



**UNIVERSITI PUTRA MALAYSIA**

**ROBUST OFFSET-FREE CONTROL OF NONLINEAR SYSTEMS USING  
MODEL PREDICTIVE CONTROL AND INTEGRAL ACTION**

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**ROBUST OFFSET-FREE CONTROL OF NONLINEAR SYSTEMS  
USING MODEL PREDICTIVE CONTROL AND INTEGRAL  
ACTION**

By

**AYMAN WILLIAM HERMANSSON**

**Thesis Submitted to the School of Graduate Studies, Universiti  
Putra Malaysia, in Fulfillment of the Requirements for the Degree of  
Doctor of Philosophy**

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## DEDICATIONS

*To Mamma och Pappa*

*To Norida, Aida, Adam and Aydeen*



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Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

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**January 2019**

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Model Predictive Control (MPC) is an advanced control setup that uses optimization to determine the controlled input. The MPC was initially a linear approach that has grown to include non-linear systems, robust stability, and offset-free control, which have increased the complexity through; more intricate modeling requirements, increased tuning demands, and a higher computational load.

In this work, the aim is to reduce the aforementioned complexities when applying MPC to nonlinear processes. The first step is to use multiple linear models as a way of describing the non-linear process. The piecewise linear (PWL) description captures the nonlinear process without requiring a non-linear model.

The first objective is to use the PWL for a multi-model description of the process giving rise to multiple model predictive control (MMPC). The PWL models are combined, using a Bayesian approach, into a single model for use in the optimization in MPC. The technique is not a new approach, but one that had not been applied to a pH-control system before.

For the next objective, an MMPC-I approach is developed to introduce integral action into the MMPC, to handle uncertainties such as disturbances and modeling errors. The new method is suggested to circumvent the complications associated with the tuning of an observer.

The combination of MPC and the integral controller was further developed by using the multi-model in a min-max approach to get min-max MPC-I. The min-max configuration using the worst-case scenario for the models rather than weighing them together. This objective would improve the handling of parametric uncertainties, reducing overshoots and oscillations.

The final objective was to develop a Robust MPC-I controller. The disturbance, parametric uncertainty, and integral controller are all accounted for in the input to state practical stability (ISpS) approach. A proof is given that the Robust MPC-I is indeed ISpS for nonlinear systems with bounded uncertainties.

The different combinations of MPC and integral controllers were tested on the pH-control system and compared to PID and observer-based MPC. The MMPC showed excellent behavior when set-point tracking giving at least 25% improvement compared to PID, concerning rise time, settling time and overshoot. However, the MMPC would not achieve offset-free control when disturbances or model errors were present. The inclusion of integral action removed the offset for both MMPC-I and the min-max MPC-I. The MMPC-I managed to reduce the settling time and overshoot for set-point tracking, disturbance rejection and model errors, leading to a 15% reduction in root mean square error (RMSE) compared to the PID. The min-max MPC-I showed similar improvements compared to the PID, though RMSE improvement were just 10%. The reduction compared to the observer-based MPC was even more significant (22%) as it could not achieve offset-free control for all cases. The Robust MPC-I was proven to be stable through mathematical proof, as well as showing improvement compared to the min-max MPC-I. The RMSE was reduced by a further 10%. Lastly, it was shown that the Robust MPC-I reduced the computational time compared to the observer-based MPC by an average of 25%.

A model predictive controller with adaptive I-controller is presented in this thesis to reduce the complexity of the controller. The steps needed in controller tuning and the computational times have been improved compared to the observer-based controller. The robust min-max-MMPC-I is shown to produce better control compared to PID and the observer based model predictive controller.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia  
sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**KAWALAN OFFSET BEBAS MANTAP BAGI SISTEM TIDAK  
LINEAR MENGGUNAKAN MODEL RAMALAN DAN AKSI  
TINDAKAN**

Oleh

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Model predictive control (MPC) adalah persediaan kawalan maju yang menggunakan pengoptimuman untuk menentukan input kawalan. Asalnya MPC adalah pendekatan linear mudah yang telah berkembang dengan meliputi sistem tidak linear, kestabilan teguh dan persediaan kawalan offset bebas dimana telah meningkatkan kompleksiti melalui kerumitan keperluan model, peningkatan permintaan sasaran dan bebanan pengiraan.

Dalam kajian ini, matlamatnya adalah untuk mengurangkan masalah kerumitan keperluan model, permintaan sasaran dan bebanan apabila menggunakan aplikasi MPC untuk proses tidak linear. Linear Piecewise (PWL) menjelaskan proses ketidaklinearan tanpa memerlukan model ketidaklinearan. PWL adalah model linear pelbagai yang menerangkan proses peningkatan kepada Kawalan ramalan model pelbagai (MMPC). PWL adalah menggunakan gabungan pendekatan Bayesian, didalam model tunggal untuk digunakan dalam pengoptimuman MPC. Dimana ianya bukanlah teknik yang baharu, tetapi ianya belum pernah diaplikasi untuk sistem pengawalan-pH. Seterusnya, pendekatan penyelesaian I-pengawal (MMPC-I) dibangunkan untuk memperkenalkan tindakan integral kedalam MMPC, bagi mengatasi ketidakpastian seperti gangguan dan kesilapan pemodelan. Kaedah baharu ini dicadangkan untuk mengelakkan komplikasi berkaitan dengan penalaan pemerhati.

Kombinasi MPC dan pengawalan tindakan (integral action) telah dibangunkan dengan menggunakan model kepelbagaian dalam pendekatan min-max untuk mendapatkan min-max MPC-I. Konfigurasi min-max menggunakan senario kes terburuk untuk model sebaliknya menimbangkan mereka bersama, Ini akan

memberi penambahbaikan dalam pengendalian ketidaktentuan parametrik, mengurangkan overshoot dan ayunan.

Akhirnya, pengawalan MPC-I yang teguh telah dibangunkan. Kesemua gangguan seerti, ketidaktentuan parametrik dan pengawalan integral telah diambilkira dalam pendekatan input menyatakan kestabilan praktikal (input to state practical stability) (ISpS). Bukti telah diberikan bahawa keteguhan MPC-I adalah ISpS untuk sistem tidak linear dengan ketidaktentuan batasan.

Kombinasi MPC yang berlainan dan pengawalan integral telah diuji ke atas sistem pengawalan-pH dan dibandingkan dengan PID dan MPC berasaskan pemerhati. MMPC menunjukkan kelakuan yang cemerlang apabila jejak set-point memberi nilai paling kurang 25% penambahbaikan berbanding dengan PID, berkaitan peningkatan masa (settling time), penetapan masa dan overshoot. Walaubagaimanapun, MMPC tidak dapat mencapai pengawalan offset-free apabila kehadiran gangguan atau kesilapan model (model errors). Kemasukkan tindakan integral telah mengeluarkan offset untuk MMPC-I dan min-max MPC-I. MMPC-I dapat mengurangkan peningkatan masa dan overshoot untuk jejak set-point, penolakan gangguan dan kesilapan models, yang menghasilkan pengurangan 15% dalam root mean square errors (RMSE) berbanding dengan PID. Min-max MPC-I menunjukkan penambahbaikan yang sama dengan PID, walaupun penambahbaikan RMSE hanya 10%. Akhirnya, keputusan menunjukkan MPC-I teguh telah mengurangkan jangkamasa pengiraan terhadap MPC berasaskan pemerhatian dengan kadar purata sebanyak 25%.

Model ramalan pengawalan dengan adaptasi pengawalan-I di bentangkan dalam tesis ini untuk mengurangkan kerumitan pengawalan, langkah-langkah yang perlu dalam penalaan pengawalan dan bilangan pengiraan telah memberi penambahbaikan berbanding pengawalan berasaskan pemerhatian (observer based controller). Keteguhan min-max MMPC-I ini telah menunjukkan pengawalan yang lebih baik berbanding PID dan model ramalan pengawalan berasaskan pemerhati.



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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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## LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Networks
ARX	Autoregressive Exogenous Model
BMI	Bilinear Matrix Inequality
CSTR	Continuously Stirred Tank Reactor
DCS	Distributed Control Systems
DMC	Dynamic Matrix Control
ELM	Extreme Learning Machine
GA	Genetic Algorithm
GPC	Generalized Predictive Control
IMC	Internal Model Control
ISpS	Input to State practical Stability
ISS	Input to State Stability
LFT	Linear Fractional Transformation
LMI	Linear Matrix Inequality
LTI	Linear time invariant
LTV	Linear time varying
MHE	Moving Horizon Estimation
MIMO	Multiple-Input-Multiple-Output
MISO	Multiple-Input-Single-Output
MMPC	Multiple Model Predictive Control or alternatively Multi-Model Predictive Control
MMPC-I	Multiple Model Predictive Control with I-controller
MPC	Model Predictive Control
MPC-I	Model Predictive Control with I-controller
NARX	Nonlinear Autoregressive eXogenous model
NMPC	Nonlinear Model Predictive Control
PFC	Predictive Functional Controller
PID	Proportional Integral Derivative Controller
PSO	Particle Swarm Optimization
PWL	PieceWise Linear
QDMC	Quadratic programming solution of DMC
RHC	Receding Horizon Control
RMHE	Robust Moving Horizon Estimation
SDP	Semidefinite Programming/Optimization
SISO	Single-Input-Single-Output
SMOC	Shell Multi-variable Optimizing Controller
SR-MPC	Safe and Robust MPC
T-S	Takagi-Sugeno

## NOTATION AND LIST OF SYMBOLS

The following notation is used throughout this thesis. Scalars are denoted by lower case letters ( $a, b$ ), vectors in bold lower case letters ( $\mathbf{x}, \mathbf{u}$ ), matrices in upper case letters ( $A, B$ ), and sets in calligraphic letters ( $\mathcal{X}, \mathcal{U}$ ).

$\dots$	...and so forth
$\triangleq$	left-hand side is dened by the right-hand side
$\subset$	is a proper subset of
$\subseteq$	is a subset of
$\in$	belongs to
$\forall$	for all
$\exists$	there exists
$\Rightarrow$	implies
$\Leftarrow$	is implied by
$\Leftrightarrow$	equivalence, if and only if
$\mathbb{R}$	the set of real numbers
$\mathbb{R}^+$	the set of positive real numbers
$\mathbb{R}^n$	space of n-dimensional vectors with real entries
$\mathbb{R}^{m \times n}$	space of matrices with real entries, m rows and n columns
$\mathbb{N}$	the set of nonnegative integers
$\mathbb{N}^+$	the set of positive integers
$\cap$	intersection
$\cup$	union
$I$	identity matrix
$0$	matrix with zero entries
$A^T$	the transpose of matrix A
$A^{-1}$	the inverse of matrix A
$\bar{\sigma}_A$	maximum eigenvalue of matrix A
$\underline{\sigma}_A$	minimum eigenvalue of matrix A
$\frac{\partial}{\partial x} f(\bar{x}, \bar{y})$	Jacobian matrix of function $f(x, y)$ with respect to $x$ evaluated at $x = \bar{x}$ and $y = \bar{y}$
$\ v\ $	norm of vector $v$
$\ v\ _p$	$p$ -norm of vector $x$
$v(k)$	vector signal at time $k$ , for discreet time systems
$v(k+j k)$	predicted value of $v$ at $k+i$ given known value at time $k$
$v(j)$	equivalent short form of $v(k+j k)$
$\hat{v}(k+j k)$	model of variable $v$
$\tilde{v}(k+j k)$	deviation variable for the model of $v$
$v_{sp}$	set-point/operating point of $v$
$n_v$	dimension of vector $v$
$x$	state vector
$u$	input vector



$y$	output vector (measurements)
$y_m$	measured value of $y$
$u_I$	vector of integral action vector
$w$	input disturbance vector
$v$	output disturbance vector
*	indicates symmetric structure
$Q, R$	weighting matrices
$J_1^{N_p}(\tilde{x}(k k))$	cost function from 1 to $N_p$ with the starting point $\tilde{x}(k k)$
$J_1^{N_p^*}(\cdot)$	optimal cost
$J_0^\infty(\cdot)$	cost function for infinite horizons
$J_0^{\infty^*}(\cdot)$	optimal cost for infinite horizons
$N_p, N_c$	prediction and control horizon
$\mathcal{X}, \mathcal{U}, \mathcal{W}$	allowable sets for $x, u, w$
$\Omega$	the set specifying the polytope of allowable models
$Co$	the convex hull spanned by all allowable models
$\lambda_i(k)$	the weight of model $i$ at time $k$
$A_i(k)$	model matrix $A$ for model $i$ computed at time $k$
$F, F(c)$	feedback matrix
$\alpha_i(\cdot)$	$\mathcal{H}_\infty$ -function
$c_n$	concentration of stream $n$ mol/l
$f_n$	flow of stream $n$
$[X]$	concentration of species $X$ mol/l

# CHAPTER 1

## INTRODUCTION

### 1.1 Background

The main focus of the thesis lies in model predictive control (MPC) of nonlinear systems. MPC is the favored control technique when an advanced control scheme is implemented (Maciejowski (2002); Camacho and Bordons (2004); Bequette (2007)). This is highlighted by the application in as various fields as the metal ore industry (Jovanovic and Miljanovic (2015)), the food industry (Kondakci and Zhou (2017)) and the nuclear industry (Eliasi et al. (2012)). The traditional process industry is where it has had its major impact (Qin and Badgwell (2003)) with a growing number of applications since its first implementation in the 1970s. The first software introduced were the IDCOM, but earlier applications were done at Shell Oil utilizing their MPC tool referred to as dynamic matrix control (DMC). Though these techniques were not direct developments from the linear quadratic controllers developed in the 1960s, they have plenty in common. Recurring features include the utilization of a linear model to predict the behavior of the process and that the control performance is obtained based on the optimization of a quadratic objective. However, one of the strengths of MPC, the constraint handling, was not addressed stringently in the early approaches. The constraint handling was rather a part of the second generation setups and software; IDCOM-M, QDMC as well as newcomers with software such as HICON and setups like predictive functional control (PCF) to name a few. One of the major developments in the 1980s was the Shell multi-variable optimizing controller (SMOC), which heralded the use of state-space models into MPC. The state-space model has more or less become the norm in research, while still not totally embraced by the industry (Qin and Badgwell (2003)). This is because most software-based model identification usually relies on response modeling, which will be the model applied the MPC as well. As could be expected the MPC performs best when the time is set aside to do fundamental modeling rather than relying solely on empirical modeling.

In the 1990s the application in industry, particularly in the process industry, continued growing, which can be seen in the quadrupling seen between the two surveys carried out in 1995 (Qin and Badgwell (1997)) and 2000 (Qin and Badgwell (2003)). This coincided with a wider interest from the academic world in the 1990s (Qin and Badgwell (2003)). The application and theory for applying MPC to linear or systems that could be considered linear enough to use a linear model was fairly well defined by the end of the 1990s. This included the setup required to achieve a guaranteed robust stability. However, already at this early stage of research, it was noted that those inclusions have increased the complexity of the MPC. This has led to an increasing demand for the process engineers as the

service and maintenance has become more complex (Qin and Badgwell (2003)). Though, the development of nonlinear considerations as well as an extension into robust stability seemed a rapid development in 2003 (Qin and Badgwell (2003)). The actual implementation of nonlinear MPC has lagged behind with a widening gap between the research and the applications (Ogawa and Kano (2008); Mayne (2015); Forbes et al. (2015)). The major explanation for this is the additional effort needed to describe the nonlinear process while combining linear MPC or PID in conjunction with manual intervention can achieve the required control (Ogawa and Kano (2008)). There is hence a certain need to reduce the complexity of the different techniques for robust nonlinear MPC to enable a wider application in industry and the control improvement that could be achieved with it. The different problems faced in robust MPC, as well as in stochastic MPC, was reviewed by Mayne (2015) and is calling for simplified approaches for robust MPC amongst others.

## 1.2 Problem Statement

The current focus of the research in the field of nonlinear MPC is dealing with robustness as well as offset-free control (Mayne (2014); Goodwin et al. (2014)). Robustness is a matter of guaranteeing stability while the control system is affected by uncertainties, whereas offset-free control is a matter of removing the control error while the control system is affected by uncertainties. Though many approaches have been proposed there has been a very low level of application of it to the process industries (Mayne (2014)). The problems relating to the offset-control is the inclusion of an observer to estimate states and disturbances. The drawbacks of using an observer are;

- the additional tuning of the observer gain, particularly for robust behavior, (Tatjewski (2014), Pannocchia (2015), Goodwin et al. (2014)).
- the increase in computational load (Mohammadkhani et al. (2015)).
- the set-up may not give offset-free control, particularly when dealing with a nonlinear system (González et al. (2008), Tatjewski (2014)).

The increased complexity associated with the two first items is mirrored for robust approaches, as it also requires more extensive tuning and increased computational load. Another issue is that most approaches focus on a single uncertainty, though, there are some examples where parametric uncertainty, bounded disturbances, and unmeasured states are considered (Ding and Pan (2016)). Thus, there is a need to produce a controller that can:

- reduce the complexity, by making the tuning needs less demanding,
- speed up the computations, and increase the applicability of the setup, by producing a controller that can handle, set-point tracking, disturbances, modeling error, and unmeasured states.
- prove that the setup is guaranteed to be robust.

## 1.3 Research Objectives

The primary aim of this work is to develop techniques that will achieve an acceptable level of control of nonlinear systems while producing an offset-free controller

that has lower complexity than the observer based approach. Following on from the problems statement the objectives of this study is:

1. to implement a multi-model predictive controller (MMPC) based on a Bayesian weighting approach for controlling the highly nonlinear pH process.
2. to develop an adaptive integral controller to combine with the MMPC (MMPC-I) to achieve offset-free control.
3. to develop the MMPC-I controller to improve handling of parametric uncertainty by combining a min-max approach with the adaptive integral action controller.
4. to develop a robust offset-free MPC and prove that the setup is robustly stable.

#### **1.4 Scope of the Study**

The focus of the study is to improve the model predictive controller to reduce the complexity of setup and application when robustness and offset-free control is desired.

Offset-free control relies on removing offset under uncertainty. The uncertainties considered in the study are; bounded disturbances, parametric uncertainty (modeling error), set-point tracking (where the control sequence is not known in advance) and an unmeasurable state (hence the exact condition for the model is not known). The primary criteria for these uncertainties are that it should be no remaining offset. However, for good control, there is also a desire to have a fast response, without having too much oscillations or large overshoot. The level of control is measured through the indicators; rise time, settling time and maximum relative overshoot. To get a qualitative comparison as well the proposed approaches are compared to the standard PID-controller as well as the observer based model predictive controller.

The robustness is studied based on mathematical analysis based on Lyapunov stability theory to prove that the system is robust under the bounded uncertainty conditions.

The proposed controllers were tested on a simulated pH-neutralization system. pH-control is one of the hardest control problems in process control and often use as a test bench for various controllers.

#### **1.5 Outline and Contributions**

The two focus points this thesis is to improve the applicability of the MPC setup by making the implementation of the MPC more straightforward and to

produce a controller that can handle a multitude of uncertainties. The scene is set to explore the MPC implementation in Chapter 2, with the review of the literature as well as introduction of the system to implement and test the controllers on. The pH system was chosen due to severely nonlinear behavior creating an excellent problem to test a controller on.

Chapter 3 introduces the Bayesian weighting as a way of getting an adaptive MPC based on multiple models. The obtained Bayesian MMPC is then implemented on the pH system to demonstrate that the approach can handle severe non-linearities. Thus demonstrating that the Bayesian MMPC approach can be implemented on a pH control system.

In Chapter 4 the adaptive integral controller is introduced to be able to achieve offset-free control for the MMPC. Integral action is usually incorporated using an observer and an augmented model. The augmented model both works by including and approximating the disturbance. Observer tuning is generally considered a difficult task, while the adaptive integral control is creating an easily implemented way of achieving offset-free control of a nonlinear system. The level of ease is based on the consideration that linear MPC as well as I-controller are both widely used control approaches and can be implemented by most control engineers. The novel MMPC I-controller combination (MMPC-I) is also tested using the pH-system to show that it can create good disturbance rejection.

Further development is discussed in Chapter 5. The MMPC-I controller was able to handle the disturbances that it was targeted for but started having issues when modeling errors were present. The standard way of dealing with the so-called parametric uncertainty is to introduce a min-max approach based on linear matrix inequalities (LMI). The adaptive integral action is combined with a min-max approach to get a novel offset-free controller with strengthened capability of handling modeling errors. The min-max MMPC-I is further tested on the pH-control system.

A robust offset-free controller is presented in Chapter 6. The adaptive integral action controller is fully incorporated into the MPC and the resulting setup is proven to be input to state practically stable (ISpS). The novel approach is thus proven to be robustly stable for the cases of bounded disturbances, parametric uncertainties as long as the adaptive integral controller output is bounded. The controller is then tested on the pH-system to demonstrate that it can achieve offset-free control for tracking of set-points, bounded disturbances, parametric uncertainties and unmeasurable states.

Lastly, Chapter 7 summarizes the findings, limitations and presents suggestions for future work.

The relation between the different chapters are further highlighted in Figure 1.1. The models for control and simulation discussed in Chapter 2 is used in all following chapter. The MMPC developed in Chapter 3 is used in Chapter 4 as well but in combination with an I-controller. The I-controller is used again in Chapter 5, but the optimization is changed to min-max to increase handling of modeling errors. Chapter 6 proves a robust behavior while using the I-controller in MPC.



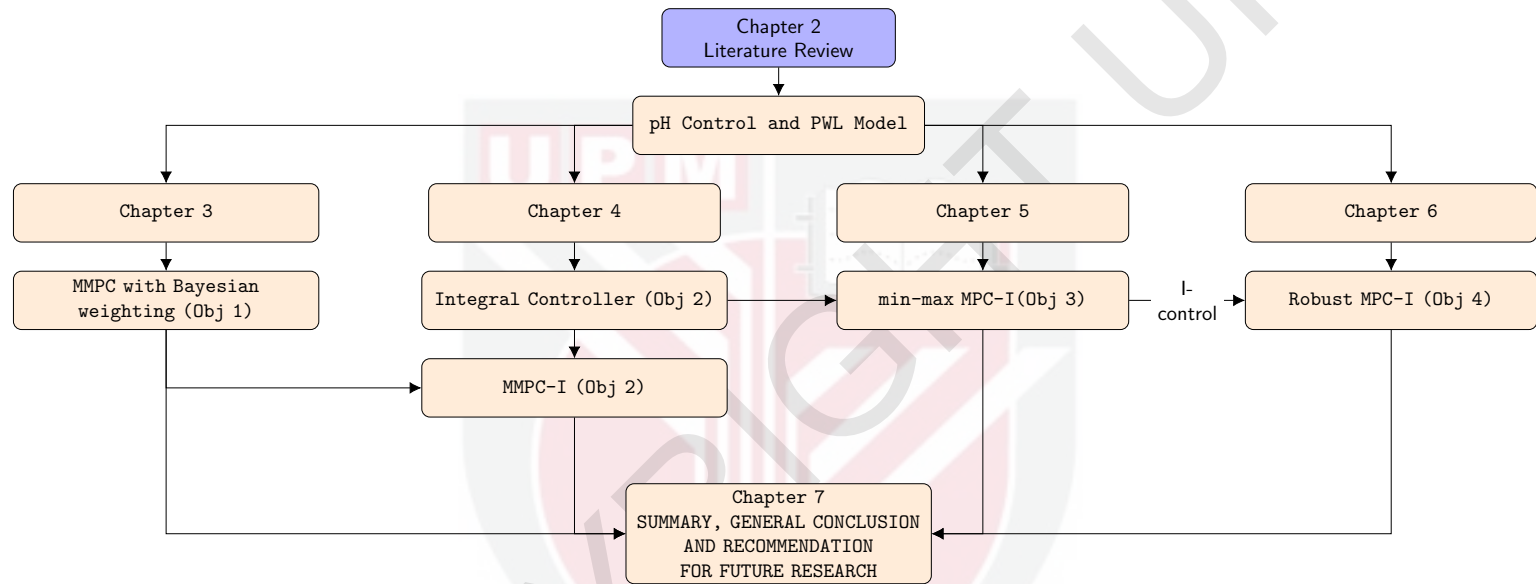


Figure 1.1: Flow chart for the thesis.

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- A.W. Hermansson, S. Syafie, and S.B. Mohd Noor. 2010. Multiple model predictive control of nonlinear pH neutralization system. In *Proceedings of the 2010 IEEE international conference on industrial engineering and engineering management (IEEM)*, 7–10 December 2010, Macau. pp. 301–304
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