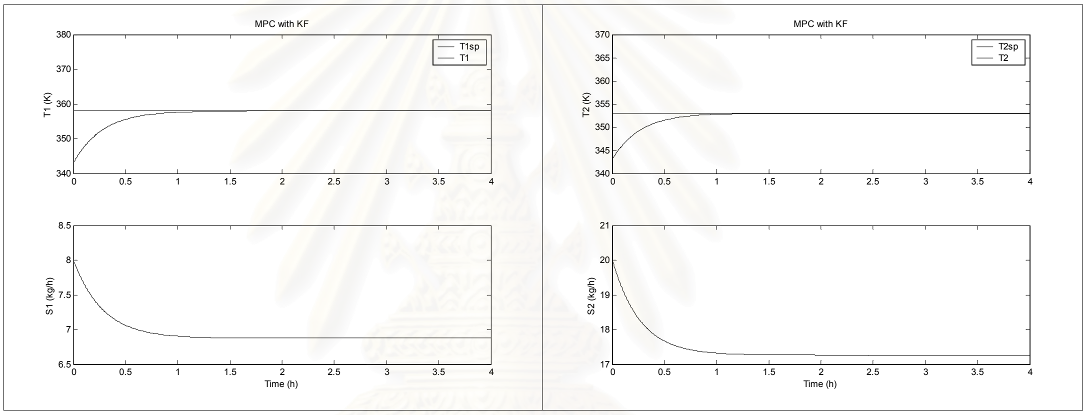
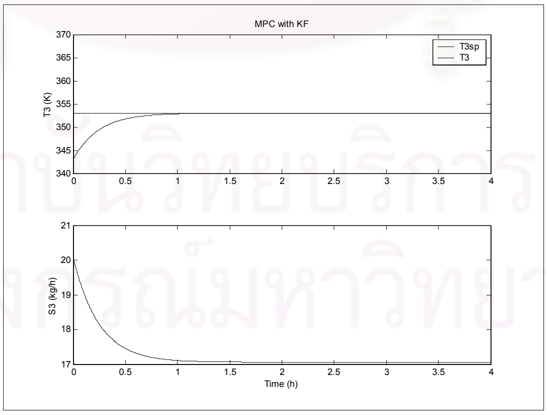


Figure 5.9 Estimate of U_1A_1 for +30% U_1 change



(a) 1st tank (b) 2nd tank



(c) 3rd tank

Figure 5.10 Control response of MPC with Kalman filter for +30% U_1 change

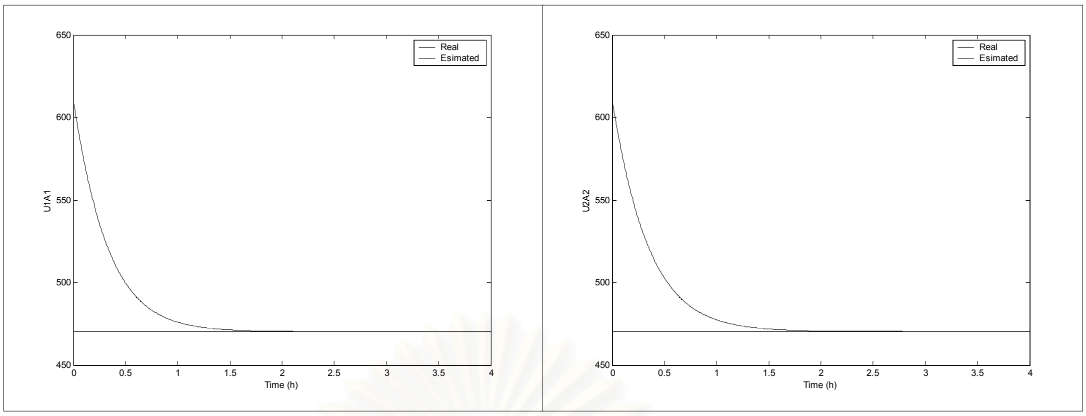
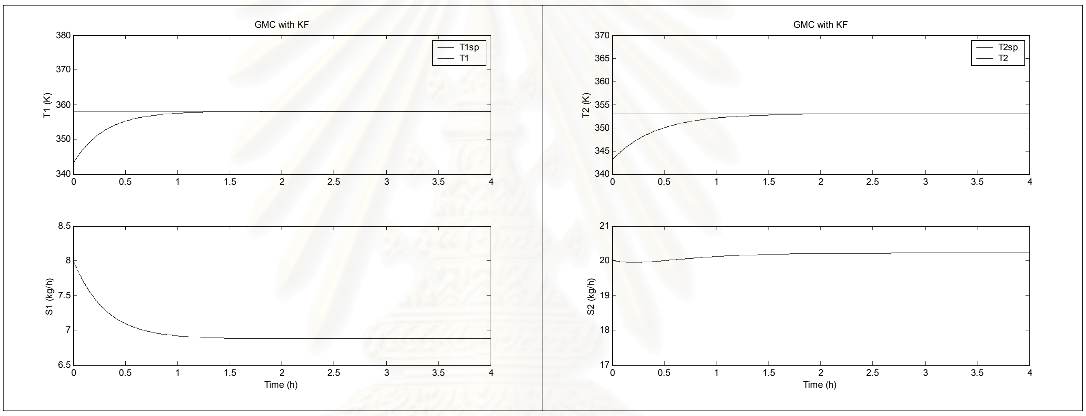
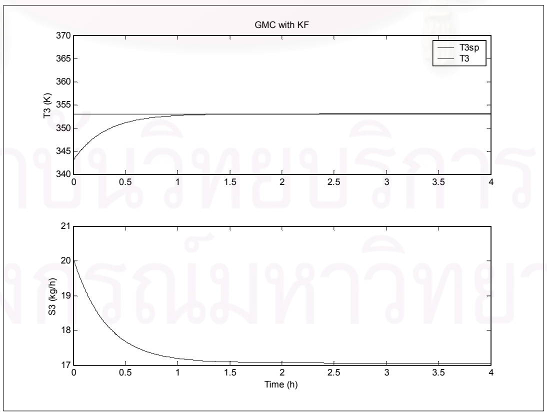


Figure 5.11 Estimate of $U_1A_1,\ U_2A_2$ for +30% $\left(U_1 \text{ and } U_2\right)$ change



(a) 1st tank (b) 2nd tank



(c) 3rd tank

Figure 5.12 Control response of GMC with Kalman filter for +30% $\left(U_1 \text{ and } U_2\right)$ change

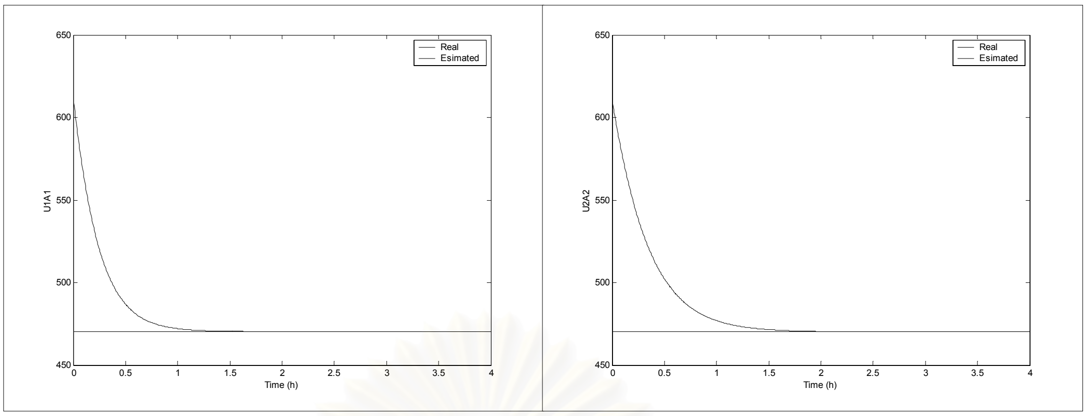
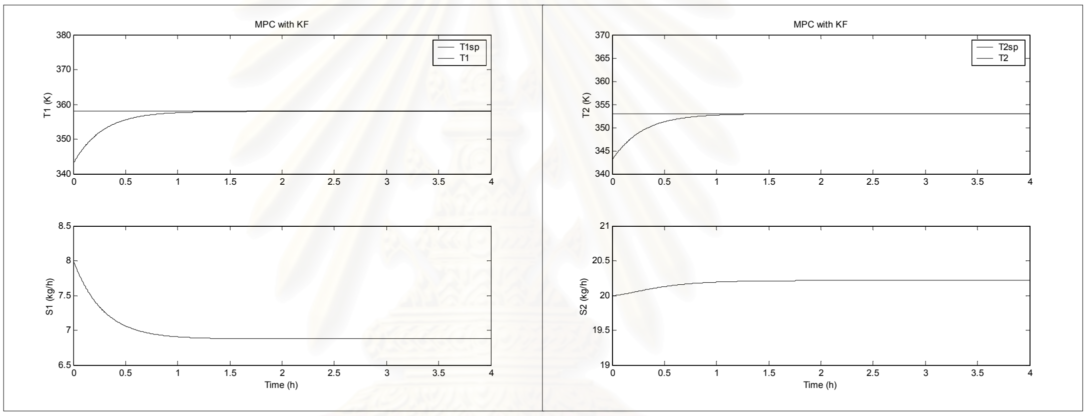
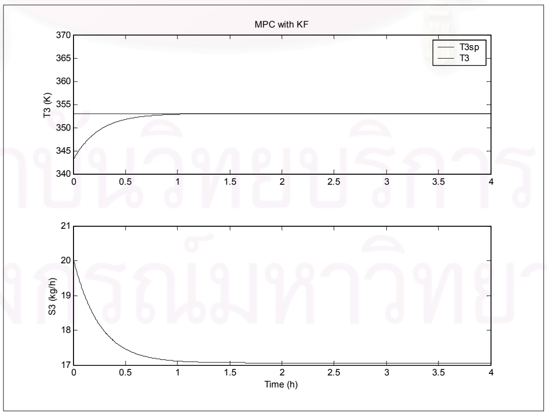


Figure 5.13 Estimate of $U_1A_1,\ U_2A_2$ for +30% $\left(U_1 \text{ and } U_2\right)$ change



(a) 1st tank (b) 2nd tank



(c) 3rd tank

Figure 5.14 Control response of MPC with Kalman filter for +30% $\left(U_1 \text{ and } U_2\right)$ change

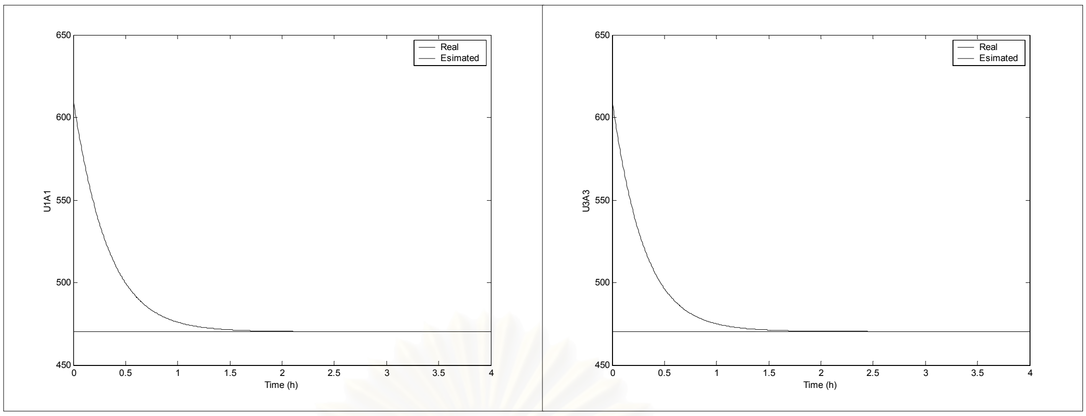
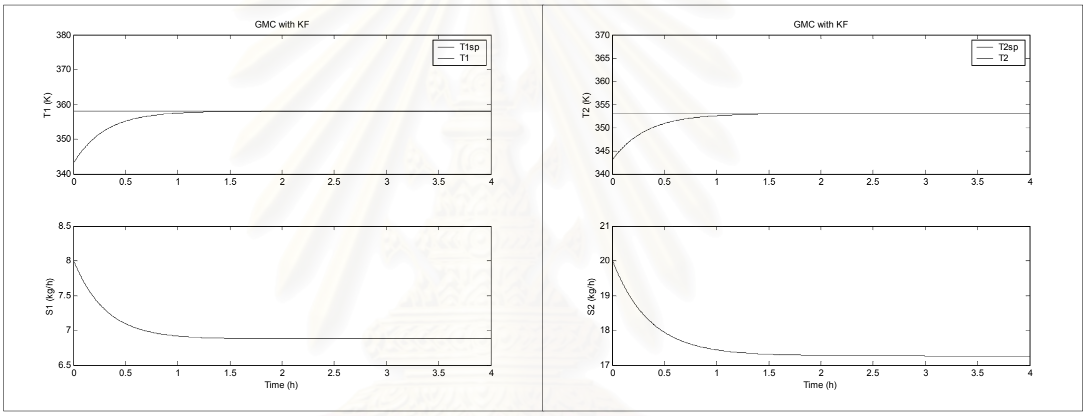
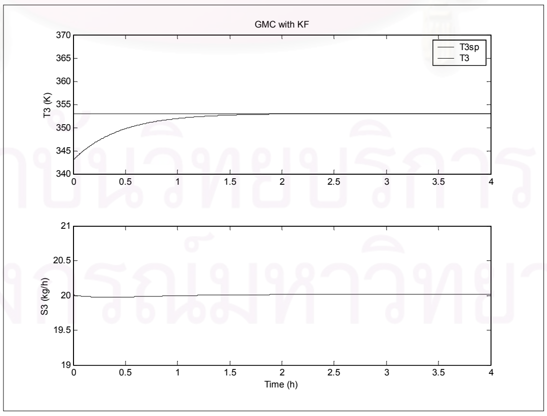


Figure 5.15 Estimate of U_1A_1, U_3A_3 for +30% $(U_1$ and $U_3)$ change



(a) 1st tank

(b) 2nd tank



(c) 3rd tank

Figure 5.16 Control response of GMC with Kalman filter for +30% $(U_1$ and $U_3)$ change

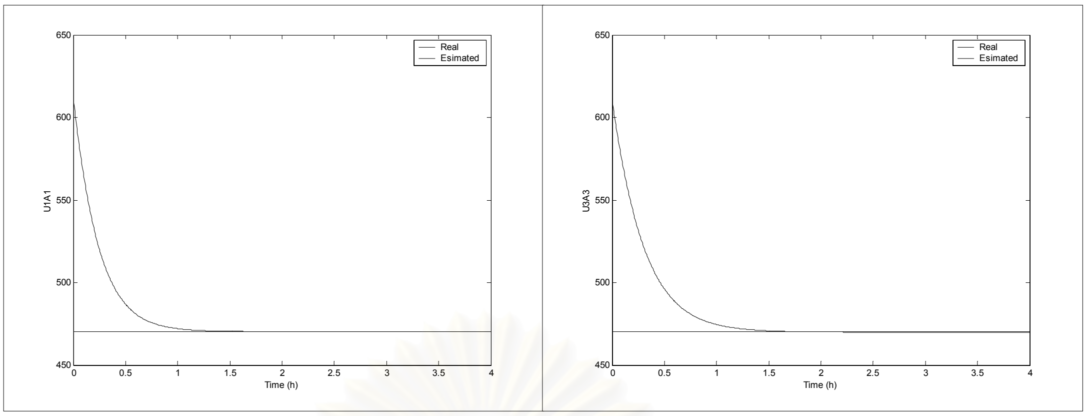
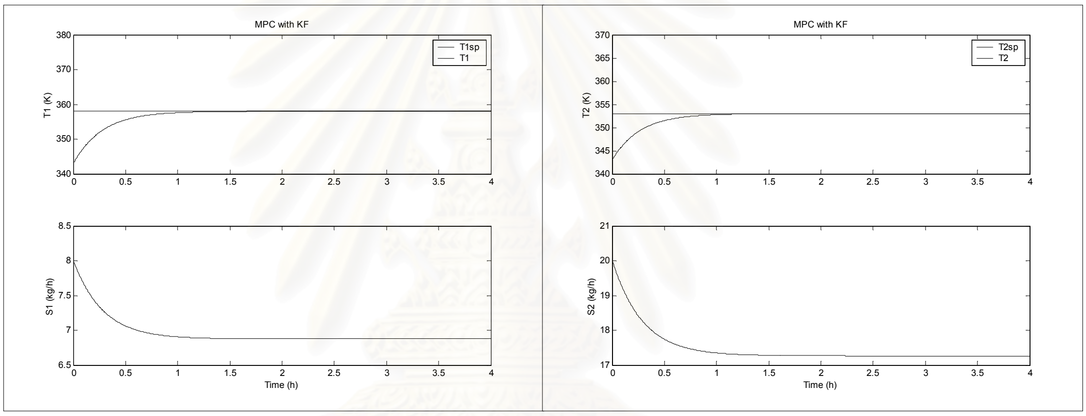
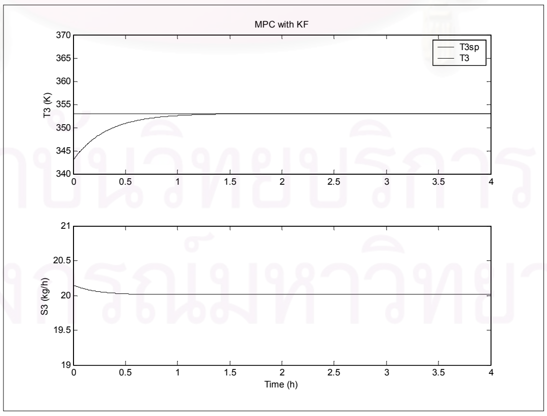


Figure 5.17 Estimate of $U_1A_1,\ U_3A_3$ for +30% $\left(U_1 \text{ and } U_3\right)$ change



(a) 1st tank (b) 2nd tank



(c) 3rd tank

Figure 5.18 Control response of MPC with Kalman filter for +30% $\left(U_1 \text{ and } U_3\right)$ change

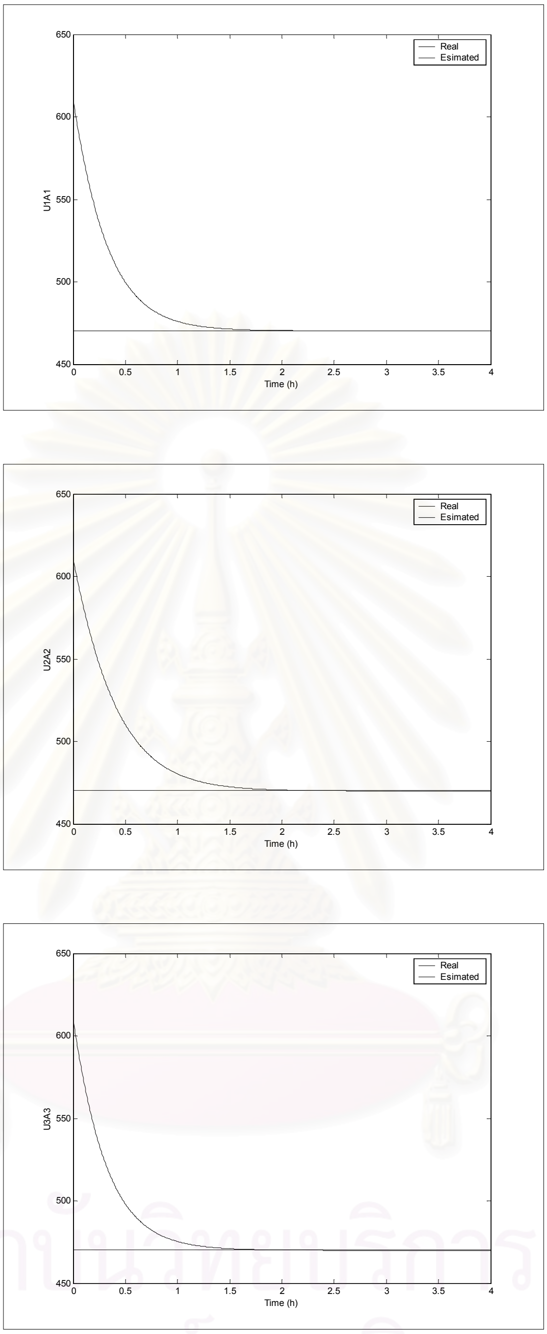
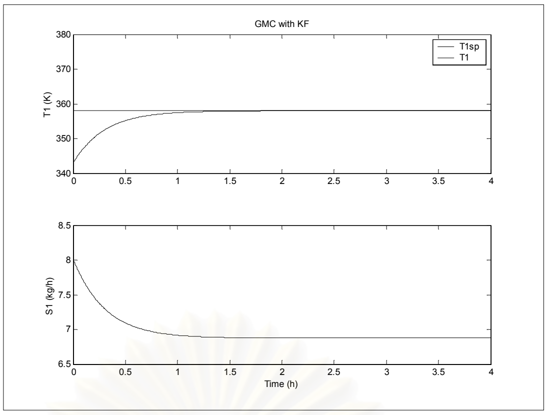
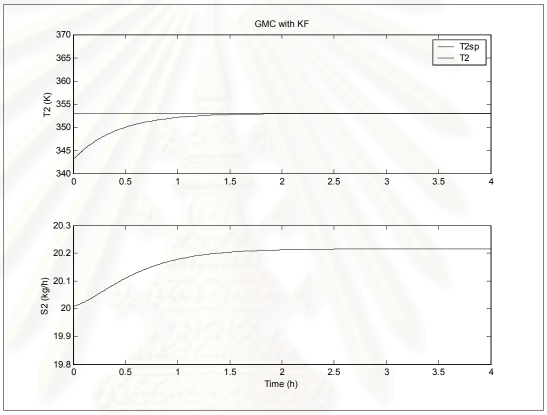


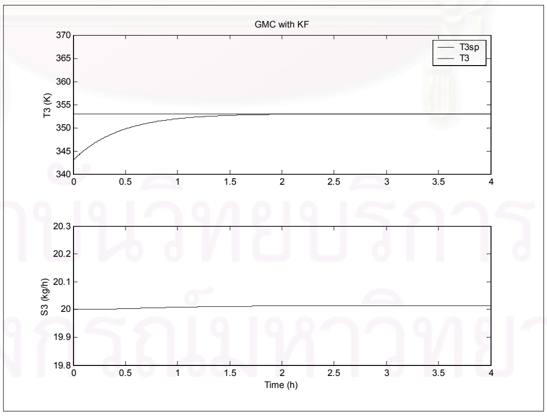
Figure 5.19 Estimate of $U_1A_1,\ U_2A_2,\ U_3A_3$ for +30% $\left(U_1,\ U_2,\ \text{and}\ U_3\right)$ change



(a) 1st tank

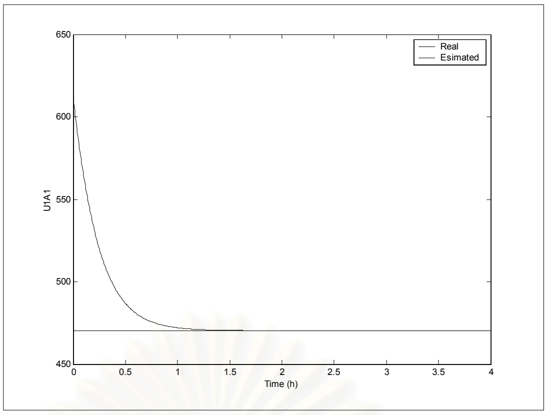


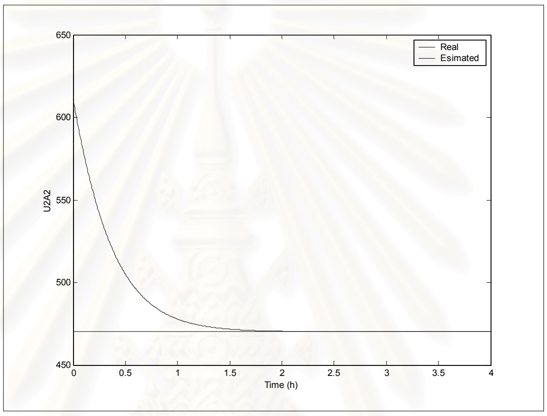
(b) 2nd tank



(c) 3rd tank

Figure 5.20 Control response of GMC with Kalman filter for +30% (U_1, U_2, and U_3) change





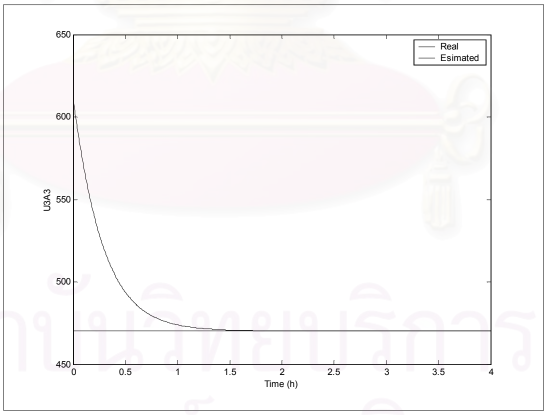
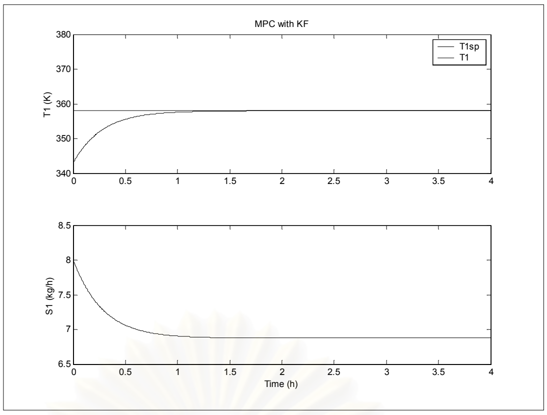
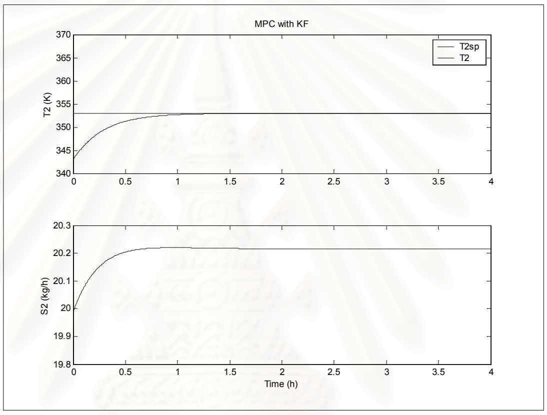


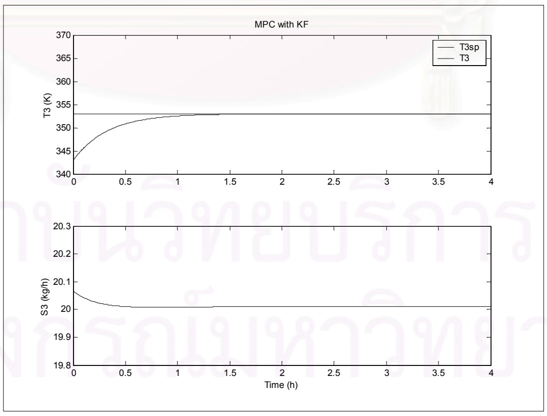
Figure 5.21 Estimate of $U_1A_1,\ U_2A_2,\ U_3A_3$ for +30% $\left(U_1, U_2, \text{and } U_3\right)$ change



(a) 1st tank



(b) 2nd tank



(c) 3rd tank

Figure 5.22 Control response of MPC with Kalman filter for $+30\%$ $(U_1, U_2, \text{and } U_3)$ change

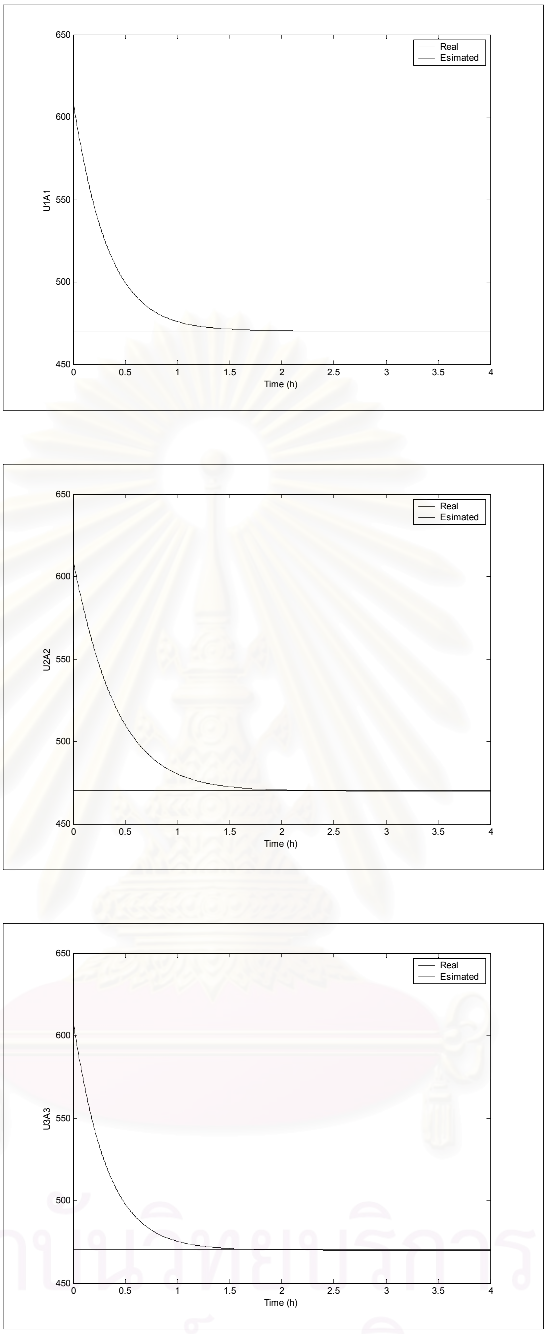
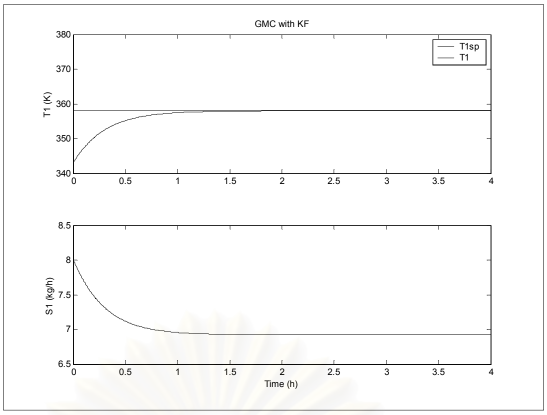
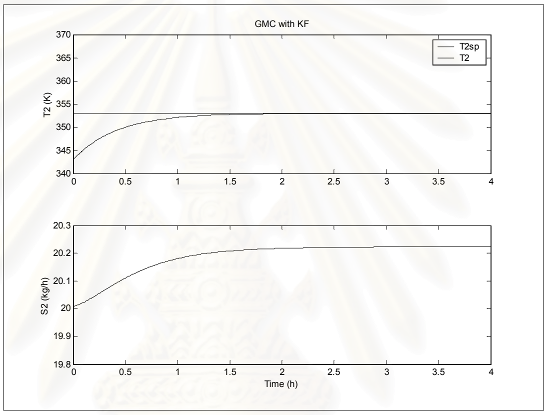


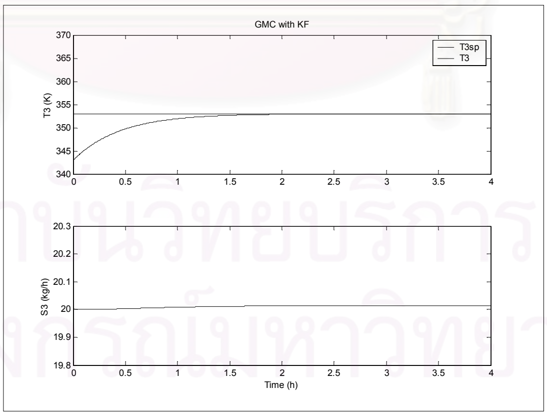
Figure 5.23 Estimate of U_1A_1, U_2A_2, U_3A_3 for +30% $\left(U_1, U_2, U_3\right)$ and +30% $\left(-\Delta H\right)$ change



(a) 1st tank



(b) 2nd tank



(c) 3rd tank

Figure 5.24 Control response of GMC with Kalman filter for +30% (U_1, U_2, U_3) and +30% $(-\Delta H)$ change

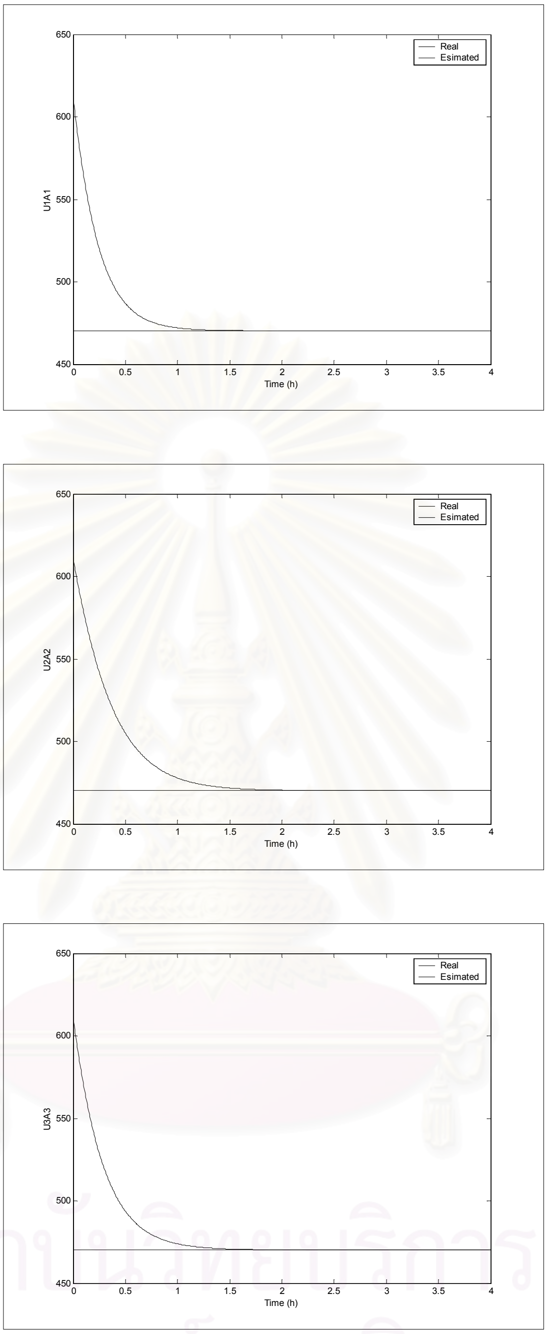
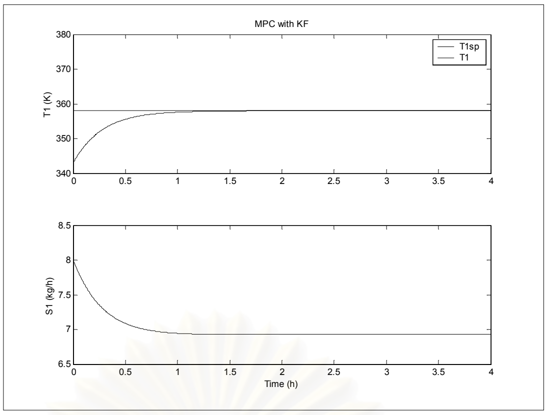
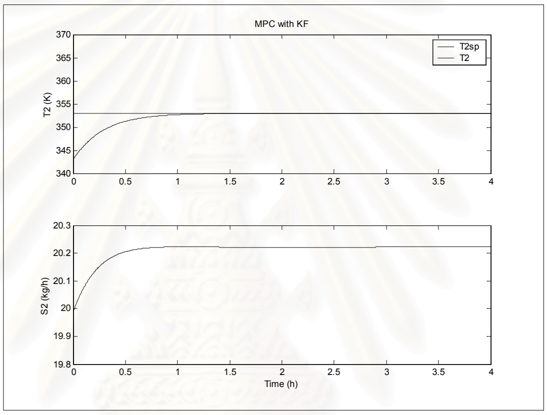


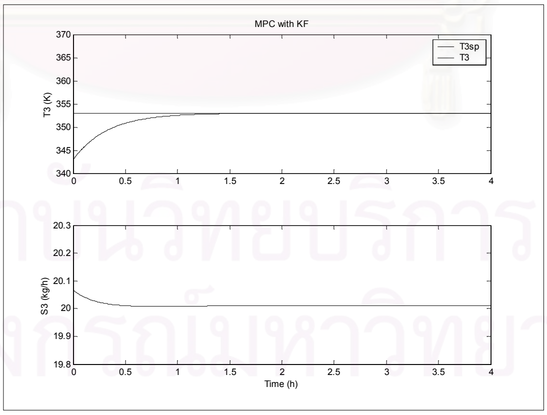
Figure 5.25 Estimate of U_1A_1, U_2A_2, U_3A_3 for +30% (U_1, U_2, U_3) and +30% $(-\Delta H)$ change



(a) 1st tank



(b) 2nd tank



(c) 3rd tank

Figure 5.26 Control response of MPC with Kalman filter for $+30\%\ (U_1, U_2, U_3)$ and $+30\%\ (-\Delta H)$ change

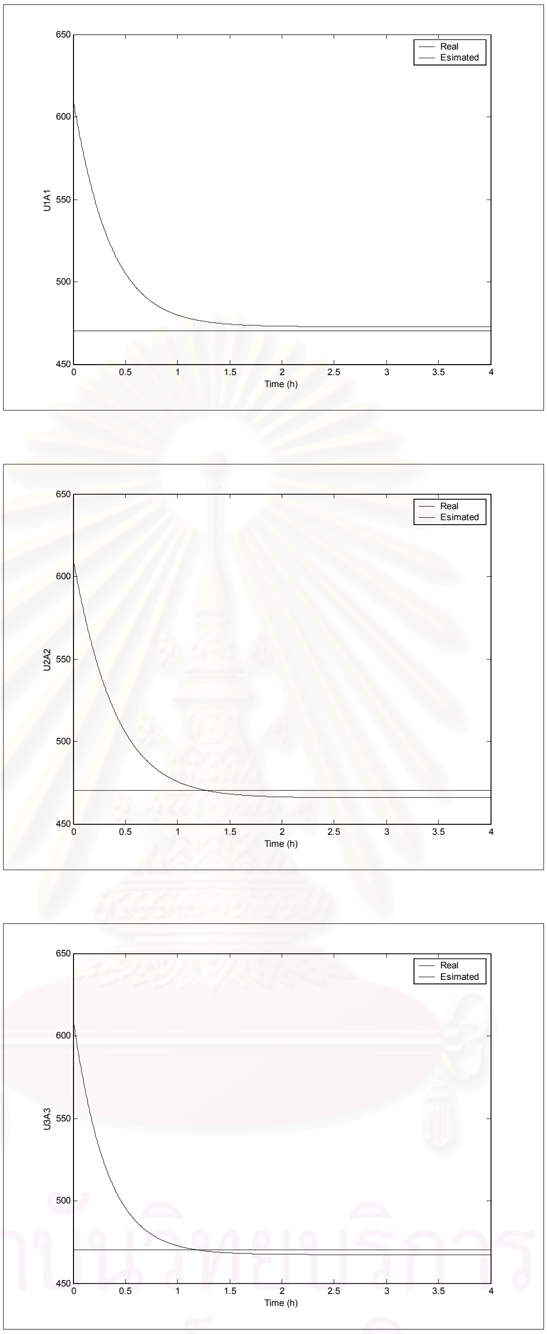
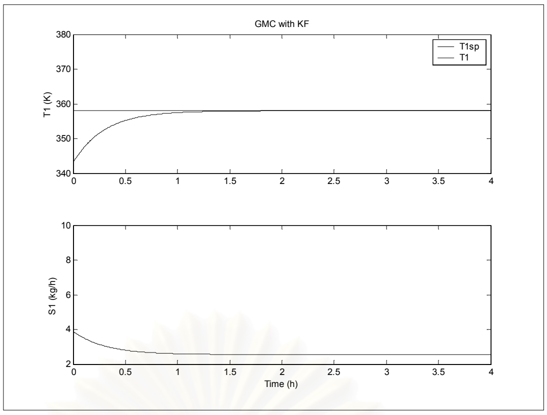
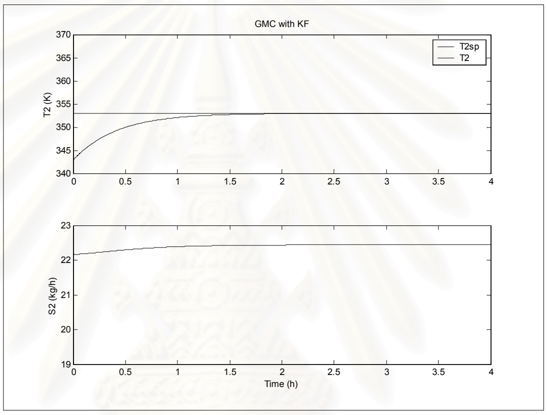


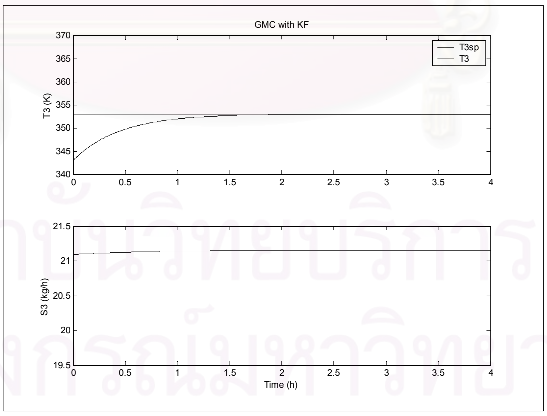
Figure 5.27 Estimate of U_1A_1, U_2A_2, U_3A_3 for $+30\%$ (U_1, U_2, U_3) and $+30\%$ (v_C) change



(a) 1st tank

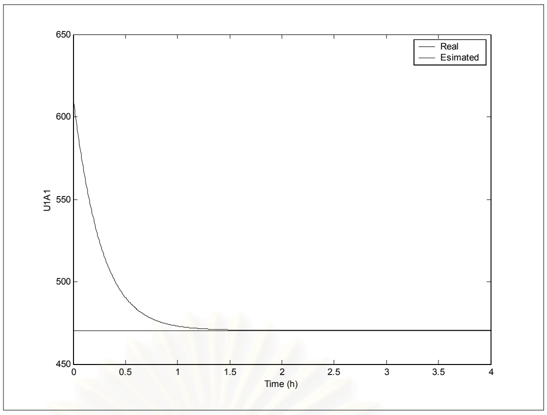


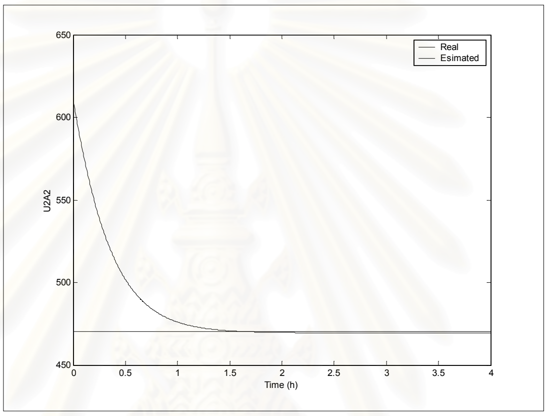
(b) 2nd tank



(c) 3rd tank

Figure 5.28 Control response of GMC with Kalman filter for $+30\%\ (U_1, U_2, U_3)$ and $+30\%\ (v_C)$ change





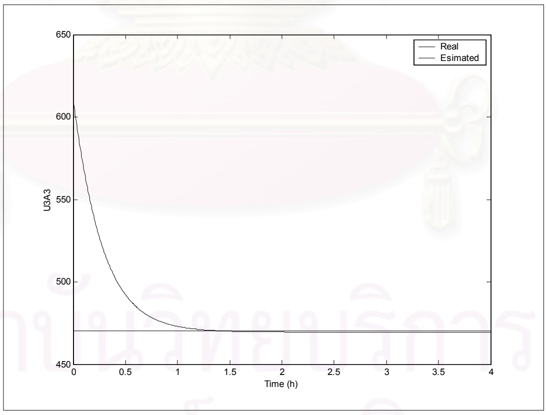
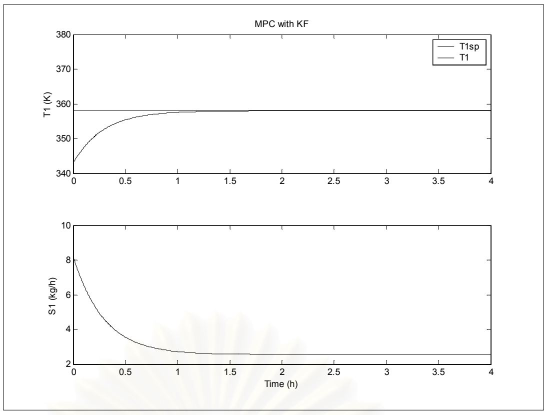
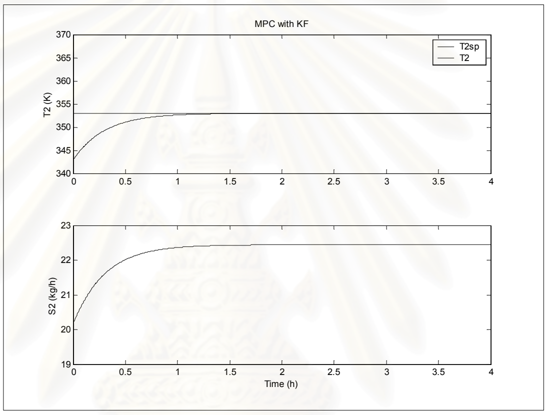


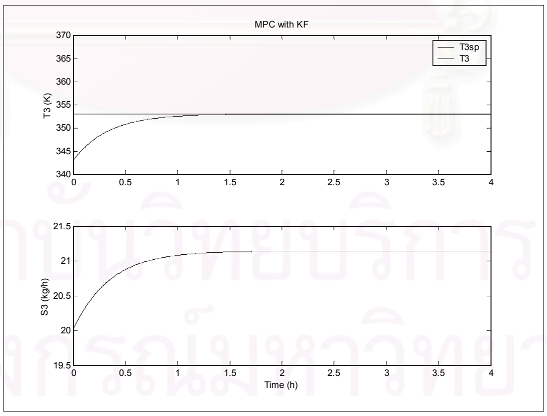
Figure 5.29 Estimate of U_1A_1, U_2A_2, U_3A_3 for $+30\%$ (U_1, U_2, U_3) and $+30\%$ (v_C) change



(a) 1st tank



(b) 2nd tank



(c) 3rd tank

Figure 5.30 Control response of MPC with Kalman filter for $+30\%\ \left(U_1,\, U_2, \text{ and } U_3\right)$ and $+30\%\ \left(v_C\right)$ change

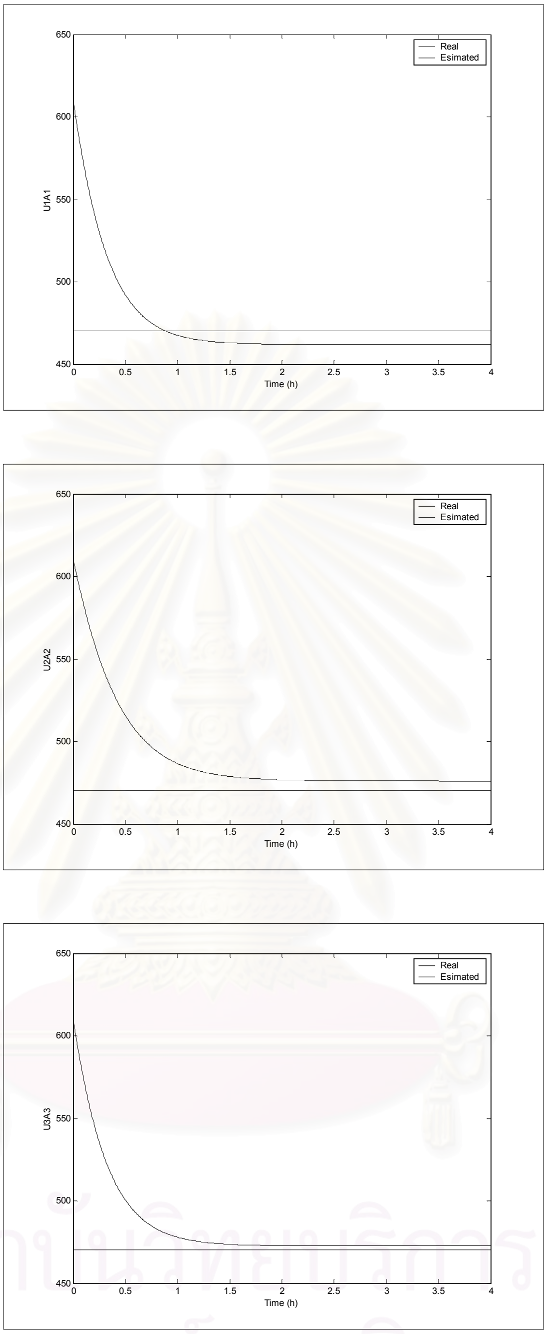
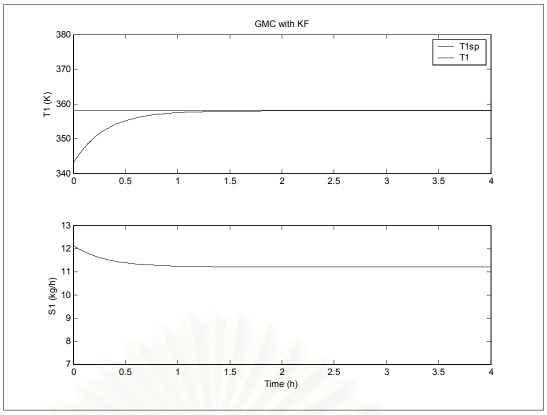
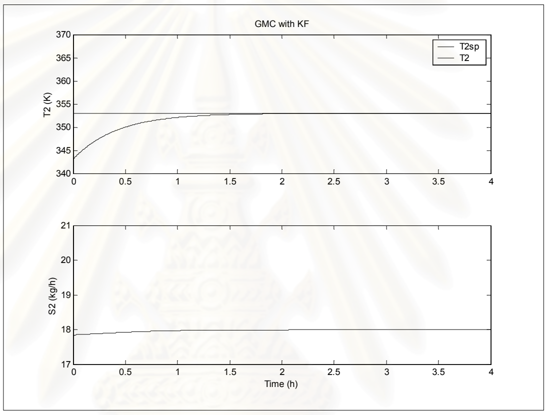


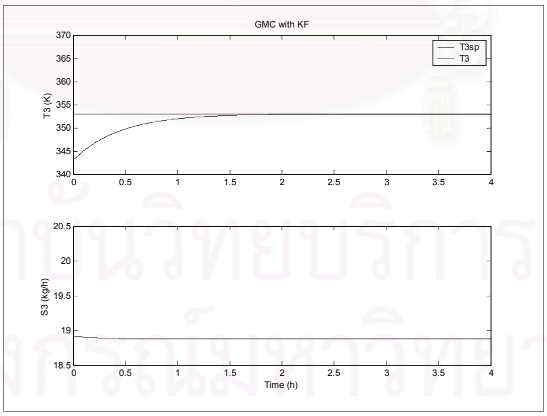
Figure 5.31 Estimate of U_1A_1, U_2A_2, U_3A_3 for $+30\%$ $\left(U_1, U_2, U_3\right)$ and -30% $\left(v_C\right)$ change



(a) 1st tank

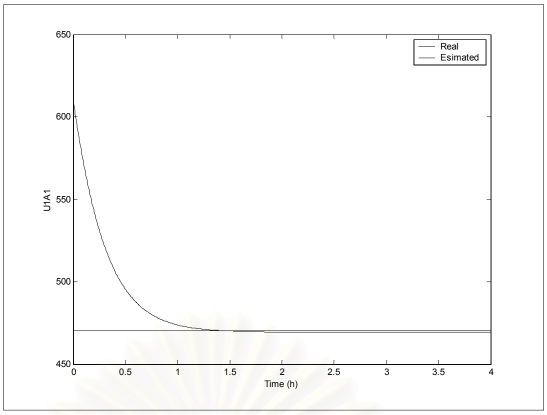


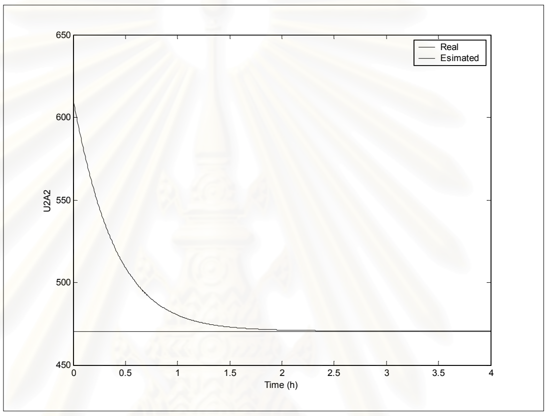
(b) 2nd tank



(c) 3rd tank

Figure 5.32 Control response of GMC with Kalman filter for $+30\%\ (U_1, U_2, U_3)$ and $-30\%\ (v_C)$ change





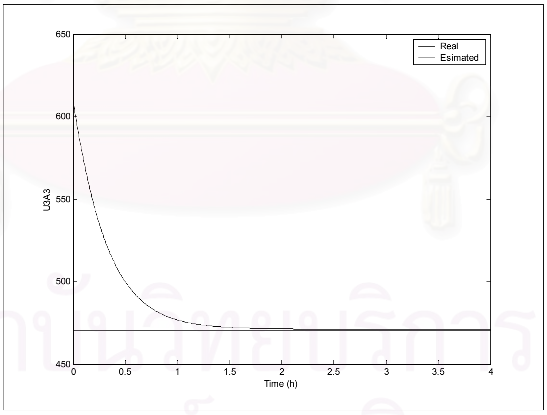
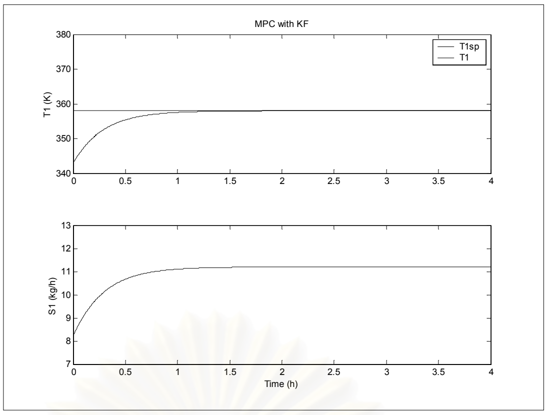
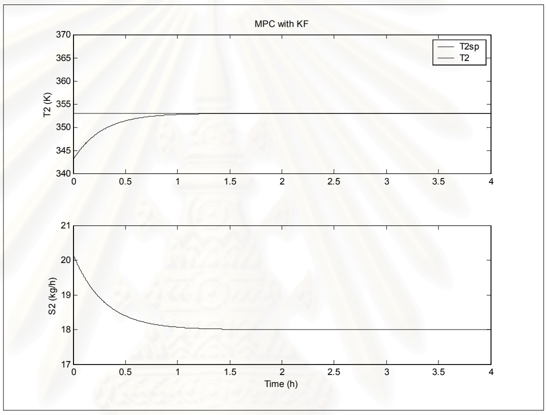


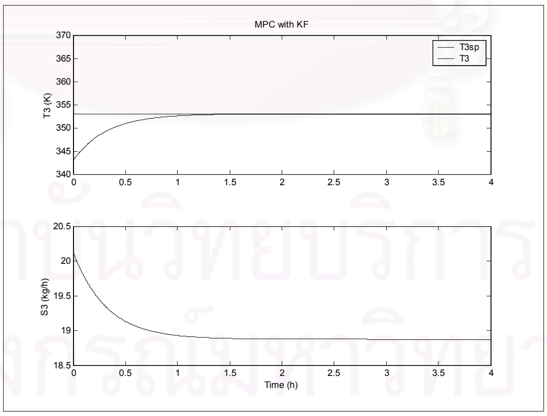
Figure 5.33 Estimate of U_1A_1, U_2A_2, U_3A_3 for $+30\%$ (U_1, U_2, U_3) and -30% (v_C) change



(a) 1st tank



(b) 2nd tank



(c) 3rd tank

Figure 5.34 Control response of MPC with Kalman filter for $+30\%$ (U_1, U_2, U_3) and -30% (v_C) change

Table 5.4 IAE and ISE of the temperature in nominal case

Tank	PID		GMC		MPC	
	IAE	ISE	IAE	ISE	IAE	ISE
1	0.25241	1.9935	0.25774	1.9077	0.21107	1.5550
2	0.30239	1.8135	0.31910	1.5833	0.26123	1.2909
3	0.28001	1.4862	0.30153	1.4814	0.24235	1.1811

Table 5.5 IAE and ISE of the temperature in parameter mismatch case

Case	Tank	GMC with KF		MPC with KF	
		IAE	ISE	IAE	ISE
I	1	0.29707	2.2076	0.27254	2.0217
	2	0.32088	1.5925	0.26147	1.2924
	3	0.30153	1.4815	0.24235	1.1811
II	1	0.29707	2.2076	0.27254	2.0217
	2	0.41423	2.0629	0.28441	1.4090
	3	0.30191	1.4835	0.24259	1.1824
III	1	0.29707	2.2076	0.27254	2.0217
	2	0.31914	1.5843	0.26125	1.2918
	3	0.44080	2.2028	0.31962	1.5820
IV	1	0.29707	2.2076	0.27254	2.0217
	2	0.41425	2.0643	0.28443	1.4101
	3	0.44080	2.2030	0.32636	1.6161
V	1	0.29709	2.2077	0.27257	2.0219
	2	0.41426	2.0643	0.28443	1.4101
	3	0.44080	2.2030	0.32636	1.6161
VI	1	0.29386	2.1613	0.28362	2.1037
	2	0.41831	2.1042	0.30196	1.5060
	3	0.44234	2.2180	0.33240	1.6512

Table 5.5 (continued) IAE and ISE of the temperature in parameter mismatch case

Case	Tank	GMC with KF		MPC with KF	
		IAE	ISE	IAE	ISE
VII	1	0.30027	2.2544	0.28316	2.1082
	2	0.41019	2.0247	0.27437	1.3584
	3	0.43927	2.1881	0.31869	1.5736

5.2.3 Discussion

5.2.3.1 Nominal case

All controllers can control the liquid temperature in each tank of a continuous fabric preparation process to the desired set point. Although the control performance index (IAE) and time to reach the set point of the PID controller are less than the GMC controller, the control respond of PID controller is oscillate and has overshoot while the control response of GMC has smooth and no overshoot.

Both control responses of GMC controller and MPC controller have no overshoot. The control response of MPC has time to reach the set point shorter than the control response of GMC controller and the control performance index of MPC controller is the better than GMC controller. Then MPC controller is the best control in a continuous fabric preparation process.

5.2.3.2 Overall heat transfer coefficient change

In this case, the results are given in figures 5.7 to 5.22. The Kalman filter is implemented to estimate UA terms in each tank. GMC with Kalman filter and MPC with Kalman filter are implemented to control the liquid temperature in each tank. Increase the overall heat transfer coefficient (U), the steam flow rate that used is increase and its effect influences to the liquid temperature. Increasing U_2 and U_3 are not effect to the liquid temperature in the first tank.

From the simulation results, a both of controllers can deliver the liquid temperature in each tank to the desired set point with no overshoot. The control response of MPC with Kalman filter has time to reach the set point shorter than GMC with Kalman filter and the control performance index of MPC controller is the better than GMC controller.

5.2.3.3 Overall heat transfer coefficient and heat of reaction change

The simulation results in this case are shown in figures 5.23 to 5.26. The Kalman filter is implemented to estimate UA terms in each tank. GMC with Kalman filter and MPC with Kalman filter are implemented to control the liquid temperature in each tank. Increase heat of reaction, it does not influence to the liquid temperature in each tank, but influences to the value of using steam flow rate.

A both of controllers can deliver the liquid temperature in each tank to the desired set point with no overshoot. From control response, MPC with Kalman filter has time to reach the set point shorter than GMC with Kalman filter and the control performance index of MPC controller is the better than GMC controller.

5.2.3.4 Overall heat transfer coefficient and fabric velocity change

In this case, the results are given in figures 5.27 to 5.34. The fabric velocity that increased is influence to the liquid temperature in all tanks. Increase the fabric velocity, time to reach the set point of the first tank is rapidly and the other tank is slowly. Decrease the fabric velocity, time to reach the set point of the first tank is slowly and the other tank is rapidly.

The Kalman filter can not be to estimate UA term, the results of estimation has the offset. However, MPC with Kalman filter and GMC with Kalman filter have still to control the liquid temperature in each tank to reach the set point. The manipulated variables from the control response of GMC with Kalman filter are change more and faster than MPC with Kalman filter. The control performance index of MPC controller is the better than GMC controller.

CHAPTER VI

CONCLUSION AND RECOMMENDATION

The work presented in this thesis studies on a model predictive control (MPC) to control the liquid temperature of a continuous fabric preparation process. The study is aimed the single-step of fabric preparation with the counter flow washing of rising step. Since the MPC controller uses a model of the process to be controlled in its algorithm to determine manipulated variables, the modeling of the process is of important. Therefore, a mathematical model of the continuous fabric preparation process is developed.

6.1 Conclusion

In this work, the temperature control can be studied in two cases. One is nominal case that implemented control algorithm of PID, GMC, and MPC controllers to control the liquid temperature of the continuous fabric preparation process to the desired set point. The other one is parameter mismatch case that implemented MPC with Kalman filter and GMC with Kalman filter to control the liquid temperature in several conditions as shown in Table 5.3.

The results in nominal case demonstrated the MPC controller is able to control the liquid temperature at its desired set point and provides a better control performance when compared with a GMC controller and PID controller. In parameter mismatch case, The Kalman filter that implemented with a both controllers can estimate UA terms when changes in the overall heat transfer coefficient and heat of reaction. While changes in the fabric velocity, estimate of UA terms has offset. The robustness of the controllers is evaluated by changing process parameters such as the overall heat transfer coefficient, heat of reaction. It has been shown that the MPC with Kalman filter can control the liquid temperature at desired set point for all case in the parameter mismatch and provides a better control performance when compared with

GMC with Kalman filter. Therefore, the MPC coupled with Kalman filter has been found to be effective and robust with respect in process parameters mismatch.

6.2 Recommendation

1. Some limitations have been investigated. The various assumptions in simplified process simulations are the limitations in study of process model.

2. Typical fabric preparation includes desizing, scouring, and bleaching. Preparation steps can also include processes, such as singeing and mercerizing, The single-step fabric preparation that studied is appropriate for some fabric, designed to chemically or physically alter kind of the fabric.

3. The performance of the continuous fabric preparation depends not only upon the operating temperature but also upon the chemical concentration, pH, and time. The researchers must take the effect of the above parameters into account in order to optimize design parameters and operating conditions.

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APPENDICES

APPENDIX A

SYSTEM TEST

State space equation is linearlization of system from equation (3.11) and (3.12) as shown below.

$$\dot{x} = Ax + Bu \tag{3.11}$$

$$y = Cx \tag{3.12}$$

where A, B and C are constant matrices

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

A.1 Controllability Testing

A mathematically based definition is that a system is completely state controllable if it is possible to cause the state vector to move from any initial value, to any other value, in a finite time.

Method of testing controllability involves finding the rank of the following partitioned matrix made up of combinations of the A and B matrices:

$$\begin{bmatrix} B & AB & A^2B & \cdots & A^{n-1}B \end{bmatrix} \tag{A.1}$$

where n is number of state variable.

This matrix will often be rectangular. If the test matrix is of full rank (that is, the rank equal to the number of rows in B), the system is completely state controllable. If it is not full rank, then the system is only partially state controllable, that is subset of elements of the state vector.

Rank of matrix can be calculated by the determinate of matrix as shown in equation (A.1). The determinate of controllability not equal zero, the matrix in equation (A.1) has rank equal full rank and the system has controllability.

A.2 Observability Test

A system is said to be completely observable if it is to reconstruct the state vector completely from measurements made at the system's output (y).

$$\begin{bmatrix} C^T & A^T C^T & \left(A^T\right)^2 C^T & \cdots & \left(A^T\right)^{n-1} C^T \end{bmatrix} \tag{A.2}$$

where n is number of state variable.

If this matrix is of full rank (that is, the rank equal to the number of rows in C), then the system is completely observable (so that the values of all the states can be found from information available at the system's output). If it is not full rank, then the system is only partially observable (meaning that some, but not all, of the system's state information can be obtained from output measurements).

APPENDIX B

TUNING OF GMC CONTROLLER

Lee and Sullivan (1988) have generalized many of the model-based techniques into a generic structure called the generic model control, which allows the incorporation of nonlinear process models directly in the control algorithm. Consider a process described by:

$$\dot{x} = f\left(x,u,t\right) \tag{B.1}$$

$$y = g\left(x\right) \tag{B.2}$$

where x is a state variable, u is the manipulated input variable, and y is the output of the process model.

In general, f and g are nonlinear functions. From equations (B.1) and (B.2), $\dot{y}$ can be written as

$$\dot{y} = G_x f\left(x,u,t\right) \tag{B.3}$$

where $G_x = \dfrac{\partial g}{\partial x}$

In a classical optimal control, the trajectory of y is usually compared against a nominal trajectory, $y^*(t)$, as a measure of system performance. As an alternative, consider the performance of the system to be such that:

$$\left(\dot{y}\right)^*\left(t\right) = r^*\left(y\right) \tag{B.4}$$

where r^* represents some arbitrary function to be specified.

When the process is away from its desired steady state y^*, the rate of change of y, y^* is selected to be such that the process moves towards steady state, i.e.

$$\dot{y} = K_1\left(t\right)\left(y^* - y\right) \tag{B.5}$$

where $K_1\left(t\right)$ is some diagonal matrix.

The process is selected to have zero offset, i.e.

$$\dot{y} = K_2(t)\int\left(y^* - y\right)dt \tag{B.6}$$

where $K_2(t)$ is some diagonal matrix.

$K_1(t)$ and $K_2(t)$ are constant with respect to time. Good control performance will be given by some combination of these objectives, i.e.

$$\left(\dot{y}\right)^* = K_1\left(y^* - y\right) + K_2\int\left(y^* - y\right)dt \tag{B.7}$$

It can be seen that by different choices of K_1 and K_2 the performance specification can be altered for each variable separately. One can use these values to select any "reasonable" desired response for the system. "Reasonable" implies that the parameters are chosen in relation to the system's natural dynamic response. How well the system matches this performance index is governed by how closely the chosen model matches the plant behavior.

Taking Laplace transform of the equation (B.7), transfer function of this equation becomes:

$$\frac{y}{y^*} = \frac{2\tau\xi s + 1}{\tau^2 s^2 + 2\tau\xi s + 1} \tag{B.8}$$

where $\tau = \dfrac{1}{\sqrt{K_2}}$ and $\xi = \dfrac{K_1}{2\sqrt{K_2}}$.

This system does not yield the same response as a classical second-order system (Stephanopoulos, 1984). However, similar plots to the classical second-order response showing the normalized response of the system y/y^* vs. normalized time t/τ with ξ as a parameter can be produced and is shown in Figure B.1.

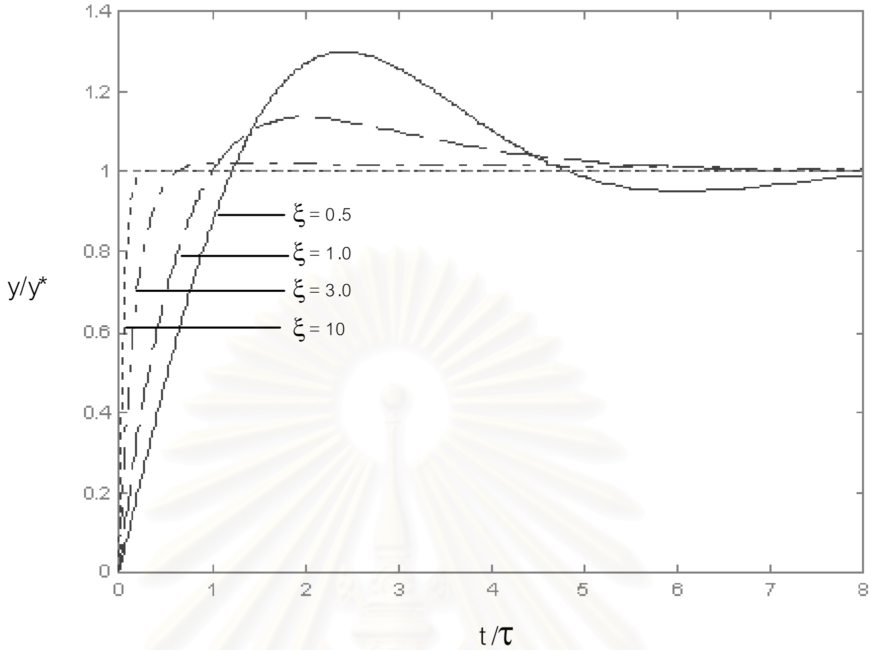

Figure B.1 Generalized GMC profile specification

The design procedure can be specified as follows:

1. Choose ξ from Figure B.1 to give desired shape of response,
2. Choose τ from Figure B.1 to give appropriate timing of response in relation to known or estimated plant speed of response,
3. Calculate K_1 and K_2 using the following equations:

$$K_1 = \frac{2\xi}{\tau} \tag{B.9}$$

$$K_2 = \frac{1}{\tau^2} \tag{B.10}$$

GMC has several advantages that make it a good framework for developing reactor controllers:

1. The process model appears directly in the control algorithm.
2. The process model does not need to be linearized before use, allowing for the inherent nonlinearity of exothermic batch reactor operation to be taken into account.

3. By design, GMC provides feedback control of the rate of change of the controlled variable. This suggests that the rate of temperature change, which as mentioned above is very important in heat-up operations, can be used directly as a control variable.
4. The relationship between feed-forward and feedback control is explicitly stated in the GMC algorithm.
5. Finally and importantly, the GMC framework permits for developing a control algorithm that can be used for both heat-up and temperature maintenance and therefore eliminates the need for a switching criterion between different algorithms; this should result in a much more robust control strategy.

APPENDIX C

INTEGRAL ERROR CRITERIA

Integral error measures indicate the cumulative deviation of the controlled variable from its set point during the transient response. The following formulations of the integral can be proposed.

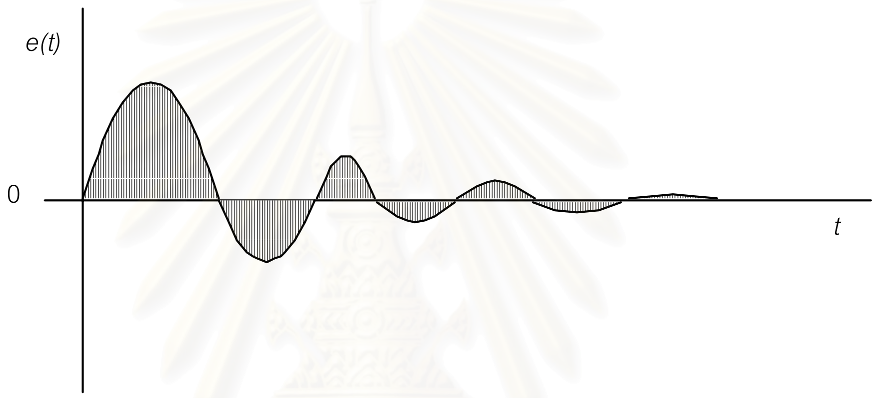

Figure C.1 Definition of error integrals

Integral of the absolute value of error (IAE)

$$IAE = \int_0^\infty |e(t)|\,dt \tag{C.1}$$

Integral of the square of error (ISE)

$$ISE = \int_0^\infty |e^2(t)|\,dt \tag{C.2}$$

Integral of time-weighted absolute error (ITAE)

$$ITAE = \int_0^\infty |e(t)|\,t\,dt \tag{C.3}$$

where e is the usual error (i.e., set point – control variable).

Each of the three figures of merit given by equation (C.1), (C.2), and (C.3) has different purposes. The ISE will penalize (i.e., increase the value of ISE) the response that has large errors, which usually occur at the beginning of a response, because the error is squared. The ITAE will penalize a response, which has errors that persist for a long time. The IAE will be less severe in penalizing a response for large errors and treat all errors (large and small) in a uniform manner. The ISE figure of merit is often used in optimal control theory because it can be used more easily in mathematical operations (for example differentiation) than the figures of merit, which use the absolute value of error. In applying the tuning rules to be discussed in the next section, these figures of merit can be used in comparing responses that are obtained with different tuning rules.

VITA

Mr.Ekachai Saechua was born in Pathumwan, Bangkok, on May 30, 1979. After graduating high school from Suankularb Wittayalay School, he entered Srinakharinwirot Unitversity in May 1996 and received his Bachelor degree of Engineering (with second class honors) in Chemical Engineering in 2000. After that he studied for Master degree in Chemical Engineering, Chulalongkorn University and joined the process control engineering group in the Department of Chemical Engineering.