Titre: Title:	Predictive and adaptive control of multiple-effect black liquor evaporators
Auteur: Author:	Michelle Jones
Date:	1996
Type:	Mémoire ou thèse / Dissertation or Thesis
Référence: Citation:	Jones, M. (1996). Predictive and adaptive control of multiple-effect black liquor evaporators [Master's thesis, École Polytechnique de Montréal]. PolyPublie. https://publications.polymtl.ca/31199/

URL de PolyPublie: PolyPublie URL:	https://publications.polymtl.ca/31199/
Directeurs de recherche: Advisors:	Michel Perrier
Programme: Program:	Unspecified

UNIVERSITÉ DE MONTRÉAL

PREDICTIVE AND ADAPTIVE CONTROL OF MULTIPLE-EFFECT BLACK LIQUOR EVAPORATORS

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MÉMOIRE PRÉSENTÉ EN VUE DE L'OBTENTION
DU DIPLÔME DE MAÎTRISE ÈS SCIENCES APPLIQUÉES
(GÉNIE CHIMIQUE)
JUILLET 1996

UNIVERSITÉ DE MONTRÉAL

ÉCOLE POLYTECHNIQUE DE MONTRÉAL

Ce mémoire intitulé:

PREDICTIVE AND ADAPTIVE CONTROL
OF MULTIPLE-EFFECT BLACK LIQUOR EVAPORATORS

présenté par: JONES Michelle
en vue de l'obtention du diplôme de: Maîtrise ès sciences appliquées
a été dûment accepté par le jury d'examen constitué de:

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DEDICATION

This thesis is dedicated to my grandmother Jean Winsor. Her life, including graduate studies in Public Health at the University of Toronto (Women's College) in 1932-33, is a powerful and constant source of inspiration, respect and love.

ACKNOWLEDGEMENTS

The individuals and organizations mentioned below are important contributors to the execution of the work described in the following chapters.

M. Perrier, as research director, is a constructive and wise leader whose time and attention is central to the success of the present work and completion of the masters program. J. Valiquette (Noranda Technology Centre) as research codirector provided vital programming assistance as well as an industrial component to the work. Dany Levesque, in her Projet de Fin d'Études (PFE) developed the dynamic model of the multiple-effect evaporator.

I was fortunate to have several sources of financial support. The Natural Sciences and Engineering Council of Canada (NSERC) awarded me a Postgraduate Scholarship (deferred since 1991). The compay Air Liquide continues to be a flexible employer, respecting my priorities and schedule throughout this period. As a student having completed undergraduate studies outside École Polytechnique, I was chosen for a 'Bourse d'excellence de l'École Polytechnique'. Finally, in addition to technical support, the Forest Process Optimization group of the Noranda Technology Centre provided funding.

RÉSUMÉ

Ce mémoire présente l'application d'un contrôleur multivariable adaptatif à un modèle nonlinéaire dynamique d'un évaporateur de liqueur noire à effets multiples. Les objectifs principaux sont de réaliser un modèle représentatif du procédé, d'y ajouter ensuite un contrôleur prédictif multivariable (MPC) à deux entrées et deux sorties selon les principes de la commande prédictive et finalement de déterminer si l'ajout d'une composante adaptative par pondération de modèles (MWAC) apporte des améliorations à la performance du contrôleur.

Le procédé en question consiste d'un évaporateur de liqueur noire à cinq effets tel qu'installé à l'usine kraft des Industries James Maclaren Inc. de Thurso, Québec. La liqueur noire est concentrée en solides en progressant d'un évaporateur à l'autre à contre-courant de la vapeur d'eau, source d'énergie d'évaporation de l'excès d'eau contenu dans la liqueur. Le modèle dynamique inclut chacun des effets étant représenté par trois équations differentielles de bilan matière des solides contenus dans la liqueur noire et du bilan matière de la vapeur d'eau. Les propriétés de la liqueur noire sont incluses dans le modèle en fonction de la concentration et de la température ainsi que celles de la vapeur d'eau saturée.

À partir du modèle dynamique nonlinéaire du procédé, un modèle linéaire a été déduit afin de faciliter les ajustements préliminaires du schéma de contrôle. Pour chaque changement du point de consigne, les essais sont effectués sur le cas de base du MPC à paramètres fixes ainsi que pour l'algorithme adaptatif prédictif MWAC + MPC. Deux cas différents d'erreur dans le délai sont implantés afin de déterminer leur effets sur la performance du contrôleur. Les essais démontrent que les deux cas d'erreur dans le délai sur le contrôleur MPC donnent des résultats pratiquement identiques à ceux du cas de base du MPC sans erreur. En conséquence de ces résultats, un seul cas d'erreur de délai est considéré sur le contrôleur MPC pour les essais de changements de point de consigne et de rejets de perturbation sur le procédé nonliéaire.

Les performances du contrôleur MWAC + MPC adaptatif prédictif sont comparables avec celles d'un contrôleur à paramètres fixes face à des rejets de perturbation et des changements de points de consigne. Afin d'expliquer ces résultats positifs, on doit prendre note du fait que le modèle du procédé pour le contrôleur prédictif à paramètres fixes correspond exactement aux réponses du procédé à boucle ouverte. Ceci est une situation pratique peu probable et constitue un standard élevé de comparaison contre lequel les performances du contrôleur adaptatif prédictif sont mesurées. Une application industrielle du contrôleur adaptatif prédictif démontre la souplesse de celui-ci grâce à son abilité d'adapter ses paramètres aux changements dynamiques du procédé.

Les résultats des travaux sont prometteurs pour l'implantation en usine de la combinaison de contrôle multivariable adaptatif prédictif. L'aspect original de cet ouvrage est d'appliquer un contrôleur MPC 2x2 incluant des paramètres adaptés via l'algorithme MWAC à un modèle de procédé nonlinéaire dynamique avec données opératoires provenant de l'usine ci-haut mentionnée. Les tests et ajustements effectués dans cet ouvrage devrait faciliter l'implantation d'un système de contrôle avancé en usine visant à minimiser les variations de qualité du produit et les coûts énergétiques.

ABSTRACT

This work presents an application of multivariable adaptive predictive control to a dynamic nonlinear model of a multiple-effect black liquor evaporator. The goals are firstly to develop a representative model of the process, secondly to implement a 2x2 predictive controller according to the Model Predictive Control (MPC) principles, and finally to determine whether adding a Model Weighting Adaptive Control (MWAC) adaptive component to the predictive controller improves performance.

The process unit modeled is a five-effect black liquor evaporator at Industries James Maclaren Inc. kraft pulp mill in Thurso, Quebec. Black liquor is concentrated as it passes from one effect to the next by evaporating steam which flows countercurrent to the liquor, supplying the energy required to drive off the excess water. In the dynamic model each effect is described by three differential equations representing the black liquor mass balance, the black liquor solids mass balance, and the vapour mass balance. Property values for black liquor at various concentrations and temperatures as well as for saturated steam are also included in the model.

From the nonlinear dynamic process model, a linear system of first order plus dead time relationships between controlled variables (strong black liquor flow and concentration) and

manipulated variables (weak black liquor flow and feed steam pressure) is identified. This simplifies preliminary tuning and testing of the control scheme. For a set point change, trials are performed on the base case of MPC with fixed parameters as well as the adaptive predictive algorithm, MWAC + MPC. Knowing that in an industrial application the process is never perfectly modeled by the MPC controller, two different cases of dead time mismatch are created in order to determine their effect on controller performance. As it turns out, the two cases of dead time mismatch in the MPC controller perform very much the same as the base case of MPC with no mismatch. For this reason, only one case of dead time mismatch in the MPC controller is carried forward to the set point change and disturbance rejection trials on the nonlinear process.

Throughout this work, the MWAC + MPC adaptive predictive controller performance is compared with the fixed parameter predictive controller performance and found to be similar in disturbance rejection and for set point changes. In order to explain why this is a good result, it is noted that the process model in the fixed parameter predictive controller matches exactly the open loop process responses. This is an unlikely practical situation which results in a high standard against which the adaptive predictive controller performance is measured. The strength of the adaptive predictive controller is that in an industrial application the parameters would adapt to changing process dynamics.

The results indicate that this combination of multivariable, adaptive predictive control shows promise for implementation in the mill. The aspect of originality in this work is application of a 2x2 MPC controller with parameters adapted by the MWAC algorithm to a dynamic nonlinear process model with design and operating values from Industries James Maclaren Inc. Testing and tuning done here should facilitate implementation of an advanced control scheme at the mill which would lead to reduced product variability and energy expenditures.

CONDENSÉ EN FRANÇAIS

Cette section présente une description condensée du travail décrit dans ce mémoire. En premier lieu, les objectifs visés sont énumérés afin de situer le problème étudié. Deuxièmement, la séquence des étapes de la recherche est présentée pour décrire le déroulement du travail. Les conclusions mettent en évidence la contribution du travail suivies des recommandations et applications futures possibles.

Le sujet du projet est le contrôle d'un évaporateur multi-effets de liqueur noire à l'usine de pâtes kraft de la compagnie Industries James Maclaren Inc. à Thurso, Québec. Cette unité d'opération se situe en aval des lessiveurs où les copeaux de bois sont mélangés avec des produits chimiques (la liqueur blanche) à haute température et haute pression; et en amont de la fournaise de récupération où les composants organiques de la liqueur noire sont brulés afin de récupérer les produits chimiques inorganiques. Le problème de contrôle consiste à maintenir dans la liqueur noire une concentration en solides et un débit aussi constant que possible étant donné les variations associées à la matière première. Ceci est important parce que durant les excursions de concentration de la liqueur noire l'efficacité du procédé est réduite et l'encrassement des équipements devient problématique.

Objectifs Visés: Le premier objectif est de mettre au point un modèle dynamique nonlinéaire qui représente l'équipement et le procédé réel de l'usine Industries James Maclaren Inc. Le second et principal objectif consiste à comparer la performance d'un contrôleur multivariable prédictif à paramètres fixes avec celle d'un contrôleur multivariable prédictif et adaptatif. Les objectifs de contrôle sont d'éliminer les perturbations dans le système tout en minimisant les excursions de la concentration et du débit de la liqueur noire à la sortie de l'évaporateur.

Étapes de la recherche: La méthodologie se devise en trois étapes commençant par la mise au point du modèle dynamique. À ce modèle est ajouté un contrôleur multivariable à paramètres fixes pour faire une comparaison entre sa performance et celle d'un contrôleur adaptatif. Le but de cette étape est de déterminer si en ajoutant une composante adaptative, la performance du contrôleur est améliorée. Le modèle dynamique est formulé avec trois équations différentielles par effet qui décrivent les bilans de matière et d'énergie en incorporant le point d'opération de l'usine ainsi que les propriétés chimiques de la liqueur noire. Le niveau de liqueur noire dans la cuve de chaque effet est réglé par un contrôleur PI. Le contrôleur 2x2 prédictif est selon l'algorithme de commande prédictive (MPC). Les variables contrôlées sont la concentration et le débit de la liqueur noire sortant de l'évaporateur (SBL). Les variables manipulées sont le débit de liqueur noire entrant l'évaporateur (WBL) ainsi que la pression de vapeur saturée (vierge) qui entre à contre-courant de la liqueur noire et fournit l'énergie requise pour évaporer l'eau de la liqueur.

L'algorithme pour adapter les paramètres du contrôleur prédictif est celui de la pondération de modèles (MWAC). Cet algorithme requiert des plages discrètes des valeurs possibles de paramètres dun modèle du procédé . Dans le cas présent, la relation entre chaque variable manipulée et chaque variable contrôlée est une fonction de transfert de premier ordre avec délai. Avec un système 2x2, il y a quatre de ces relations. Les paramètres à estimer sont le gain, la constante de temps et le délai. Pour éviter une quantité excessive de combinaisons possibles, la constante de temps est fixée, tandis quune plage discrète de gains et de délais sont considérés. Par exemple, la relation entre D22, la concentration à la sortie, et F16, le débit à lentrée, est estimée par une constante de temps (1.5 minutes) une plage de gains (0.7, 0.8, 0.9 ,1.0); et une plage de délais (0, 0.5, 1 1.5, 2, 2.5, 3, 3.5, 4 minutes). À chaque instant déchantillonnage, les estimations possibles avec les combinaisons de paramètres sont faites. Un poids normalisé est calculé pour chaque modèle en vue d'obtenir un modèle composé. Le calcul du poids est une fonction de lerreur destimation et dune combinaison de paramètres aux intervalles précédents. La procédure dadaptation favorise les combinaisons qui estiment bien les variables de sortie du procédé. Lestimation composée sadapte aux changements de dynamique du procédé en recalculant le poids de chaque modèle. Le calcul se fait de la façon suivante:

$$\tilde{P}_c(q^{-1}) = \sum_i \sum_j w_{c1,\,ij} \frac{g_{c1,\,i}(1-\alpha)}{1-\alpha q^{-1}} q^{-(c1,\,j)-1} + \sum_i \sum_j w_{c2,\,ij} \frac{g_{c2,\,i}(1-\alpha)}{1-\alpha q^{-1}} q^{-(c2,\,j)-1}$$
$$= \frac{(1-\alpha)q^{-1}}{1-\alpha q^{-1}} \sum_j \gamma_{c1,\,j} q^{-(c1,\,j)} + \frac{(1-\alpha)\,q^{-1}}{1-\alpha q^{-1}} \sum_j \gamma_{c2,\,j} q^{-(c2,\,j)}$$

avec $\dot{P}$ l'estimation, w le poids, g le gain, i l'indice des gains, j l'indice des délais.

Résultats: Des tests sur le modèle dynamique démontrent que le comportement du procédé réel est bien représenté. Par la suite, le réglage des paramètres du contrôleur prédictif permet un fonctionnement selon les critères choisis et décrits plus loin. Les paramètres de l'algorithme adaptatif sont choisis selon l'identification du procédé. Finalement, les résultats des essais avec les contrôleurs à paramètres fixes et adaptatifs suite à des perturbations et à des changements de point de consigne sont présentés.

Pour démontrer que le modèle représente bien l'usine, les valeurs de concentration ~~et~~ du débit de WBL sont celles établies lors de la conception. Celles-ci décrivent les entrées de liqueur au train d'évaporateurs. Le débit et la concentration des variables de sortie sont comparables aux calculs de conception avec une déviation d'environ 1%. Cependant le bilan global des solides et de l'eau boucle avec des écarts de 0.4%. Les différences de valeurs de propriétés physiques de la liqueur peuvent aussi expliquer l'écart.

Le schéma de contrôle comprend le débit à la sortie de l'évaporateur qui est à la fois manipulé par le contrôleur de niveau au dernier effet. Pour alléger le travail informatique durant le réglage préliminaire du contrôleur prédictif à paramètres fixes, un modèle linéaire du système est identifié à partir de la réponse des variables contrôlées à un échelon sur chaque variable manipulée.

$$\begin{bmatrix} F22 \\ D22 \end{bmatrix} = \begin{bmatrix} \dfrac{0.87e^{-0.05s}}{0.025s+1} & \dfrac{-0.41e^{-0.05s}}{0.0042s+1} \\ \dfrac{-0.18e^{-0.033s}}{0.077s+1} & \dfrac{0.195e^{-0.033s}}{0.083s+1} \end{bmatrix} \begin{bmatrix} F16 \\ P1002 \end{bmatrix}$$

F22 représente le débit de SBL, *D22* la concentration de SBL, *F16* le débit de WBL, et *P1002* la pression de vapeur vierge. Le temps est mesuré en heures. Les délais du modèle ci-dessus ne proviennent pas de l'identification du système. Leur amplitude est arbitraire et reste à être confirmée lors de tests à l'usine.

Les paramètres principaux du contrôleur prédictif sont les horizons du modèle, de la prédiction et de contrôle. Pour éviter d'avoir plus de 200 constantes dans le modèle de convolution mais sans avoir un pas de temps si grand que la dynamique d'une réponse soit perdue, l'horizon du modèle est de 60 minutes, et ceux de la prédiction et de contrôle sont de 30 et 10 minutes, respectivement. Pour chacune des deux variables contrôlées, il y a un poids relatif à déterminer sur la pénalité d'excursions du point de consigne. Puisqu'à l'opération suivant l'évaporateur, la fournaise de récupération, il est essentiel que la quantité d'eau dans la liqueur ne soit pas trop élevée (combustion inefficace) ni trop faible (encrassement) la concentration de la liqueur SBL reçoit un poids plus grand que le débit de SBL, soit 20 et 1, respectivement. Les poids associés aux changement des variables manipulées sont fixés à 15 pour le débit WBL et 10 pour la vapeur vierge.

Les paramètres de réglage de lalgorithme MWAC sont la constante de temps, la plage de gains, et la plage de délais. Le réglage est fait à partir de quatre réponses à léchelon: soit la réponse de D22 et F22, la concentration et le débit du produit (les variables contrôlées à un échelon de F16, le débit de liqueur à lentrée et P1002, la pression de vapeur vierge (les variables manipulées).

Une fois les paramètres ajustés, la performance des contrôleurs prédictifs à paramètres fixes et adaptatifs est comparée lors dun changement de point de consigne et de la réjection dune perturbation. Des essais préliminaires sont faits avec le procédé linéaire et un changement de point de consigne du débit de liqueur à la sortie, F22. La trajectoire de F22 vers le nouveau point de consigne ainsi que celles des variables manipulées ne montre pas une différence entre les contrôleurs. Quant à D22, seul le contrôleur à paramètres fixes avec une erreur dans lestimation du délai répond légèrement plus lentement que les contrôleurs à paramètres fixes sans erreur destimation de délai, et le contrôleur à paramètres adaptatifs. Les derniers essais sont faits avec le modèle nonlinéaire du procédé. Pour le changement de point de consigne ainsi que la perturbation, les performances sont quasi identiques.

Conclusions: La performance du contrôleur adaptatif est similaire à celle du contrôleur à paramètres fixes. On peut supposer quà lusine, avec des changements dans la dynamique du procédé, le contrôleur MWAC + MPC aura une performance au moins équivalente ou supérieure au contrôleur à paramètres fixes.

Applications / Recommandations: Lapplication du contrôleur prédictif adaptatif à lusine Industries James Maclaren Inc constitue la suite logique de ce travail. Quant au modèle, il serait intéressant de mettre à jour les propriétés de la liqueur noire et les délais et de vérifier la correspondance entre les conditions dopération réelles et celles utilisées en simulation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

Numbers in parentheses after descriptions refer to the equation in which the symbol first appears.

Letter Symbols

A	cross-sectional area of the separator (2.2.1)
A	constant state space matrix (3.1.1)
A	dynamic matrix (3.3.10)
$a_{ij,t}$	step response model coefficient for controlled variable i, manipulated variable j, and coefficient number t (3.3.2)
$\hat{c}_{i,n+1}$	predicted value of controlled variable i at sampling instant n + 1 (3.3.1)
C	conversion factor for mass to pressure from ideal gas law (2.2.3)
C_p	heat capacity of the liquor (2.2.6)
$c_{i,n}$	controlled variable i at sampling instant n (3.3.4)
$\hat{c}_{i,n}$	output prediction for controlled variable i at sampling instant n (3.3.1)
$c^*_{i,n}$	corrected prediction of controlled variable i at sampling instant n (3.3.4)
D	delay (3.4.1)
d	disturbance (3.2.2)
d	delay (3.4.2)
D16	WBL concentration
D22	SBL concentration (4.2.1)
$E_{i,n}$	process error in controlled variable i at sampling instant n (3.3.5)

$\hat{E}'$	open-loop error prediction (3.3.5)
$\hat{E}$	closed-loop error prediction (3.3.6)
$\mathscr{F}_d$	family of candidate models (3.4.3)
F_1	feed flow rate (2.2.1)
F_2	product flow rate (2.2.1)
F_3	circulating flow rate (2.2.7)
F_4	vapour flow rate (2.2.1)
F_5	condensate flow rate (2.2.3)
F16	WBL flow (4.2.1)
F22	SBL flow (4.2.1)
F_{100}	steam flow rate (2.2.10)
F_{200}	cooling water flow rate (2.2.11)
F_{IN}	flow into vessel (2.3.1)
F_{OUT}	flow out of vessel (2.3.1)
f	forgetting factor (3.4.8)
G_{cp}	controller (predictive) transfer function (Figure 3.1)
G_d	disturbance transfer function (Figure 3.1)
G_m	process model for predictive controller transfer function (Figure 3.1)
G_p	process transfer function (4.3.1)
g	process gain (3.4.1)

h	hour
h_{ijt}	impulse response coefficient for output variable i, input variable j, and coefficient number t (3.3.1)
K_c	proportional tuning parameter (2.3.2)
K_c	controller gain (3.2.1)
$\mathrm{K_c}$	matrix of feedback gains for MPC (3.3.10)
K_{cSS}	controller gain at steady state (3.2.1)
K_{FB}	feedback control matrix (3.2.2)
K_{FF}	feedforward control matrix (3.2.2)
K_{GS}	gain scheduling contribution to controller gain (3.2.1)
K_I	integral control matrix (3.2.2)
K_{sp}	set point control matrix (3.2.2)
L	level in vessel (2.3.2)
L_2	separator level (2.2.1)
M	amount of liquid in the evaporator (2.2.2)
$m_{i,n+1}$	manipulated variable i at time sampling instant n + 1 (3.3.1)
N_k	size of family of candidate models (3.4.12)
P	process model (3.4.1)
$P_{ij,V}$	projection vector of controlled variable i, manipulated variable j, on prediction horizon point V
P_2	operating pressure (2.2.3)

P_{100}	steam pressure (2.2.8)
P1002	steam pressure (4.2.1)
Q	move suppression factor (3.3.11)
Q_1	move suppression factor for manipulated variable 1 (3.3.13)
Q	controlled variable weighting matrix (3.1.1)
Q_{100}	heater duty (2.2.6)
Q_{200}	condenser duty (2.2.11)
R	manipulated variable weighting (3.1.1)
S_j	term j of projection vector (3.3.4)
T	model horizon
T_1	feed temperature (2.2.6)
T_2	product temperature (2.2.5)
T_3	vapour temperature (2.2.4)
T_{100}	steam temperature (2.2.8)
T_{200}	cooling water inlet temperature (2.2.11)
T_{201}	cooling water outlet temperature (2.2.11)
T_I	integral tuning parameter (2.3.2)
t	tonne (1000 kg)
U	control horizon (3.3.2)
UA_1	heater overall heat transfer coefficient times the heat transfer area (2.2.7)

UA_2	condenser overall heat transfer coefficient times the heat transfer area (2.2.12)
u	manipulated variable (3.1.1)
V	volume (2.4.1)
V	prediction horizon (3.3.2)
W	controlled variable weighting (3.3.11)
W_1	controlled variable 1 weighting (3.3.13)
w	weighting coefficient for candidate models (3.4.5)
X_1	feed composition (2.2.2)
X_2	product composition (2.2.2)
x_{p}	process state variables (3.2.2)
y	output (3.2.2)
$\tilde{y}$	prediction error (3.4.4)
y_{sp}	desired value of y (3.2.2)

Superscripts

T	matrix transpose (3.1.1)

Subscripts

max	maximum (2.3.6)

Greek Characters

α	time constant conversion between Laplace domain and z-transform (3.4.2)
γ	product of gain and weighting parameters in MWAC algorithm (3.4.6)
Δ	magnitude of change (2.3.5)
λ	latent heat of vaporization of the liquor (2.2.6)
λ_s	latent heat of steam (2.2.10)
ν	error norm (3.4.8)
ξ	damping coefficient (2.3.3)
ρ	liquid density (2.2.1)
σ	variance (3.4.10)
τ	time constant (2.3.3)
ε	process error (3.4.4)

Abreviations

BPR	boiling point rise
CV	controlled variable
CW	cooling water
DMC	Dynamic Matrix Control
FB	feedback

FF	feedforward
FOPDT	first order plus dead time
GMC	Generic Model Control
IMC	Internal Model Control
MAC	Model Algorithmic Control
mm	mismatch (dead time)
MPC	Model Predictive Control
MRAC	Model Reference Adaptive Control
MV	manipulated variable
MWAC	Model Weighting Adaptive Control
QP	quadratic programming
RD	relative degree
SBL	strong black liquor
SP	set point
WBL	weak black liquor

Mathematical Operations

$\triangleq$	defined as
$\uparrow$	increasing
$\downarrow$	decreasing

~	approximately
$\bar{a}$	upper limit of a
$\underline{a}$	lower limit of a
$\in$	member of
card	cardinality: number of elements (3.4.3)
exp	exponential function
$J[x] = f$	objective function with solution of f that minimizes x (3.3.11)
q	shift operator $q^{-1} y_t = y_{t-1}$
s	Laplace domain variable

CHAPTER I

INTRODUCTION

1.1 Problem Statement

Effective process control is seen as a means to the end of reduced product variability. The pulp and paper industry is not untouched by the current trend toward advanced control strategies and systems. Given that one quarter of the energy requirements in a bleach grade kraft mill are for black liquor evaporation, allocation of resources for development of a control strategy is justified [3]. Kraft pulping consists of several steps beginning with combining wood chips with cooking (white) liquor at elevated temperatures in the digester. Exiting pulp is washed and directed to storage or bleaching. Due to chemical costs and environmental concerns, approximately 95-97% of the chemicals added to the digester are recovered [8]. The first step in this recovery process is to remove water from the black liquor such that the organic wood residuals can be burned in the recovery furnace without supplemental fuel. The unit operation under consideration is evaporator number three (#3) at Industries James Maclaren Inc. of Thurso, Québec which produces 620 tons/day of bleached hardwood kraft pulp [15]. Installed in 1989, this train of falling film evaporators was chosen because it is the most recent in the mill and is controlled by a distributed control system (DCS). The problem motivating this work is variation in strong black liquor (SBL) entering the concentrator and eventually the recovery boiler. Variability in the SBL is problematic for several reasons including decreased efficiency of the overall kraft process and excessive fouling of the evaporator tubes.

1.2 Objectives

The goals are: firstly, to develop a nonlinear dynamic process model that is representative of the Industries James Maclaren Inc. installation; secondly, to design a multivariable predictive controller with fixed parameters; and finally, to determine whether adding an adaptive component to the predictive controller improves performance. The control objectives are to eliminate disturbances in the evaporator system with minimal deviation of the controlled variables.

1.3 Methodology

The approach is three tiered: develop a dynamic model, add a multivariable controller with fixed parameters, determine whether controller performance improves with adaptive parameters. Chapter 2 presents the model which is a system of nonlinear differential equations developed from the work of Newell and Lee [14] and Levesque [10] with operating and design values from the mill. In Chapter 3, a 2x2 model predictive control

(MPC) algorithm is added with SBL concentration and flow controlled by manipulating weak black liquor (WBL) flow and steam feed pressure. The results of tuning the controller for smooth, stable operation during rejection of system disturbances are presented in Chapter 4. Also in Chapter 4, the model weighting adaptive control (MWAC) algorithm is used for adaptation of the predictive controller parameters and enhanced multivariable controller performance. Finally, conclusions as well as possible extensions of the work are in Chapter 5.

CHAPTER II

DYNAMIC MODEL OF THE MULTIPLE-EFFECT BLACK LIQUOR EVAPORATOR #3 AT INDUSTRIES JAMES MACLAREN INC.

The focus of this chapter is the process model used later for predictive and adaptive control studies. In order to place the current work in the context of what others have already done, an outline of the publications of several authors on dynamic modelling of evaporators is given in the first section. The next three sections describe the development of the model starting firstly with a single effect, secondly, extending to five effects and finally customizing the model based on design and operating values for evaporator #3 at Industries James Maclaren Inc. The single effect evaporator model published by Newell and Lee [14] is presented in the second section as it is the basis of the dynamic model developed in this chapter. With operating values from an example material and heat balance by Grace [7], extension of the model to a train of five effects is discussed in section three. The final refinements, as found in the fourth section, were made based on design calculations and equipment specifications of evaporator #3 at Industries James Maclaren Inc. The chapter concludes with a summary of the material presented.

2.1 Previous Work in Evaporator Modelling

A compilation by Fisher and Seborg [5] of work with various co-authors, including Newell, concerns a pilot scale double effect evaporator. The first effect of Fisher and Seborg's double effect evaporator has a short-tube vertical calandria design with natural circulation and the second a long-tube vertical configuration. In one article, Newell and Fisher [13] divide the evaporator up and model each component (steam chest, heat transfer surface, solution holdup) separately from first principles consistent with the mass and energy balances of the present work which are presented in subsequent sections. The strength of this approach is the flexibility it affords when considering a variety of industrial equipment configurations. When applied to their double-effect evaporator, a system of ten nonlinear differential equations resulted. This was linearized about the steady state operating point and put in state-space form. Subsequently, the system was reduced to fifth, third and second order for control studies. According to Fisher and Seborg, the nonlinear dynamic model was more effective for off-line simulations than any of the state-space versions they developed. It was not used in their on-line control studies however, since results with the above mentioned linear models were satisfactory. Hernández, Montano and Silva [9] start with the same nonlinear model as Fisher and Seborg but reduce the order by adding a PI controller and assuming the level constant. Newell and Lee [14] simplify the Fisher and Seborg process by only considering the second, long tube forced circulation evaporator effect. This model is described in detail in section 2.2.

Wang and Cameron [22] start from the Newell and Lee system of differential equations and remove the assumptions that the liquid hold-up in the evaporator and the operating temperature have negligible rates of change. The model is further refined by maintaining the heating vapour pressure constant due to operation near the upper bound. Although this would appear to make the model more realistic and flexible, these improvements do not come without the price of special tuning techniques and relaxed performance tolerance.

The Bayer process of alumina production is an example of an industrial multiple-effect evaporator which is modeled by To et al. [21]. Whereas the preceding authors considered an overall solute balance, in this case the solute balance is over the flash tank, or separator. The reason for this is that in the reported system, recycle flow is variable and ~~a~~ principal disturbance to the system, which is not the case of the present work. Unlike the model described in sections 2.2 - 2.4 below, liquor in the evaporator is heated by a steam heater which undergoes wash cycles and thus the energy balance is subjected to disturbances. Secondly, product flow is subject to disturbances caused by downstream processes. Since the overall balances are unaffected by the evaporator internals design, the equations describing mass and energy balances are identical to those of Fisher and Seborg as well as Newell and Lee.

A double-train five-effect evaporator for sugar concentration is modeled by Mulholland and Love [12]. Although the configuration is different, including vapour lines that connect condensate flash from both the evaporator trains, the first principles used in deriving the mass and energy balances are similar to those in the present work. Unlike the present work, in addition to process control, a further objective was to model the effects of fouling on heat transfer coefficients. The main disturbance was thus liquor concentration which, along with scaling, influences the effective heat transfer coefficient.

A seventeen effect desalination evaporator was modeled by Burdett and Holland [4] with heat balance over individual tubes in the heat exchanger section. This is neither practical nor necessary in the present work since no temperature measurements are made of the internal and external tube temperatures and the overall heat balance will be shown in Chapter 4 to be adequate.

The following major assumptions were made of the models in this chapter: negligible heat-of-solution effects, saturated steam in all vapour spaces, no subcooling of the steam condensate streams, zero concentration of solute in the overhead vapour streams. Finally, heat losses through the evaporator vessels and piping are considered small.

2.2 Single Effect Evaporator Model

This model follows the principle of a forced circulation evaporator as in Figure 2.1 which concentrates a solution by boiling off solvent. Feed is mixed with recirculating liquid and pumped upward through the evaporator tubes. The process liquid is maintained at boiling by heating with steam which condenses on the outside of the tubes. At the outlet of the tubes, vapour and concentrated process liquid are separated with the vapour being condensed in a water cooled exchanger. Most of the concentrated process liquid is recirculated and some drawn off as product.

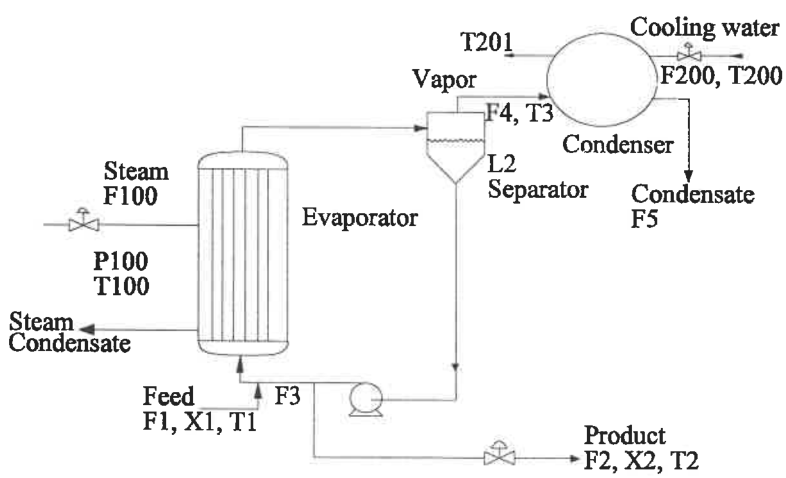

Figure 2.1 Newell and Lee Evaporator System

Three differential equations can be written to describe the evaporator mass balance. Respectively, the overall mass balance, the solute mass balance, and the vapour mass balance (in terms of the pressure in the system) are as follows:

$$\rho A\ dL_2/dt = F_1 - F_4 - F_2 \tag{2.2.1}$$

$$M\ dX_2/dt = F_1 X_1 - F_2 X_2 \tag{2.2.2}$$

$$C\ dP_2/dt = F_4 - F_5 \tag{2.2.3}$$

with ρ the liquid density, A the cross-sectional area of the separator, M the mass of liquid in the evaporator, F_i mass flows and X_i concentrations in percent solids. The conversion factor between vapour mass and pressure, C, is derived from the ideal gas law given that the operating pressure is near atmospheric [14].

Energy balances are calculated assuming the liquid perfectly mixed and at boiling temperature. Both vapour (T_3) and liquid (T_2) temperatures are calculated by linearization around steady state values of the saturated water curve [14]. The liquid temperature (T_2) includes a second linear term in equation (2.2.5) accounting for the effect of boiling point rise (BPR), which is the difference between the boiling temperature of the liquid and that of water. The point at which water vapour is driven off of black liquor is the boiling temperature, T_3 whereas T_2 is the saturated steam temperature at which the water vapour condenses in the next effect.

$$T_3 = 0.507\ P_2 + 55.0 \tag{2.2.4}$$

$$T_2 = 0.5616\,P_2 + 0.3126\,X_2 + 48.43 \tag{2.2.5}$$

Further, assuming no heat losses to the environment, no energy input from the pump, constant latent heat and liquid heat capacity, and very fast dynamics of the energy balance, we obtain,

$$F_4 = (Q_{100} - F_1\,C_p(T_2 - T_1))/\lambda \tag{2.2.6}$$

For F_4, latent heat of liquor (λ) is considered large compared to the sensible heat difference between T_2 and T_3. The first term in the preceding equation (2.2.6), the rate of heat transfer to the liquor (Q_{100}), is calculated knowing the steam temperature and considering the overall heat transfer coefficient times the heat transfer area of the heater section (UA_1) a function of the flow through the evaporator tubes. Equation (2.2.7) is a linearization in terms of flow through the evaporator tubes (F_1 + F_3) about the operating point of the heat transfer coefficient times the heat transfer area (UA_1 = 9.6 kW/°C). Assuming steam at saturated conditions, a linearization around steady-state values produces the function relating steam pressure P_{100} to temperature T_{100} in equation 2.2.8 [14]. Lastly, in equation 2.2.10 the saturated steam flow rate is obtained assuming constant latent heat of steam, λ_s. A distinction is made between latent heat of steam λ_x and that of liquor λ which is larger due to the boiling point rise.

$$\mathrm{UA}_1 = 0.16\,(F_1 + F_3) \tag{2.2.7}$$

$$T_{100} = 0.1538\,P_{100} + 90.0 \tag{2.2.8}$$

$$Q_{100} = UA_1 \, (T_{100} - T_2) \tag{2.2.9}$$

$$F_{100} = Q_{100}/\lambda_s \tag{2.2.10}$$

The final energy balances describe the water cooled heat exchanger, or condenser, with assumed fast dynamics and constant overall heat transfer coefficient times the heat transfer area (UA_2). Cooling water warms as heat is removed from condensing process vapour.

$$Q_{200} = F_{200} \, C_p \, (T_{201} - T_{200}) \tag{2.2.11}$$

$$Q_{200} = UA_2 \, (T_3 - 0.5 \, (T_{200} + T_{201})) \tag{2.2.12}$$

In equation 2.2.12 above, the arithmetic average temperature difference is used to calculate the rate of heat transfer in the condenser rather than the log mean temperature difference (LMTD). This linearization about the operating point simplifies the following equation. Combining the above two equations, T_{201} can be eliminated then isolated and condensate flow rate can be calculated.

$$Q_{200} = \frac{UA_2(T_3 - T_{200})}{1 + UA_2/(2C_pF_{200})} \tag{2.2.13}$$

$$T_{201} = T_{200} + Q_{200}/(F_{200} \, C_p) \tag{2.2.14}$$

$$F_5 = Q_{200}/\lambda \tag{2.2.15}$$

2.3 Extension to Five Effects

The tubular falling film evaporator design illustrated in Figure 2.2 represents the installation at Industries James Maclaren Inc. Liquor is pumped upward through a central section at the top of which is a distributor. Flow of liquor and evolving steam is downward through the tubes. The vapour body has a liquor outlet as well as an entrainment separator for exiting vapours.

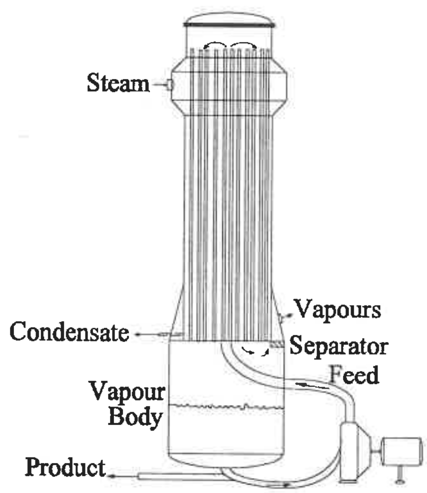

Figure 2.2 Tubular falling film evaporator

Five evaporator effects are arranged in series with countercurrent steam and liquor flow as illustrated in Figure 2.3. Defining flow in the direction of the steam, liquor enters the last effect at 14% solids and travels upstream through each effect exiting at 43% solids. Liquor discharge from one effect is fed to the preceding stage with part of the stream recycled as in the single effect model. The train of evaporators is numbered 2 through 6 with the first effect being a crystallizer that concentrates SBL from 43% solids to around 70% solids.

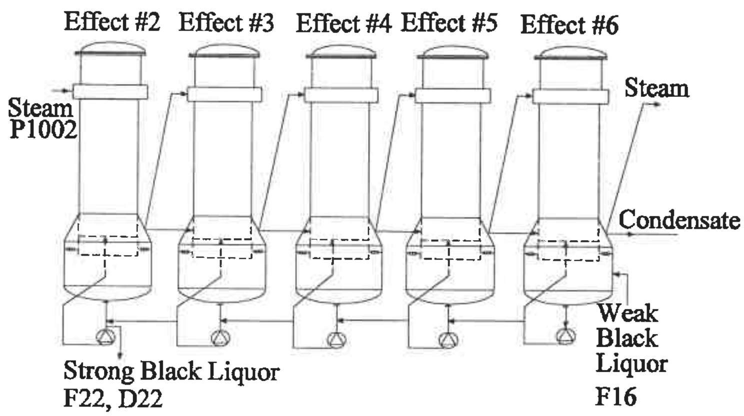

Figure 2.3 Multiple Effect Evaporator

The heat balance by Grace [7] includes, for each stage, physical properties and heating values such as density, heat capacity, and latent heat of vaporization which are assumed constant at the steady state conditions of a given effect. The heat balance includes an overall heat transfer coefficient times the heat transfer area (UA). Instead of a condenser at every stage, steam removed from process liquor is passed to the next effect where it condenses on the outside of the tubes and thus supplies the energy required for evaporation. Condensate accumulates and flows downstream, transferring sensible heat to the liquor in a preheating function. Only after the final effect is there a water cooled condenser. Since vapour boiled off in all but the last effect does not pass through a condenser, the flow calculation relates the square root of vapour pressure difference from one effect to the next, to vapour flow.

As done by Fisher and Seborg [5], liquor level is maintained by manipulating discharge flow from each effect. In the present case, a proportional-integral (PI) controller is tuned for tight level control as described by Marlin [11] and characterized by a damping coefficient and a maximum allowable level deviation (ΔL_{max}) corresponding to a maximum step disturbance in discharge flow (ΔF_{max}). Calculation of the proportional (K_c) and integral (T_I) tuning parameters is derived according to Marlin as follows.

Using deviation variables, the process is described by a differential equation:

$$A\frac{dL}{dt} = F_{IN} - F_{OUT} \qquad (2.3.1)$$

The PI controller equation is:

$$F_{OUT} = -K_c(L + \frac{1}{T_I}\int_0^t Ldt) \qquad (2.3.2)$$

By substituting the second equation into the first and then taking the Laplace transform the following expressions arise:

$$\frac{L(s)}{F_{IN}(s)} = \frac{(\frac{T_I}{(-K_c)})s}{\tau^2 s^2 + 2\tau\xi s + 1} \qquad (2.3.3)$$

$$\tau = \sqrt{\frac{AT_I}{(-K_c)}} \qquad \xi = \frac{1}{2}\sqrt{\frac{T_I(-K_c)}{A}} \tag{2.3.4}$$

For a step in feed flow such as $\Delta F_{in}/s$, the response in the time domain is

$$L = \frac{\Delta F_{IN} t}{A} \exp^{-t(-K_c)/2A} \tag{2.3.5}$$

The chosen maximum level (ΔL_{max}) and flow (ΔF_{max}) changes are, respectively, 2.5% and 10% of steady state values while the damping coefficient is 1. By differentiating the preceding equation the time corresponding to the maximum level is $t_{max} = 2A/(-K_c)$. This time, when substituted into equation 2.3.5 gives an expression in terms of the level deviation corresponding to the maximum inlet flow step

$$\Delta L_{max} = 0.736 \frac{\Delta F_{max}}{(-K_c)} \tag{2.3.6}$$

The above equation along with equation 2.3.4 are used to calculate the tuning constants. Performance of tight level control is characterized by small deviations from the level set point with whatever flow manipulation is required.

2.4 Model of Evaporator #3 at Industries James Maclaren Inc.

With design calculations and equipment specifications, the multieffect model of section 2.3 was modified to represent the installation at Industries James Maclaren Inc. Mill values of steady state liquor flows, levels and vapour pressures as well as constants such as cross-sectional area and feed conditions were added. For a single effect (as in Figure 2.2), the overall mass balance is:

$$dV/dt = (F_1 - F_2 - F_4)/\rho \qquad (2.4.1)$$

with V the volume of liquor in the effect a product of cross-sectional area and level ($V = A$ x L), F_1 the feed mass flow, F_2 the product flow and F_4 the vapour flow. Assuming perfect mixing, a balance on the solute is as follows:

$$d\,(V\,X2)/dt = (F_1\,X_1 - F_2\,X_2)/\rho \qquad (2.4.2)$$

Expanding and substituting equation (2.4.1) with L the liquid level leads to a mass balance without assuming a constant amount of liquid in a given effect.

$$X_2\,dV/dt + V\,dX_2/dt = (F_1\,X_1 - F_2\,X_2)/\rho \qquad (2.4.3)$$

$$X_2\,(F_1 - F_2 - F_4)/\rho + VdX_2/dt = (F_1\,X_1 - F_2\,X_2)/\rho \qquad (2.4.4)$$

$$VdX_2/dt = (F_1\,(X_1 - X_2) + F_4\;X_2)/\rho \qquad (2.4.5)$$

$$dX_2/dt \;=\; \frac{F_1(X_1 - X_2) \;+\; F_4X_2}{\rho AL} \qquad (2.4.6)$$

Newell and Lee assumed the amount of liquid in the evaporator to be constant for the purpose of their mass balance (equation 2.2.2). Wang and Cameron [22] did not make the above assumption and their model includes equation (2.4.6). The energy balance is a function of steam and liquor temperatures as well as a liquor flow-dependant UA (equation 2.2.7), as in the Newell and Lee model. In this model a distinction is made between the heat transfer surface in the energy balance and the cross-sectional area used in material balance. The heating surface for the falling liquor film consists of the walls of the vertical tubes whereas the volume of liquor is calculated based on the size of the evaporator sump in the vapour body.

2.5 Summary

This chapter presented a dynamic nonlinear model of the multiple effect evaporator #3 at Industries Maclaren Inc. Previously published work of others was examined in the first section. A model by Newell and Lee was the starting point and therefore presented in detail in section 2.2. Extension of the model to five effects was the focus of section 2.3. The final version of the model was discussed in section 2.4. With the dynamic process model, a control strategy can be developed and tested in order to ease implementation at some later time. The next chapter discusses the controller with predictive and adaptive behaviour which will be used to control the process model.

CHAPTER III

MULTIVARIABLE MODEL PREDICTIVE CONTROL (MPC) AND MODEL WEIGHTING ADAPTIVE CONTROL (MWAC)

The next two steps in this work are firstly to add a predictive controller and secondly an adaptive function to the predictive controller. The goal is to determine whether predictive controller performance is improved with adaptability. The predictive control algorithm, MPC, is well developed and several previous applications and their relation to the present work are described in section 3.1 together with various other predictive methods. A review of some previously published adaptive control strategies is the focus of section two. This is followed by a description in the third section of multivariable (2x2) MPC. The MWAC algorithm for adaptive control is described in detail in section 3.4.

3.1 Literature Review of Predictive Control of Evaporators

Newell and Lee [14] developed a predictive controller for their single effect evaporator. The design procedure is similar to that described in section 3.2 below in that it is based on a convolution model and minimization of the predicted error across the model horizon. The difference arises in the 'pseudo-inverse' solution with weighting constants on both the output variables and the control move size (Q, and R respectively).

$$\Delta u = (A^T Q A + R)^{-1} A^T Q e \tag{3.1.1}$$

In equation (3.1.1), Δu is the control move and e is the process error.

Instead of solving the above equation in this form, Newell and Lee use a numerical technique called singular value decomposition to calculate the pseudo-inverse of the matrix A (the dynamic matrix). They then use a design method called principal component analysis to calculate the control moves. Despite these numerical differences, the implementation follows the same steps as in section 3.3.

Alevisakis and Seborg [1], [2] have addressed the problem of process time delays in their multivariable Smith predictor control strategy. Like MPC, the Smith predictor is a model based controller. The development reported in these papers is an extension of the algorithm to the multivariable case. The authors argue that removing the delay from the characteristic equation of the closed-loop system, broadens the selection of controller designs available.

Ricker [18] describes the design and testing of a constrained predictive controller that shares with the present work both a quadratic programming (QP) approach to the constraints and a convolution model based predictive controller design which falls into the category of internal model control (IMC). The important similarities among predictive control strategies such as Dynamic Matrix Control (DMC), Model Algorithmic Control (MAC), and now Internal Model Control IMC are the use of a process model to predict present and future control actions by executing an on-line optimization. The fact that calculations are performed in real time allows consideration of pertinent constraints. Ricker's choice of quadratic programming over linear programming is made because in the former case an unconstrained solution is not possible since the result of linear programming is always along a boundary or at an intersection of constraints. A comparison between the constrained multivariable predictive controller and a conventional PI controller confirmed the basic assumption of the present work that the QP IMC strategy provides easier tuning for better performance. In a subsequent publication, Ricker et al. [19] note that their QP IMC algorithm is not only effective for controller tuning off-line but also allows the controller to incorporate future set point changes into its prediction by pre-programming the target progression. These features are both present in the QP MPC algorithm. The Ricker control problem closely resembles the present work in that the manipulated variables are WBL flow and heating steam flow (versus saturated steam pressure) and the control objectives are firstly to maintain solids content of the SBL and secondly WBL throughput (compared with SBL flow). Ricker et al. tested both QP IMC and PI controllers and found that SBL concentration was maintained to within 1% of the target value during normal operation of the plant. This performance was acceptable to operations personnel. For programmed changes in WBL throughput of ±5% only the QP IMC algorithm delivered acceptable performance. In order to reduce the computational burden a technique called blocking is implemented with the QP IMC algorithm in which, for a specified interval, certain manipulated variables are held constant.

3.2 Previous Work in Adaptive Control

Newell and Lee [14] acknowledge the limitations of fixed parameter controller designs and therefore consider two methods of adaptive control: gain scheduling (GS) and self-tuning. In gain scheduling during excursions from the steady state operating point, the controller gain (K_c) is adapted as a function of a proportional steady state gain (K_{cSS}), a proportional gain scheduling constant (K_{GS}) and the error signal (the difference between the set point, *SP*, and the controlled variable, *CV*).

$$K_c = K_{cSS} - (SP - CV) * K_{GS} \tag{3.2.1}$$

This method of controller gain adaptation differs from MWAC in that the change is made based on the process error rather than the prediction error. There is therefore no predictive element to foresee control requirements. From the gain scheduling relation (3.2.1) it is obvious that the range of possible controller gain values is limited whereas the MWAC family of candidate models may be very diverse. Also, only the gain is adapted, whereas MWAC adjusts both the gain and the delay. The second adaptive method evaluated by

Newell and Lee consists of an on-line process identification by auto-regressive moving average (ARMA) followed by PID controller parameter calculation. The main drawbacks of this approach, relative to the present work, are that the PID has neither a multivariable nor a predictive component.

Oliver, Seborg and Fisher [16], [17] derive adaptive control algorithms such that stability of the closed-loop system is guaranteed by requiring the total time derivative of the Liapunov function to be at least negative-semidefinite. Oliver, Seborg and Fisher call the design method model reference adaptive control (MRAC) since it is based on a reference model that has desired behaviour. The control objective is to minimize the error between the actual process values and the state-space reference model response. The manipulated variables are determined by a control law that includes feedback (FB), feedforward (FF) and integral (I) action with provisions for set point changes (sp).

$$u = K_{FB} x_p + K_{FF} d + K_I \int_0^t y \, dt + K_{sp} y_{sp} \qquad (3.2.2)$$

The control matrices (K_{FB}, K_{FF}, K_I, K_{sp}) are calculated based on Liapunov's direct method which requires process values of the state (x_p), disturbance (d), output (y) and set point (y_{xp}) variables. A limiting aspect of this approach is the linear state-space format requirement of the reference and process models. The two advantages of the MRAC approach stated by the authors are, no on-line process identification and a readily tuned controller, both of which are dealt with by the MWAC and MPC algorithms developed later in this chapter. Another shared underlying assumption is that multivariable control is more effective than single loop arrangements. A strength of the MRAC approach is that in the simulations and experimental tests, the initial controller parameters were able to recover from very poor initializations. This is not essential to the present work since the process model is representative and so, therefore, are the initial controller parameters. Conversely, a characteristic that is relevant to the present case is that MRAC controller performance improved with subsequent upsets which inevitably occur in any industrial application. It follows then that the controller adaptation is slowed in the region of steady state, which is not the case of MWAC.

Hernández, Montano and Silva [9] do not use the name MRAC for their method but it has the same approach of tracking a reference model using a Liapunov design approach. The control strategy is applied to a single loop in a double effect evaporator. Using a first order model outlet concentration is controlled by steam flow rate. As in the present work, level is maintained by PI control. The results do not appear overly encouraging as the authors describe their results as "slightly better" than a PI controller.

Table 3.1 below is presented in order to summarize the bibliographical work discussed in sections 3.1 and 3.2 above that deals with the specific problem of evaporator control.

Table 3.1 Summary of Published Evaporator Control Studies

Authors	Control Algorithm	Variables & Model	Algorithm	Results
Alevisakis & Seborg 1973	Predictive	Linear multivariable	Smith predictor	Extension of Smith predictor (continuous and discrete time) for multivariable systems with delays in CV & MV
Alevisakis & Seborg 1974	Predictive	5th order state space model CV: product conc'n 1st & 2nd effect level MV: steam flow 1st & 2nd effect product flow	multiloop: SISO proport'l control multivar'l: MIMO optimal multivar'l FB + Smith predictor	Experimental & simulations: process with delays + multivar'l similar to process without delays + multiloop Simulations: robustness & gain ↑ with Smith predictor + error in gain & delay
Hernández, Montano, Silva 1993	Adaptive, PI	1. nonlinear 2. linearized models CV: output conc'n MV: steam flow	1.adaptive FB 2.PI	For CV set point change, 1. slightly better than 2.
Mulholland & Love 1993	Kalman filter	black liquor evap.: heat transfer coef. U product concent'n C	Kalman filter	Predict change in U from change in C, extend to predict scaling
Newell & Fisher 1972	PI, Inferential Feedforward Optimal MIMO State-Driving	5th order linear model CV: product conc'n 1st & 2nd effect level MV: steam flow 1st & 2nd effect product flow	PI Inferential FF + PI Optimal MIMO State-driv'g	Off-line tuning has gain too high for experimental Better than PI for product concentration control Better than PI only Best experimental performance Must have very good model

Table 3.1 Summary of Published Evaporator Control Studies (Cont.)

Authors	Control Algorithm	Variables & Model	Algorithm	Results
Oliver, Seborg & Fisher Part 1 1973	Adaptive	5th order state space model CV: product conc'n 1st & 2nd effect level MV: steam flow 1st & 2nd effect product flow	MIMO MRAC	Add adaptive integral and set point control Simulation: for disturbance, MRAC + FB is better than open loop gain ↑ oscillations ↑ small improvement in adding FF to FB performance in set point changes ↑ with repetition
Oliver, Seborg &Fisher Part 2 1973	Adaptive	Same as Part 1	MRAC	Double Effect Evaporator Experimental: gain ↑ oscillation ↑ initial tuning ↑ performance ↑ controller adapts from poor initial tuning and repetition adaptive parameters ↓ computation ↓ and performance acceptable away from model linearization point, can adapt
Ricker 1985	Predictive	Multieffect Evap. Simulation CV: SBL solids MV: WBL flow	QP + IMC filtering vs. blocking	IMC with blocking is near-perfect but on border of instability with good model IMC tuning easier PID less accurate than IMC and too sensitive to plant noise constraints have no negative effect QP algorithms better to start with optimum than 0

Table 3.1 Summary of Published Evaporator Control Studies (Cont.)

Authors	**Control Algorithm**	**Variables & Model**	**Algorithm**	**Results**
To et al. 1995	GMC vs. PI	Evap. simulat'n CV: product density flash tank inventory (liquid discharge temp) MV: CW flow feed liquor flow (heater discharge temp)		Robustness tested with disturb. in product flow modelling errors ↑, performance ↓
			Input-output lineariz'n	best results, flexible, robust, effective control
			GMC	subset of input-output lineariz'n better than local linearization
			Su-Hunt-Meyer transfm'n (PI)	add 3rd CV and MV more sensitive to modelling error better than local linearization
			Local linearizt'n 2 PI's	~ 10 x longer than any above (nonlinear) to return to steady state
Wang & Cameron 1994		Evap. simulat'n CV: separator level product composition operating pressure MV: steam pressure or recirculation rate product flow rate		product composition set point change
			optimal control	good for minimal time and energy deviations
			GMC (un)constrained	performance ↓as model RD↑ two-step tuning, pseudo RD1 and cascade all improve performance constrained GMC better than unconstrained even away from bounds

3.3 Review of Model Predictive Control (MPC) principles

Model Predictive Control is the generic name for a centralized control strategy which employs measurements of output (controlled) and input (manipulated) variables as well as a dynamic model of the process for control calculations as seen in Figure 3.1. Note that G_d is the function relating a disturbance to the controlled variable (CV); G_{cp} is the controller function relating the process error to the manipulated variable (MV); G_p is the process function which relates MV to CV; and G_m is the modeling function relating MV to predicted CV. Among the specific strategies are IMC, DMC, and MAC which have been extensively described by others [11],[19], [20].

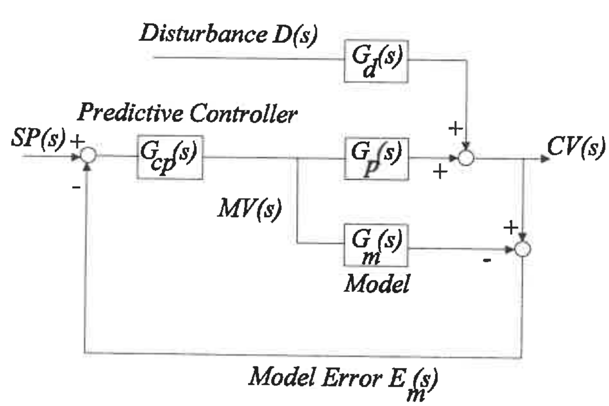

Figure 3.1 Predictive Control Block Diagram

Following is an outline of the approach used for a 2x2 controller for the black liquor evaporator studied in the present work.

In order for the controller to predict future values of the output variables, a relationship between each input variable and the output variables must be established. For a given sampling period, performing an open loop step change in a manipulated variable and recording the response of each of the controlled variables yields a step response convolution model. The response time, or model horizon, should be equal to or longer than the settling time of the slowest response. The model is normalized by first subtracting the steady state value to get a deviation variable and then dividing by the manipulated variable step. Impulse coefficients are obtained by taking the first backward difference of the step response model. The approach mentioned above is effective for systems which are not accurately modeled by first or second order transfer functions as is the case of the multieffect evaporator. The response of the SBL flow includes unavoidable overshoot due to the five PI level controllers tuned for tight control. The predictive model for the 2x2 system under consideration is:

$$\begin{aligned} \hat{c}_{1,n+1} &= \sum_{i=1}^{T} h_{11i} m_{1,n+1-i} + \sum_{i=1}^{T} h_{12i} m_{2,n+1-i} \\ \hat{c}_{2,n+1} &= \sum_{i=1}^{T} h_{21i} m_{1,n+1-i} + \sum_{i=1}^{T} h_{22i} m_{2,n+1-i} \end{aligned} \qquad (3.3.1)$$

with $\hat{c}$ the prediction, h the impulse coefficients, m the manipulated variables, i the convolution model increment, and n the sampling instant.

In addition to the previously mentioned model horizon, two other horizons are central to the MPC algorithm. The control horizon, U, is the number of manipulated variable changes calculated. The controller objective is to reduce the difference between the controlled variable predictions and set points to zero within V, the prediction horizon, sampling intervals. It follows then that the control horizon (U) is always shorter than the prediction horizon (V).

The model prediction for a series of manipulated variable changes is calculated as follows:

$$\begin{bmatrix} \hat{c}_{1,1} \\ \hat{c}_{1,2} \\ \hat{c}_{1,3} \\ \cdot \\ \cdot \\ \cdot \\ \hat{c}_{1,V} \\ \hat{c}_{2,1} \\ \hat{c}_{2,2} \\ \hat{c}_{2,3} \\ \cdot \\ \cdot \\ \cdot \\ \hat{c}_{2,V} \end{bmatrix} = \begin{bmatrix} a_{11,1} & 0 & \cdots & 0 & a_{12,1} & 0 & \cdots & 0 \\ a_{11,2} & a_{11,1} & & 0 & a_{12,2} & a_{12,1} & & 0 \\ \cdot & & & \cdot & \cdot & & & \cdot \\ \cdot & & & \cdot & \cdot & & & \cdot \\ \cdot & & & \cdot & \cdot & & & \cdot \\ a_{11,V} & a_{11,V-1} & \cdots & a_{11,V-U+1} & a_{12,V} & a_{12,V-1} & \cdots & a_{12,V-U+1} \\ a_{21,1} & 0 & \cdots & 0 & a_{22,1} & 0 & \cdots & 0 \\ a_{21,2} & a_{21,1} & & 0 & a_{22,2} & a_{22,1} & & 0 \\ \cdot & & & \cdot & \cdot & & & \cdot \\ \cdot & & & \cdot & \cdot & & & \cdot \\ \cdot & & & \cdot & \cdot & & & \cdot \\ a_{21,V} & a_{21,V-1} & \cdots & a_{21,V-U+1} & a_{22,V} & a_{22,V-1} & \cdots & a_{22,V-U+1} \end{bmatrix} \begin{bmatrix} \Delta m_{1,0} \\ \Delta m_{1,1} \\ \Delta m_{1,2} \\ \cdot \\ \cdot \\ \cdot \\ \Delta m_{1,U-1} \\ \Delta m_{2,0} \\ \Delta m_{2,1} \\ \Delta m_{2,2} \\ \cdot \\ \cdot \\ \cdot \\ \Delta m_{2,U-1} \end{bmatrix} \qquad (3.3.2)$$

The step response model coefficients are represented by a. Incremental changes in the manipulated variables from one sampling interval to the next are denoted by Δm whereas in preceding equations m represented the value of the manipulated variable.

With rearranging and time interval shifting, a recursive form of the model in terms of the incremental control moves is

$$\begin{aligned} \hat{c}_{1,n+j} &= \hat{c}_{1,n+j-1} + \sum_{i=1}^{T} h_{11i}\Delta m_{1,n+j-i} + \sum_{i=1}^{T} h_{12i}\Delta m_{2,n+j-i} \\ \hat{c}_{2,n+j} &= \hat{c}_{2,n+j-1} + \sum_{i=1}^{T} h_{21i}\Delta m_{1,n+j-i} + \sum_{i=1}^{T} h_{22i}\Delta m_{2,n+j-i} \end{aligned} \tag{3.3.3}$$

$j=1,2,\ldots,V$

Note that the above predicts the behaviour of the system across the prediction horizon, V.

A corrected prediction, $c_{i,n}^{*}$, is made using measured values from the preceding time instant, $c_{i,n-1}$, rather than predicted values, $\hat{c}_{i,n-1}$. In the case of a plant installation, on-line measurement of the controlled variables is available whereas in the present simulation, the process model described in Chapter 2 generates these values for feedback to the predictor. A second modification of equation 3.3.3 is to separate the summation terms into those involving past and future control moves. The projection vector, $P_{cm,i}$, anticipates the effect of past moves on future outputs while the first term in the matrix representation below takes into account future control moves.

$$
\begin{bmatrix} c^*_{1,n+1} \\ c^*_{1,n+2} \\ c^*_{1,n+3} \\ \vdots \\ c^*_{1,n+V} \\ c^*_{2,n+1} \\ c^*_{2,n+2} \\ c^*_{2,n+3} \\ \vdots \\ c^*_{2,n+V} \end{bmatrix}
=
\begin{bmatrix}
a_{11,1} & 0 & \cdots & 0 & a_{12,1} & 0 & \cdots & 0 \\
a_{11,2} & a_{11,1} & & 0 & a_{12,2} & a_{12,1} & & 0 \\
\vdots & & & \vdots & \vdots & & & \vdots \\
a_{11,V} & a_{11,V-1} & \cdots & a_{11,V-U+1} & a_{12,V} & a_{12,V-1} & \cdots & a_{12,V-U+1} \\
a_{21,1} & 0 & \cdots & 0 & a_{22,1} & 0 & \cdots & 0 \\
a_{21,2} & a_{21,1} & & 0 & a_{22,2} & a_{22,1} & & 0 \\
\vdots & & & \vdots & \vdots & & & \vdots \\
a_{21,V} & a_{21,V-1} & \cdots & a_{21,V-U+1} & a_{22,V} & a_{22,V-1} & \cdots & a_{22,V-U+1}
\end{bmatrix}
\begin{bmatrix} \Delta m_{1,n} \\ \Delta m_{1,n+1} \\ \Delta m_{1,n+2} \\ \vdots \\ \Delta m_{1,n+U-1} \\ \Delta m_{2,n} \\ \Delta m_{2,n+1} \\ \Delta m_{2,n+2} \\ \vdots \\ \Delta m_{2,n+U-1} \end{bmatrix}
+
\begin{bmatrix} c_{1,n}+P_{11,1}+P_{12,1} \\ c_{1,n}+P_{11,2}+P_{12,2} \\ c_{1,n}+P_{11,3}+P_{12,3} \\ \vdots \\ c_{1,n}+P_{11,V}+P_{12,V} \\ c_{2,n}+P_{21,1}+P_{22,1} \\ c_{2,n}+P_{21,2}+P_{22,2} \\ c_{2,n}+P_{21,3}+P_{22,3} \\ \vdots \\ c_{2,n}+P_{21,V}+P_{22,V} \end{bmatrix}
$$

$$
\begin{aligned}
P_{cm,i} &= \sum_{j=1}^{i} S_j \\
S_j &= \sum_{i=j+1}^{T} h_{cm,i} \Delta m_{cm,n+j-i} \qquad (3.3.4) \\
i,\ j &= 1,2,\ldots,V \\
c,\ m &= 1,2 \ \textit{for 2 controlled, 2 manipulated variables}
\end{aligned}
$$

The corrected prediction of (3.3.4) is used in the controller design described next. With set point trajectories across the prediction horizon, $r_{c,n+j}$, $j = 1,2,\ldots,V$, the purpose of the controller is to reduce the difference between the corrected prediction and the set point. In so doing, two vectors of predicted errors are defined. The first is an open-loop prediction (no feedback) since it consists of the projection vectors $P_{cm,i}$ which only consider past control moves as well as the process error at the current sampling instant, $E_{c,n} = r_{c,n} - c_{c,n}$.

$$\hat{E}' = \begin{bmatrix} E_{1,n} - P_{11,1} - P_{12,1} \\ E_{1,n} - P_{11,2} - P_{12,2} \\ E_{1,n} - P_{11,V} - P_{22,V} \\ E_{2,n} - P_{21,1} - P_{22,1} \\ E_{2,n} - P_{21,2} - P_{22,2} \\ \cdot \\ \cdot \\ \cdot \\ E_{2,n} - P_{21,V} - P_{22,V} \end{bmatrix} \qquad (3.3.5)$$

The second vector of predicted errors takes into consideration not only past control moves but also current and future inputs.

$$\hat{E} = \begin{bmatrix} r_{1,n+1} - c^*_{1,n+1} \\ r_{1,n+2} - c^*_{1,n+2} \\ \cdot \\ \cdot \\ r_{1,n+V} - c^*_{1,n+V} \\ r_{2,n+1} - c^*_{2,n+1} \\ r_{2,n+2} - c^*_{2,n+2} \\ \cdot \\ \cdot \\ \cdot \\ r_{2,n+V} - c^*_{2,n+V} \end{bmatrix} \tag{3.3.6}$$

It follows then that the matrix representation of (3.3.4) can be rewritten in terms of the two predicted error vectors defined above

$$\hat{E} = -A\ \Delta m + \hat{E}' \tag{3.3.7}$$

Remembering the purpose which is to reduce the difference between the corrected prediction and the set point, the objective function to be minimized is the sum of the errors squared or, in vector form,

$$J[\Delta m] = \hat{E}^T\hat{E} \tag{3.3.8}$$

Since U is always less than V, matrix A is not square. The solution is the well known pseudoinverse or linear least squares solution of

$$\partial J / \partial \Delta m = 0 \tag{3.3.9}$$

which is

$$\Delta m = (A^T A)^{-1} A^T \hat{E}' = K_c \hat{E}' \tag{3.3.10}$$

This implies that K_c is an approximate inverse of the model in the controller and is constant in time. In later sections an enhancement of the algorithm will be presented, adapting K_c at each sampling period thus accounting for time varying plant dynamics and modelling errors. For now though, the controller parameters are fixed and tuning constants are added. By expanding the objective function with an additional term penalizing control moves called the move suppression factor, a total of four tuning parameters are available.

$$J[\Delta m] = \hat{E}^T W \hat{E} + \Delta m^T Q \Delta m \tag{3.3.11}$$

This leads to the controller

$$K_c = (A^T W A + Q)^{-1} A^T W \tag{3.3.12}$$

in the 2x2 case with controlled variables c = 1,2 and manipulated variables m = 1,2 the controlled variable weighting is $W_c = w_c I_V$ and the move suppression factor is $Q_m = q_m I_U$ with $w_{1,2}$ and $q_{1,2}$ the four tuning constants. In matrix form:

$$W = \begin{bmatrix} W_1 & 0 \\ 0 & W_2 \end{bmatrix} \qquad Q = \begin{bmatrix} Q_1 & 0 \\ 0 & Q_2 \end{bmatrix} \tag{3.3.13}$$

Note that the impact of any one tuning constant depends on its value relative to the others. For example, the difference in magnitude between the two controlled variables is compensated for by the relationship W_1/W_2. Also, if one input is allowed more variability than the other, this will be reflected in Q_1/Q_2. These interactions must be taken into consideration during the tuning process.

Control moves are calculated by $\Delta m = K_c\hat{E}'$. The result is a vector Δm twice the length of the control horizon. The first U moves are for the first controlled variable while the last half is for the second output. Since the calculation is repeated at each sampling instant, only the first control move for each manipulated variable is actually implemented. In other words, only two rows of K_c, the first and the $U+1^{st}$, are useful.

The final performance enhancement of the MPC algorithm is to accommodate the reality in any process of physical constraints. In the present case, for example, both flow and pressure must be non-negative while concentration may not exceed 100%. This situation is dealt with by reformulating the quadratic objective function to include explicitly constraints on each of the controlled and manipulated variables as well as control move size. The result is a quadratic programming (QP) problem which is implemented in the controller algorithm.

3.4 Model Weighting Adaptive Control (MWAC) Principles

The strength of adaptive control strategies is compensation for time varying plant dynamics as well as modelling inaccuracies by modifying the controller model at each sampling instant based on the prediction error. The structure of the model weighting adaptive controller used in this study is illustrated in Figure 3.2.

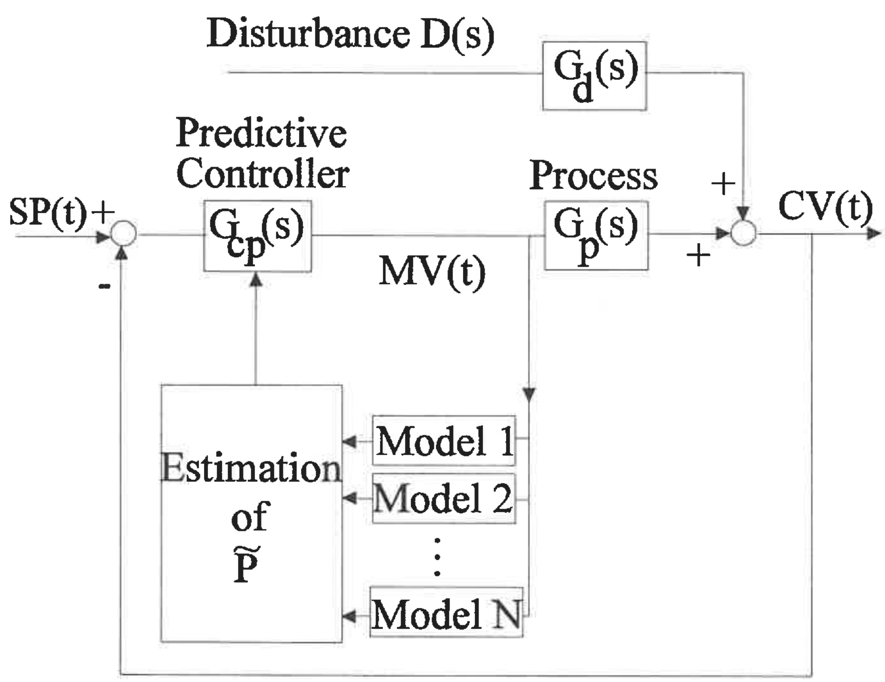

Figure 3.2 Adaptive Predictive Control Block Diagram

The basis of the control design developed by Gendron et al. [6] is a first order plus time delay model which has three parameters: process gain (g), delay (D), and time constant (τ).

$$P(s) = \frac{g \exp(-Ds)}{1 + \tau s} \tag{3.4.1}$$

Identification of the gain and delay is in the form of a discrete range of values. This allows controller adaptation of these parameter estimates within the specified range. A single value of the time constant parameter is identified rather than a discrete range since error in the time constant estimate affects closed-loop stability less than error in the gain and delay. Also, the number of adaptive parameters is kept to a minimum since each additional parameter increases substantially the number of possible combinations and hence the computations.

The transfer function in (3.4.1) is rewritten in discrete form since the implementation is digital.

$$P(q^{-1}) = \frac{g(1-\alpha)q^{-d-1}}{1-\alpha q^{-1}} \tag{3.4.2}$$

Notice that the discretized delay (d) is an integer multiple of the sampling period.

As mentioned above, only an approximate range of values of the gain and delay are known from both physical limitations experience with the process. A family of candidate models is established by discretizing these ranges of the gain and delay:

$$\mathcal{F}_d \triangleq \{\, P(q^{-1}) | g \in [\underline{g}, \bar{g}],\ d \in [\underline{k}, \bar{k}] \,\} \tag{3.4.3}$$

with $\underline{g}$, $\underline{k}$ the lower and $\bar{g}$,$\bar{k}$ the upper limits of the discrete ranges of gains and delays, respectively. The criteria for forming the group of models is that it is small enough to remain manageable and large enough that an intermediate value can be stabilized between two group members.

The MWAC approach is to design one controller which is made up of contributions from each of the N members of the family of candidate models where N $\triangleq$ card $\mathscr{F}_d$. The weight placed on each model contribution is calculated such that the controller prediction ($\tilde{y}$) error is minimized. With the actual plant model, G, output, y, and input, u:

$$\begin{aligned} \varepsilon(t) &= y(t) - \tilde{y}(t) \\ &= y(t) - \sum_{i=1}^{N} w_i y_i(t) \\ &= G(q^{-1})u(t) - \sum_{i=1}^{N} w_i P_i(q^{-1})u(t) \\ &= (G(q^{-1}) - \tilde{P}(q^{-1}))u(t) \end{aligned} \tag{3.4.4}$$

Note that $\tilde{p}$ is the controller model made up of contributions from all member models while $P_i \in \mathscr{F}_d$.

Also, the sum of weights is normalized to unity.

$$\sum_{i=1}^{N} w_i = 1 \tag{3.4.5}$$

By combining weightings with gains,

$$\gamma_j = \sum_i w_{ij} g_i \tag{3.4.6}$$

it follows that the process model made up of all combinations of gain and delay parameters is

$$\begin{aligned} \tilde{P}(q^{-1}) &= \sum_i \sum_j w_{ij} \frac{g_i(1-\alpha)}{1-\alpha q^{-1}} q^{-j-1} \\ &= \frac{(1-\alpha)q^{-1}}{1-\alpha q^{-1}} \sum_j \gamma_j q^{-j} \end{aligned} \tag{3.4.7}$$

Of the two steps remaining in this discussion the first is to calculate the weighting attributed to each model in the family of candidates. Secondly, the algorithm must be expanded to accommodate the 2x2 control problem.

The weights are calculated by considering the prediction error of each model in the family of candidates and penalize those with large errors. Given the actual plant input u(t), the output of each candidate model P_i is $y_i(t)$. This leads to a predicted error of $\epsilon_i(t) = y(t) - y_i(t)$. With this and $f \in [0,1]$ (which is defined below), the l_2 error norm is defined as follows and the inverse is used in the calculation of model weights.

$$v_i(t) = \|\varepsilon_i(t)\|_2^f \triangleq \left(\sum_{n=0}^{t} f^{t-n} \varepsilon_i^2(n)\right)^{1/2} \tag{3.4.8}$$

$$w_i = \frac{1/v_i^2}{\sum_n 1/v_n^2} \tag{3.4.9}$$

Two cases of the l_2-norm above are when $f = 1$ and $f<1$. The former is the normal l_2-norm and the latter exponentially favours the most recent data. Since implementation is digital, the recursive form of the l_2-norm is

$$\sigma_i(t) = f\,\sigma_i(t-1) + \varepsilon_i^2(t) \tag{3.4.10}$$

$$v_i(t) = \sqrt{\sigma_i(t)} \tag{3.4.11}$$

Notice that one strength of MWAC is that the calculation of weights is made at each sampling instant and can therefore vary with the process. The f in the recursive equation is a forgetting factor that dictates how fast model weights adapt to changing conditions and is calculated using $N_k = \text{card}\,[\underline{k}, \bar{k}]$.

$$f = \frac{N_k - 1}{N_k} \tag{3.4.12}$$

As stated above, the MWAC algorithm must be extended to the 2x2 case for implementation.

Since the MPC algorithm is based on four input-output relationships, the combinations of candidate models quadruple.

$$\begin{aligned}\tilde{P}_c(q^{-1}) &= \sum_i \sum_j w_{c1,\,ij} \frac{g_{c1,\,i}(1-\alpha)}{1-\alpha q^{-1}} q^{-(c1,\,j)-1} + \sum_i \sum_j w_{c2,\,ij} \frac{g_{c2,\,i}(1-\alpha)}{1-\alpha q^{-1}} q^{-(c2,\,j)-1} \\ &= \frac{(1-\alpha)q^{-1}}{1-\alpha q^{-1}} \sum_j \gamma_{c1,\,j} q^{-(c1,\,j)} + \frac{(1-\alpha)\,q^{-1}}{1-\alpha q^{-1}} \sum_j \gamma_{c2,\,j} q^{-(c2,\,j)}\end{aligned} \tag{3.4.13}$$

with c [1,2] the two controlled variables. And the combination leads to the model below

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \tilde{P}_{11} & \tilde{P}_{12} \\ \tilde{P}_{21} & \tilde{P}_{22} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \tag{3.4.14}$$

3.5 Summary

The above sections presented the predictive and adaptive strategies applied to the process model developed in Chapter 2. Extension of MWAC to the 2x2 case was a recent development. None of the prior work described an application of the combination of predictive and Model Weighting Adaptive Control which is the novelty of the present work. In the next chapter results of the simulations are presented and discussed which lead to conclusions on the success and potential of this approach.

CHAPTER IV

RESULTS AND DISCUSSION

This chapter presents and discusses performance of the fixed parameter predictive controller along with the adaptive predictive controller in disturbance rejection and a set point change. But first, various inspections of the model are presented in section 4.1 in order to develop confidence in the representation of the true process. The second section, 4.2, describes the steps involved in adjusting the predictive control algorithm parameters. It follows next that the adaptive algorithm is customized to the system under study in section 4.3. The final component of this chapter is a presentation of control studies with fixed parameter predictive as well as adaptive predictive control action for a set point change and disturbance rejection.

4.1 Nonlinear Model Behaviour

The ideal method of validating the process model is to compare operating values at the mill with those generated by the simulations. Unfortunately, the scope of the present work does not include identification of all the parameters required to make a comparison between mill operating dynamics and the process model developed here. Therefore, in order to establish the nonlinear model as a valuable representation of the multiple effect evaporator #3 at Industries James Maclaren Inc., several checks were made such as comparing key model variables at steady state with plant design values; verifying overall material balances; and introducing step disturbances to the model in order to observe the responses. The liquor level in each effect is regulated by a PI controller and the model response is otherwise open loop.

The model includes design values of WBL flow and concentration as feed to the evaporator effect #6. Table 4.1 shows that the model very nearly delivers design values of SBL at the discharge of effect #2.

Table 4.1 Comparison of Model and Design SBL

Variable	Model	Design	% Deviation
F22 (t/h)	43831	43591	0.55
D22 (% solids)	42.9	43.4	-1.1

Similarly, overall balances on solids and water according to steady state model values close to within small margins as illustrated in Table 4.2 below.

Table 4.2 Overall Solids and Water Balances

	In	Out	% Difference
Solids (t/h)	18.637	18.584	0.3
Water (t/h)	121.391	120.908	0.4

The difference between the present model outputs and design values (observed in the tables above) can be attributed to variations in the physical property values of black liquor.

Table 4.3 below indicates the behaviour of process variables as a result of step disturbances introduced to the model as new steady states were achieved. For a given disturbance; a variable response in the same direction is indicated by the plus sign (+), an inverse response with the minus sign (-) and no interaction with a zero (0).

Table 4.3 Model Variable Interactions

Disturbance	Levels	SBL Solids	Vapour Press.	Temperature	SBL Flow
WBL Feed	0	-	+	+	+
WBL Solids	0	+	-	-	+
Feed Steam	0	+	+	+	-
CW Flow	0	+	-	-	-
CW Temp	0	-	+	+	+

4.2 Model Predictive Control (MPC) Tuning

Several authors agree [18], [3] that the variables to control are SBL concentration (D22) and flow (F22) at the discharge of effect #2, by manipulation of saturated heating steam pressure fed to effect #2 (P1002) and WBL flow (F16) which enters the evaporator at effect #6. In practice, Ricker et al. [19] choose to control WBL over SBL flow with WBL flow both a controlled and a manipulated variable. The reason stated, in addition to a reduction in interaction, is the difficulty in modelling the SBL flow response. Similarly, in the present system SBL flow (F22) is both a manipulated variable in the PI of effect #2 and a controlled variable in the MPC algorithm.

The solid curves of Figures 4.1 and 4.2 show that the open loop responses of SBL flow (F22) to WBL flow, F16, and steam pressure, P1002, respectively are not easily modeled first order plus dead time (FOPDT) systems. Note that the solid curve plots in Figures 4.1 through 4.8 are normalized flows and concentrations calculated following the example in equation 4.2.1 below for Figure 4.1 with $F22$ the controlled variable, $F22_{SS}$ the steady state value and $\Delta F16$ the manipulated variable step size:

$$F22_{Normalized} = \frac{F22 - F22_{SS}}{\Delta F16} \tag{4.2.1}$$

In essence, the plots are of deviation variables normalized by the manipulated variable step. The broken lines of Figures 4.1 through 4.8 are part of the discussion of tuning the adaptive predictive controller in the next section. Due to the existing pressure control valve at Industries James Maclaren Inc., saturated steam pressure is manipulated whereas Ricker uses steam flow.

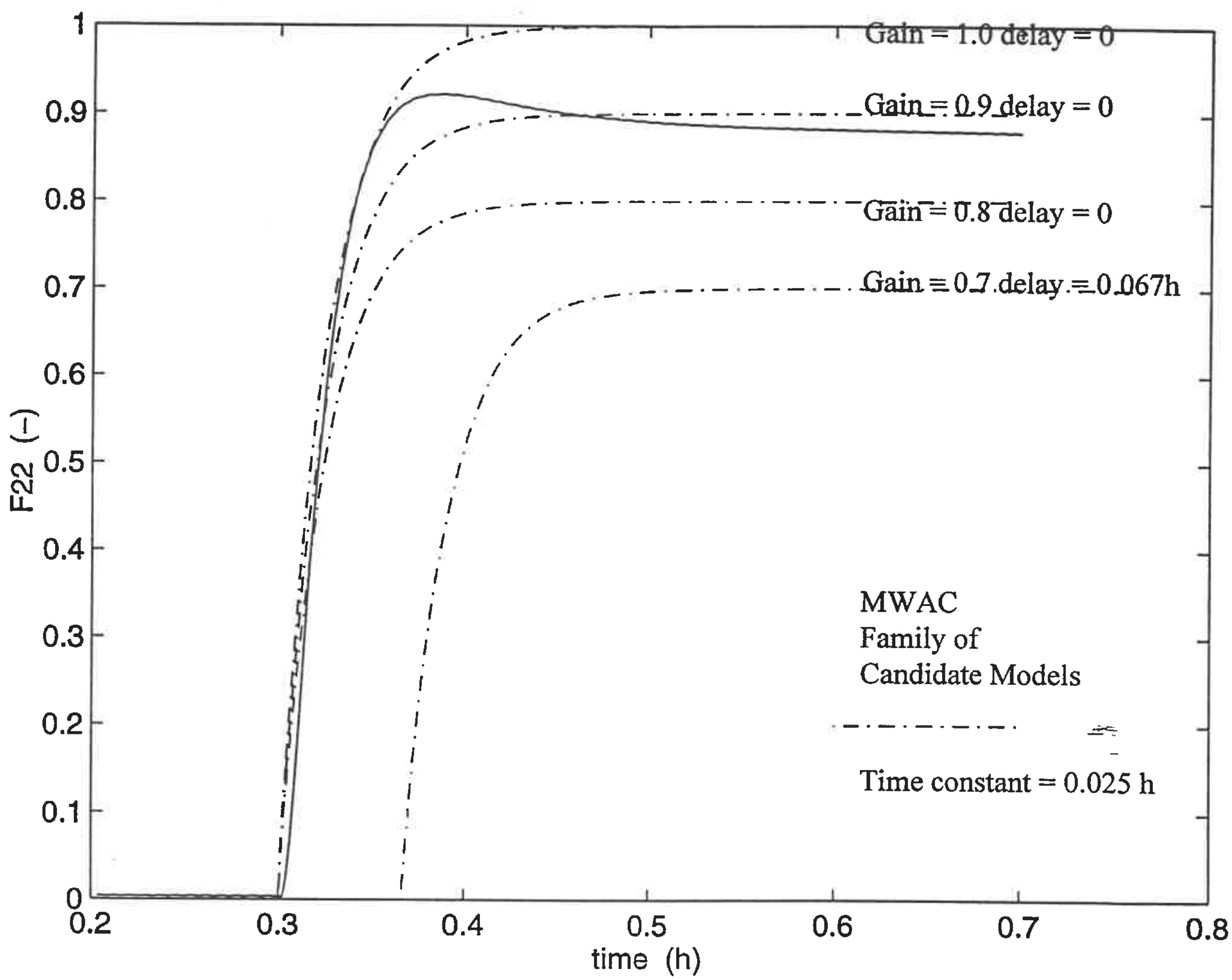

Figure 4.1 Normalized SBL flow (F22) response to step change in WBL flow (F16)

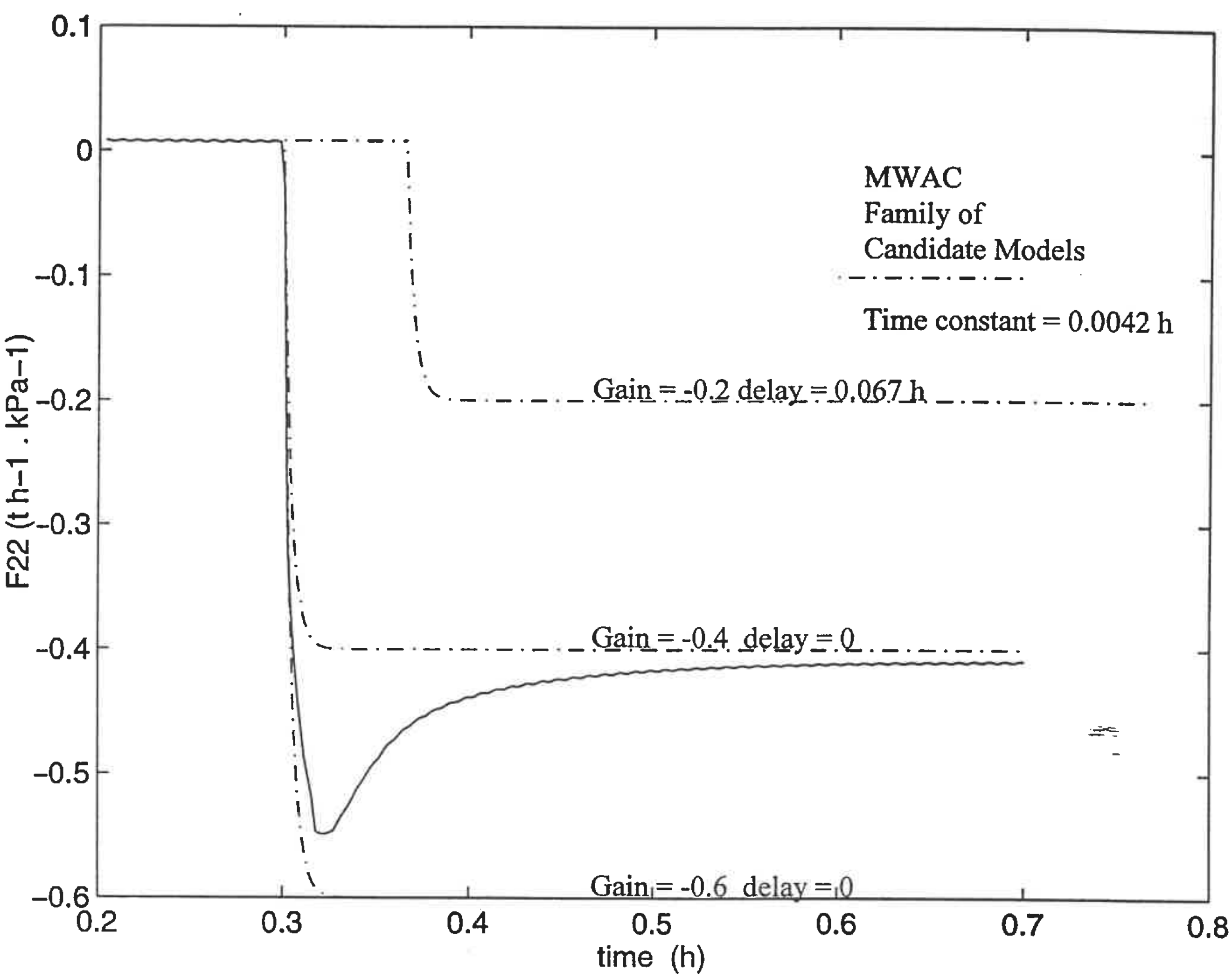

Figure 4.2 **Normalized SBL flow (F22) response to step change in steam pressure (P1002)**

Since computation time of the nonlinear model increases as the control scheme becomes more and more elaborate, a linear model was identified and used for preliminary tuning of the MPC parameters. Each of the four combinations of input and output variables as described in Table 4.4 were plotted and are found in Figures 4.1, 4.2, 4.3, and 4.4.

Table 4.4 Linear Process Model Identification

Figure	Step in manipulated var.	Response of controlled var.
4.1	WBL flow (F16)	SBL flow (F22)
4.2	Feed steam press. (P1002)	SBL flow (F22)
4.3	WBL flow (F16)	SBL concentration (D22)
4.4	Feed steam press. (P1002)	SBL concentration (D22)

From these, four first order transfer functions were identified. Similarly, a first order relationship between product concentration and steam pressure was also developed by Newell & Fisher [13].

$$\begin{bmatrix} F22 \\ D22 \end{bmatrix} = \begin{bmatrix} \dfrac{0.87e^{-0.05s}}{0.025s+1} & \dfrac{-0.41e^{-0.05s}}{0.0042s+1} \\ \dfrac{-0.18e^{-0.033s}}{0.077s+1} & \dfrac{0.195e^{-0.033s}}{0.083s+1} \end{bmatrix} \begin{bmatrix} F16 \\ P1002 \end{bmatrix} \tag{4.2.2}$$

The preceding identification was based on a +10% step test.

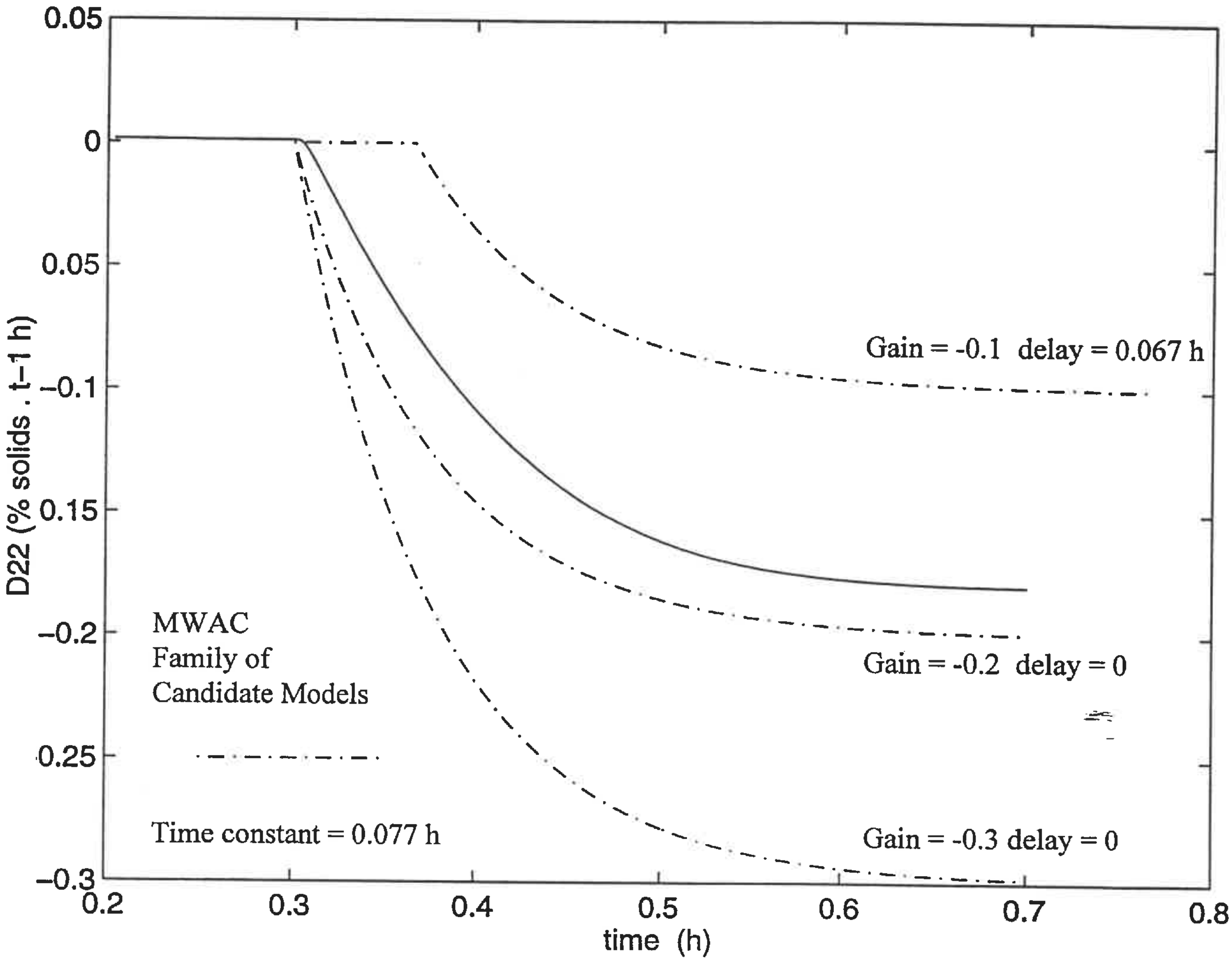

Figure 4.3 **Normalized SBL concentration (D22) response to step change in WBL flow (F16)**

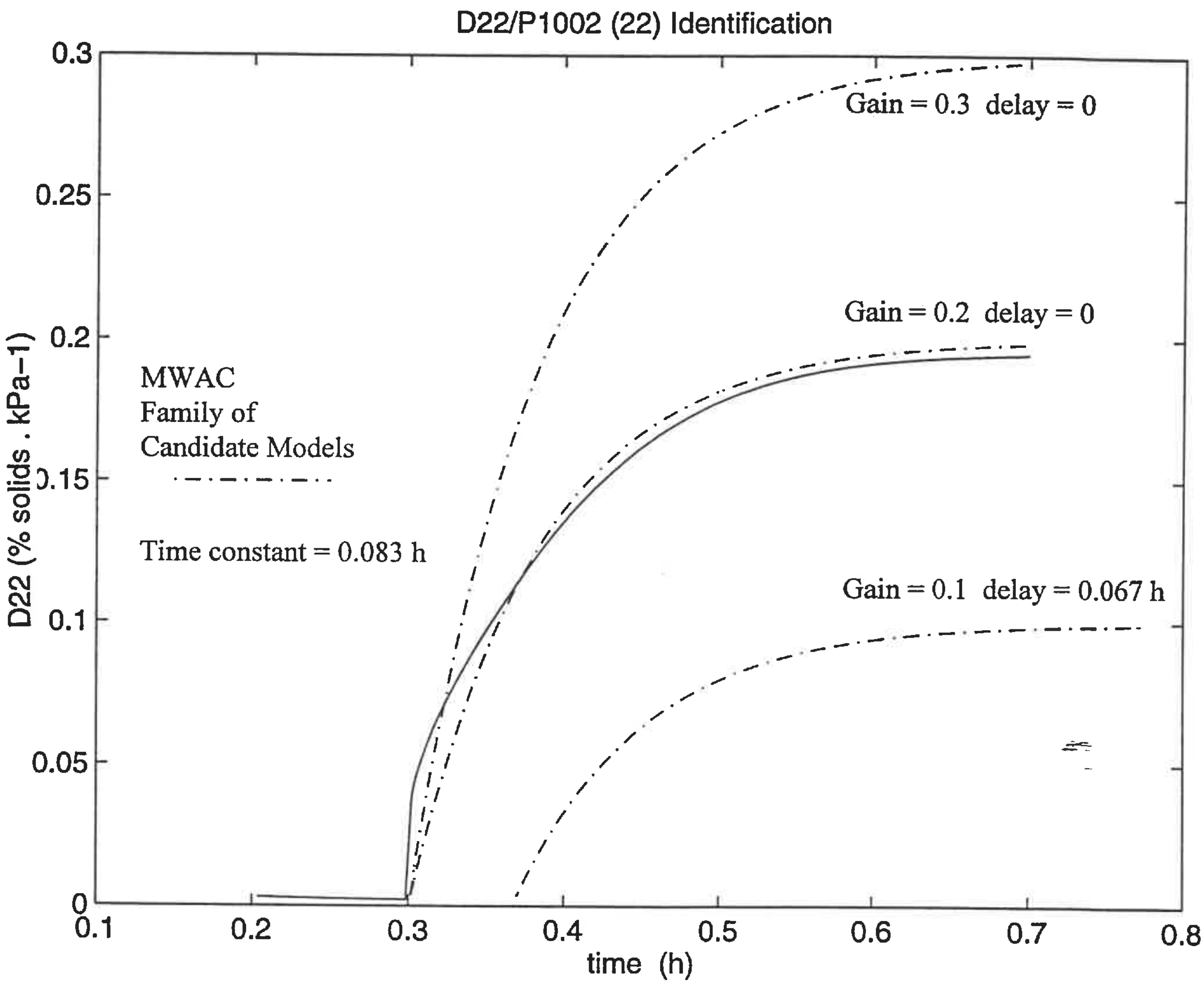

Figure 4.4 Normalized SBL concentration (D22) response to step change in steam pressure (P1002)

There was no apparent dead time in the four observed responses of the nonlinear model. Given that there is certainly dead time in the plant installation, delays were added to the model. In order to simulate process delay in output (or controlled) variables, each transfer function associated with a given output must have the same size delay. Due to unavailability of plant operating information, the size of delays (0.033 and 0.05 h for the product flow (F22) and concentration (D22) respectively) added to the process models is arbitrarily small in order to minimize the computational burden without overlooking their existence. The delays are present in both the linear and nonlinear process models during the set point change and disturbance elimination trials described in section 4.4 Controller Performance.

With the above linear process model, the Relative Gain Array [20] is calculated to evaluate process interactions. For the linear 2x2 system above, the relative gain λ has a value greater than 1 ($\lambda_{11} = 1.8$) which indicates that the second pair of input and output variables (D22 and P1002 respectively) reduces the gain between the first pair (F22 and F16) as well as confirming control loop interaction.

In order to establish that the model behaves similarly further away from the steady state operating point, responses to a second step of +10% are plotted in Figures 4.5, 4.6, 4.7, and 4.8. The purpose of a second step change is to compare the gain at different starting points. The physical significance of this is that in a nonlinear process, a given change in manipulated

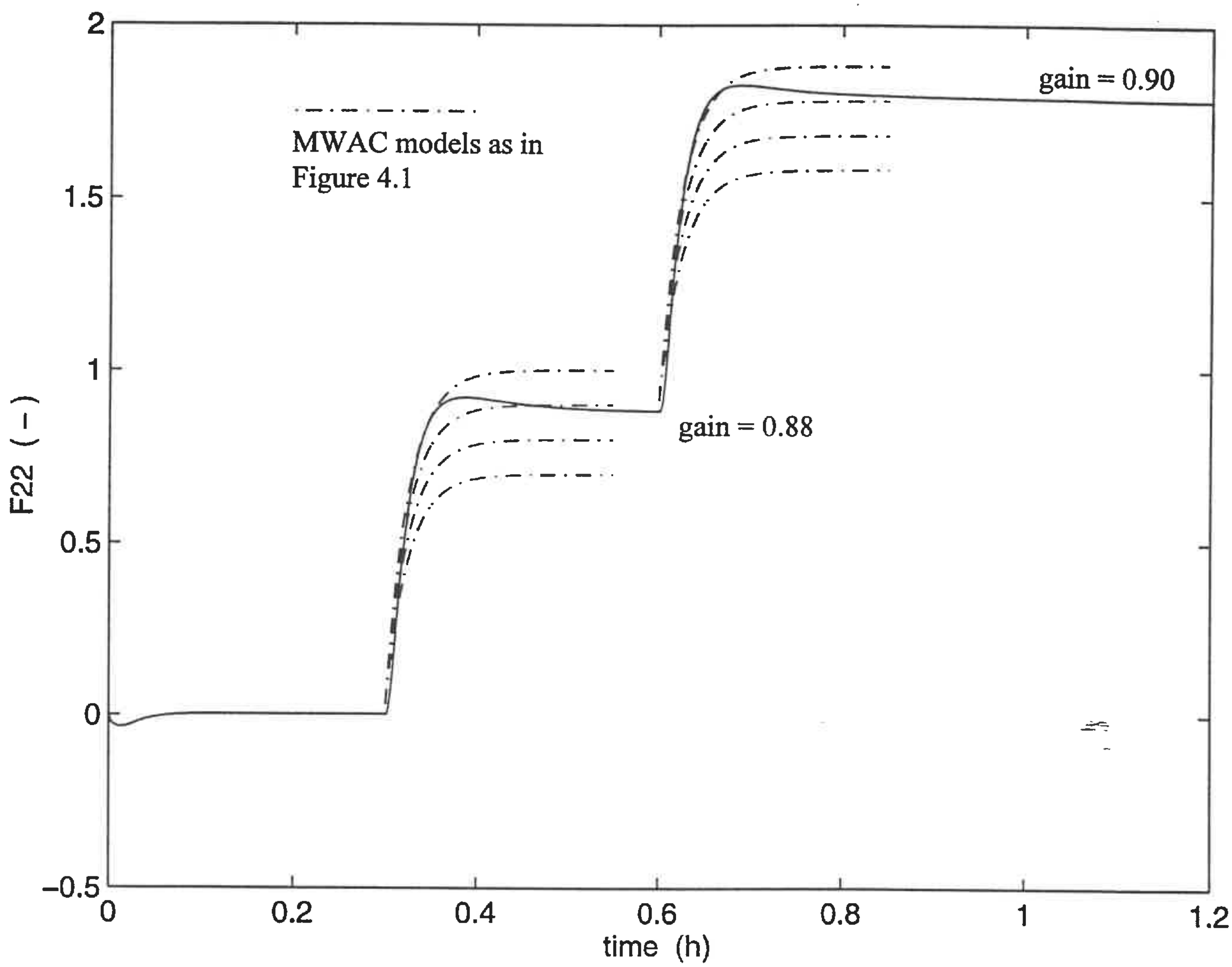

Figure 4.5 Normalized SBL flow (F22) response to two step changes in WBL flow (F16)

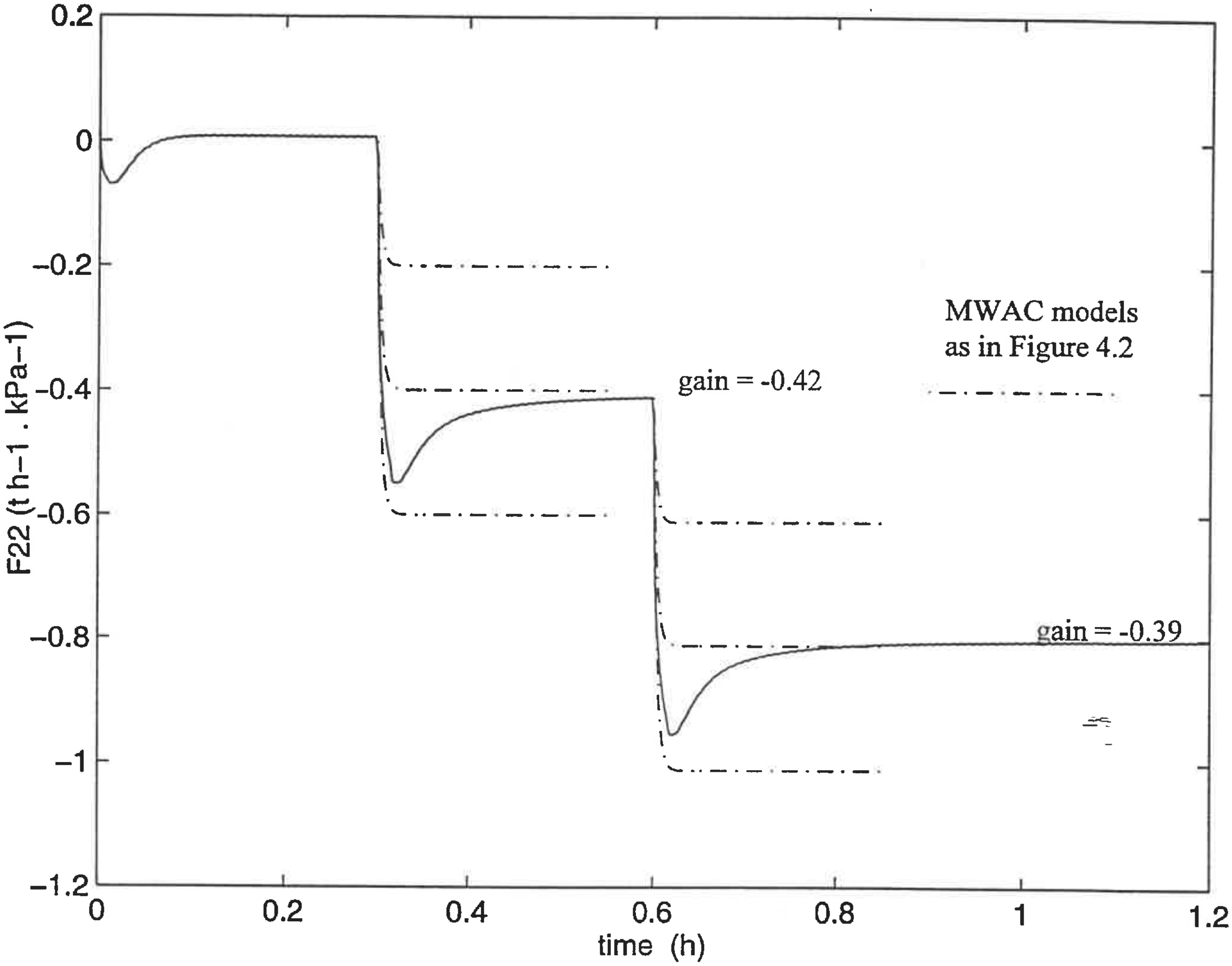

Figure 4.6 Normalized SBL flow (F22) response to two step changes in steam pressure (P1002)

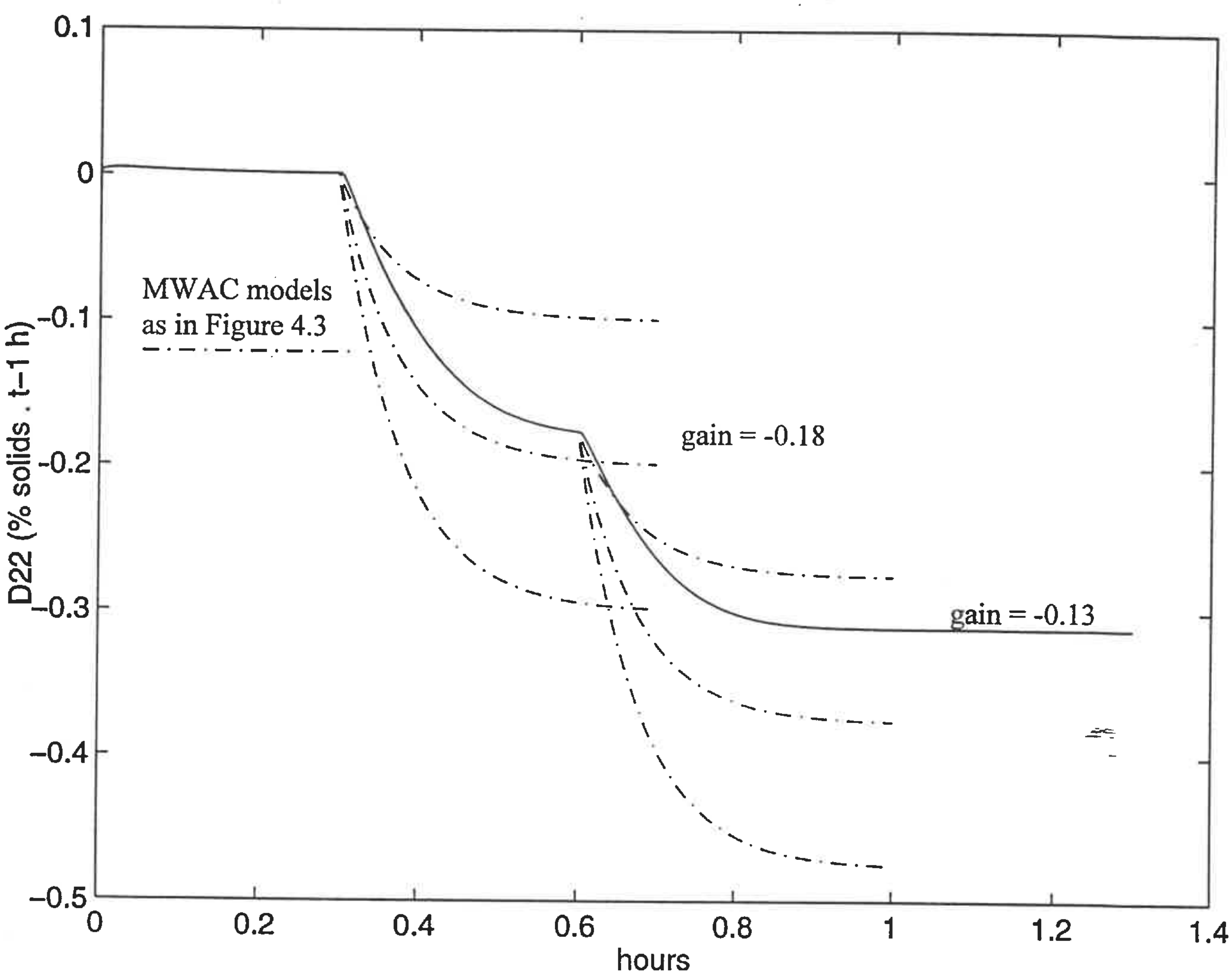

Figure 4.7 Normalized SBL concentration (D22) response to two step changes in WBL flow (F16)

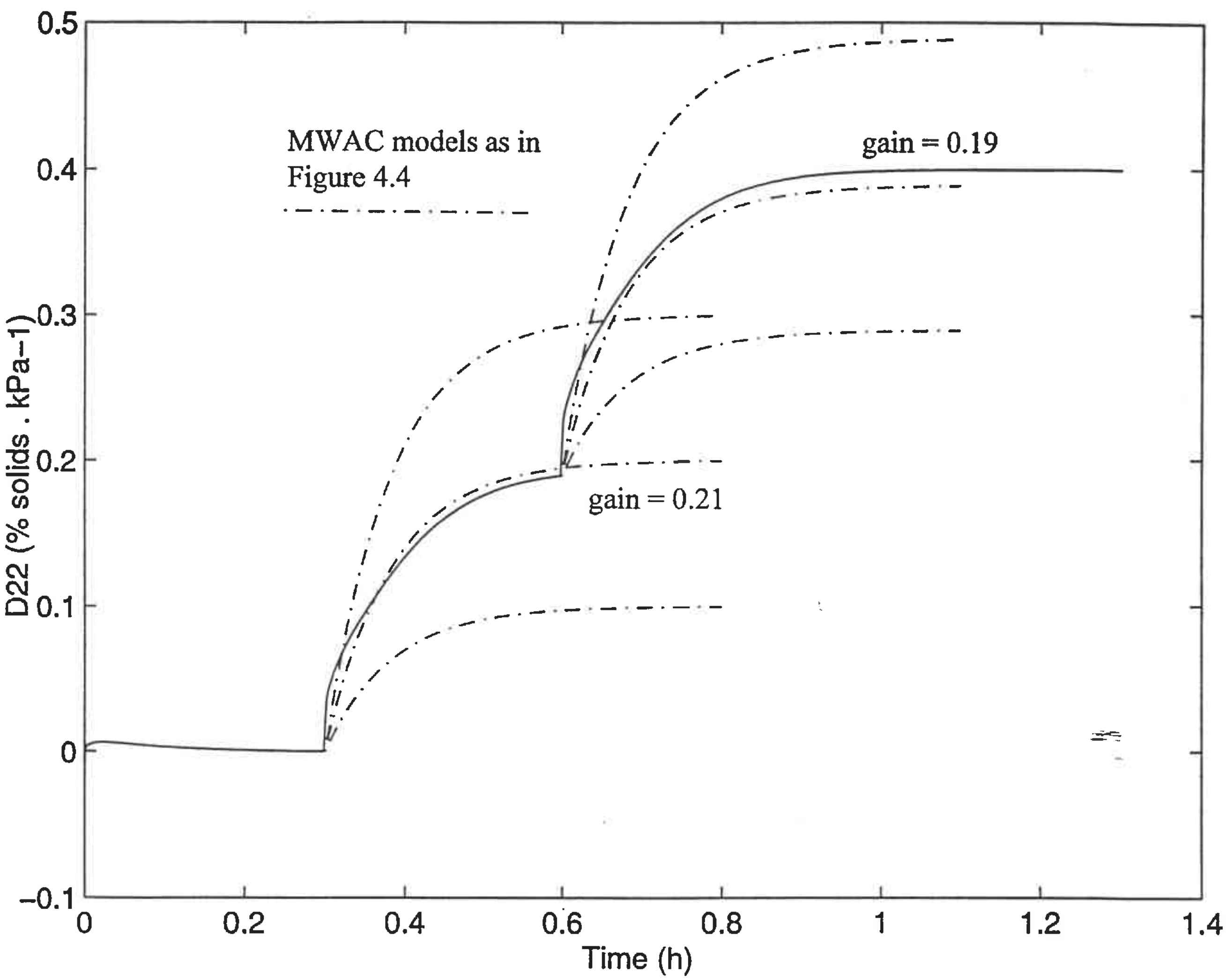

Figure 4.8 Normalized SBL concentration (D22) response to two step changes in steam pressure (P1002)

variable will produce a different response in the controlled variable, depending upon the starting point of the controlled variable. It is clear from these figures that the preliminary identification holds for excursions of up to 20% from steady state.

The prediction and control horizons (*V* and *U* respectively) that gave the best controller performance were 60 and 20 respectively. Since the control objective is supervisory, a sampling interval of 30 seconds was selected such that the prediction horizon neither truncates nor overlooks open loop model response dynamics but still comprises fewer than 200 impulse coefficients. Design parameters used by Ricker et al.[19] such as a prediction horizon of 62 minutes and samplingtime of one minute are in the same order of magnitude as 30 minutes and 30 seconds respectively in the present simulations. Design values used by Newell and Lee [14] listed in Table 4.4 along with those used in the present work:

Table 4.5 MPC Parameters

	Present Work	Newell and Lee
Model horizon (min)	60	150
Prediction horizon (min)	30	50
Control horizon (min)	10	25
Sample time	30 seconds	1 minute

In the plant application, outlet SBL is fed to a concentrator and eventually the recovery boiler, it is therefore important to maintain SBL concentration in order to avoid excessive fouling, due to high solids, or conversely, extreme steam requirements in the case of dilute product liquor. For this reason, the output weights for SBL flow (F22) and concentration (D22) are 1 and 20 respectively which means that excursions from the concentration set point are heavily penalized relative to flow. Tuning of the move suppression factors (input weights) was a compromise between small values that led to oscillatory responses and larger weights that led to sluggish behaviour. Weights of 15 for WBL flow (F16) and 10 for feed steam pressure (P1002) yielded acceptable results.

4.3 Model Weighting Adaptive Control (MWAC) Tuning

Closed-loop time constants and discrete ranges of gain and delay values are inputs to the MWAC algorithm. A single time constant is identified and the broken lines of Figures 4.1, 4.2, 4.3 and 4.4, represent the range of gains chosen. Since the controlled variables F22 and D22 have delays of 0.05 and 0.033 hours respectively in the simulated process, ~~the~~ range of dead times input to the MWAC controller is 0 to 0.067 hours. Given the preceding ranges of gain and dead time, as well as a time constant for each of the four relations, the MWAC algorithm makes a FOPDT estimate for each possible combination. For the sake of comparison, the same MPC tuning constants were used for the adaptive and predictive controller as in the fixed-parameter predictive controller.

The MWAC algorithm as it stands presently assumes that the process can be adequately modeled by a combination of FOPDT responses. The open loop step responses of SBL flow (F22) to steps in WBL flow (F16) is in fact more characteristic of the following transfer function due to the initial rapid rise and subsequent overshoot

$$G_p = \frac{K(\tau_1 s + 1)}{(\tau_2 s + 1)(\tau_3 s + 1)} \tag{4.3.1}$$

$$\tau_3 > \tau_2$$
$$\tau_1 > \tau_3$$

Also, the rapid initial increase in SBL flow (F22) in response to a step in steam pressure (P1002) is more characteristic of the following transfer function than a FOPDT.

$$G_p = \frac{K(\tau_1 s + 1)}{(\tau_2 s + 1)(\tau_3 s + 1)}$$

$$\tau_3 > \tau_2$$
$$\tau_1 < \tau_3$$

4.4 Controller Performance

With the tuning parameters adjusted as discussed above, the linear model and subsequently the nonlinear system are tested for set point changes. It is important that the controller handle set point changes as these are required for plant turndown. Lastly, the nonlinear system is tested for disturbance elimination which is a scenario that represents a common function of the controller.

In practice, process delays are not known precisely and therefore trials (plotted with broken lines in Figures 4.9, 4.10, 4.11, and 4.12) are made with mismatch between the process model and the MPC convolution model delays. The 2x2 matrices of delays shown in Table 4.5 correspond to the different combinations of dead time mismatches used in the simulations. These are compared to the solid line plots with no mismatch in Figures 4.9 - 4.12.

Table 4.6 Process and Controller Dead Time (in Hours)

Transfer Function	Process Model Delays	Mismatch # 1 Figures 4.9 - 4.12	Mismatch #2 Figures 4.9 - 4.12	Mismatch Figures 4.13 - 4.20
F22/F16 F22/P1002	0.05 0.05	0.025 0.058	0033 0.05	0.025 0.058
D22/F16 D22/P1002	0.033 0.033	0.042 0.042	0.017 0.067	0.042 0.042

From the Figures (4.9 - 4.12), it is clear that in all but the D22 case (Figure 4.10), this mismatch does not lead to appreciable controller performance degradation. Although there is a larger discrepancy between D22 responses, the difference is never larger than one tenth of a percent solids (0.1 %).

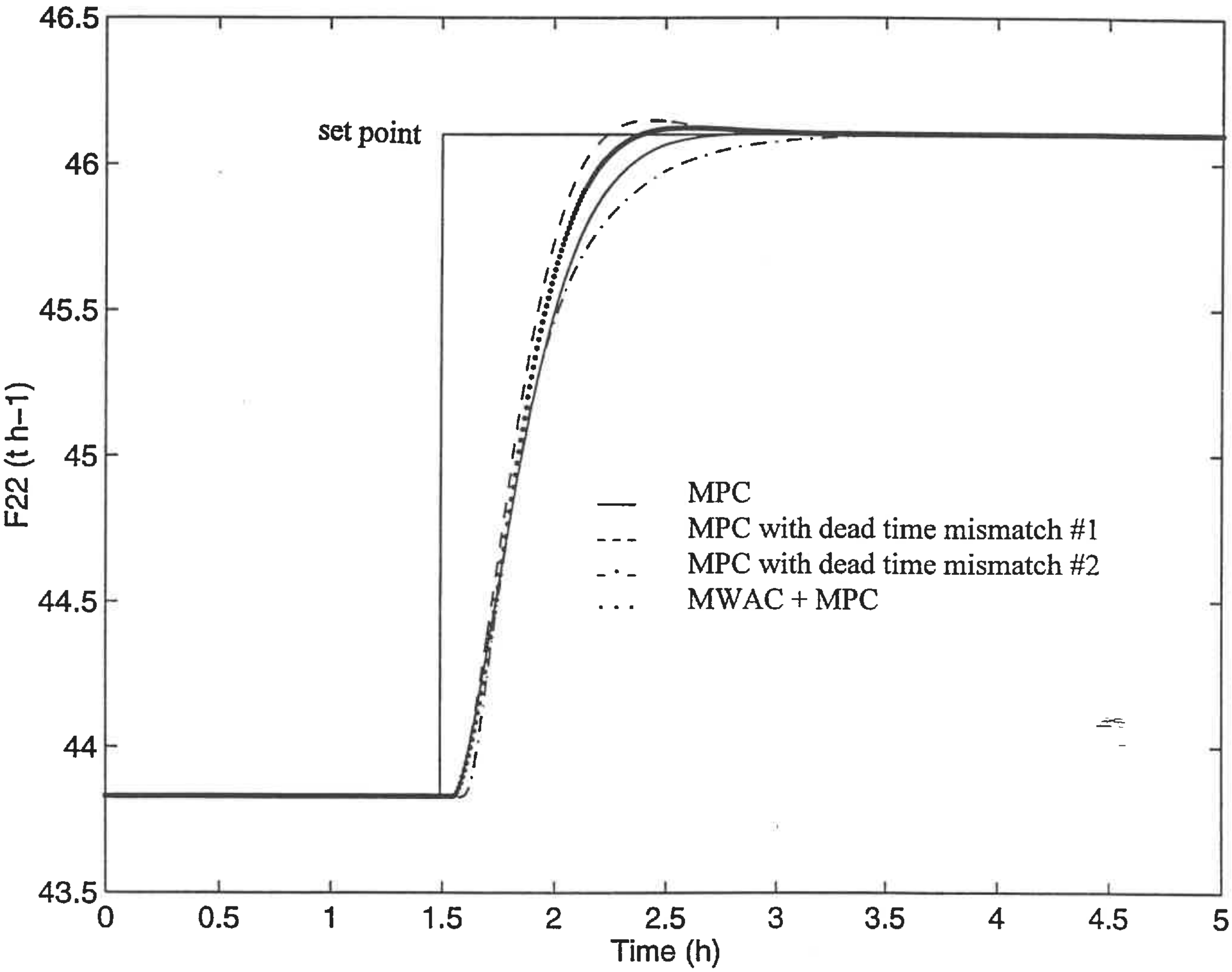

Figure 4.9 Linear process model SBL flow (F22) set point change

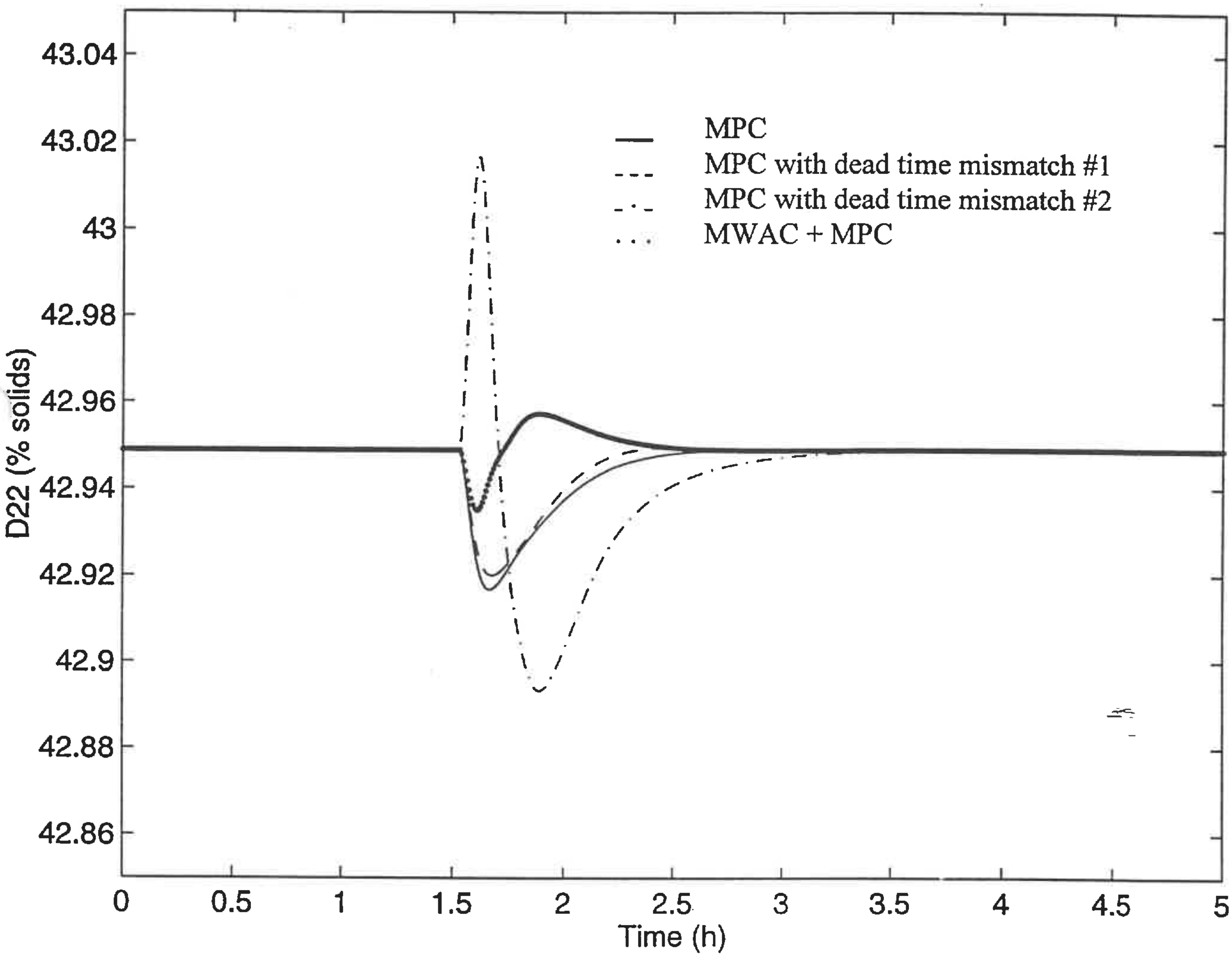

Figure 4.10 Linear process model SBL concentration (D22) response to SBL flow (F22) set point change

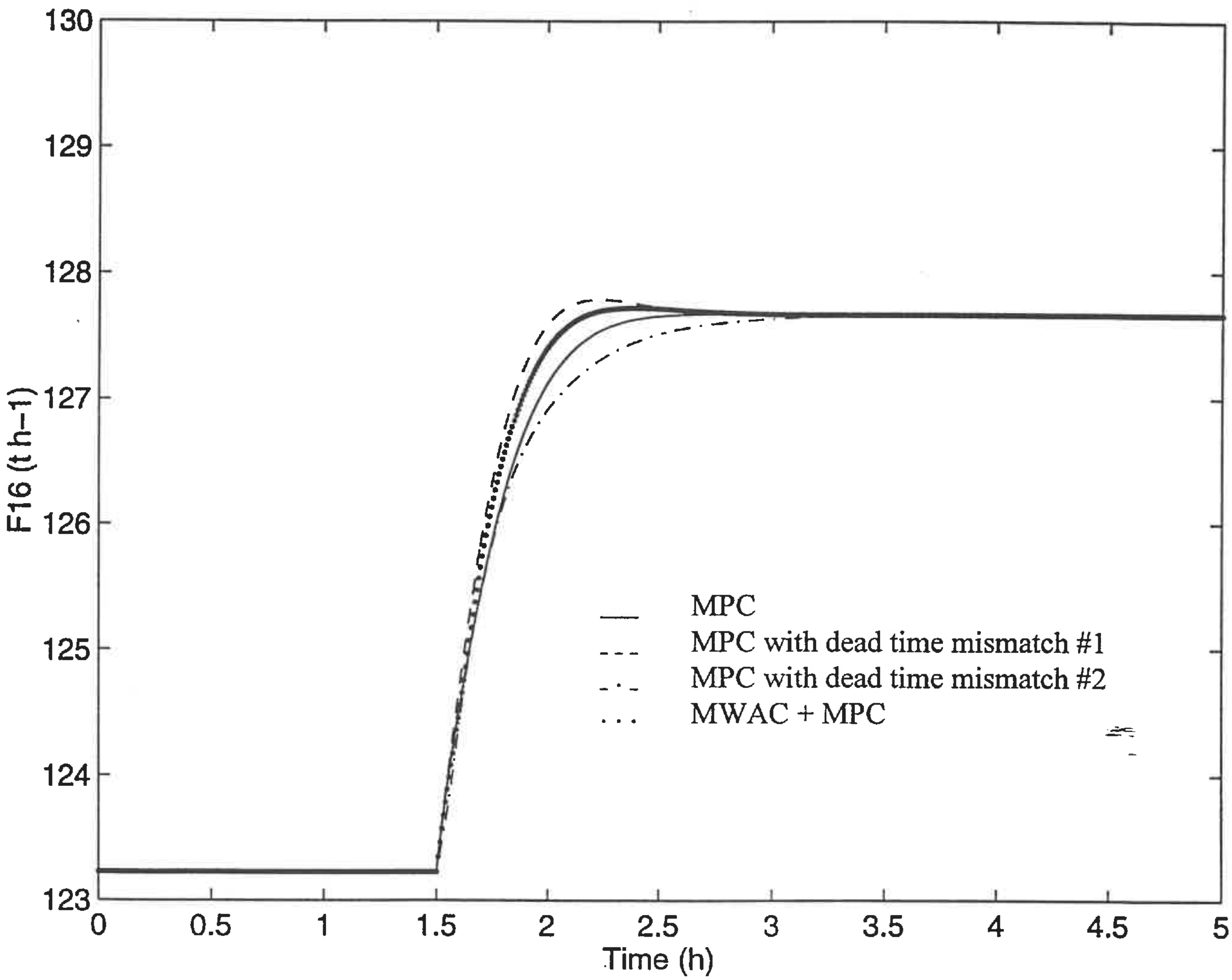

Figure 4.11 Linear process model WBL flow (F16) response to SBL flow (F22) set point change

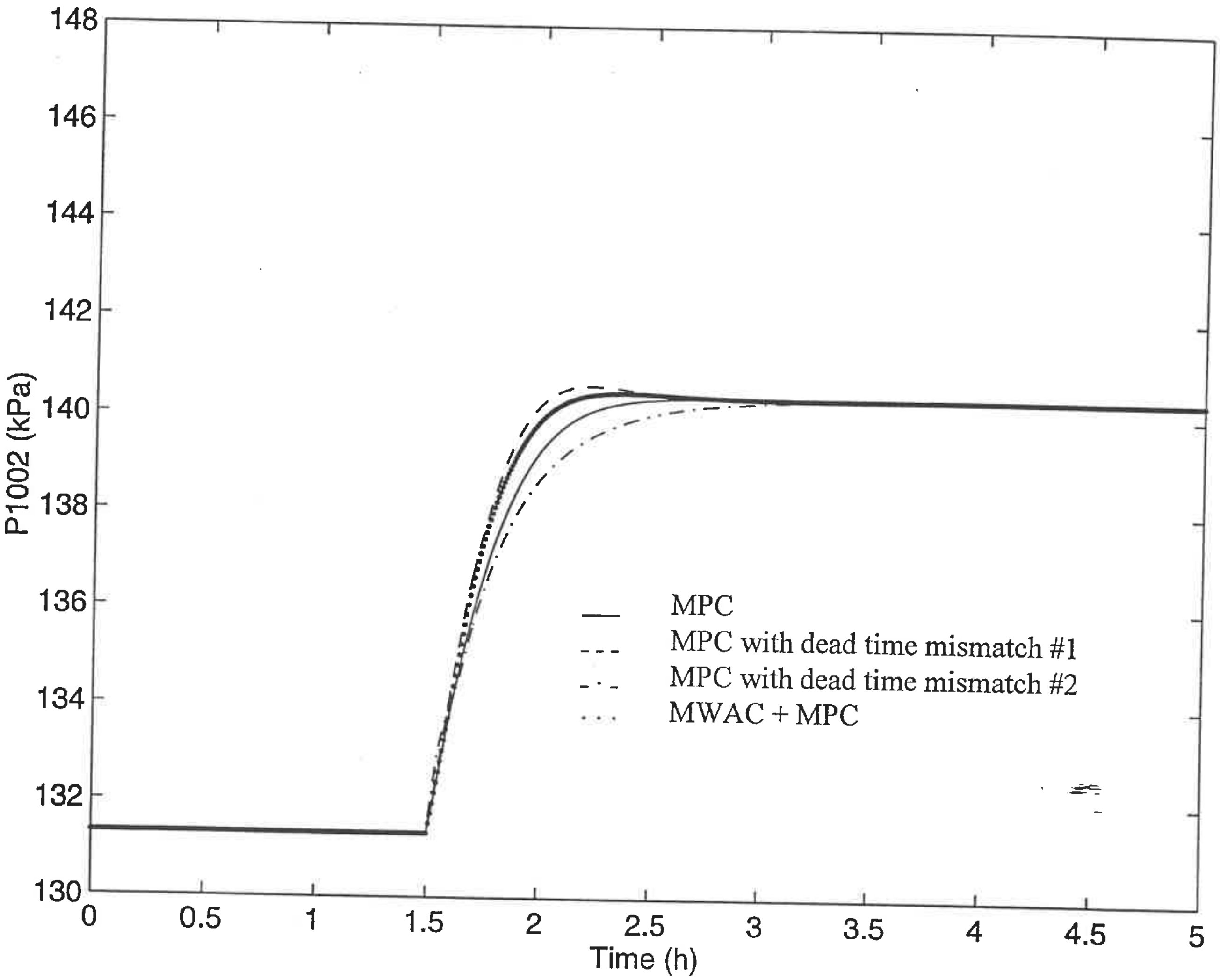

Figure 4.12 Linear process model steam pressure (P1002) response to SBL flow (F22) set point change

The combination of an MPC controller with adaptation by MWAC yields promising results plotted in Figures 4.9 -4.12 with dotted lines. In Figure 4.9, the new SBL flow (F22) set point is attained faster with the MPC + MWAC algorithm than any of the MPC trials, with small overshoot. During the F22 set point change, D22 (SBL concentration) is best maintained at target by the MPC + MWAC algorithm with maximal excursion from set point of 0.02% solids. The two manipulated variables, WBL flow (F16) and feed steam pressure (P1002) behave consistently, regardless of the controller tested. The following tables summarize the results plotted in Figures 4.9 - 4.12.

Table 4.7 Control Studies of MPC, MPC with Dead Time Mismatches, and MWAC + MPC Controllers with Linear Process Model

Figure	Y vs. X	Model	Set Point / Disturbance	Observations
4.9	F22 vs. t	linear	F22 set pt.	all responses similar to first order
4.10	D22 vs. t	linear	F22 set pt.	MWAC + MPC performs better than MPC with dead time mismatches
4.11	F16 vs. t	linear	F22 set pt.	all responses similar to first order
4.12	P1002 vs. t	linear	F22 set pt.	all responses similar to first order

In the preceding series of trials, two different dead time mismatches proved not to have significantly differing performance. With this in mind, only one such case will be examined in the following tests of the MPC and MPC + MWAC algorithms for control of the nonlinear process model.

Figures 4.13, 4.14, 4.15 and 4.16 illustrate the results of a set point change in SBL flow (F22). The first obvious difference between this series of plots and the preceding one (Figures 4.9 - 4.12) is the time scale. Whereas the linear model is in transition between old and new set points for less than an hour, the nonlinear model requires at least three hours. In Figure 4.13 the SBL flow (F22) behaviour is consistent for the MPC without mismatch, MPC with mismatch, and MPC + MWAC algorithms. SBL concentration (D22) remains within ±0.1 % solids of the target value while the manipulated variables have essentially identical responses, regardless of the control algorithm.

The trials which best portray MPC and MPC + MWAC algorithm performance in practical application are plotted in Figures 4.17, 4.18, 4.19 and 4.20. This is the case of disturbance elimination. A +10% step in WBL concentration (D16) is introduced to the system and each of the controllers under examination returns the outputs (F22 and D22) to target values by manipulating the inputs (F16 and P1002). In Figure 4.17, MPC with dead time mismatch allows the smallest and shortest excursion, followed very closely by MPC without delay mismatch and finally MPC + MWAC which behaves similarly with a larger and slightly longer deviation. Conversely, in the case of the SBL concentration D22), MPC + MWAC returns the output to target faster than MPC either with or without delay mismatch. Again, the behaviour is similar with no appreciable differences. Both inputs (F16 and P1002) show

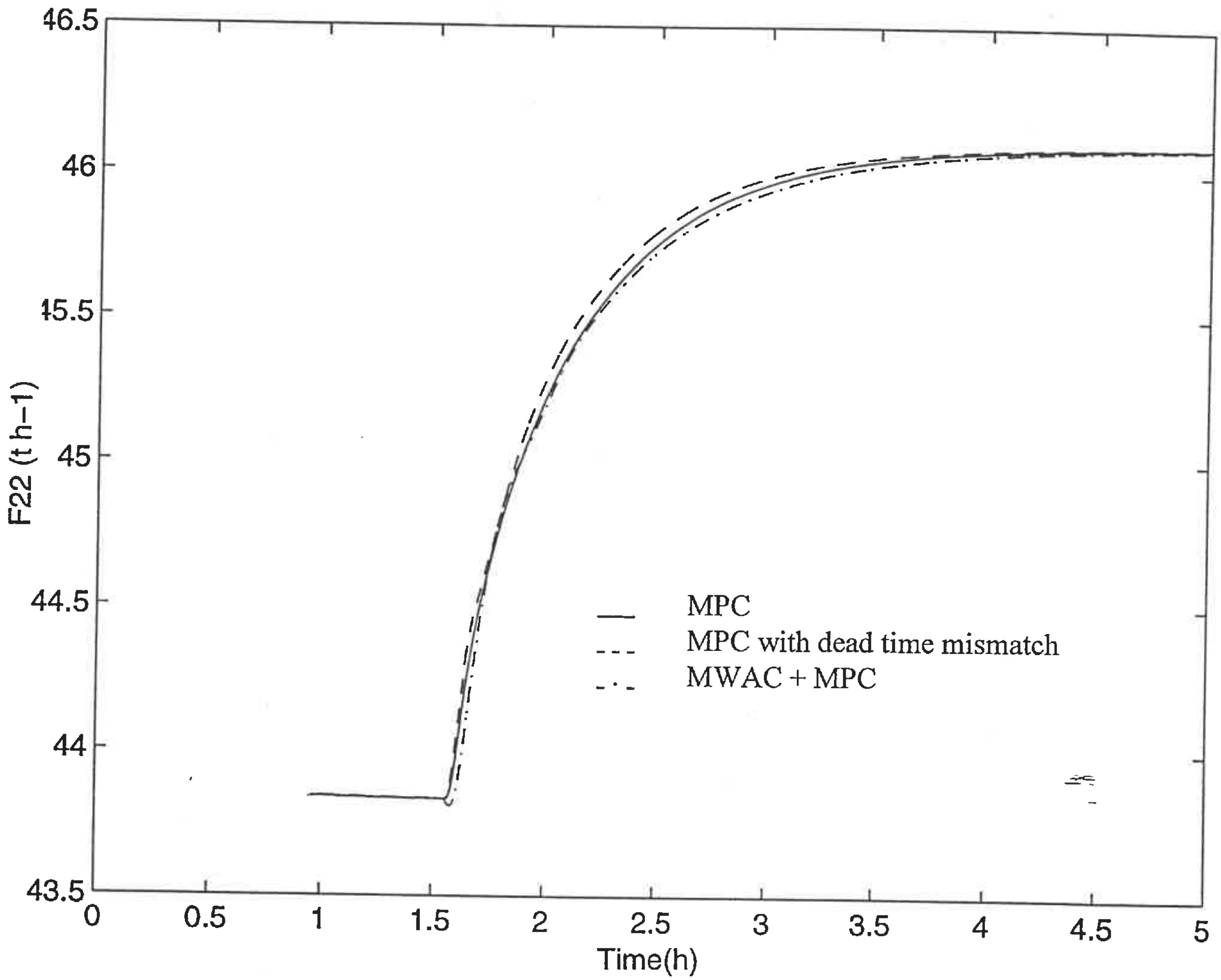

Figure 4.13 Nonlinear process model SBL flow (F22) set point change

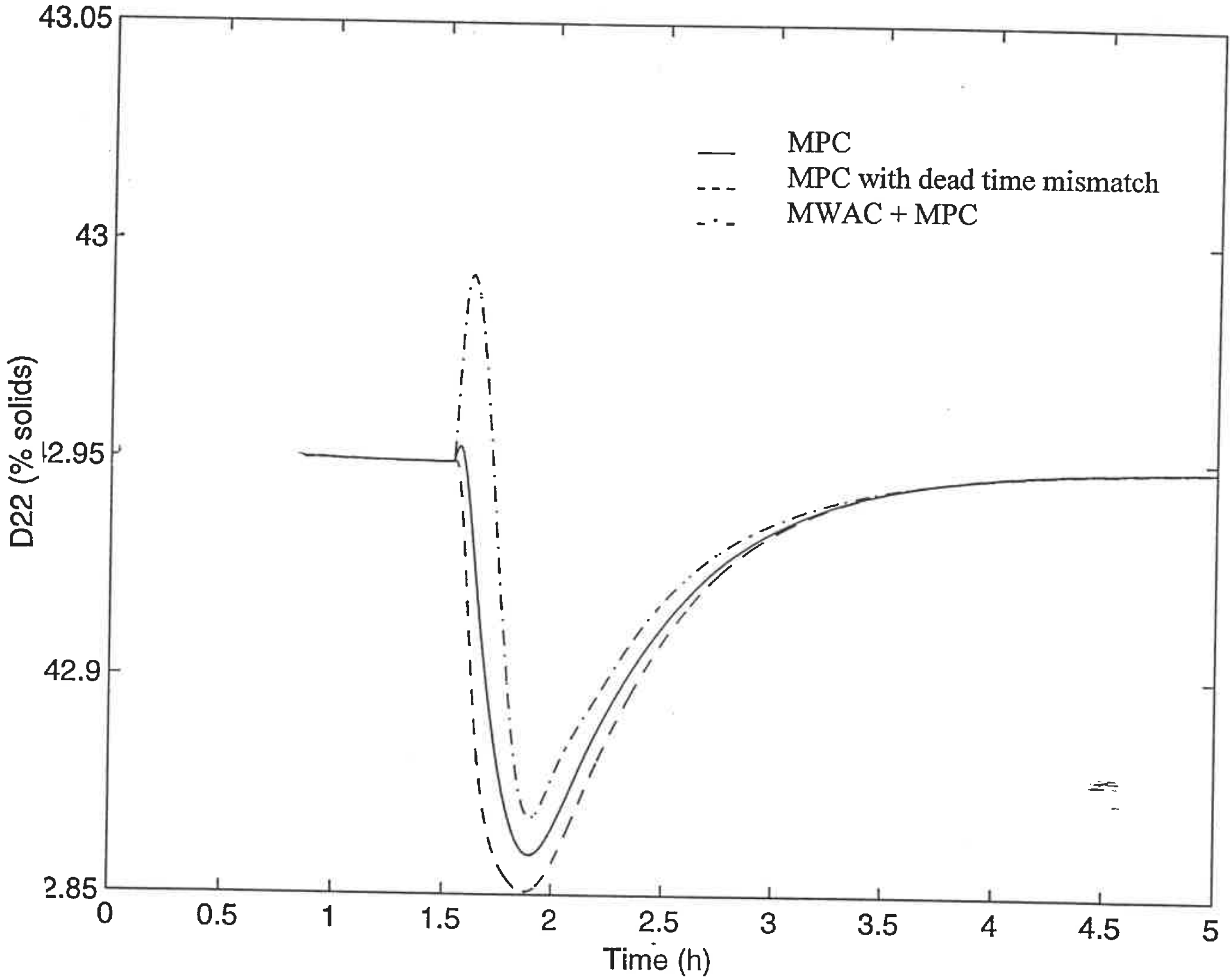

Figure 4.14 Nonlinear process model SBL concentration (D22) response to SBL flow (F22) set point change

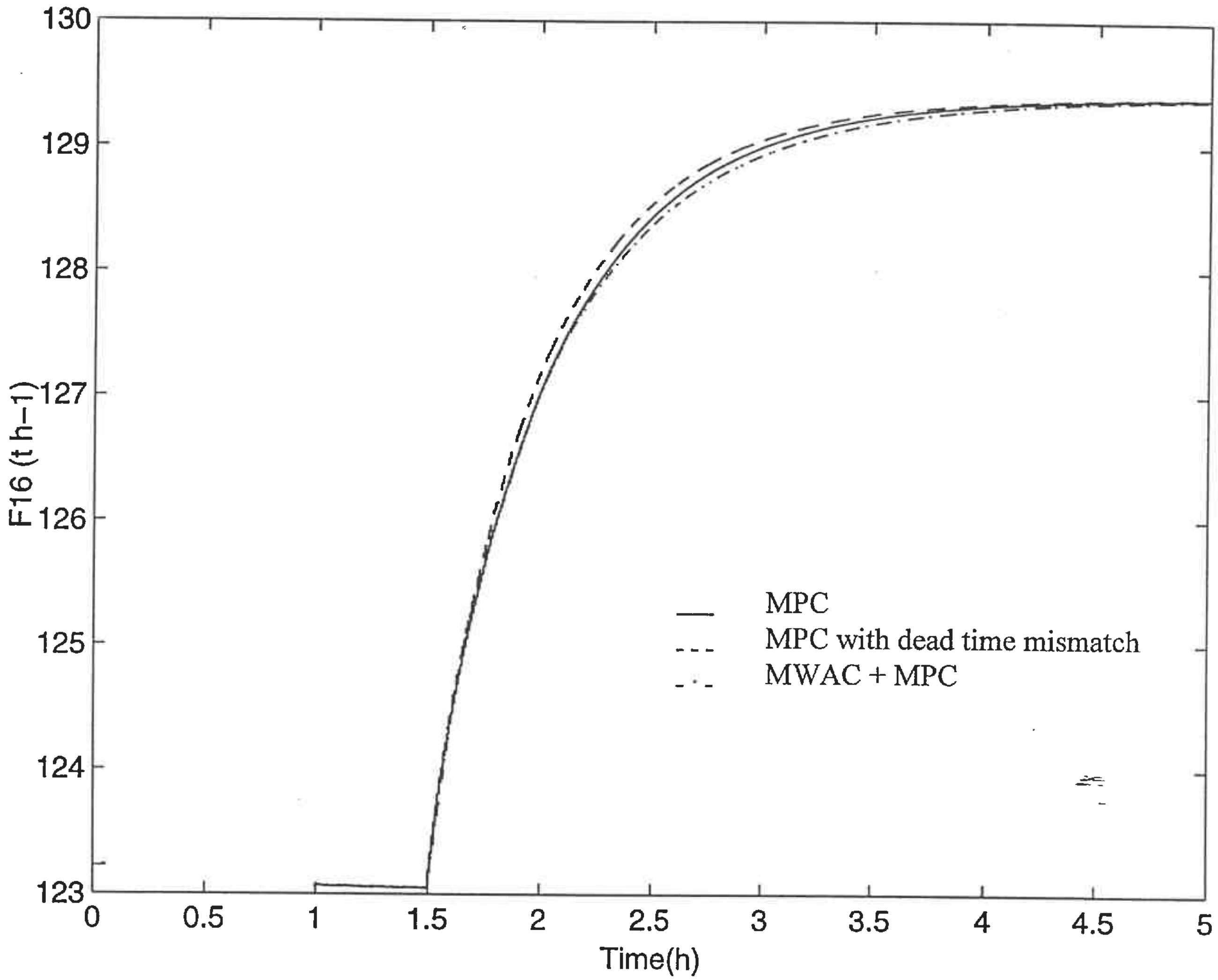

Figure 4.15 Nonlinear process model WBL flow (F16) response to SBL flow (F22) set point change

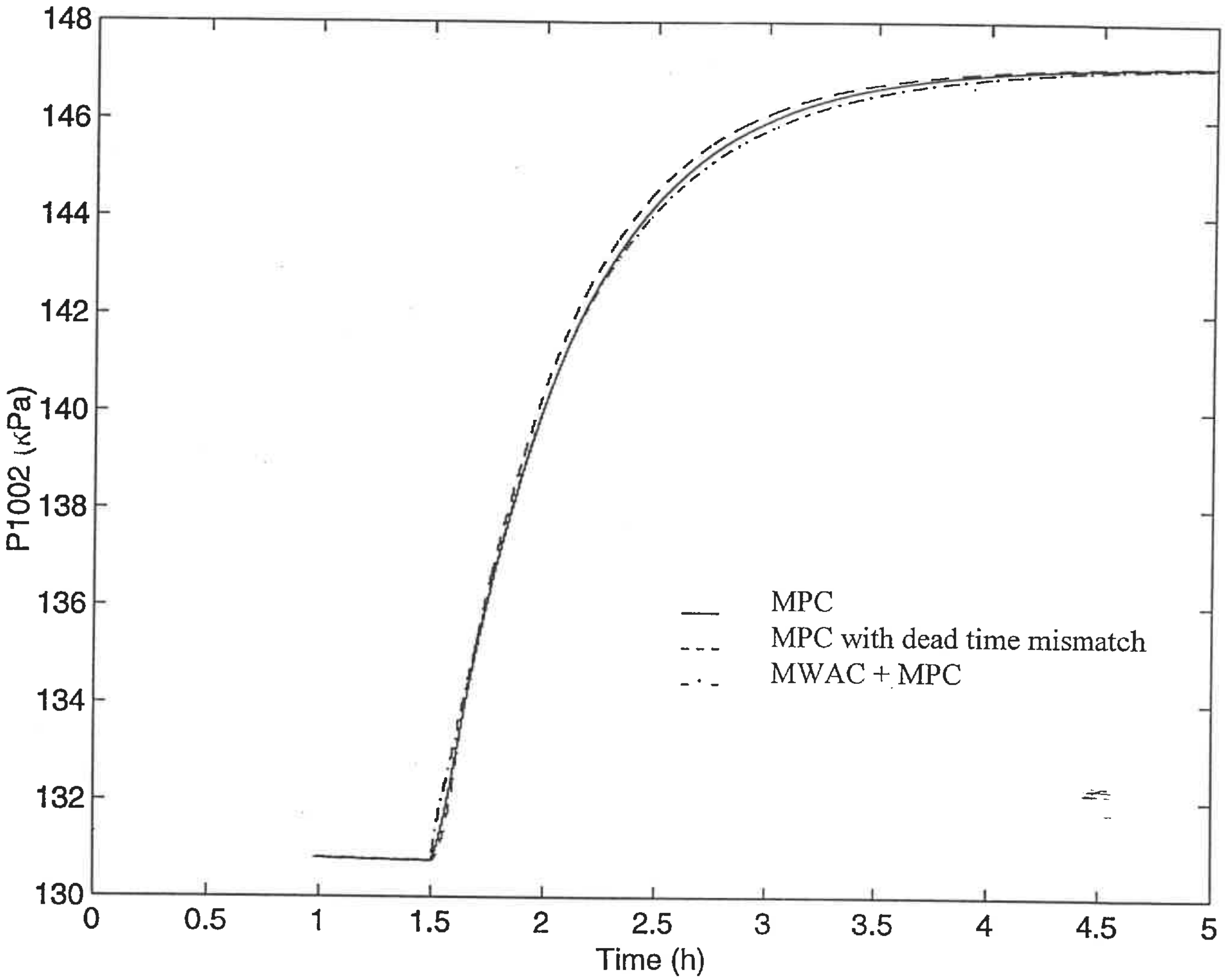

Figure 4.16 Nonlinear process model steam pressure (P1002) response to SBL flow (F22) set point change

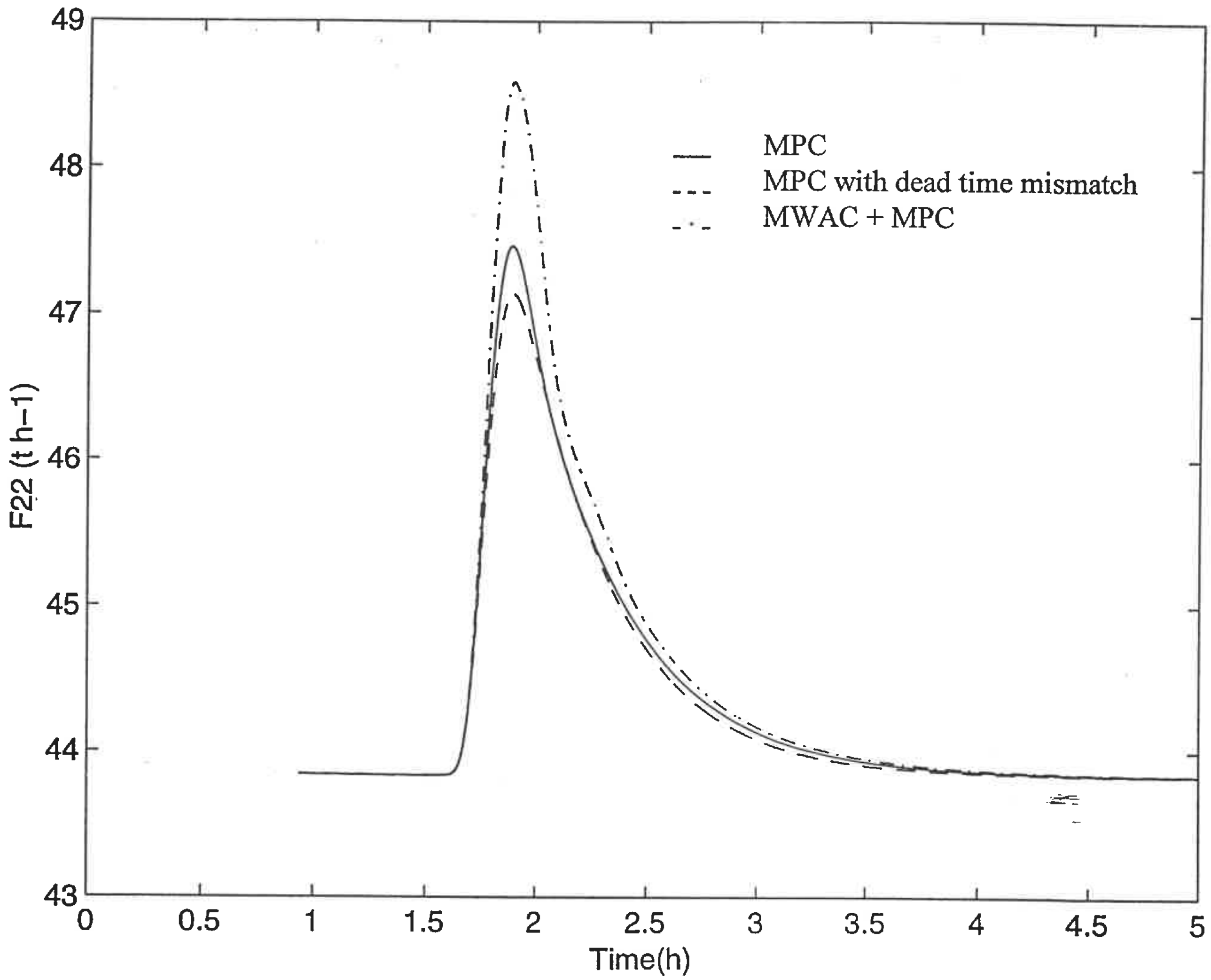

Figure 4.17 Nonlinear process model SBL flow (F22) response to WBL concentration (D16) disturbance

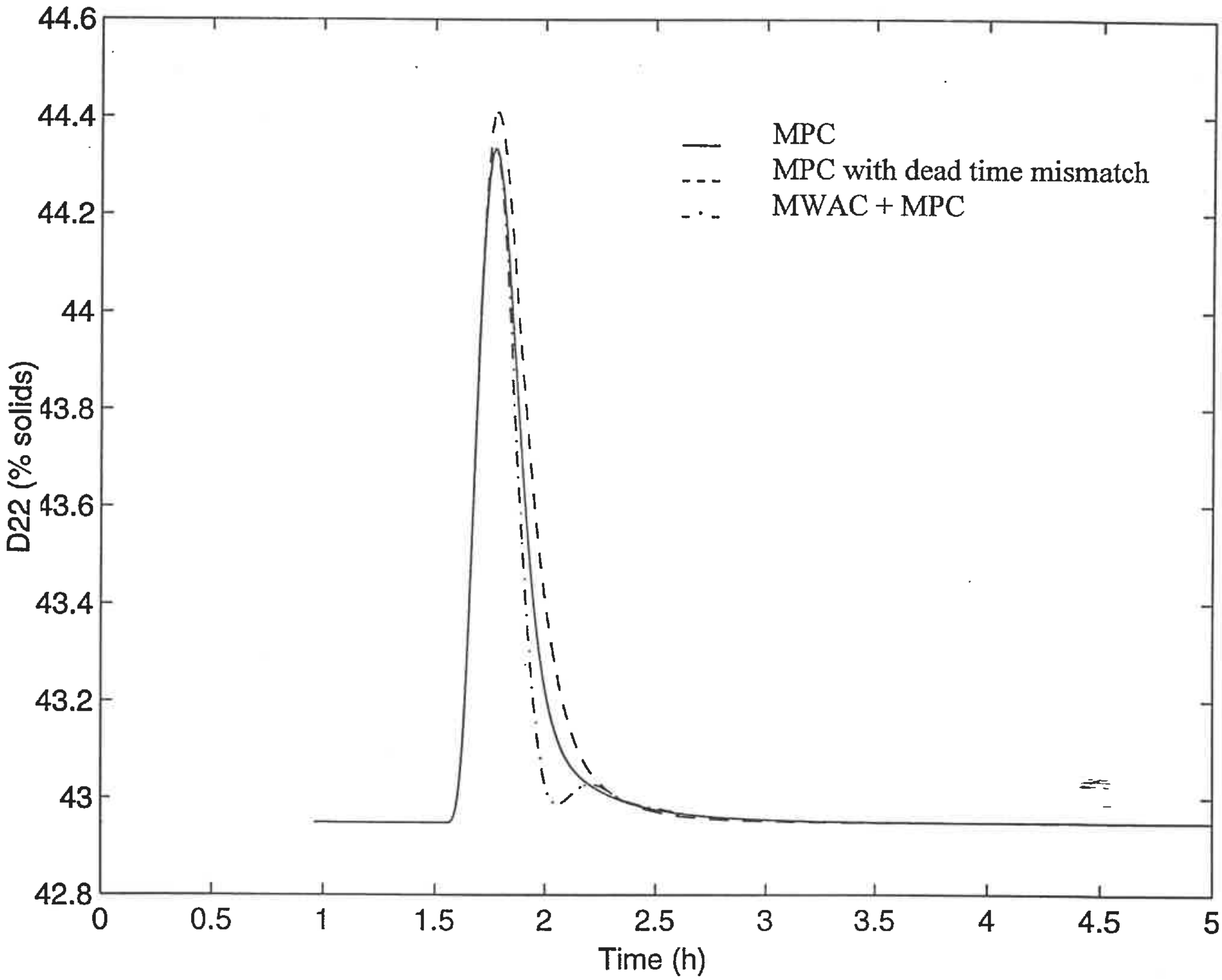

Figure 4.18 Nonlinear process model SBL concentration (D22) response to WBL concentration (D16) disturbance

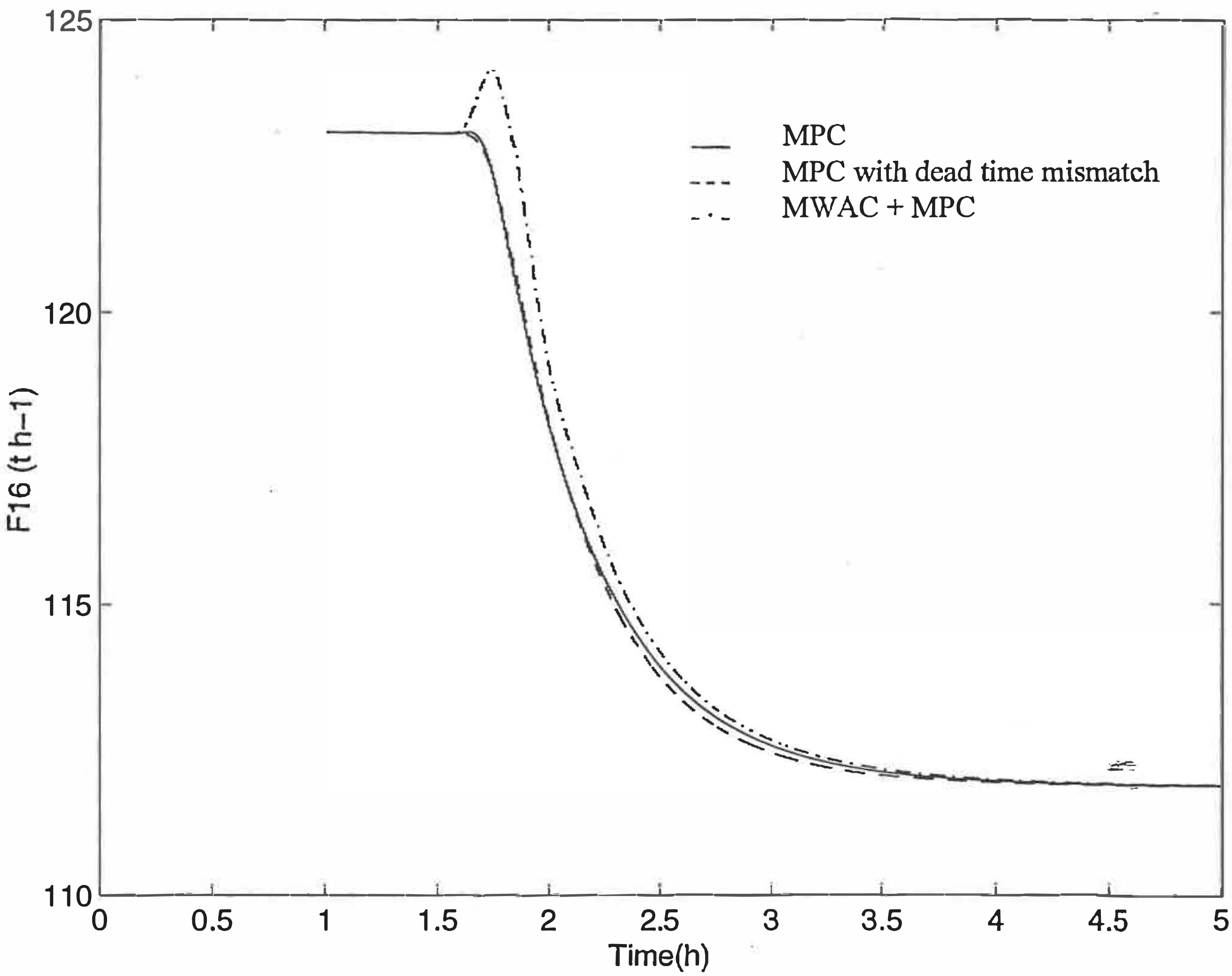

Figure 4.19 Nonlinear process model WBL flow (F16) response to WBL concentration (D16) disturbance

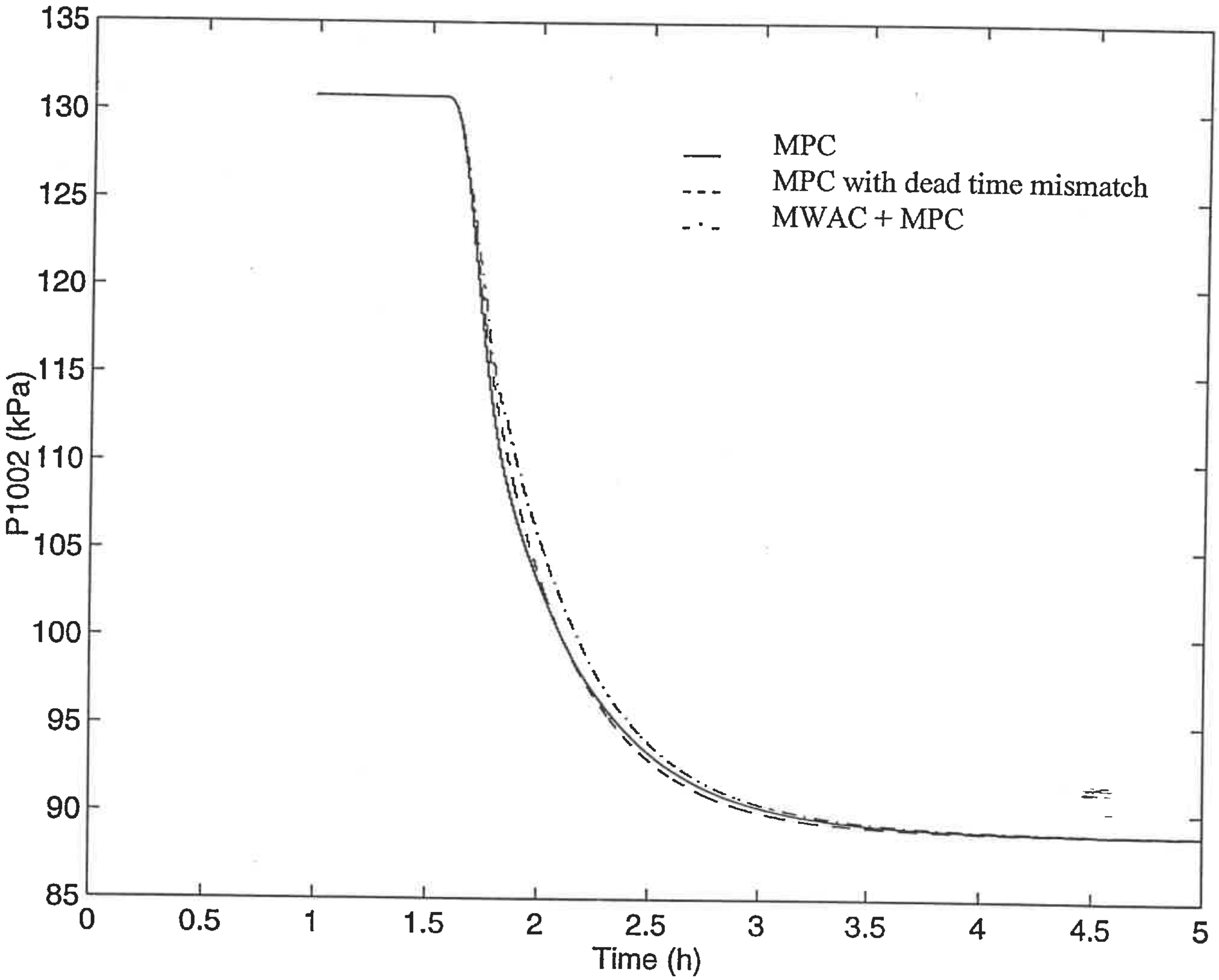

Figure 4.20 Nonlinear process model steam pressure (P1002) response to WBL concentration (D16) disturbance

slightly slower responses to the disturbance but certainly well within the range of acceptability, relative to the MPC performance.

The following tables summarize the results plotted in Figures 4.13 - 4.20.

Table 4.8 Control Studies of MPC, MPC with Dead Time Mismatch, and MWAC + MPC Controllers with Nonlinear Process Model

4.13	F22 vs. t	nonlinear	F22 set pt.	all responses similar to first order
4.14	D22 vs. t	nonlinear	F22 set pt.	initially, MWAC + MPC is slightly slower than MPC controllers
4.15	F16 vs. t	nonlinear	F22 set pt.	all responses similar to first order
4.16	P1002 vs. t	nonlinear	F22 set pt.	all responses similar to first order
4.17	F22 vs. t	nonlinear	D16 disturb.	MWAC + MPC is slightly slower than MPC controllers
4.18	D22 vs. t	nonlinear	D16 disturb.	MWAC + MPC is slightly slower than MPC controllers
4.19	F16 vs. t	nonlinear	D16 disturb.	MWAC + MPC is slightly slower than MPC controllers
4.20	P1002 vs. t	nonlinear	D16 disturb.	all controllers behave similarly

The trials presented and discussed in this chapter show that for a simulated process, the adaptive predictive controller performs as well as the fixed-parameter predictive controller. When implemented in an actual plant, the parameters of an MWAC + MPC controller will adapt to changes in the process dynamics caused by, for example, unmeasured disturbances and evaporator fouling. In this case, it is expected to outperform the fixed-parameter predictive controller. A second reality of plant implementation is that the process model used by the fixed-parameter controller will not match the process response as is possible in simulation.

4.5 Summary

This chapter presented the results of implementing multivariable (2x2) predictive controllers with both fixed and adaptive parameters. The process was simulated first by a linear system of four FOPDT transfer functions with which the controller parameters were adjusted. Finally the control algorithms were implemented on the nonlinear process model in order to observe a set point change and disturbance elimination. Since the convolution model in the fixed-parameter predictive controller was taken directly from process responses, it was a better model than would be possible in practice. Thus the results were promising in that the predictive plus adaptive controller performed similarly to the fixed-parameter predictive controller. The next and final chapter contains conclusions and extensions of the present work.

CHAPTER V

CONCLUSIONS AND EXTENSIONS OF WORK

5.1 Conclusions

The main conclusion of the present work is that the adaptive algorithm MWAC performs well when combined with a multivariable MPC controller in simulations with a nonlinear dynamic process model. This result is based on trials for set point changes and disturbance rejection in which the adaptive plus predictive controller behaves similarly to the fixed-parameter predictive controller. It may not be obvious that this justifies the promise of adding an adaptive component to the scheme. The fixed-parameter predictive controller contains convolution models that are the exact responses of the simulated process. In practice, the process model in a predictive controller can never be a perfect description of the real system due to the difficulty in identifying pure open-loop step responses without unmeasured disturbances, changing plant dynamics, and other factors. It is then clear that the standard against which the adaptve plus predictive controller is compared is unrealistically tough. This is the justification for concluding that an adaptive plus predictive scheme that has comparable performance to the fixed-parameter predictive system is promising.

In arriving at this conclusion, several intermediate stages are necessary. The simulated process is a five-effect black liquor evaporator in the Industries James Maclaren Inc. kraft pulp mill at Thurso, Quebec. Each effect is dynamically modeled by three differential equations describing the mass and energy balances as well as black liquor properties that vary with concentration. Black liquor is concentrated by removing water in each stage with heating energy supplied by countercurrent flow of steam.

With the process model, the open-loop responses required by the fixed-parameter predictive controller can be recorded. For the adaptive controller, discrete ranges of gain and delay as well as an estimated time constant are required as input. With this information, a simplified linear version of the process model makes tuning faster and easier. It becomes apparent that dead time mismatch in the fixed-parameter predictive controller does not substantially alter performance.

The final trials are with the nonlinear process model. In the specific case of disturbance rejection or regulatory control, the MWAC + MPC algorithm respects the controlled variable weights by returning the SBL concentraiton (D22) to set point faster than any of the fixed-parameter predictive controllers. Consequently, the SBL flow (F22) excursion is slightly greater than the case of the fixed-parameter predictive controllers with the same weights. The set point change was handled virtually identically by all the controllers.

A major strength of the MWAC algorighm is that the parameter estimation procedure is independent of system excitation, unlike other adaptive methods. This implies that MWAC performance does not degrade or drift during periods of operation near steady state but rather settles within the initial parameter ranges.

5.2 Extensions of Work

The ultimate extension of this work is to implement the controller in the plant control system. For the purpose of justifying implementation of an advanced control strategy, it would be essential to do a feasibility study in order to make an estimate of the potential gains against which the costs could be measured.

In order to further prove that the nonlinear dynamic process model is representative of the evaporator #3 at Industries James Maclaren Inc. plant step tests should be performed in order to compare the actual responses with those predicted by the model. This could lead to new identification of the convolution models utilized by the predictive controller. The MWAC algorithm presently assumes that the process can be adequately modeled by a combination of FOPDT responses. The open loop step responses of SBL flow (F22) to steps in WBL flow (F16) as well as steam pressure (P1002) may be more accurately modeled by alternative transfer function structures. Although time delays are present in the current process model, these should be validated with plant data. The range of dead times in the MWAC algorithm is 0 to 0.067 hour but the minimum process delay is greater than zero so it would be logical to reduce the range of dead times, eliminating those less than the minimum process delay.

Another approach to the existing PI level control would be to remove the controllers and insert hard constraints on the levels. Conversely, the individual level controllers could include feed forward rather than, or in addition to, the feedback PI action. Alternatively, the 2x2 controller could be enlarged to include the levels and discharge flows as, respectively, controlled and manipulated variables. This larger structure would multiply the computational burden but the advantages of increased decoupling may offset the higher computer time.

The process model could be improved by updating the physical and heat properties of black liquor based on operating and bibliographical data. Since many model parameters are taken from the design calculations of the evaporator, it should be confirmed that the plant, in operation near steady state, does indeed reflect the design conditions. The model could also be extended to include the crystallizer, which concentrates SBL from approximately 40% to 70%, as well as the steam jet injection system and the liquor recycle loop. Simulations using the nonlinear model were lengthy in computation time such that it would be advisable to improve the code for faster execution. This may be realized using the recently released Matlab compiler.

RÉFÉRENCES

1. ALEVISAKIS, G., and D. E. SEBORG, "An Extension of the Smith Predictor Method to Multivariable Linear Systems Containing Time Delays", *International Journal of Control*, **17**, No. 3, 541 (1973).
2. ALEVISAKIS, G., and D. E. SEBORG, "Control of Multivariable Systems Containing Time Delays Using a Multivariable Smith Predictor", *Chemical Engineering Science*, **29**, No. 2, 373 (1974).
3. BREWSTER, D. B., editor, *Pulp and Paper Manufacture Vol. 10 Mill-Wide Process Control &Information Systems*, The Joint Textbook Committee of the Paper Industry, Montreal, QC (1993).
4. BURDETT, J. W., and C. D. HOLLAND, "Dynamics of a Multiple-Effect Evaporator System", *AIChE Journal*, **17**, No. 5, 1080-1089 (1971).
5. FISHER, D. G., and D. E. SEBORG, *Multivariable Computer Control A Case Study*, North Holland/Elsevier, New York, (1976).
6. GENDRON, S., M. PERRIER, J. BARRETTE, M. AMJAD, A. HOLKO, and N. LEGAULT, "Deterministic Adaptive Conrol of SISO Processes Using Model Weighting Adaptation", *International Journal of Control*, **58**, No. 5, 1105-1123 (1993).
7. GRACE, T. M., and E. W. MALCOLM, editors, *Pulp and Paper Manufacture Vol. 5 Alkaline Pulping*, Technical Section Canadian Pulp & Paper Association, Montreal, QC (1989).

8. GREEN, R. P., and G. HOUGH, *Chemical Recovery in the Alkaline Pulping Processes*, TAPPI Press, Atlanta, GA (1992).

9. HERNÁNDEZ, V. M., A. MONTANO, and G. SIVA, "Adaptive Nonlinear Control of a Double Effect Evaporator", *12th World Congress IFAC 18-23 July Sydney Austrailia*, **4**, 431(1993).

10. LÉVESQUE, D., Projet de fin d'études en procédé 4.495, École Polytechnique de Montréal, 1995.

11. MARLIN, T. E., *Process Control: Designing Processes And Control Systems For Dynamic Performance*, McGraw-Hill, New York, (1995).

12. MULHOLAND, M. and D. J. LOVE, "Real-Time Identification of a Five-Effect Evaporator System", IFAC 12th World Congress, **4**, 421-426, Sydney, Australia 1993.

13. NEWELL, R. B., and D. G. FISHER, "Model Development, Reduction, and Experimental Evaluation for an Evaporator", *Ind. Eng. Chem. Precess Des. Develop.*, **11**, 213-221 (1972).

14. NEWELL, R. B., and P. L. LEE, *Applied Process Control A Case Study*, Prentice Hall, Englewood Cliffs, N. J. (1989).

15. NOËL, A., M. SAVOIE, H. BUDMAN, and L. LAFONTAINE, "Advanced Brownstock Washer Control: Successful Industrial Implementation at James Maclaren", *Tappi Journal*, **79**, No. 1, 121-127 (1996).

16. OLIVER, W. K., D. E. SEBORG, and D. G. FISHER, "Model Reference Adaptive Control Based on Liapunov's Direct Method Part I: Theory and Control System Design", *Chemical Engineering Communications*, **1**, No. 3, 125-132 (1973).

17. OLIVER, W. K., D. E. SEBORG, and D. G. FISHER, "Model Reference Adaptive Control Based on Liapunov's Direct Method Part II: Hybrid Computer Simulation and Experimental Application", *Chemical Engineering Communications*, **1**, No. 3, 133-140 (1973).

18. RICKER, N. L., "Use of Quadratic Programming for Constrained Internal Model Control", *Industrial Engineering for Chemical Process Design and Development,* **24**, 925-936 (1985).

19. RICKER, N. L., T. SUBRAHMANIAN, and T. SIM, "Case Studies of Model-Predictive Control in Pulp and Paper Production", *IFAC Model Based Process Control Invited Industrial Case Studies*, Georgia,USA, 13-22 (1988).

20. SEBORG, Dale E., Thomas F. EDGAR, and Duncan A. MELLICHAMP, *Process Dynamics and Control*, John Wiley and Sons, New York,1989.

21. TO, L.C., M. O. TADÉ, M. KRAETZ, and G. P. LEPAGE, "Nonlinear Control Of A Simulated Industrial Evaporation Process", J. Proc. Cont., **5**, 173-182 (1995).

22. WANG, F. Y., and I. T. CAMERON, "Control studies on a model evaportion process-constrained state driving with conventional and higher relative degree systems", *J. Proc. Cont.*, **4**, 59-75 (1994).