To the Graduate Council:

I am submitting herewith a thesis written by Brandon Thomas Schmidt entitled "Analysis of Closed-Loop Control Strategies for a Wastewater Treatment Plant." I have examined the final copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree Master of Science, with a major in Chemical Engineering.

Tse-Wei Wang

Tse-Wei Wang, Major Professor

We have read this thesis and recommend its acceptance:

Charles F. Moore

Chris Cox

Accepted for the Council:

Cuminkel

Associate Vice Chancellor and Dean of the Graduate School

ANALYSIS OF CLOSED-LOOP CONTROL STRATEGIES FOR A WASTEWATER TREATMENT PLANT

A Thesis

Presented for the

Master of Science

Degree

The University of Tennessee, Knoxville

Brandon Thomas Schmidt

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Dedication

This thesis is dedicated to my parents

Thomas Walter Schmidt and Nancy Josephine Schmidt;

my siblings

Lara, Cameron, Rachel, Allan, Joel, and Crosby;

and my nephews

Rocco and Tucker

whose love and support I could never do without

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Abstract

The focus of this study is to evaluate and compare two alternate control strategies for a multi-stage wastewater treatment plant, in the attempt to offer insight into what benefits first level automated closed-loop control may have over manual open-loop control. The plant under study is being built in Victoria, Texas by the DuPont Corporation, with the potential of several other DuPont plants being modeled after this one. The evaluation and comparison of the alternate control strategies is based upon the ability of each control system to render the overall closed-loop system stable over long term, and to meet plant treatment performance criteria in the face of setpoint and disturbance perturbations. The ability to maintain stability may come as a sacrifice of some degree of desirable performance. The greater the margin of stability, the poorer the performance, and vice versa. The ease of controller tuning is also an important part of the evaluation and comparison considerations, so as to gain operator acceptance.

The wastewater treatment plant is based on an anoxic/oxic model. This features an anoxic reactor, an aerobic reactor, and a clarifier aligned in series. The output concentrations of interest are effluent concentrations of carbonaceous waste (BOD), ammonia, and nitrate. The treatment objectives are to reduce the carbonaceous wastes and nitrogen compounds to water, carbon dioxide, and nitrogen gas. The input variables being considered to control the output variables are the recirculation ratio and the sludge age.

Two-by-two decentralized feedback controllers were designed for the plant. Two approaches are considered: a Proportional-Integral-Derivative (PID) based and a model

based predictive control (MPC). Simulation results show that with the first level feedback control strategy of decoupled PID, long term stability issue is a big problem for those loops that exhibit delay times and inverse response characteristics. Additional compensatory control elements, such as lag filters, Smith predictors, and inverse response compensators would need to be added to improve the stability. However, controller complexity is also increased greatly, leading to increasingly complex tuning. Although, instability with pure PID controllers is manifested only very gradually (>100 days), its implications in application will be discussed in this report. On the other hand, decoupled model based control, the next level up in controller design hierarchy, such as the internal model control (IMC), can be easily tuned to yield long term stability of the closed-loop system, even when plant/model mismatch is present. However, the large and rapid control actions called for at times may not be feasible for implementation. In addition, the long time constant required in reaching a steady state may also not be feasible. In this case an advanced multivariable controller that can handle either input or output constraints explicitly would need to be considered. But this would be at a major technical and financial investment on the part of the industrial practitioner. If only a first level feedback controller is to be considered, then model based control appears to be more preferable to that of PID based because of its stability yielding characteristics, ease of tuning, and the ability to incorporate plant/model mismatch into the controller design. If a pure PID based controller is employed, very close monitoring and frequent returning of the controller is required in order to insure closed-loop stability. This need for constant vigilance may obviate any advantage of implementing an automated feedback controller over manual open-loop control by an experienced operator. Details of simulation results of the two approaches will be presented in this thesis.

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Nomenclature

Abbreviations

ATP	Adenosine Tri-Phosphate
BOD	Biochemical Oxygen Demand
COD	Chemical Oxygen Demand
CSTR	Continuosly Stirred Tank Reactor
DMC	Dynamic Matrix Control
IAWPRC	International Association on Water Pollution Reasearch and Control
IAWQ	International Association on Water Quality
IMC	Internal Model Control
MIMO	Multi-Input Multi-Output
PI	Proportional-Integral (controller)
PID	Proportional-Integral-Derivative (controller)
QDMC	Quadratic Dynamic Matrix Control
RGA	Relative Gain Array
SISO	Single-Input Single-Output

Symbols, Upper Case

C	Transfer function matrix for controller	
C(0)	Transfer function matrix C, steady state limit	
C(s)	Transfer function matrix for controller	
C_i	Component i concentration in reactor	mass/volume
C_{io}	Component i concentration in influent	mass/volume
$C_5H_7NO_2$	Empirical formula for microbe mass	
$CaCO_3$	Calcium carbonate	
CO_2	Carbon dioxide	
G	Transfer function matrix for plant	
G^{-1}	Inverse of transfer function matrix G	
G(0)	Transfer function matrix G, steady state limit	
G(s)	Transfer function matrix for plant	
H	Overall system transfer function matrix; G(s)C(s)	
H(0)	Transfer function matrix H, steady state limit	
H(s)	Overall system transfer function matrix; G(s)C(s)	
H_2O	Water	
H_2CO_3	Carbonic Acid	
HCO^-_3	Bi-Carbonate Ion	
I	Identity matrix	
K	Open loop gain of linearized plant and model	

K_c	Proportional gain of PID controller	
K_{NH}	Ammonia half-saturation coefficient for autotrophs	mass N-NH_4/volume
K_O	Switching constant for heterotrophic growth	mass O_2/volume
$K_{O,A}$	Oxygen half-saturation coefficient for autotrophs	mass O_2/volume
K_S	Monod half-saturation constant	mass/volume
$K_{S[COD]}$	K_S for heterotrophic consumption of COD	mass COD/volume
$K_{S[N-NH4]}$	K_S for autotrophic consumption of ammonia	mass N-NH_4^+/volume
$K_{S[N-NH4]low}$	K_S for heterotrophic consumption of ammonia	mass N-NH_4^+/volume
$K_{S[N-NO3]}$	K_S for heterotrophic consumption of nitrate	mass N-NO_3^-/volume
$K_{S[O,A]}$	K_S for autotrophic consumption of oxygen	mass O_2/volume
$K_{S[O,H]}$	K_S for heterotrophic consumption of oxygen	mass O_2/volume
$K_{S,x}$	K_S for hydrolysis process	mass COD/volume
$K_{S,i}$	K_S for substrate for microbe i	mass/volume
N	Nitrogen	
NAD^+	Nicotinamide adenine dinucleotide	
NADH	Reduced nicotinamide adenine dinucleotide	
$NADP^+$	Nicotinamide adenine dinucleotide phosphate	
NADPH	Reduced nicotinamide adenine dinucleotide phosphate	
NH_3	Ammonia	
NH_4-N	Ammonium ion as nitrogen	mass ammonia as N
NO_3 -N	Nitrate ion as nitrogen	mass nitrate as N
NH_4^+	Ammonium ion	
NO_3^-	Nitrate ion	
O_2	Oxygen	
Q	Volumetric flow rate	volume/time
S	Substrate concentration	mass/volume
S	Soluble component concentration	mass/volume
S_{ALK}	Alkalinity	molar units
S_I	Soluble inert organic matter	mass COD/volume
S_{ND}	Soluble biodegradable organic nitrogen	mass N/volume
S_{NH}	Concentration of ammonia	mass N-NH_4/volume
S_{NO}	Concentration of nitrate	mass N-NO_3/volume
S_O	Dissolved oxygen level	-COD mass/volume
S_S	Readily biodegradable substrate	mass COD/volume
TKN	Kjeldahl nitrogen	mass N/volume
V_r	Reactor volume	volume
X	Concentration of particulate mass (typically mass of microbes)	mass/volume
X_0	Concentration of microbes at time = 0	mass/volume
$X_{B,A}$	Active autotrophic biomass concentration	mass COD/volume
$X_{B,H}$	Active heterotrophic biomass concentration	mass COD/volume

X_I	Particulate inert organic matter	mass COD/volume
X_{ND}	Particulate biodegradable organic nitrogen	mass N/volume
X_P	Particulate products arising from biomass decay	mass COD/volume
X_S	Slowly biodegradable substrate	mass COD/volume
Y	Maximum yield coefficient	microbe produced/ substrate consumed
Y_A	Maximum yield coefficient, autotrophs	microbe produced/ substrate consumed
Y_H	Maximum yield coefficient, heterotrophs	microbe produced/ substrate consumed
Y_i	Maximum yield coefficient, microbe i	microbe produced/ substrate consumed

Symbols, Lower Case

b_a	Decay rate of autotrophs	$time^{-1}$
b_h	Decay rate of heterotrophs	$time^{-1}$
c_{ij}	ij^{th} element of the compensator matrix	
d	Differential of mathematical function	
det()	Determinant of matrix inside of parenthesis	
f_p	Fraction of biomass yielding particulate products	
g_{ci}	i^{th} diagonal element of controller matrix C(s)	
g_{ij}	ij^{th} element of plant matrix G(s) (i^{th} row, j^{th} column)	
h_a	Hydrolysis rate	$time^{-1}$
i_{xB}	Mass of N incorporated in cell mass/COD cell mass	mass N/mass COD
i_{xP}	Mass of N incorporated in products from biomass	mass N/mass COD
k_A	Ammonification rate	$time^{-1}$
k_d	Endogenous decay coefficient or death rate	$time^{-1}$
pH	pH level, measure of acidity	
s	Laplace variable	
t	Time	time
u_i	Input variable i for plant	
$u_{j,0}$	Input variable j value for initial steady state	
$u_{j,f}$	Input variable j value for final steady state	
u_1	Input variable one for plant	
u_2	Input variable two for plant	
y_i	Output variable i for plant	
$y_{j,0}$	Output variable j value for initial steady state	
$y_{j,f}$	Output variable j value for final steady state	
y_1	Output variable one for plant	

y_2	Output variable two for plant	
$y_i sp$	Setpoint for output variable i for plant	
z	Transfer function lead time constant or zero	time

Greek Characters

η_g	Correction factor for anoxic growth of heterotrophs	
η_h	Correction factor for anoxic hydroysis	
λ	Internal model control tuning paramter	
μ	Microbe growth rate	$time^{-1}$
μ^{-1}	Mu-interaction measure boundary	
μ_B	Specific growth rate, microbe B	$time^{-1}$
μ'_H	Specific growth rate, heterotrophs	$time^{-1}$
$\mu_{max,A}$	Maximum growth rate, autotrophs	$time^{-1}$
$\mu_{max,B}$	Maximum growth rate, microbe B	$time^{-1}$
$\mu_{max,H}$	Maximum growth rate, heterotrophs	$time^{-1}$
$\mu_{max,i}$	Maximum growth rate, microbe i	$time^{-1}$
τ	Transfer function lag time constant or pole	time
τ_I	Integral control time constant or reset time	time
τ_D	Derivative control time constant	time
θ	Transfer function delay time	time

Note that the common symbols and abbreviations, such as those designating standard metric system units or common mathematical operations, are not listed in the List of Symbols and Abbreviations.

Chapter One

Introduction

The focus of this study is to evaluate and compare two alternate control strategies for a multi-stage wastewater treatment plant in the attempt to offer insight into what benefits first level automated closed-loop control strategy may have over manual open-loop control. The plant under study is being built in Victoria, Texas by the DuPont Corporation, with the potential of several other DuPont plants being modeled after this one. The evaluation and comparison of the alternate control strategies is based upon the ability of each control system to render the overall closed-loop system stable over long term, and to meet plant treatment performance criteria in the face of setpoint and disturbance perturbations. This ability to maintain stability may come as a sacrifice of some degree of desirable performance. The greater the assurance of stability, the poorer the performance, and vice versa, the greater the performance, the less the assurance of stability. The ease of controller tuning is also an important part of the evaluation and comparison considerations, so as to gain operator acceptance.

A. Motivation

Biological treatment of wastes in water is based on the simple and readily repeated observation that polluted water left standing and open to air undergoes chemical and biochemical changes which finally result in clarification. Wastewater treatment in the United States is based primarily on the activated sludge process (Grady and Lim, 1980). An anoxic/oxic system is an example of an activated sludge process. It incorporates the use of microbes in an anoxic reactor (without oxygen) and the use of microbes in an aerobic reactor (with oxygen) to ultimately convert organic carbonaceous wastes in the water stream to carbon dioxide and water, along with the conversion of ammonia, nitrite, and nitrate to nitrogen gas. The inlet waste streams to a wastewater treatment plant usually have a high variability of the influent waste load rates and concentrations (Metcalf and Eddy, 1991). When a system is operating at a proposed steady state, fluctuations in the influent concentrations and loading rates disrupt the system, causing it to deviate from this ideal steady state, thus requiring control action in order to bring the system back to its proposed steady state. If the fluctuations are large enough, the system may go uncontrollably unstable, due to the nonlinearity of the plant dynamics possibly creating a very dangerous situation in the plant and forcing the operator to shut down the system.

Grove (1995) studied the open loop dynamic steady state response of a multi-stage waste system to perturbations and identified which variables are most affected by which perturbations, and which variables may be used as the most effective manipulated variables to compensate for the anticipated perturbations. The present study seeks to close the control loop and compare the effectiveness of model based control strategy to the traditional Proportional-Integral-Derivative (PID) control strategy, both implemented as 2 x 2 single-input single-output (decentralized) feedback loops.

In designing decentralized controllers, specification of pairing of an input to an output variable is an important consideration. Decentralized controllers are the most common type of multivariable controller utilized in the process industries systems, because these controllers are easier to design and implement than a true multivariable controller designed to fully utilize the interactions between the inputs and the outputs. However, decentralized control strategy has the drawback of reduced stability margin (how close the closed-loop system is to the point of instability) because interloop interactions are ignored. PID based decentralized controllers are usually the first control strategy to be considered by plant personnel to control a system. PID based controllers have been in use for decades and are very well understood by engineers and plant operators. However, there are limitations to the PID based controller, especially when the system is more complex and displays increasingly non-ideal dynamic characteristics. These non-idealities limit the PID based controller effectiveness in sustaining a stable system to within the proposed effluent discharge constraints. Thus, the PID based controller may not be robust enough to handle the many operating requirements placed on a wastewater treatment plant, such as the long term stability and controlling the average daily organic and nitrogen concentrations in the effluent discharge, to within the desired level in the presence of disturbances and model drift. Process performance may be improved by the use of more advanced control modes. The simpler of these could be the addition of filters to the PID based controller to take into account such non-ideal characteristics as dead time and inverse response (Andrews, 1973), but at the expense of increasing the controller complexity. The next level of control strategy would be the use of model based controllers. Model based controllers have an advantage over the PID based controller in that they have built-in capabilities to compensate for some of the non-idealities of the process, mentioned above, because the controller is an approximate inverse of the process. In addition, the stability issue of the model based controller is much simpler to analyze than that of PID. For that reason alone, it is more desirable to implement even a PID controller in the format of a model based controller (Garcia and Prett, 1988).

Recently, progress has been made in the area of model based controllers, (summarized in Ogunnaike and Ray, 1994), which are more effective in handling operating constraints and system non-idealities in achieving a desired output behavior. There are several algorithms for the design of model based controllers and most agree that they are easier to tune and better accommodate uncertainty associated with the description of the plant model than that of PID. One of the more advanced, and more complex, model based control is the quadratic dynamic matrix control (QDMC), which has the ability to explicitly consider constraints on both the manipulative and controlled variables, but to inexperienced personnel the QDMC would be rather complex to design and maintain. A simpler version of model based control is the internal model control (IMC), but IMC lacks the ability to handle constraints explicitly. IMC would be the next step up from conventional PID based control (Prett, *et al.*, 1986), in the hierarchy of controller design complexity. It is desired that the marginal benefit as well as the limitations of IMC be studied and identified, so as to help industrial practitioners in judging its adequacy as the final control strategy for the wastewater treatment system. If the results are acceptable, then the need for a more complex and sophisticated controller can be avoided.

A comparison between the workings of the conventional PID control strategies and that of the more modern model based control strategies (IMC), and their respective performances, on a wastewater treatment plant, along with a better understanding of their benefits and shortcomings will help in developing and implementing a control system that may be both effective and simpler to design. In addition, an understanding of the incremental effort involved in using model based controllers over that of conventional PID will better help plant managers in evaluating the choice of the final control strategy. If neither strategy proves to be satisfactory, then an advanced version of model based control (e.g. QDMC) with contraints, or a true multivariable controller should be the choice of control strategy, but it would be at the expense of much increased need for expert personnel and cost.

B. Description of the Wastewater Treatment Plant

The wastewater treatment plant to be analyzed is a facility under construction at Victoria, Texas by the DuPont Corporation. The computer simulation model of the plant has been developed by James Grove (1995) and this study is a continuation of his open-loop study of the control analysis of the wastewater treatment plant. In this study, the loop(s) will be closed, and two decentralized control strategies (PID and IMC) will be designed and compared by evaluating their performance in the face of perturbations and operational constraints and by their relative ease of tuning.

The wastewater treatment plant is based on an anoxic/oxic process (Metcalf and Eddy, 1991). It consists of an anoxic reactor (which allows the oxygen concentration level to reach zero) and an aerobic reactor (which maintains a consistant level of oxygen concentration) aligned in series. There is a recirculation stream from the output of the aerobic reactor to the inlet of the anoxic reactor. After the aerobic reactor is a clarifier which uses the force of gravity to settle out most of the solid waste. There is also a recycle stream from the output of the clarifier to the inlet of the anoxic reactor. The main reactions of the system are denitrification (conversion of nitrate to nitrogen gas), chemical oxygen demand (COD) degradation, and nitrification (conversion of ammonia to nitrate, and eventually into nitrogen gas). Figure 1-1 is a flowsheet representation of the system.

In the activated sludge process the principle objectives of process control are: dampening out the effect of input variation, minimization of effluent variation, and prevention and recovery from process upsets. Control of these three factors is directly related to process reliability in terms of meeting discharge requirements (Schroeder, as presented by Arthur, 1983).

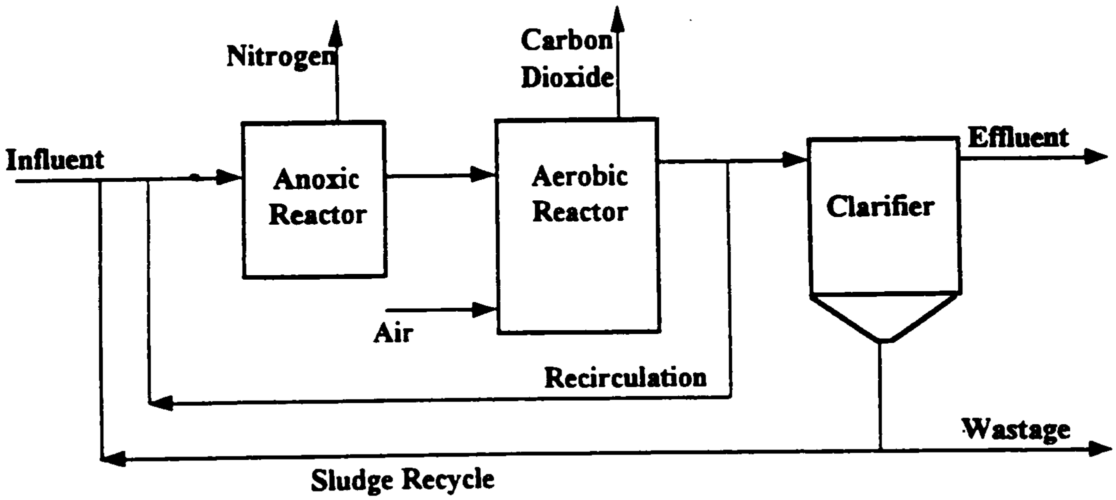

Figure 1-1. Bardenpho Process for Victoria, Texas Plant

C. Objective

The objective of this study is to analyze the effect of plant setpoint change and disturbance perturbations on the characteristics of the final effluent and the effectiveness of PID based control strategy in comparison to a first level unconstrained (IMC) model based control strategy to compensate for these perturbations. This will allow plant personnel and control engineers to better understand the advantages and disadvantages of conventional PID based feedback control and the first level model based control of the wastewater treatment plant, and will aid in choosing the final control design for the plant.

Chapter Two

Background

A. Waste Characteristics

Wastewaters from most industrial manufacturing of organic chemicals cannot be characterized very easily. In most chemical insustial process there are numerous components being utilized during the process. Trace amounts of all these components and their products and by-products usually contaminate the wastewater stream of the plant (Foster *et al.*, 1977). It is nearly impossible to calculate the exact concentration of all of these components in the waste stream.

Carbonaceous material, or organic wastes, in the waste stream must be removed or oxidized prior to the release of the wastewater into a waterway. If not, they are consumed by bacteria that in their metabolism reduce the oxygen content of the water. Thus, depletion of oxygen is a common result of the assimilation of organic wastes by bacteria (Arcievala, 1981). Bacteria assimilation of organic matter may also result in the production of excessive amounts of carbon dioxide, which is toxic.

In the study of an individual manufacturing plant, all of these possible pollutants should be identified. Analysis of the wastewater should recognize any that may be of polluting significance. It is not always necessary nor desirable to evaluate each specific chemical. Analytical methods have not been developed for some substances and the wastewater composition is often too complex to permit detailed analysis. It is usually adequate to analyze the wastewater for broad chemical classes, such as aldehydes or hydrocarbons.

Analysis of compound or class of compound is useful in tracking down sources of pollution and in planning in-plant control of wastewater. However, for overall pollution control, it is easier to use the more general, although cruder, parameters familiar to pollution control agencies. These include the biochemical oxygen demand (BOD), chemical oxygen demand (COD), color turbidity, suspended solids, and similar tests; plus more specific tests necessitated by the particular waste, for example, toxicity, grease, and foaming characteristics (Bessilure, 1969).

B. Organic Load

All organic wastes, of course, contain compounds of carbon. These carbon compounds usually include hydrogen and oxygen, and often nitrogen, sulfur, chlorine, phosphorous, or any of the other chemical elements. Most organic wastes exhibit a significant BOD; noteworthy exceptions being organic wastes that are relatively immune to biological degradation (such as some hydrocarbons and ethers), compounds that resist degradation until the available microorganisms have adapted or become acclimated to them, and toxic compounds that retard or even stop biological activity. Dilution, time, and acclimation of organisms may cause even these resistant substances to exert an oxygen demand. High BOD and/or COD concentrations in a waste stream that is being discharged to a waterway can greatly upset and even destroy the balance of life in that environment by depleting the amount of life sustaining oxygen in the waterway (Wheatstone, 1977).

The chemical oxygen demand (COD) test is frequently used to measure the strength of organic wastes, in place of the BOD, because it has a quicker turn-around time and is not affected by materials toxic to microorganisms. However, a COD test is usually inferior to a test on the BOD, which is more representative of the ability of the waste to affect the oxygen levels in the disposal waterway. This is because some classes of chemicals resist chemical breakdown in the COD test. These are usually not the chemicals that resist the BOD test. There is no general correlation between the two tests; however, valuable empirical relationships can often be established in comparing wastes from a single plant or unit (Wheatstone, 1977).

All organic compounds are "volatile" in the sense that they are evaporated or oxidized in the conventional muffle furnace test for "volatile materials." Determination of weight loss under 600°C conditions in an air atmosphere may be a useful adjunct to the BOD and COD tests in evaluation of gross organic load in an uncharacterized waste (Dickinson, 1974). The test can be applied to total residue on evaporation, to residue from a filtered sample, to suspended matter in the waste, or to any other fraction of significance.

C. Basic Reactions and Solids/Liquid Separation in the Activated Sludge Process

The activated sludge process, such as the one upon which the Victoria wastewater treatment plant is based, consists of two basic systems working together to stabilize waste matter and separate solids and liquids. One is the biological system and the other a physical system (Arthur, 1982).

1. The Biological System

Biodegradable organic compounds that are found in the wastage stream of a waste water treatment plant may be harmful to the environment by placing an oxygen demand on the receiving waterway. Therefore, it is necessary for the waste water treatment plant to reduce the amount of biodegradable organic compounds in the influent stream prior to discharge into a waterway. In an activated sludge process this is normally accomplished by utilizing heterotrophic organisms to consume organic compounds in an aerobic environment and, ultimately, converting inorganic nutrients to carbon dioxide, water, cell mass, and a few other end products (Metcalf and Eddy, 1991). Grove (1995) presents a detailed theory of the mechanism for the sequence of events required to metabolize these materials.

Under certain conditions a form of biological oxidation known as nitrification occurs. In this reaction, ammonia is oxidized to nitrite and nitrate using two highly specialized species of bacteria, nitrosomonas and nitrobacter, both of which are autotrophic bacteria (Arthur, 1982). The nitrite and nitrate from both the raw influent stream and that produced during nitrification undergo denitrification in the anoxic reactor. The heterotrophic microorganisms in the anoxic reactor utilize nitrate as an oxidizing agent while consuming the carbonaceous waste present for growth. Excess amounts of nitrogen discharged into a waterway may be toxic to the living organisms in the waterway.

2. The Physical System

The separation of suspended solids and liquids is a final step in the activated sludge process. This is accomplished in the clarifier using the force of gravity to separate the suspended solids from the liquid. The majority of the separated suspended solids are recycled back to the anoxic reactor with the remainder exiting through a bottoms wastage stream. The separated liquid is discharged through the supernatant stream.

D. Dynamic Simulator

A dynamic simulator for the wastewater treatment plant kinetics has been developed using the Simulink programming environment of Matlab employing the *Activated Sludge Model No. 1* (Henze *et al.*, 1986) as a theoretical basis (Grove, 1995). The kinetics is based on a lumped and unstructured modeling approach based on the conservation of mass principle. Birdstrup and Grady (1987) also used the *Activated Sludge Model No. 1* as a basis for development of a simulator. Through personal communication with Grady (1996), it was validated that their *Simulation of Single-Sludge Process* (SSSP) agreed with data from wastewater treatment plants. Grove's simulator is constructed around a modular design for a continuously stirred tank reactor (CSTR) and a standardized data stream capable of calculating the concentrations of twenty-one components simultaneously. The model simulates denitrification in the anoxic reactor and combined aerobic BOD degradation and nitrification in the aerobic reactor. Both reactors are treated as continuously stirred tank reactors. The reactors are almost identical, except for their difference in size (the aerobic reactor is twice that of the anoxic reactor, in accordance to DuPont specifications) and the use of an oxygen-rich environment in the aerobic reactor compared to the oxygen-depleted environment in the anoxic reactor. A layout of the anoxic/oxic process was shown previously in Figure 1-1.

There is a recirculation stream from the output of the aerobic reactor back to the inlet of the anoxic reactor. The recirculation ratio is defined as the ratio of the recirculation flow from the aerobic reactor to the anoxic reactor divided by the raw influent flow to the wastewater plant. Following the two reactors is a clarifier that utilizes the force of gravity to separate out the solids. The supernatant of the clarifier is discharged, while the underflow is split into two streams. Most of the underflow is recycled back to the anoxic reactor for microbe seeding and denitrification and a smaller fraction goes to wastage. The recycle ratio is defined as the ratio between the rate of recycle water flow from the bottom of the clarifier to the effluent water flow from the top of the clarifier. The wastage rate, which can be set by the operator, is determined by the desired solids retention time. The wastage rate can, in turn, dictate the concentration loads in the overall effluent. The recirculation ratio from the aerobic reactor to the anoxic reactor can also be set by the operator. This has an effect on the final effluent concentrations. These two variables can be manipulated in order to control the wastewater treatment process (Grove, 1995). Figure 2-1 is a flowsheet of the Simulink Dynamic Simulator created by J. Grove (1995).

Grove (1995) presented the planned plant configurations that were decided upon by the DuPont Corporation and relayed to Grove by many conversations (Robertaccio, 1995). They are once again presented in Table 2-1.

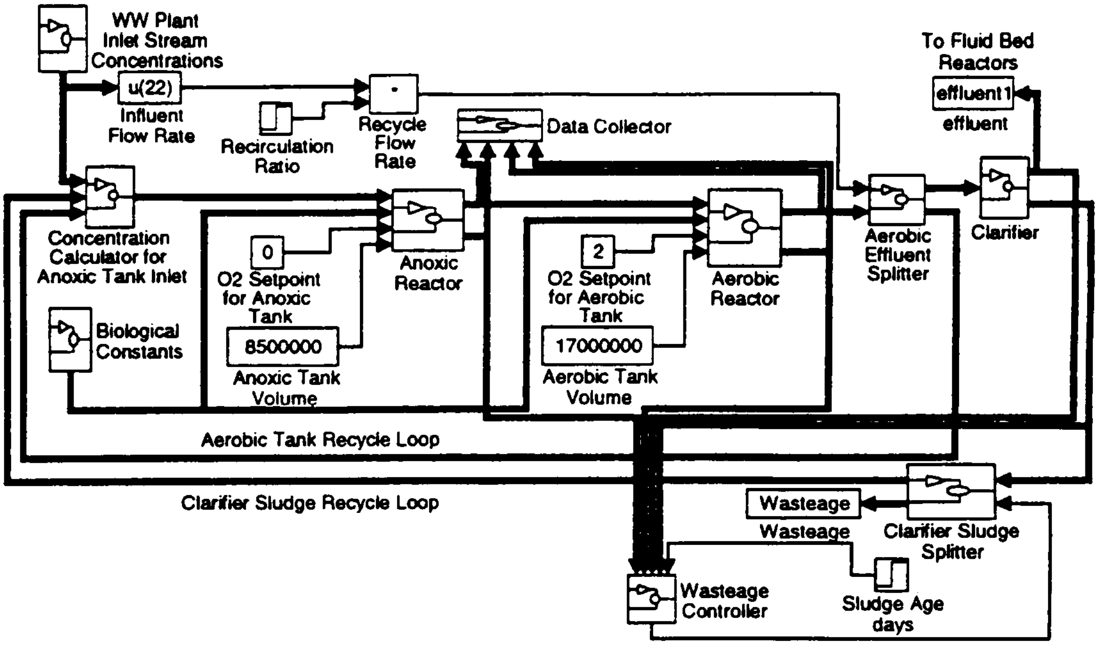

Figure 2-1. Simulink Dynamic Simulator of the Wastewater Treatment Plant (Grove, 1995)

Table 2-1. Plant Configuration for Design Study (Grove, 1995)

Parameter	Value
Anoxic Tank Size	8,5000,000 liters
Aerobic Tank Size	17,000,000 liters
Oxygen Level, Aerobic Tank	2.0 mg/liter
Clarifier Size	500,000 liters
Recirculation Ratio	3.5
Sludge Age	30 days
Recycle Ratio	0.5

Grove (1995) also presented the expected average flow rates and organic concentrations of the influent waste stream that were based upon DuPont's flow sheets of the plant (DuPont, 1994). They are shown in Table 2-2.

Table 2-2. Wastewater Influent Parameters (Grove, 1995)

Parameter	**Value**
Volumetric Flow Rate	5,450,000 liters/day
Readily biodegradable soluble substrate	9,500 mg COD/liter
Slowly biodegradable soluble substrate	500 mg COD/liter
Soluble inert carbonaceous waste	150 mg COD/liter
[N-NH_4^+] concentration	300 mg N-NH_4^+/liter
[N-NO_3^-] concentration	1000 mg N-NO3-/liter

E. *Activated Sludge Model No. 1*

The *Activated Sludge Model No. 1* (Henze *et al.*, 1986) was the basis for the kinetics incorporated by Grove's dynamic simulator. It is a generic model for wastewater treatment reactors involving the activated sludge process and utilizing Monod kinetics in an unstructured and unsegregated modeling approach. The *Activated Sludge Model No. 1* also uses the principle of conservation of mass to account for the production and consumption of the reactor components. It assumes that all reactors are well-mixed, continuously stirred tank reactors (CSTR). By definition in a well mixed CSTR, the concentrations of the components in the reactor are assumed to be consistent throughout the reactor. These assumptions result in a mass balance around the reactor where the rate of accumulation of mass is equal to the rate of inflow of mass, minus the rate of outflow of mass, plus the rate of the net production of mass. This is shown in equation 2-1.

$$[dC_i/dt] = QC_{io} - QC_i + V_r r'_p \quad (2\text{-}1)$$

where dC_i/dt = rate of change of component I concentration in the reactor, measured in terms of mass of COD (or mass of N) per (volume*time)

V_r = reactor volume

Q = flow rate, volume/time

C_{io} = concentration of component I in influent, mass of COD (or N) per volume

C_i = concentration of component I in reactor, mass of COD (or N) per volume

r'_p = rate of component production in reactor, mass of COD (or N) per (volume*time)

There are a total of thirteen components involved in the dynamic simulator and an ordinary differential equation (ODE) similar to the one shown in equation 2-1 is incorporated for each one. The dynamic simulator uses these ODEs that are developed from the *Activated Sludge Model No. 1* and simultaneously solves them to establish the output concentrations of all components as a function of time. Grove (1995) details the kinetics involved in the *Activated Sludge Model No. 1,* which are based on Monod kinetics.

F. Conventional Process Control

Between the measuring device and the final control element comes the controller. Its function is to receive the measured output signal $y_m(t)$ and after comparing it with the desired setpoint, y_{sp} to produce an actuating signal c(t) so as to render the output, y, close to the desired value, y_{sp}. Usually, the input to the controller is the error $\varepsilon(t) = y_{sp} - y_m(t)$, while the output of the controller is the value for the manipulated variable. The various types of continuous feedback controllers differ in the way they calculate c(t) from ε(t) (Anand, 1974). Some basic forms of PID based process control, as well as the more modern model based control design principles, will be briefly reviewed below. For a more detailed coverage of the latter, please see the reference *Robust Process Control*, (Morari and Zafiriou, 1989).

1. Proportional Control

Proportional control is characterized by producing a controller output, c(t), proportional to the error input to the controller. It is parameterized by the proportional gain K_c or equivalently, by the proportional band PB, where PB=100/K_c. The proportional band characterizes the range over which the error must change in order to drive the actuating signal (the equivalent of the controller output signal) of the controller over its full range. The actuating output is proportional to the error by the equation 2-2.

$$c(t) = K_c\varepsilon(t) + c_s \tag{2-2}$$

where K_c = proportional gain

c_s = the steady state value of the actuating signal, or the bias signal

ε = the error signal

In most controllers, c_s can be adjusted so that it effects the required output signal when the control system is at steady state and ε = 0. The equivalent transfer function G, for a proportional controller is shown in equation 2-3.

$$G(s) = K_c \tag{2-3}$$

where s denotes the Laplace variable.

The larger the gain, K_c, or equivalently, the smaller the proportional band, then the higher the sensitivity of controller's actuating signal to deviations ε. With proportional action only, the control system is able to arrest the rise of the controlled variable and ultimately bring it to rest at a new steady state value. The difference between this new steady state value and the desired setpoint value is called 'offset'. Having an offset is a hallmark of proportional only control. Proportional only control is employed in situations in which the exact output level is not critical but must remain in the neighborhood of some safe level.

2. Proportional-Integral Control

In order to eliminate the undesirable offset with proportional only control, integral model of control is frequently added. Most common proportional-integral control is known as proportional-plus-reset control. The actuating signal is related to the error by the equation 2-4.

$$c(t) = K_c\varepsilon(t) + \int_0^t \frac{K_c}{\tau_I}(\hat{t})\varepsilon(t)d\hat{t} + c_s \tag{2-4}$$

where τ_I is the integral time constant or reset time, and c_s is the steady state bias signal.

K_c, as well as the reset time, are adjustable parameters. Some manufacturers do not calibrate their controllers in terms of τ_I but in terms of it reciprocal, $1/\tau_I$, which is known as the reset rate. The equivalent transfer function of a proportional-integral controller is shown in equation 2-5.

$$G(s) = K_c\left(1 + \frac{1}{\tau_I s}\right) \tag{2-5}$$

where s it the Laplace variable.

Consider that the system is initially at steady state and that error changes by a step of magnitude, ε, at a time designated $t=0$. The initial output of the controller will be $K_c\varepsilon$ (only the contribution of the proportional term, because the contribution of the integral term is zero). If ε remains constant, then after a time period of τ_I the contribution of the integral term is shown in equation 2-6.

$$\int_0^{\tau_I} \frac{K_c}{\tau_I}(t)\varepsilon(t)dt = \frac{K_c}{\tau_I}\varepsilon\tau_I = K_c\varepsilon \qquad (2\text{-}6)$$

The integral control action has "repeated" the response of the proportional action. This repetition takes place every τ_I time period. Therefore, reset time is the time needed by the controller to repeat the initial proportional action change in its output, assuming the error remains constant.

The integral action causes the controller c(t) to change so long as an error exists in the process output. Unlike the proportional only controller, the addition of integral action eliminates the offset. The controlled variable ultimately converges to the setpoint value, provided there is no plant/model mismatch. However, the addition of integral action has the disadvantage of possibly resulting in greater oscillatory behavior, because the order of the system is increased by the presence of the integral controller. Rules of thumb exist for heuristic tuning of the two controller parameters, K_c and τ_I. One of the most common methods was developed by Ziegler and Nichols and is presented in Ogunnakie and Ray (1995).

3. Proportional-Integral-Derivative Control

In industrial practice this is commonly known as proportional-plus-reset-plus-rate control. This is a more desirable controller because it allows for a smoother approach of the process output to the setpoint value. The output of this controller is shown by equation 2-7.

$$c(t) = K_c\varepsilon(t) + \int_0^t \frac{K_c}{\tau_I}(\hat{t})d\hat{t} + K_c\tau_D\frac{d\varepsilon}{dt} + c_s \tag{2-7}$$

where τ_D is the derivative time constant.

With the presence of the derivative term ($d\varepsilon/dt$), the PID controller anticipates what the error will be in the immediate future and applies a control action proportional to the current rate of change in the error. Due to this property, the derivative control action is sometimes referred to an anticipatory control. The equivalent transfer function for a PID controller is shown in equation 2-8.

$$G(s) = K_c\left(1 + \frac{1}{\tau_I s} + \tau_D s\right) \tag{2-8}$$

The addition of derivative action to the PI action gives a definite improvement in the response. The rise of the controlled variable is arrested more quickly as the process output approaches that of the setpoint. The response is returned rapidly to the setpoint value with little or no oscillation. The major drawbacks of the derivative control action are the following:

1. For a response with constant non-zero error it gives no additional control action since $d\varepsilon/dt=0$.
2. For a noisy response, but with almost zero average error, it can compute a large and rapidly changing derivative and thus yield large control action. However, large control action is not needed.

The PID based controller has a total of three tuning parameters, K_c, τ_I, and τ_D. Effective and coordinated tuning of these parameters is paramount to its proper action.

PID controllers alone usually cannot compensate for the effect of process dead time and the presence of inverse response (where in a positive step test the process output first decreases then increases toward the new step level). Dead time is a common feature in many chemical engineering processes. In the presence of considerable process dead time and inverse response, the usual approach is to severely detune the PID controllers (e.g. decrease the K_c) in order to avoid potential stability problems. Significant detuning usually results in degraded controller performance (e.g. sluggish response), and still may not avoid ultimate instability.

G. Model Based Control

Model based control is an alternative approach to process control in which the desired dynamic behavior of the control system is specified first; unlike the case of PID control where the controller structure is specified first. The exact structure of the controller will vary, depending on the specification of the process model. In model based control, after the specification of the desired behavior, the controller design approach is invoked to derive the controller (the structure as well as the parameters) that will achieve prespecified objectives. This completely different controller design paradigm involves an explicit use of a process model. Essentially, the controller is a 'stable' inversion of the plant model. Therefore, this technique is referred to as model based control. Model based control has demonstrated its effectiveness during the past fifteen years (Morari and Lee, 1990), since its debut.

Consider the block diagram shown in Figure 2-2 where the control system includes the blocks marked controller and model. The structure enclosed in the dashed lines constitutes the whole controller and has as its input the setpoint and as its output the manipulated variable, u. This is a typical Internal Model Control (IMC) structure, one of the basic model based controller structures (Ogunnaike and Ray, 1994). Other structures are the dynamic matrix control (DMC) and quadratic dynamic matrix control (QDMC) (Morari and Lee, 1990). When compared to PID based control, model based control offers several advantages. Tuning is made easier and model based control has built-in capability for compensating for dead time and inverse response. In addition, it is easier to incorporate design techniques that will take care of plant/model mismatch. The latter (plant/model mismatch) is a woe to all process control practitioners.

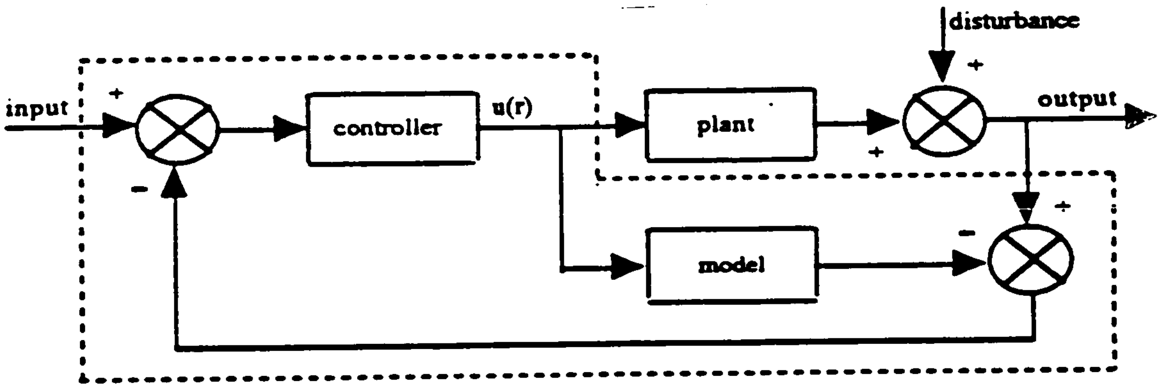

Figure 2-2. Internal Model Control Structure (Morari and Zafiriou, 1989)

Therefore, in all model based schemes, there is a model in parallel with the actual plant model, used for predicting purposes. When either plant/model mismatch or a disturbance to the process exists, the predicted process output and the actual output will differ. This difference, along with the desired process output setpoint, is the input to the controller. The structure of the model based controller is essentially an inversion of the plant model process. Overall stability is insured, after inversion, by incorporating enough process lag elements to make the overall controller transfer function stable and proper. For a single-input single-output process, there is usually only one tuning parameter associated with IMC; in contrast to three for a PID controller.

The Internal Model Controller partially imitates the role of a feedforward controller. However, the IMC controller does not exhibit the typical problems associated with a conventional feedforward controller. The IMC has the ability to cancel the influence of unmeasurable disturbances because the feedback signal includes the effect of this influence and causes the controller to modify the control action. In effect, this will cancel out the effect of the disturbance (Garcia and Prett, 1988).

In addition, the stability of the IMC controller alone implies the stability of the overall closed-loop, provided the process is open-loop stable (Morari and Zafiriou, 1989). In contrast, stability of the overall closed-loop process cannot be implied by the stability of the PID controller alone. The overall stability of the closed-loop process must be reassessed everytime the PID controller is retuned, even if the process is open-loop stable (Garcia and Prett, 1988).

For most control systems, it is impossible to exactly model the process. For the IMC, when there is plant/model mismatch, the feedback signal expresses the combined signals of unmeasured disturbances and the effect of the model error. Modeling errors usually give rise, in feedback, to possible stability problems (Morari and Zafiriou, 1989). In other words, controllers usually have to be detuned significantly, at the expense of reduced controller performance, to accommodate for modeling error. Recently, techniques have been developed explicitly to incorporate modeling error into controller design. This characteristic allows controllers to maintain long term closed-loop stability and is referred to as robustness (Doyle and Stein, 1986). IMC design more easily takes into consideration the modeling error than that of PID design. This is partially due to the fewer number of tuning parameters associated with IMC design (Garcia and Morari, 1982). This study also incorporates the effect of modeling error into the IMC design.

H. Advantages of IMC Control over PID Control

Theoretically, Internal Model Control (IMC) has advantages over conventional PID control. For one, if there is no plant/model mismatch then the relationship between any input and output is affine (a linear relationship) in the IMC controller, Q. Contrarily, this is not true for a PID controller, C, because the relationship between the input and the output is a nonlinear function of the PID controller. From a mathematical point of view, it is significantly easier to optimize an affine function than a nonlinear function (Garcia and Prett, 1988).

A second theoretical advantage is that the IMC controlled closed-loop system is stable as long as the controller, Q, is internally stable, provided there is no plant/model mismatch. This is not true for PID closed-loop controlled systems. For PID controlled systems to be stable, both the system model, G, and the control system, C, must be internally stable (Garcia and Prett, 1988).

Thirdly, the IMC controller imitates the role of a feedforward controller, giving it the ability to help reduce the time elapsed before proper operating conditions are restored, after a disturbance to the system (Andrews, 1994). In addition, the feedback loop helps to compensate for model inadequacies that are detrimental to feedforward controllers.

I. Decentralized Control

The trend in chemical process industries is toward increased process integration. In turn, this trend has created a need for more advanced high performance control systems. Practicing control engineers are now frequently faced with the task of designing controllers for multivariable plants with more than just one or two inputs and outputs (Grosdidier and Morari, 1987).

Ideally, a multivariable plant would be controlled by a full multivariable controller, where the control action of each manipulated variable is a function of all the process output variables. However, full multivariable control is very difficult to design, implement, and maintain, especially for the unskilled engineer or operator. The more common and simpler practice is to favor a simpler "decentralized" control design approach. By "decentralized", it is meant that instead of the control action of each manipulated variable being a function of all output variables, the control action of each manipulated variable is the function of only the one variable that is discerned to have the most effect on the control action. Which one variable having the most effect must be determined by predetermined selecting criteria. Thus, the action of each manipulated variable must be calculated from only one output variable, the one selected to be paired with it, ignoring interactions from all other output variables. An example would be the simple heating of a liquid filled vessel. Instead of basing the amount of heat needed to be added upon both the temperature and the volume of the vessel; the amount of heat needed to be added would be based only on the temperature.

Decentralized control structures are considered first by industrial practitioners because they offer many practical advantages. Not least among these is the fact that by carefully selecting the variable pairings, a multivariable control problem can sometimes be effectively reduced to several single-input single-output (SISO) problems. Not only does this result in simpler tuning procedures, but the tuning can be left to relatively unspecialized personnel. In contrast, a full multivariable controller would almost invariably require the presence of an experienced specialist (Grosdidier and Morari, 1987).

Decentralized controllers are also used when more complex multivariable controls are not necessary. If the off-diagonal components of a system (signifying the interaction terms) transfer function are minute (i.e. contribute little) compared to the diagonal components of a plant, then the off-diagonal components can essentially be ignored with little ill effect. This set of circumstances allows for a decentralized controller. The exclusion of these minute off-diagonal elements may decrease the controller performance, but the resulting controller simplicity may be judged well worth the sacrifice in its performance.

The task of determining which input and output elements of a system should be paired is not an easy task. Grosdidier and Morari (1987) developed an interaction parameter to aid in this determination. The factors under consideration are stabilizability, controllability, actuator-sensor failure tolerance and sensitivity. Consider the 2 x 2 system with transfer function:

$$G(s) = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$

There are two alternatives for decentralized control. The decentralized controller can be implemented on the diagonal or the off-diagonal transfer functions:

$$\tilde{G}(s) = \begin{bmatrix} g_{11} & 0 \\ 0 & g_{22} \end{bmatrix} \quad \text{or} \quad \tilde{G}(s) = \begin{bmatrix} 0 & g_{12} \\ g_{21} & 0 \end{bmatrix}$$

In other words, pairing input 1 with output 1 and input 2 with output 2, or the other way, input 1 with output 2 and input 2 with output 1. The number of alternatives grows rapidly for systems with more than two inputs and two outputs. The selection of control structure is of significant importance when dealing with more complex systems. The purpose of the interaction measure would be to assist the control engineer in this selection by quantifying the difference between the full plant G(s) and its approximate diagonal $\tilde{G}(s)$.

Interaction measure should also guide the engineer in tuning the block diagonal controller C(s) for the full plant G(s). Even if the difference between full plant G(s) and diagonal $\tilde{G}(s)$ is small, selecting C(s) such that the feedback loop around $\tilde{G}(s)$ is stable does not guarantee the stability of the feedback loop around the real plant G(s) (Grosdidier and Morari, 1987). This is because the off diagonal blocks do have an effect on the other blocks in the system. Ignoring the off diagonal blocks results in interactions which can lead to performance deterioration and even instability.

Consider the decentralized controller given by the diagonal transfer function:

$$C(s) = \text{diag}[C_1(s), C_2(s), C_3(s), \ldots, C_m(s)] \tag{2-9}$$

which is to be designed based on the noninteracting system:

$$\tilde{G}(s) = \text{diag}\,[G_{11}(s), G_{22}(s), \ldots, G_{mm}(s)] \tag{2-10}$$

such that the block-diagonal, closed-loop system with the transfer matrix:

$$\tilde{H}(s) = \tilde{G}(s)C(s)(I + \tilde{G}(s)C(s))^{-1} \tag{2-11}$$

is stable. An interaction measure expresses the constraints imposed upon the choice of the closed-loop transfer matrix $\tilde{H}(s)$, thus on C(s) such that the stability of the closed-loop system with the real and interacting plant G(s):

$$H(s) = G(s)C(s)(I + G(s)C(s))^{-1} \tag{2-12}$$

is guaranteed (Grosdidier and Morari, 1987). In other words, how large can C be (C is calculated based on a diagonal $\tilde{G}$) such that when the loop is closed with the full plant (full G) in operation, the overall closed-loop will not become unstable. The bigger the off-diagonal elements of G, (i.e. the higher the interaction among loops), the more severe the constraints become and the more conservative C(s) has to be tuned.

The relative error arising from the approximation of the full system G(s) by the block diagonal system $\tilde{G}(s)$ is defined by:

$$E(s) = (G(s) - \tilde{G}(s))\tilde{G}(s)^{-1} \tag{2-13}$$

and from E(s), one can arrive at an upper limit for tuning of the diagonal C(s).

J. μ-Interaction Measure

The μ-Interaction Measure is a concept developed by Grosdidier and Morari (1987) to measure the closed-loop stability of a controlled system H(s). The stability analysis using the μ-interaction measure is based in the frequency domain. Morari theorizes that if G(s) and $\tilde{H}(s)$ are stable, then the closed-loop system H(s) is stable if

$$\|\tilde{H}(j\omega)\| < \|E(j\omega)\|^{-1} \tag{2-14}$$

where $\|A\|$ denotes the induced norm of A, ω denotes the frequency, and j denotes the imaginary number.

By definition, $\|E(j\omega)\|$ is an interation measure. It has the disadvantage of being very conservative (i.e. constrictive). A less conservative bound can be derived, if it is assumed that the diagonal blocks of $\tilde{H}(s)$ are norm-bounded in the sense of the spectral norm (Grosdidier and Morari, 1987)

$$\|\tilde{H}_i(j\omega)\|_2 = \sigma_{max}(\tilde{H}(j\omega)) < \delta(\omega) \qquad \forall i, \omega \tag{2-15}$$

where $\sigma_{max}(A(j\omega))$ is the maximum singular value of A at every ω. A real positive function, $\mu(E(j\omega))$, can be defined in order to satisfy the stability requirement of the closed-loop system H(s), assuming that G(s) and $\tilde{H}(s)$ are stable and if and only if

$$\sigma_{max}(\tilde{H}(j\omega)) < \mu^{-1}(E(j\omega)) \tag{2-16}$$

$\mu^{-1}(E(j\omega))$ is the "optimal" Interaction Measure because equation 2-16 constitutes the tightest possible norm bound (Grosdidier and Morari, 1987).

The μ-Interaction Measure treats the block-diagonal system $\tilde{H}(s)$ in a unified "optimal" manner. This offers the advantage that, independent of the number of system inputs and outputs, the design engineer can determine from a single curve if the selected control structure would lead to possible instability and to significant performance deterioration (Grosdidier and Morari, 1987). A major drawback of the μ-Interaction Measure is the calculation of μ. For higher order systems there is no precise numerical method of calculation, but for 2 x 2 systems this interaction measure was the same as that proposed by Rijnsdorp (1965) and Bristol (1966). This interaction measure can be calculated by:

$$\kappa(s) = g_{12}(s)g_{21}(s)/g_{11}(s)g_{22}(s) \qquad (2\text{-}17)$$

where the g_{ij} are the ij^{th} elements of the plant transfer function matrix, G(s).

The following relationship can be made with μ (Grosdidier and Morari, 1987):

$$\mu(E(j\omega)) = [|\kappa(j\omega)|]^{1/2} \qquad (2\text{-}18)$$

where $|\kappa(j\omega)|$ refers to the absolute value of the complex κ at frequency (jω).

Thus, if G(s) and H(s) are stable, then the closed-loop system H(s) is stable if

$$|\tilde{h}_i(j\omega)| < |\kappa(j\omega)|^{-1/2} = \mu^{-1}(E(j\omega)) \qquad \forall i, \omega \qquad (2\text{-}19)$$

where i denotes each of the single feedback loops and $\tilde{h}_i$ denotes the i^{th} diagonal element of the matrix $\tilde{H}$ which is based on the diagonal controller.

Equation 2-19 provides a criteria by which to judge when the controller tuning of C(s) will render a stable closed-loop system, when implemented on the fully interactive, multivariable system. Note that the controller C(s) has been designed assuming that no interaction exists in the original system. Therefore, it is not necessary to explicitly calculate for the poles of the multivariable closed-loop transfer function in order to assess its stability (a daunting task).

K. Linear Modeling

The wastewater treatment exhibits nonlinear dynamics. However, it is mathematically easier to approximate the nonlinear plant by a linear model, so that linear controllers such as PID and IMC can be used. Both are designed based on a linear description of the plant. Therefore, the first step in this study was to develop the linear approximation of the original nonlinear plant. It should be noted that a linear model of a nonlinear system may represent the true dynamics only to within a certain range. Operating values outside of this range may lead to the linearized model being an erroneous representation of the original nonlinear model.

A step input in each of the inlet variables will affect each of the output variables causing them to exhibit different characteristics in gain, lead or lag time, delay time, inverse response, and/or a combination of all of these. A linear model between each input-output pair will be derived from the step response of the original nonlinear plant. The linear model characteristics will be briefly explained below.

1. Gain

This is the simplest and the most common element of all responses. It is represented by a simple constant, K. The constant K can be any real number from negative infinity to positive infinity, inclusively. Values of either negative infinity or positive infinity demonstrate a truly unstable system that will have output values growing without bound due to a unit change in the input. Determination of K is based on the new steady state value of the output variable, after implementation of a step change in an input variable, minus the original steady state value of the output variable. It is the simple, steady state change in the output after a unit change in the input. In this study, all gain changes are computed on a percentage basis, plus or minus percentage change from the nominal value.

2. Lag

A lag response is represented in Laplace transform by $1/(\tau s + 1)$, where $\tau>0$ ($\tau<0$ is an inherently unstable system) represents the lag time constant of the process. Normally, a system with only a gain response is a true step response, i.e. the new steady state is reached instantaneously after a step change in the input. A lag response causes the instantaneous step response to become "sluggish," thus increasing the time needed to reach the new steady state. The larger the value of τ, the more "sluggish" the system. The value of τ is approximated by drawing a tangent to the inflection of the "sluggish" step response and subtracting the x-intercept value of this tangent line from the x-value at which the response has reached 0.632 of the final steady state rise (or K). This is demonstrated in graphic form, as shown in Figure 2-3, and is more commonly known as the Fit 2 Method (Coughanowr, 1991). The greater the lag time, usually implies the greater the controller gain required in order to speed up the overall system response. The approximate dead time is θ. Note explanation of θ later in this study.

3. Lead

A lead response is represented in Laplace transform by $(zs+1)$, where $z>0$. A lead response causes the system to be more "aggressive", initially starting out at a level higher than the new steady state and then converging to the new steady state. In most cases, this causes the system to overshoot the new steady state and extra time is needed for the system to “settle” down to the new steady state. The larger z is, the greater the overshoot.

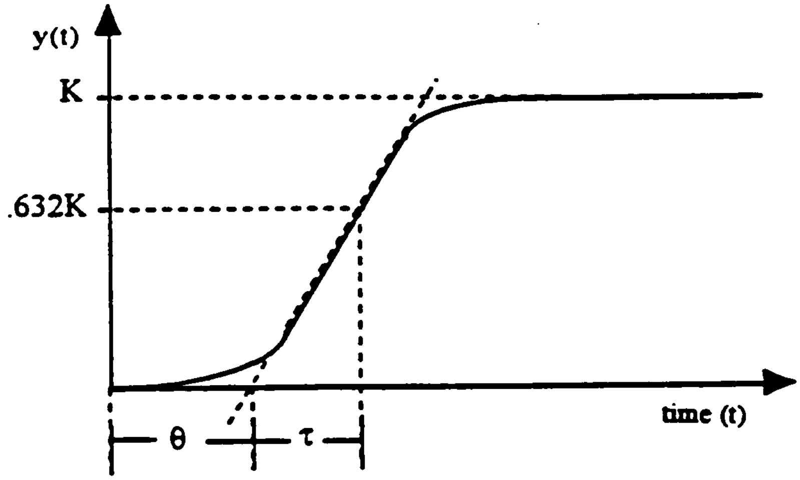

Figure 2-3. Fit 2 Method Determination of Lag Time Constant, τ, and Dead Time, θ

4. Inverse

An inverse response is represented by (zs+1), with the zero defined as z<0. The system initially responds in a direction opposite to the direction of its eventual new steady state gain after a step input. For example, if an increased (positive) step change in the input variable resulted in an increased (positive) change in the new ultimate steady state of the output variable, an inverse response would initially result in the system decreasing (negative) until the other terms in the transfer function “overtake” the inverse term. This can be seen in Figure 2-4. The larger |z| is, the greater the inverse response. The presence of an inverse response usually requires the PID controllers to be detuned (backing off on the tuning) in order to insure overall system stability. Figure 2-4 depicts an inverse response.

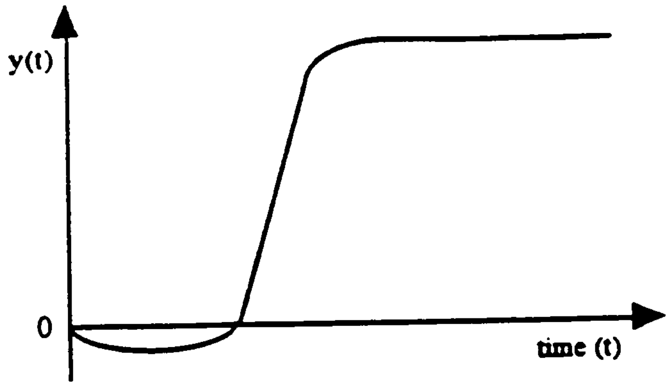

Figure 2-4. Inverse Response

5. Delay (or Dead Time)

A delay is exactly what it sounds like, a delay in the response of the system to a change in the input. It is represented by $e^{-\theta s}$, where $\theta>0$, signifies the dead time. If a step change is implemented at time $t=0$, then a delay will cause the system not to respond until a certain time $t=\theta$ later. The larger θ is, the longer the delay in the response. The presence of a large delay time also necessitates a significant detuning (backing off on the tuning) of the PID controller parameters to insure overall system stability.

Chapter Three

Study Approach

The objective of this study is to evaluate and compare two possible control strategies for a proposed industrial wastewater treatment plant. The treatment plant in the study is under construction in Victoria, Texas by DuPont Corporation, with the potential of several other plants being modeled after this one. One of the two control schemes under comparison, the PID based decentralized scheme, is more commonly used in industrial process control applications; whereas the second approach, a model based approach, is a relatively newer scheme and appears to work well in situations in which dead time and/or inverse response are present. Successful industrial applications of model based control have been widely reported during the past few years (Morari and Zafiriou, 1989) and more are emerging every day. The evaluation and comparison of the different control strategies is based upon the ability of each control system to remain stable and to meet performance criteria in the face of setpoint and disturbance perturbations. The ease of tuning will also be used to evaluate and compare the two control systems. Several steps are involved in the research strategy to accomplish the study objective.

a. Utilize the dynamic simulator based on the Matlab platform (Grove, 1995) to develop approximate linear transform function models for each of the possible input-output pairs, based on step changes in the corresponding input.

b. Identify the optimum control pairings for each set of manipulated-controlled variables to be used in decoupled, multiple single-input single-output (SISO) feedback control loops, so as to minimize inter-loop interactions.

c. Design decoupled, multiple SISO feedback control loops for all the optimum configurations identified above. Simulate, analyze, and appropriately tune the controllers for setpoint changes and disturbance rejection responses. This is to be done for both conventional PID control and model based control.

d. Assess the ability of the two control schemes in tolerating plant/model mismatch with respect to performance and stability of the closed loop system. This will be done by utilizing simulations in the time domain; as well as analysis in the frequency domain of the system, as described previously using the μ-interaction measure.

A. Relative Gain Array

The Relative Gain Array (RGA) provides a measure of interaction among potential control loops for a multi-input, multi-output system, based on system responses to selected perturbations from a nominal steady state (Bristol, 1966). By providing a measure of interaction between input variables and output variables in a plant, the RGA gives a control system designer a means by which the best pairing for a set of input and output variables can be chosen in order to minimize the interaction among the individual control loops. The Relative Gain Array has been widely used for nearly thirty years. RGA is primarily an empirical tool, with little theoretical basis (Grosdidier and Morari, 1987).

RGA can provide information on those pairing configurations expected to lead to severe closed-loop problems.

The Relative Gain Array is determined from the steady state input-output gain information for a given process. Therefore, RGA does not require any dynamic information of the system. Often, only the steady state gain information for the process can be obtained without too much trouble; while the dynamic characteristics of the process are harder to obtain (Grosdidier and Morari, 1987). From the steady gain array, the RGA can be used to determine the best manipulated, variable-controlled variable pairing for a given set of variables, in decoupled, decentralized, multiple SISO feedback control strategies, which is usually much simpler to design than a true full multi-input multi-output (IMO) control system. Calculations of the RGA are detailed in several references, such as *Process Dynamics, Modeling, and Control* (Ogunnaike and Ray, 1994).

The following gives the guideline in using the RGA. Consider the values of the RGA with n rows and m columns. The number of output variables, y, is n and the number of input variables, u, is m. Every row and every column of the RGA must sum to one. A value of 0 in the nm^{th} position of the array indicates that the corresponding y_n is completely unaffected by the corresponding u_m. A value of 1 in the nm^{th} position of the array indicates that the corresponding y_n is affected only by the corresponding u_m. Thus, the ideal matching of manipulating input variables with output variables would be those that have corresponding array elements near the value of 1. In addition, pairing with a negative RGA number should be avoided because of potential instability problems. An example of ideal and non-ideal pairing for a 2 x 2 system is shown in Figure 3-1. The obvious, and most logical, pairing would be y_1 with u_1 and y_2 and u_2.

sum = 1

$$\text{RGA} = \begin{array}{cc} \begin{bmatrix} 0.90 & 0.10 \\ 0.10 & 0.90 \end{bmatrix} & \begin{array}{c} y1 \\ y2 \end{array} \\ \begin{array}{cc} u1 & u2 \end{array} & \end{array}$$

sum = 1

Pairings Should Be
y1-u1 and y2-u2

Figure 3-1. Pairing of Input-Output Variables According to the Relative Gain Array

B. Interactions among Decentralized Multivariable Systems

The degree of interactions among the various input-output pairs is extremely important if decoupled, multiple single-input single-output (SISO) feedback control loops are considered. In multiple SISO feedback control loops, an output is chosen to be paired with a manipulated input, and it is best chosen when this manipulated input is the primary contributor to the output variable.

What characterizing a process as a multi-input multi-output system model, characteristic of most chemical processes, the open-loop transfer function between an input u_j and an output y_i is defined in equation 3-1.

$$(dy_i/du_j)_{ol} \equiv g_{ij}(s) \tag{3-1}$$

where $g_{ij}(s)$ = the ij^{th} element of the open loop transfer function matrix $G(s)$

dy_i = change in the i^{th} output variable response of the system due to a change in the input variable

du_j = change in the j^{th} input variable to the system.

For a two input (u_1 and u_2) and two output (y_1 and y_2) system, each output is the net effect of changes of both inputs and changes in each input affects all outputs. Figure 3-2 is a diagram representing the interactions between two inputs and two outputs in an open loop 2 x 2 system. As one can determine, the interactions among the system become more complex as the number of input and output variables increases. In a 2 x 2 system, the transfer function for the overall system can be written as in equations 3-2 and 3-3.

$$y_1(s) = g_{11}(s)u_1(s) + g_{12}(s)u_2(s) \tag{3-2}$$

$$y_2(s) = g_{21}(s)u_1(s) + g_{22}(s)u_2(s) \tag{3-3}$$

Equations 3-2 and 3-3 can be rewritten in matrix notation as in equation 3-4.

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} g_{11}(s) & g_{12}(s) \\ g_{21}(s) & g_{22}(s) \end{bmatrix} \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} \tag{3-4}$$

This model approach is applicable to any open loop system with n inputs and m outputs as long as the transfer function matrix, G(s), has the form of equation 3-5. The input vector, u(s), would then have n elements while the output vector, y(s), would contain m elements

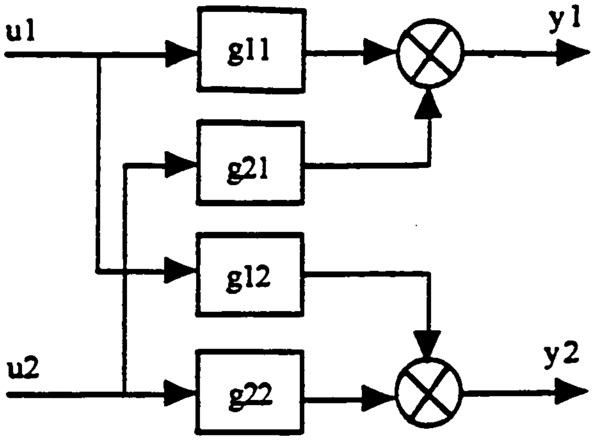

Figure 3-2. Transfer Function Diagram for a 2 x 2 System

Where g_{ij} = element ij of the plant transfer matrix; transfer function between the j^{th} input and the i^{th} output

y_i = i^{th} plant output variable

u_j = j^{th} input variable for plant.

$$G(s) = \begin{bmatrix} g_{11}(s) & g_{22}(s) & \cdots & \cdots & g_{1m}(s) \\ g_{21}(s) & g_{22}(s) & \cdots & & \vdots \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & & & \ddots & \vdots \\ g_{m1}(s) & \cdots & \cdots & \cdots & g_{mn}(s) \end{bmatrix} \tag{3-5}$$

and

$$y(s) = G(s)u(s)$$

Figure 3-3 features the system outlined in Figure 3-2 with two decoupled single-input single-output (SISO) conventional feedback controllers added. This is now a closed-loop, decoupled, multiple SISO feedback system where y_1 is controlled by manipulating u_1 and y_2 is controlled by manipulating u_2. The conventional controller is represented by the transfer function for a PI controller as defined in equation 3-6. Derivative control is not being added, because the response of the system is expected to be noisy with little error. This would cause the controller to compute large derivatives and thus yield large and rapidly changing control action, although it is not needed.

$$g_{ci} = K_c\left(1 + \frac{1}{\tau_I s}\right) \tag{3-6}$$

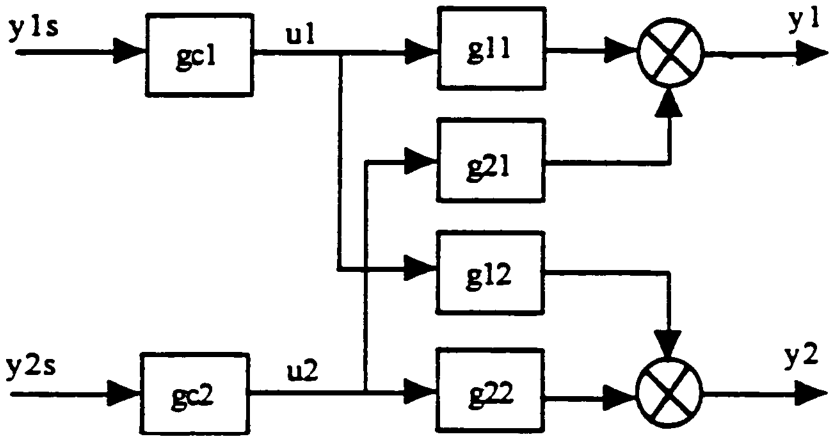

Figure 3-3. Transfer Function Diagram for a 2 x 2 System with Two Single Loop Conventional Controllers (Ogunnaike and Ray, 1994)

Where g_{ij} = element ij of the plant transfer matrix; transfer function between the j^{th} input and the i^{th} output

g_{ci} = i^{th} element of controller transfer matrix, $G_c(s)$; or the controller transfer function for the i^{th} loop.

y_i = i^{th} plant output variable

y_{is} = setpoint of i^{th} plant output variable

u_j = j^{th} input variable

For Model Based control, the configuration of the closed-loop multiple SISO system is very different. Figure 3-4 depicts the system outlined in figure 3-2 with two decoupled single-input single-output (SISO) Internal Model (IMC) controllers added in the feedback loops. Once again, this is now a closed-loop, decoupled, multiple SISO feedback system where y_i is controlled by manipulating u_1 and y_2 is controlled by manipulating u_2. However, the basic design of PID and IMC controllers differ theoretically. The IMC controller is represented by the transfer function defined in equation 3-7.

$$g_{ci} = 1/g_{ij}^{+} \tag{3-7}$$

where g_{ij}^{+} is the invertable part of the plant transfer function $g_j(s)$.

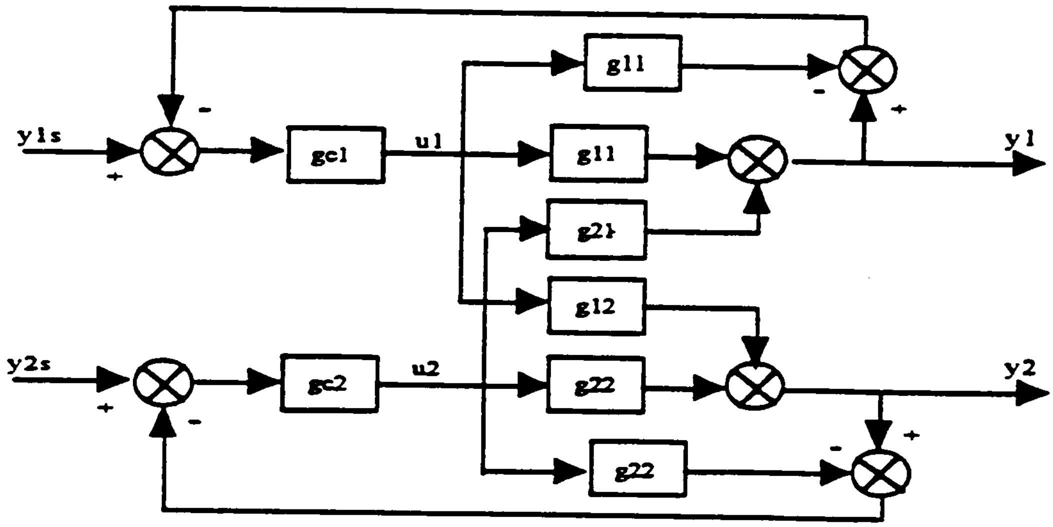

Figure 3-4. Transfer Function Diagram for a 2 x 2 System with Two Decoupled Single Loop Internal Model Controllers (Ogunnaike and Ray, 1994)

Where g_{ij} = element ij of the plant transfer matrix; transfer function between the j^{th} input and the i^{th} output

g_{ij} = nominal model of element ij of the plant transfer matrix.

g_{ci} = i^{th} element of controller transfer matrix, $G_c(s)$; or the controller transfer function for the i^{th} loop.

. y_i = i^{th} plant output variable

y_{is} = setpoint of i^{th} plant output variable

u_j = j^{th} input variable

C. Derivation and Tuning of Controller Transfer Functions

There are several ways to calculate the initial settings of the tuning parameters for both the conventional PID control and the model based control. A common and well-tested method for conventional PID control is the use of the Ziegler-Nichols rules which involve first finding the ultimate gain, K_υ, and the ultimate period, P_υ, of the process. As for model based controllers, Morari and Zafiriou (1989) have not only outlined the derivation of an internal model controller, but have also developed a systematic tuning rule, presented below. Note that PID controllers have three tuning parameters; whereas IMC controllers have only one.

1. Conventional Control (Proportional Plus Integral, PI)

If the derivative mode is not considered, PI has two tuning parameters. The transfer function for a conventional PI controller is independent of the system transfer function. No matter how complicated the system is, the PI controller transfer function will always be of the form shown earlier in equation 3-6, and once again below:

$$g_{ci} = K_c\left(1 + \frac{1}{\tau_I s}\right)$$

where the two tuning variables are the controller gain, K_c, and the integral time constant (or reset time), τ_I.

Ziegler-Nichols control setting rules were first proposed by Ziegler and Nichols in 1942. Based on their experience with the transients from many types of processes, they developed a heuristic tuning method still used today in one form or another (Coughanowr, 1991). When their rules were first proposed, frequency response methods and process models were not generally available to control engineers. Therefore, they intended that the ultimate gain, K_u, and the ultimate period, P_u, could be calculated using an open-loop frequency response, such as a Bode plot.

Consider the selection of a controller for the system represented in the Bode plot of Figure 3-5. It should be emphasized that the controller is omitted from the plot, thus the plot is only of the process and measuring transfer function elements in series (Coughanowr, 1991), in the frequency domain.

As noted on the figure the crossover frequency (the frequency at which the phase is -180) for the process is ω_{co}. At the crossover frequency, the overall gain is A, as indicated. The ultimate gain, K_u, is defined as the gain that would cause the system to be on the verge of instability. This is defined in equation 3-8

$$K_u = 1/A \qquad (3\text{-}8)$$

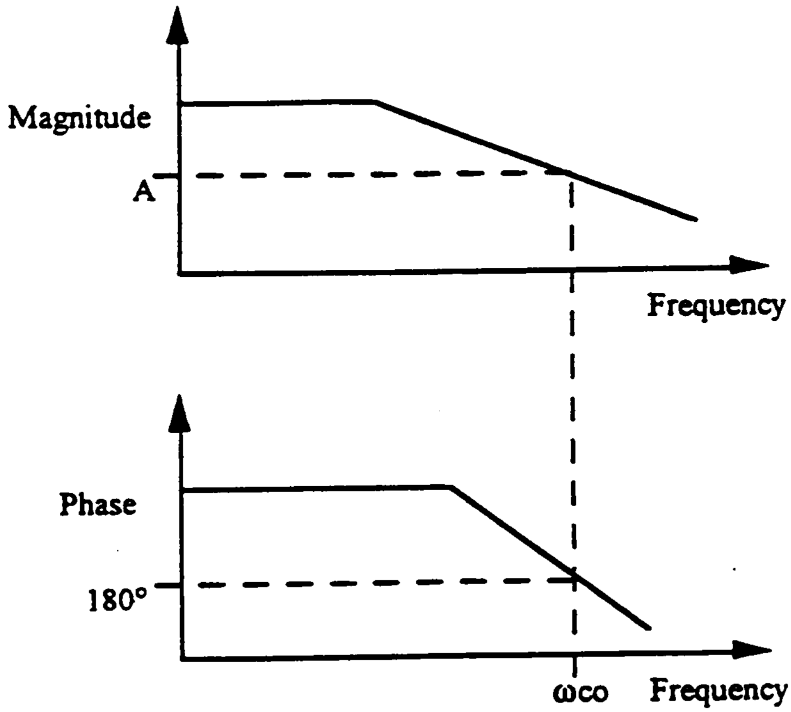

Figure 3-5. Open Loop Bode Diagram for a Typical Control System
(Coughanowr, 1991)

The ultimate period, P_u, is then calculated by equation 3-9

$$P_u = 2\pi/\omega_{co} \qquad (3\text{-}9)$$

The Ziegler-Nichols settings for controllers are determined directly from K_u and P_u according to the rules summarized in Table 3-1. Other controller tuning guidelines, such as Integral-Squared-Error (ISE) or Integral-Absolute-Time-Error (ITAE) can also be used. They yield proximal settings to that of Ziegler-Nichols.

a. Limitations of the Conventional PID Controller

The initial tuning thus arrived at needs to be further fine-tuned in order to best fit the process at hand. This final phase of "fine tuning" is what usually escapes a new

Table 3-1. Ziegler-Nichols Controller Settings (Coughanowr, 1991)

Type of Control	$G_c(s)$	K_c	τ_I	τ_D
Proportional	K_c	$0.5K_u$		
Proportional-Integral (PI)	$K_c(1+1/\tau_I s)$	$0.45K_u$	$P_u/1.2$	
Proportional-Integral-Derivative (PID)	$K_c(1+1/\tau_I s+\tau_D s)$	$0.6K_u$	$P_u/2$	$P_u/8$

operator due to inexperience. Such conventional "know-how" is the result of the accumulation of a vast amount of actual operating experience. In addition, for processes with "nasty" characteristics, such as large dead time, inverse response or plant/model mismatch, no amount of "fine tuning" will result in satisfactory controller performance. This is due to the inherent inability of the conventional PID controller to compensate for these characteristics. Often, additional compensators, such as the Smith Predictor (to compensate for the delay time) and inverse response compensator are designed to be added to the main PID controller. The result is an increase of the controller structure complexity; and the presence of additional tuning parameter(s). Furthermore, proper functioning of these additional compensators depends on knowing the plant model exactly, a rare fact in practice. Lacking such total knowledge, instability may occur and no amount of tuning will circumvent it.

2. Model Based Control (Internal Model, IMC)

Contrary to PI controllers, the transfer function for IMC controllers is dependent on the nominal transfer function of the system. For developing a decentralized IMC controller, q, one only has to consider the nominal process model, $\tilde{p}$, for each loop independently. Assuming that $\tilde{p}$ is stable, it can then be factored into an allpass portion, $\tilde{p}_a$, and a minimum phase (MP) portion, $\tilde{p}_m$, as shown in equation 3-10 (Morari and Zafiriou, 1989)

$$\tilde{p} = \tilde{p}_a \tilde{p}_m \tag{3-10}$$

where $\tilde{p}_a$ includes all the right half plane RHP zeros, (i.e. $z < 0$), and delays of $\tilde{p}$. In other words, $\tilde{p}_a$ includes everything that will force the system to be unstable when inverted. The MP portion will then contain all constants, left half plane (LHP) zeros, and poles (by definition of $\tilde{p}$ being stable, all poles are LHP). Similarly the input, v, is factored as in equation 3-11. For this study all inputs are considered to be step inputs, thus having no allpass portion and represented by equation 3-12.

$$v = v_a v_m \tag{3-11}$$

$$v = 1/s \tag{3-12}$$

The first part of the controller, represented by $\tilde{q}$, is given by

$$\tilde{q} = (\tilde{p}_m v_m)^{-1} \{\tilde{p}_a^{-1} v_m\}_* \tag{3-13}$$

where the operator, $\{\tilde{p}_a^{-1} v_m\}_*$ denotes that after a partial fraction expansion of the operand, all terms involving the poles of $\tilde{p}_a^{-1}$ are omitted (Morari and Zafiriou, 1989). This eliminates all of the unstable elements of the inverted plant. In general, the initial part of the controller transfer function is not proper. Properness is defined by having a numerator order equal to or less than the denominator order. An improper function is not physically realizable. This is of no concern at this point, because it is to be augmented by a low-pass filter in the second step of the IMC design procedure. Note that $\tilde{q}$ at this point involves no tunable parameter.

The second step is comprised of developing a low-pass filter for the controller, in order to make it proper. Typically, this single parameter filter is of the form

$$f(s) = \frac{1}{(\lambda s + 1)^n} \tag{3-14}$$

where λ is the adjustable filter parameter and n is an integer selected just large enough to make the controller q ($q = \tilde{q}f$) proper. The controller, q, is then calculated by combining the first design part $\tilde{q}$ with the filter, as shown in equation 3-15.

$$q = \tilde{q} f = \frac{\left(\bar{p}_M \, v_M\right)^{-1} \left\{\bar{p}_A^{\;-1} \, v_M\right\}_*}{(\lambda s + 1)^n} \tag{3-15}$$

Once again, n is chosen just large enough to render q proper. Note that q has only one tuning parameter, λ. The tuning rules for λ are dependent upon whether one wishes to have the model based controller act as an equivalent PI or a PID controller. These guidelines are shown in Table 3-2 (Ogunnaike and Ray, 1994), where θ is the dead time of the plant and τ is the plant time constant.

Table 3-2. IMC Approximate Model Controller Tuning Rules
(Ogunnaike and Ray, 1994)

Controller Type	Recommended Choice of λ ($\lambda > 0.2\tau$ Always)
Proportional-Integral (PI)	$\lambda/\theta > 1.7$
Proportional-Integral-Derivative (PID)	$\lambda/\theta > 0.25$

a. Advantages of the IMC Controller

Like the PID based controller, the IMC based controller is to be further fine tuned in order to best fit the process at hand. But, where the "fine tuning" for the PID based controller is complex and difficult to the inexperienced operator, the IMC based controller is simpler and more transparent to any operator. This is due to the single parameter, λ, as opposed to the several parameters in PID based control. In addition, for processes with "nasty" characteristics, such as large dead time, inverse response or plant/model mismatch, there is still only one parameter, λ, for the IMC based controller that needs to be tuned. With PID control, several filters, thus additional tuning parameters, must be added in order to guarantee the stability of the system.

Morari and Zafiriou (1989) derived the general relationship between the classic PID based feedback controller, c, and the IMC controller, q, when the process model is p. This is shown in equation 3-16.

$$c = \frac{q}{1-\tilde{p}q} \tag{3-16}$$

Using this relationship, along with the general equation for a PID controller with added compensating filters (equation 3-17), and assuming a step input to the process, one can calculate and demonstrate how the single parameter, λ, in the IMC based controller contains all of the PID based parameters (K_c, τ_I, and τ_D), plus any and all additional filters, τ_{F1} and τ_{F2}, needed to compensate for "nasty" characteristics, such as large dead time and inverse response.

$$c = K_c\left(1+\frac{1}{\tau_I s}+\tau_D s\right)\left(\frac{1}{\tau_F s^2+\tau_F s+1}\right) \tag{3-17}$$

Appendix A contains the calculations for these equivalencies for several common first order lag systems with added dead time, lead, and inverse response. Table 3-3 summarizes how to calculate the equivalent PID tuning parameters and filter parameters for these systems.

Table 3-3. IMC Controllers for Models Interpreted as PID Controllers with Filter

Model p	$\tilde{p}q$	K_cK	τ_I	τ_D	τ_{F1}	τ_{F2}
First Order Lag plus Dead Time $\dfrac{Ke^{-\theta s}}{\tau s+1}$	$\dfrac{e^{-\theta s}}{\lambda s+1}$	$\dfrac{\tau+\beta}{2\beta+\lambda}$	$\tau+\beta$	$\dfrac{\tau\beta}{\tau+\beta}$	0	$\dfrac{\lambda\beta}{2\beta+\lambda}$
First Order Lead-Lag plus Dead Time $\dfrac{K(zs+1)e^{-\theta s}}{\tau s+1}$	$\dfrac{e^{-\theta s}}{\lambda s+1}$	$\dfrac{\tau+\beta}{2\beta+\lambda}$	$\tau+\beta$	$\dfrac{\tau\beta}{\tau+\beta}$	$\dfrac{\lambda\beta z}{2\beta+\lambda}$	$\dfrac{\lambda\beta+2\beta z+\lambda z}{2\beta+\lambda}$
First Order Lag plus Dead Time and Inverse Response $\dfrac{K(-zs+1)e^{-\theta s}}{\tau s+1}$	$\dfrac{(-zs+1)e^{-\theta s}}{(zs+1)\lambda s+1}$	$\dfrac{\tau+\beta}{2\beta+\lambda+2z}$	$\tau+\beta$	$\dfrac{\tau\beta}{\tau+\beta}$	$\dfrac{\lambda\beta z}{2\beta+\lambda+2z}$	$\dfrac{\lambda(\beta+z)}{2\beta+\lambda+2z}$

D. Plant/Model Mismatch

One of the issues that has always arisen in control system design is how sensitive the controlled system is to expected variation in the process parameters. For example, if the controller (it makes no difference if it is PID based or model based) is tuned for a particular loop, how will this control loop behave if the process gain changes by, say, 20% or the time delay changes by, say, 30%? This is a question of process sensitivity and the robustness of the control design. A highly desirable feature of a controller design is its ability to render the closed-loop stable at all times, even when the process has changed.

There are two practical situations that lead to problems with robustness. Both would lead to plant/model mismatch and arise as a consequence of the following situations (Ogunnaike and Ray, 1994):

1. Process Variability: in which an otherwise adequate model no longer matches the observed plant behavior because the process itself has changed. Catalyst decay and heat exchanger fouling are two examples of mechanisms underlying such process variability.
2. Inadequate Modeling: in which the model is an inadequate representation of the true plant behavior. This may be because the model structure is a fundamentally poor approximation (as when a linear model is used to represent a severely nonlinear process), or it may be because of poor estimates of the model parameters in an otherwise adequate model structure.

This plant/model mismatch may cause the closed-loop process to go unstable under certain conditions because the controllers are no longer adequate enough to maintain a stable system. This can be due to their sometimes severe over tuning. The problem is usually remedied by conservatively tuning the controller, thus making the process response more sluggish but more robust. For a nonlinear process, conservative tuning of the PID based controller usually only achieves stability over a limited time span. This may be sufficient, depending upon one's needs. To completely rectify the situation, additional lag filters must be added to the PID based controller to make it less aggressive and to increase its stability margin (how close to the point of instability). Model based controllers need no added filters (thus added additional tuning parameters) because they inherently contain necessary filters and the coordinated tuning of all filters is included in the tuning of the single parameter, λ. It is only necessary to change the λ value (by increasing it) to make the IMC controller more robust.

E. Summary of Advantages and Disadvantages

In summary, the advantages and disadvantages of conventional PID and model based controllers are summarized in Table 3-4 below:

Table 3-4. Summary of Control Strategy Advantages and Disadvantages

	Advantages	Disadvantages
PID Based	Well tested through decades of use	Several tuning parameters K_c, τ_I, τ_D
	Easier to design	Stability problems with "nasty" systems
	Details of fine-tuning well understood by experienced operators	Additional filters, thus added parameters, needed to compensate "nastiness"
		Difficult to understand details of fine-tuning for new operators
IMC Based	Only one tuning parameter, λ	Not is wide use in industry
	Can maintain stability for "nasty" systems	Slightly more coplex to design
	Additional compensating filters included in one parameter, λ	
	Very simple and transparent fine-tuning	

Chapter Four

Results and Discussion

This study evaluates and compares two alternate control strategies for a multistage wastewater treatment plant. The evaluation and comparison of the alternate control strategies is based upon the ability of each control system to render the overall closed-loop system stable over long term, and to meet plant treatment performance criteria in the face of setpoint and disturbance perturbations. The ease of controller tuning is also an important part of the evaluation and comparison considerations.

Grove (1995) studied the open loop dynamic and steady state response of the system to perturbations and identified which variables are most affected by which perturbations, and which variables may be used as the most effective manipulated variables to compensate for the anticipated perturbations. The present study seeks to close the control loop and compare the effectiveness of Model Based control strategies to the traditional Proportional-Integral-Derivative (PID) controllers, both implemented as multiple single-input single-output (decentralized) feedback loops.

A. Control Strategies

In designing decentralized controllers, specification of pairing of an input to an output variable is an important consideration. Decentralized controllers are the most common type of controller utilized in the process industries for multiple-input multiple-output (MIMO) systems, because these controllers are easier to implement than a full controller designed to fully utilize the interactions between the inputs and the outputs. If the controller pairings are chosen carefully, a multivariable control problem (such as a wastewater treatment plant) may sometimes be effectively reduced to several single-input single-output (SISO) problems. Not only does this result in simpler procedures, but tuning can be left to relatively unspecialized personnel. In contrast, a full MIMO controller would almost invariably require the presence of a specialist (Grosdidier and Morari, 1987).

PID based decentralized controllers are usually the first to be considered by plant personnel to control a system. PID based controllers have been in use for decades and are very well understood by engineers and operators. But, there are limitations to the PID based controller, especially when the system is more complex and displays increasingly non-ideal characteristics. These non-idealities limit the PID based controller effectiveness in sustaining a stable system. Thus, the PID based controller may not be robust enough to handle the effects of disturbances or the occurrence of plant/model mismatch. This is when the model based controller has an advantage over the PID based controller, because model based controllers have built-in capabilities to compensate for some of the non-idealities of the process, such as dead time, and it can also accommodate design modification required to accommodate plant/model mismatch.

Recently, progress has been made in the area of Model Based controllers (summarized in Ogunnaike and Ray, 1994) which are more effective in handling operating constraints and system non-idealities in achieving a desired output behavior. There are several algorithms for the design of model based controllers and most agree that they are easier to tune and better accommodate uncertainty associated with the description of the plant model. A comparison between the workings of the conventional PID control strategies, and that of the more modern model based control strategies, and their respective performances on a wastewater treatment plant, will help in developing and implementing a control system that is both effective and simpler to design. In addition, an understanding of the incremental effort involved in using model based controllers over that of conventional PID will better help plant managers in evaluating the choice of the final control strategy.

B. Review of the Dynamic Simulator (Grove, 1995)

A dynamic simulator for the wastewater treatment plant kinetics was developed by Grove (1995) using the Simulink programming environment of Matlab employing the *Activated Sludge Model No. 1* as a theoretical working model for the treatment kinetics. The kinetics are based on a lumped and unstructured modeling approach using the conservation of mass principle. The simulator is constructed around a modular design for a continuously stirred tank reactor (CSTR) and a standardized data stream capable of calculating the concentrations of twenty-one components simultaneously. The model simulates denitrification in the anoxic reactor and combined aerobic COD degradation and nitrification in the aerobic reactor. Both reactors are treated as CSTRs. Following the two reactors is a gravity based clairifier, with a recirculation and supernatant effluent streams coming out of it.

There are five main input variables to be considered for the simulator. They are shown in Table 4-1 along with their nominal inlet rates. The sludge age is determined by the desired solids retention time, which in turn can influence the concentration loads in the overall effluent. The recirculation ratio is defined as the ratio of the recirculation flow from the aerobic tank to the anoxic tank divided by the raw influent flow to the wastewater plant. The three output variables of interest are the effluent concentrations of biochemical oxygen demand (BOD), ammonia, and nitrate.

C. Development of Approximate Linear Models for the Treatment Plant

The wastewater treatment plant may exhibit very nonlinear dynamics. However, one needs to approximate the nonlinear plant via a local linear model, because only linear,

Table 4-1. Plant Input Parameters and Nominal Rates (Grove, 1995)

Input Parameter	Nominal Value
Volumetric Flow Rate	5,450,000 liters/day
Influent Ammonia Concentration	300 mg $N\text{-}NH_4^+$/liter
Influent Nitrate Concentration	1000 mg $N\text{-}NO_3^-$/liter
Sludge Age	30 days
Recirculation Ratio	3.5
Influent BOD Level	10,000 mg/liter

decentralized SISO controllers are to be considered for the plant. This is because the theories of both PID and model based controllers are based on linearity of the plant. The former is the most frequently employed feedback controller in industry. The latter is an emerging controller in industrial practice. Therefore, the first step in the study was to develop the linear approximation of the original nonlinear plant. This was done by using the dynamic simulator developed by Grove (1995) and implementing positive and negative step changes in each of the five inlet parameters in turn; while monitoring the output responses of the effluent concentrations of BOD, ammonia, and nitrate.

Linear models were then designed using the output response graphs and the Fit 2 method for determining first order lag plus delay models. Several of the output responses were more complex than a first order lag plus delay system. A few had an additional lead response or inverse response and one had a double lag, or second order, response. These were modeled using engineering judgment and comparison with the simulator output graphs. In many cases, the response to a positive step change was not the mirror image of a response to a negative step change indicating nonlinearity. The overall gains and time constants would vary slightly, because of the nonlinearity of the system. In these situations, the final values for the parameters in the linear model were the average of their values in both step responses.

Table 4-2 is a listing of the approximate linear transfer function models that relate the controlled variables to the two manipulative variables; sludge age and recirculation ratio. This approach gave the possibility of six different control pairing cases.

Table 4-2. Approximate Linear Transfer Functions Relating the Controlled Variables to the Manipulative Variables

		Manipulative Variables	
		Recirculation Ratio	Sludge Age
Controlled Variables	Effluent BOD	$\frac{0.093(1.77s+1)e^{-0.5s}}{(s+1)}$	$\frac{0.032e^{-0.5s}}{(10.25s+1)}$
	Effluent Ammonia	$\frac{0.00145(-55s+1)e^{-0.5s}}{(10.89s^2+3.63s+1)}$	$\frac{0.194(-12s+1)e^{-0.1s}}{(24.36s+1)}$
	Effluent Nitrate	$\frac{-1.9e^{-s}}{(3.2s+1)}$	$\frac{2.89e^{-0.5s}}{(9.1s+1)}$

As one can see, all the transfer functions are not first order lag plus delay. They contain more complex attributes, such as first order lead, inverse response, and second order lag. These types of responses are more difficult for a traditional PID based controller to handle effectively. Very conservative tuning of the PID controller would be required to render stability over a certain time range; but eventually, the system may still go unstable. Additional compensators, such as a Smith predictor for dead time and an inverse response compensator, need to be added (along with their additional tuning parameters) in addition to the PID based feedback controller for effective control and to enhance long term stability (Ogunnaike and Ray, 1994). Model based controllers, on the other hand, such as Internal Model Controllers (IMC), do not have the need for additional compensators, because they intrinsically include compensators for dead time and inverse response kinetics, and involve only a single tuning parameter, λ. Morari and Zafiriou

(1989) demonstrated how an IMC controller is equivalent to a PID controller with an additional first order lag filter in series with it. The mathematical calculations for this equivalency can be found in Appendix A.

It has long been common practice when controlling wastewater treatment plants to concentrate on manipulative variables of sludge age and recirculation ratio. Feed flow rate is a tempting alternative as a manipulative variable, but major manipulation of what is being fed to the plant is impractical from an industry point of view, because its use necessitates the use of an equalizer tank, an often expensive alternative. Therefore, this study employs only the sludge age and recirculation ratio as the manipulative variables to control effluent BOD, ammonia, or nitrate levels (two of the three). Since only two manipulative variables are used and there are three output variables (an under defined system), one of the output variables will be left "free" for each two-input two-output control configuration.

D. Comparison of the Linear Model to the Non-Linear Model

A major concern with linear modeling of a non-linear process is how well the linear model represents the non-linear model when more than one value is changing. For the linear model, the rule of superposition holds true. That is, the effect of two variables on the system is the sum of the effects of each individual variable alone on the system. For a non-linear model, this does not necessarily hold true. However, the linear model may give a reasonable approximation of the non-linear model within a certain narrow variation from the point of linearization. The degree of the ability of the linearized model to accurately represent the non-linear model was studied by varying the recirculation ratio and the sludge age in the open-loop linear model, and comparing the results to the same changes in the recirculation ratio and the sludge age in the open-loop non-linear model developed by Grove (1995).

Figure 4-1 is a graph of the responses of the non-linear and linear systems to a 50% change in the recirculation ratio (both positively and negatively). The linear response is shown by the lines (solid and dashed), while the non-linear response is shown by the X's and O's. The responses are similar. Figure 4-2 is a graph of the non-linear and linear system responses to a 50% change in sludge age (both positively and negatively). The qualitative aspects are similar, but the overall gains are somewhat different and the linear model may not be a reasonable approximation of the non-linear model. This is because the linear system gain was modeled utilizing the average gain of the system due to an increase and a decrease of the same magnitude in sludge age in the non-linear system. The two gains are not mirror images of each other. Consequently, the linear model will vary from the non-linear model.

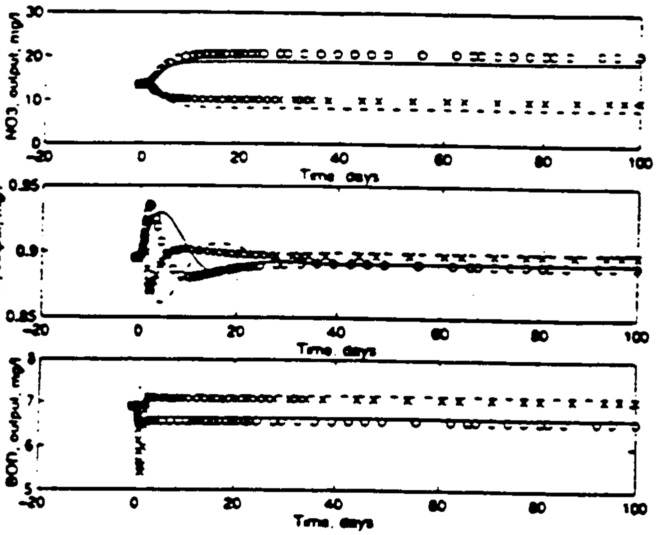

Figure 4-1. Linear and Non-Linear Responses to a 50% Change in Recirculation Ratio;
Positive Change in Recirc. Ratio: Linear Response, – – –; Non-Linear Response, x x x;
Negative Change in Recirc. Ratio: Linear Response, —; Non-Linear Response, o o o;

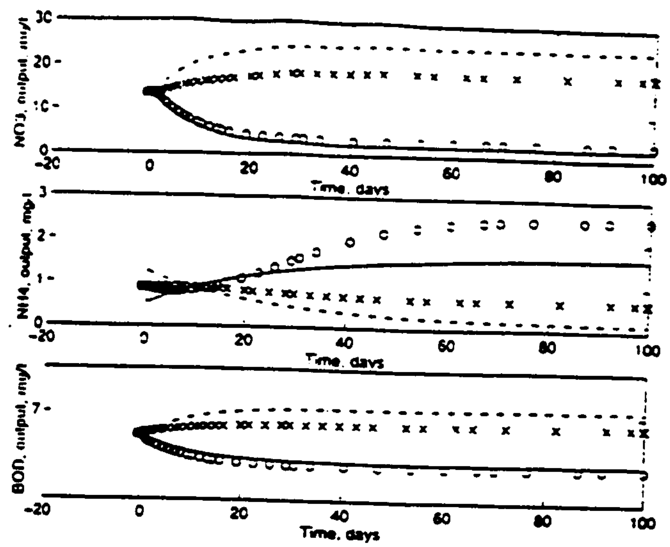

Figure 4-2. Linear and Non-Linear Responses to a 50% Change in Sludge Age; Positive Change in Sludge Age: Linear Response, – – –; Non-Linear Response, x x x; **Negative Change in Sludge Age:** Linear Response, —; Non-Linear Response, o o o;

When combining these two 50% changes in the recirculation ratio and the sludge age and introducing them to the open-loop linear and non-linear systems, it is seen in Figure 4-3 that the linear system response is the addition of the individual responses to a change in recirculation ratio and a change in sludge age. This is not necessarily the case for the non-linear system responses. As seen in Figure 4-2, there seems to be significant divergence between the nonlinear and linear systems whenever sludge age is varied by 50%. This also implies that the linear model may not be an acceptable approximation of the non-linear model, especially when the sludge age is varying 50% from its nominal value. The controllers would have to be detuned somewhat to accomodate this discrepancy, if the two manipulated variables do change by this much.

A larger change in the decrease of recirculation ratio and sludge age was implemented on the linear system and non-linear system and the differences between the responses become more evident than that for the 50% change. Figure 4-4 is a graph of the response to a 60% decrease in the sludge age and the recirculation ratio simultaneously for the linear system and the non-linear system. The overall new steady states are very divergent. This demonstrates that the results of the linear modeled system, as in this study, become even a poorer representative of the true system as the changes in the recirculation ratio and the sludge age approach and surpass a 50% change from their nominal steady state values. In the random disturbance simulations, this mainly occurred for large disturbances in feed flow rate and influent BOD.

E. Use of Relative Gain Array Analysis in Input-Output Pairing

The relative gain array (RGA) provides a measure of interaction among potential control loops for a MIMO system, based on system responses to selected perturbations from a nominal steady state (Bristol, 1966). By providing a measure of interaction between input variables and output variables in a plant, the RGA gives a control system designer a means by which the best pairings for a set of input and output variables can be chosen so as to minimize the interaction among the control loops. This may reduce the more complicated MIMO system into a simpler multiple SISO system with acceptable performance. The relative gain array had been in wide use for nearly thirty years, but is primarily an empirical tool, with little theoretical basis until recently (Grosdidier, *et al.*, 1985). The rows of the RGA correspond to the control (or output) variables, y_i (i.e row 1 corresponds to y_1). The columns of the RGA correspond to the manipulative (or input) variables, u_j (i.e. column 2 corresponds to u_2). The sum of each row and the sum of each

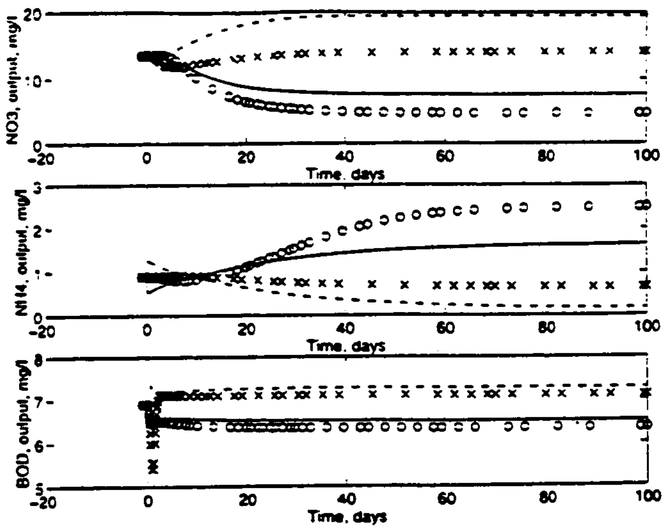

Figure 4-3. Linear and Non-Linear Responses to Simultaneous 50% Changes in Recirculation Ratio and Sludge Age;
Positive Changes: Linear Response, – – –; Non-Linear Response, x x x;
Negative Changes: Linear Response, —; Non-Linear Response, o o o;

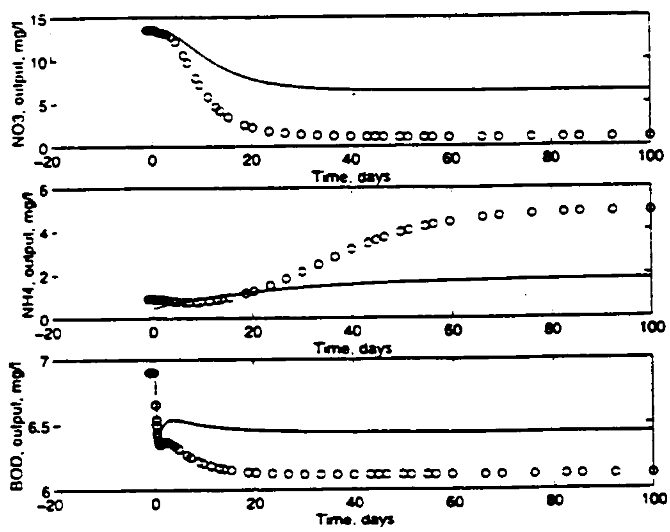

Figure 4-4. Linear and Non-Linear Responses to a Simultaneous 60% Negative Change in Recirculation Ratio and Sludge Age;
Negative Changes: Linear Response, —; Non-Linear Response, o o o;

column is equal to one. The ijth element is the ratio of the influence of the jth u on the ith y in the open loop to the closed-loop configuration. Therefore, the element in each ij position is similar to the percentage of influence that each particular u_j has on the corresponding y_i. It measures how much the impact of the jth u on the ith y changes when all other loops are closed. Thus, the nearer to one that element ij is, the more ideal the pairing of y_i and u_j, and the more decoupled the multiple SISO systems are.

The RGA was determined for all six different cases of possible pairings between the two manipulative variables and the three controlled variables. It was determined that three pairings out of the six were more ideal. Ideal implies that they were almost completely decoupled. This is logical because the three rejected pairings are the opposite of the three accepted pairings; thus they were almost completely coupled. The three accepted cases are in Table 4-3 along with their corresponding RGAs. Therefore, these three cases are chosen for further simulation in subsequent control studies.

F. Controller Design

After selecting pairings, two separate decoupled SISO controllers must be designed and tuned for each of the cases. The PID based controllers will be discussed first, because they are the most widely used and they do not differ in structure. They are only different in the tuning of their parameters.

1. Proportional-Integral (PI) Controller

Derivative control is not being added, because the response of the system is expected to be noisy with little error. This would cause the controller to compute large derivatives and thus yield large and rapidly changing control action, although it is not needed. This results in a two parameter PI controller. The structure of a PI controller G_C, in Laplace form is shown below in equation 4-1.

$$G_c = K_c\left(1+\frac{1}{\tau_I s}\right) \tag{4-1}$$

Table 4-3. Accepted Pairings and Corresponding Relative Gain Arrays

	Pairing (Manipulative-Control)	**RGA**
Case I	Recirc. Ratio-Effl. BOD and Sludge Age-Effl. Ammonia	$\begin{bmatrix} 0.997 & 0.003 \\ 0.003 & 0.997 \end{bmatrix}$
Case II	Recirc. Ratio-Effl. BOD and Sludge Age-Effl. Nitrate	$\begin{bmatrix} 0.822 & 0.178 \\ 0.178 & 0.822 \end{bmatrix}$
Case III	Sludge Age-Effl. Ammonia and Recirc. Ratio-Nitrate	$\begin{bmatrix} 1.012 & -0.012 \\ -0.012 & 1.012 \end{bmatrix}$

where the tuning parameters are the controller gain, K_C, and the integral time constant τ_I. Initial tuning for each controller was done using Ziegler-Nichols tuning rules as discussed in Chapter Three. Smaller values of K_C and larger values of τ_I make the system more robust but sluggish (i.e. more stable, but less responsive). Larger values of K_C and smaller values of τ_I make the system more responsive to perturbations, but the stability margin is compromised. The Ziegler-Nichols tuning rules give a first estimate of the tuning parameters, but additional fine tuning may be necessary to make the system more or less robust, and to better simulate the desired output effect in response to anticipated perturbations. This fine tuning is to be determined using the μ-Interaction Measure and time domain simulations, in order to take into consideration the inter-loop interactions.

2. Internal Model Controller (IMC)

IMC based controllers differ from PID in basic structure. Discussion of how IMC controller is developed from the system model is found in Chapter Three. Differences among the detailed IMC controllers occur when the system transfer functions differ (i.e. the presence or lack of dead time, inverse response, etc.). However, there is only one tuning parameter associated with each IMC control loop. This is in direct contrast to two for the PI and three for the PID loop. For a first order lag plus delay system (such as the recirculation ratio-effluent nitrate pairing of Case III), the IMC controller q, has the general form:

$$q = \frac{\tau s + 1}{K(\lambda s + 1)} \tag{4-2}$$

where K and t correspond to the system gain and time constant and the only tuning parameter is λ.

The presence of an inverse response (a right half plane zero) to the first order lag plus delay system (as seen in the sludge age-effluent ammonia pairing of Case III) adds an additional pole to the IMC controller. Its value is fixed in the left half plane and corresponds to the mirror image of the right half plane zero. Once again, the only tuning parameter is λ.

$$q = \frac{\tau s + 1}{K(\lambda s + 1)(ps + 1)} \tag{4-3}$$

The presence of a lead response (a left half plane zero) to the first order lag plus delay system transfer function (such as in Case I with the recirculation ratio-effluent BOD pairing) is similar to adding an inverse response. However, the additional pole is equivalent to (and not the mirror image of) the zero of the system transfer function. There is only one tuning parameter, λ.

$$q = \frac{\tau s + 1}{K(\lambda s + 1)(ps + 1)} \tag{4-4}$$

Initial tuning was done according to guidelines summarized by Ogunnaike and Ray (1994) and discussed earlier in Chapter Three. The larger the value of λ, the more robust but sluggish the system. The lower the value of λ, the more responsive but less stable the system. As always, the controller performance is traded off against overall stability of the system. Once again, additional fine tuning may be necessary. This will be discussed along with the μ-Interaction Measure and time domain simulations.

Additional controller tuning is generally required to take care of the effects of inter-loop interaction, such that long term closed-loop stability can be achieved. The μ-Interaction Measure (Morari, *et al.*, 1987) provides a quantitative measure to guide the systematic fine tuning of the decentralized controller so as to render long term system stability.

G. μ-Interaction Measure in Fine Tuning of Decentralized Controller

The μ-Interaction Measure is a concept developed by Grosdidier and Morari (1987) to measure the closed-loop interaction and stability of a controlled system H(s) characterized by its closed-loop. It is a measure in the frequency domain of the lowest possible upper bound for stable operation of a system and all of its possible configurations due to perturbations and disturbances. This boundary line is referred to as mu-inverse (μ^{-1}). The system's closed-loop transfer function, H(s) must lie beneath this upper bound in the frequency domain to guarantee stability for the full multivariable closed-loop system. If the system H(s) violates the μ^{-1} boundary, the controller can usually be conservatively detuned (made more robust) by appropriately changing the tuning parameters, until the system lies below the μ^{-1} boundary, unless significant dead time and/or inverse response are present in the process dynamics.

Generic PID based controllers usually have difficulties with systems that contain inverses, leads, and dead times, which add 'zeros' to the numerator of the system transfer function. In these instances, the system H(s) may violate the μ^{-1} boundary in the high frequency range, and it is impossible to correct by manipulating only K_C and τ_I. The violation is due to the effects of the added terms in the numerator which keep the plot of H(s) from mimicking the "rolling off" characteristic that the μ^{-1} boundary has at high frequencies. One of the ways for PID controllers to guarantee closed-loop stability with these systems is to add additional lag filters that will counteract the ill effects of inverses and dead times. Of course, this would involve the tuning of additional filter parameters. The addition of first order lag filters force the frequency plot of the system to lie below the μ^{-1} boundary at all frequencies; thus guaranteeing stability. On the other hand, IMC based controllers do not have this problem. All model based controllers inherently contain dead time as well as inverse response compensators, because model based controllers are designed based on the process model dynamics. For IMC control, these compensators are inclusive in the single tuning parameter, λ. The μ-Interaction Measure test was applied to all three cases for both PID and model based controlled systems. The results are presented below.

1. Case I

This is the case where recirculation ratio and sludge age are used to control effluent BOD and effluent ammonia concentrations, respectively, and effluent nitrate concentration is the free variable. In the first loop of the system, $h^1(s)$, the manipulative variable is recirculation ratio and the controlled variable is effluent BOD. In the second loop of the system, $h_2(s)$, the manipulative variable is sludge age and the controlled variable is effluent ammonia. Figures 4-5 and 4-6 are frequency graphs for the μ-interaction of Case I for systems with PI and IMC controllers, respectively. The failure of the PI controller to compensate for the complexity of the system is clearly visible at high frequency. In contrast, the IMC controller yields a stable system.

Figure 4-7 is a frequency graph depicting the effect when additional lag filters are implemented in series with the PI controllers in order to compensate for the high frequency failings of the PI controller alone.

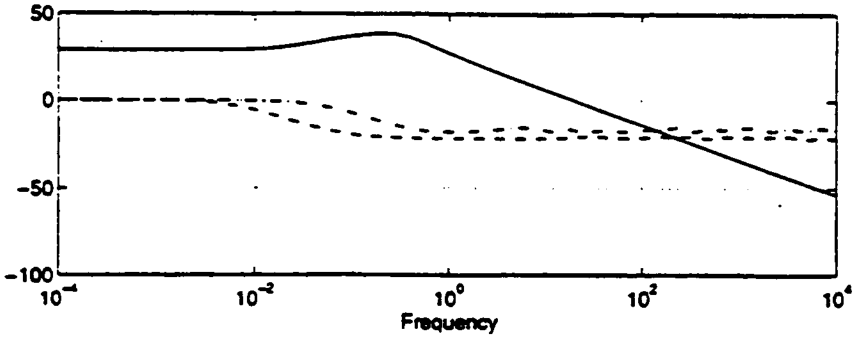

Figure 4-5. Frequency Response of μ-Interaction for Case I with PI Controllers;
μ^{-1}, — ; loop 1, —·— ; loop 2, - - -

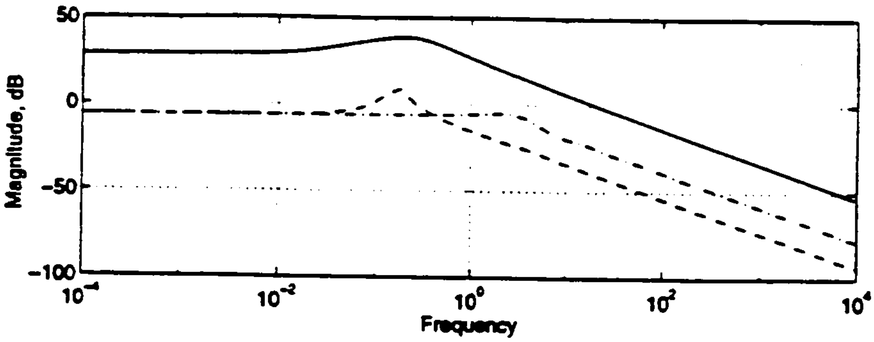

Figure 4-6. Frequency Response of μ-Interaction for Case I with IMC Controllers;
μ^{-1}, — ; loop 1, —·— ; loop 2, - - -

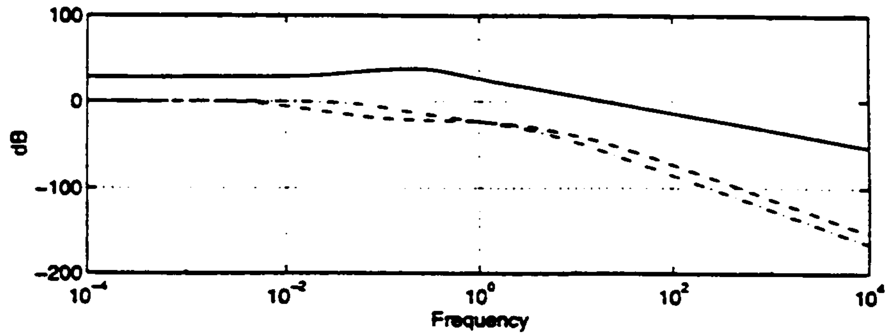

Figure 4-7. Frequency Response of μ-Interaction for Case I with PI Controllers plus Compensating Filters in Each Loop; μ^{-1}, — ; loop 1, —·— ; loop 2, - - -

2. Case II

The first loop $h_1(s)$, in Case II is the same as that in Case I, recirculation ratio is paired with effluent BOD. The second loop $h_2(s)$ still has sludge age as the manipulative variable, but now it is paired with effluent nitrate and the free variable is now effluent ammonia. Figures 4-8 and 4-9 are the frequency plots for the μ-interaction of Case II with PI alone and IMC controllers, respectively. Once again, in the system with PI controllers, additional filters are needed to compensate at the high frequency violation of the μ^{-1} boundary, in order to render the closed-loop system stable.

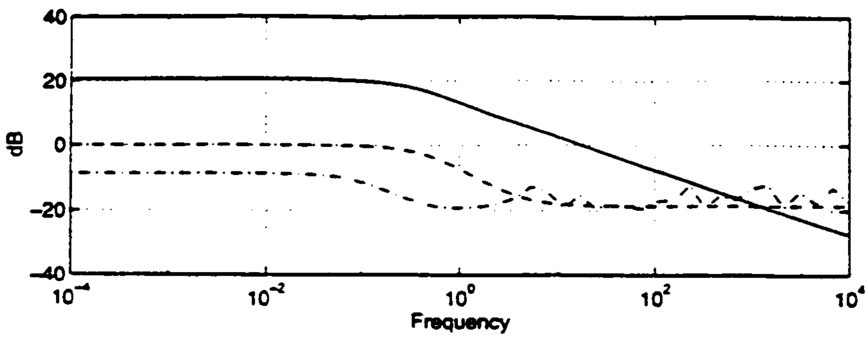

Figure 4-8. Frequency Response of μ-Interaction for Case II with PI Controllers;
μ^{-1}, — ; loop 1, -·- ; loop 2, - - -

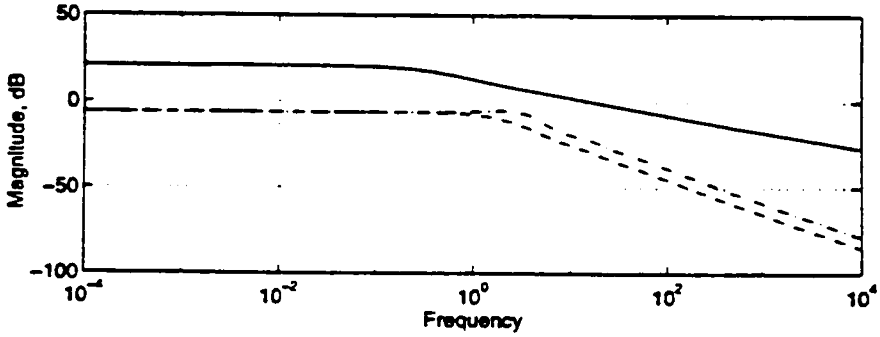

Figure 4-9. Frequency Response of μ-Interaction for Case II with IMC Controllers;
μ^{-1}, — ; loop 1, -·- ; loop 2, - - -

3. Case III

In this case, effluent BOD is now the free variable. Effluent ammonia is controlled in the first loop $h_1(s)$, by manipulating the sludge age, and the second loop $h_2(s)$, controls effluent nitrate by manipulating the recirculation ratio. Figures 4-10 and 4-11 are the frequency responses for Case III with PI and IMC controllers, respectively. The inadequacy of the PI controllers without additional filters is obvious.

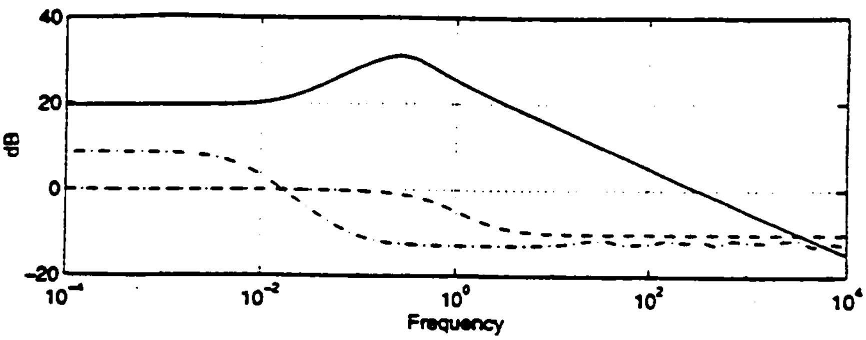

Figure 4-10. Frequency Response of μ-Interaction for Case III with PI Controllers; μ^{-1}, — ; loop 1, -·- ; loop 2, - - -

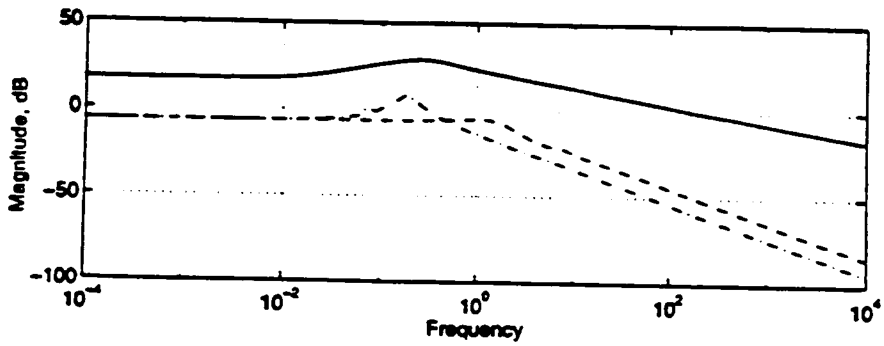

Figure 4-11. Frequency Response of μ-Interaction for Case III with IMC Controllers; μ^{-1}, — ; loop 1, -·- ; loop 2, - - -

H. Servo Control and Regulator Control

Once the controllers are fine tuned using the μ-Interaction Measure so that the system's closed-loop transfer function, H(s) lies below the μ^{-1} boundary or, in the cases with PI controllers, so that the system, H(s) lies below the boundary at lower frequency; then the control system can be considered from the point of view of its ability to handle either of two types of situations. In the first situation, referred to as the servomechanism-type (or servo) problem, it is assumed that there is no change in the load (or disturbances) and that one is interested in changing the monitored effluent concentrations (Coughanowr, 1991). For this problem, the setpoint of the controlled variable would be changed in accordance with the desired variance in the controlled variable. The second situation is the regulator problem. In this case, the desired setpoint value is to remain fixed and the purpose of the control system is to maintain the controlled variable at this desired setpoint in spite of changes in the load (disturbances) (Coughanowr, 1991). In the time domain simulations, to be presented below, additional fine tuning was done to achieve more satisfactory results. Examples of more satisfactory behavior are the decrease of oscillatory behavior and/or the reduction of overshoot.

1. Servo Control (Setpoint Tracking)

The majority of problems that may be simulations described as the servo type come from fields other than the chemical industry (Coughanowr, 1991), but it is critical to operate the wastewater treatment plant within the acceptable limits of many constraints. The controller system needs the ability to accurately track setpoints for effluent discharge concentrations. If at some point during operation, the output concentrations were running high, then it would be necessary to permanently lower the setpoint for the effluent concentration value to meet specified discharge constraints, such as the weekly concentration average of nitrate discharge. This document reports simulation results of 25% reductions from the nominal steady state value in the setpoints of all three output variables for each of the three pairing cases.

a. Case I

This is the case where effluent BOD and effluent ammonia concentrations are controlled by recirculation ratio and sludge age, respectively, and effluent nitrate concentration is the free variable. The nominal steady state value of effluent ammonia is 0.89 mg/l (reported by Grove, 1995) and a 25% setpoint reduction in this value would ideally bring the new steady state value to 0.67 mg/l. A 5% reduction in the steady state effluent BOD value lowers the setpoint from 6.90 mg/l to 6.56 mg/l. Figure 4-12 is a plot of the input variables u_i, and the output variables y_i, after a setpoint change in BOD (loop 1) at time, t=10 days, for the PI controlled system. Figure 4-13 is a plot of a setpoint change in BOD at time, t=10 days, for the IMC controlled system. Where the IMC controlled system is stable, the PI controlled system begins to become unstable after a period of time. However, a few cautions should be noted. A desired setpoint change of over -5% of nominal in BOD is never fully reached because the manipulative variable for the loop (recirculation ratio) "bottoms out" at a value of zero (i.e. it becomes a total outflow with zero recirculation). This agrees with the steady state gain associated between the two variables (gain = 0.07 for every 1 percent change in input, u) which calls for a drastic change in recirculation ratio to achieve a moderate change in effluent BOD. The maximum amount of reduction in effluent BOD that can be achieved by using

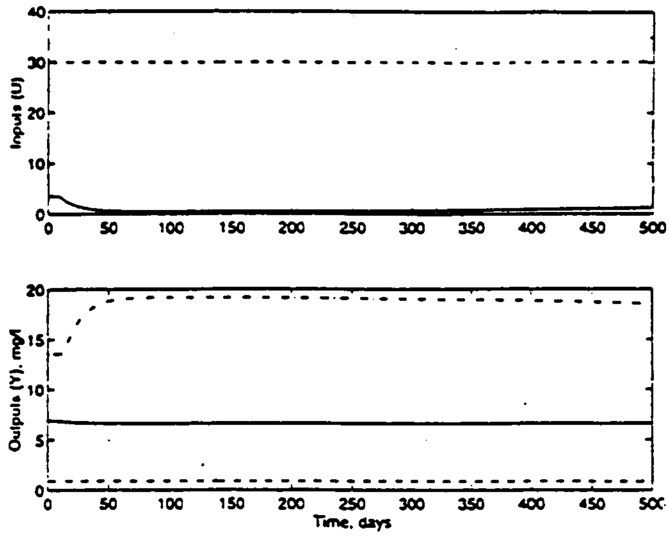

Figure 4-12. PI Based Servo Control for a Setpoint Change in Effluent BOD (I);
(a) Inputs: recirculation ratio, —; sludge age, – – –;
(b) Outputs: BOD, —; $[NH_4^+]$, – – –; $[NO_3^-]$, –·–·

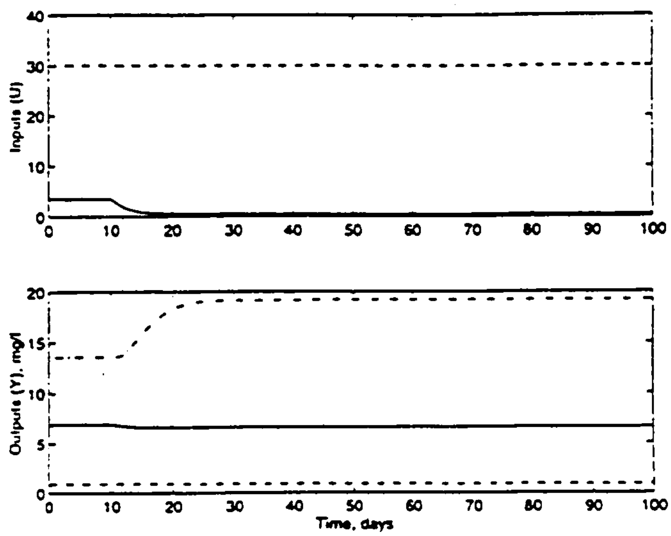

Figure 4-13. IMC Based Servo Control for a Setpoint Change in Effluent BOD (I);
(a) Inputs: recirculation ratio, —; sludge age, – – –;
(b) Outputs: BOD, —; $[NH_4^+]$, – – –; $[NO_3^-]$, –·–·

recirculation ratio as the control variable is approximately 7%, or a drop from 6.90 mg/l to 6.42 mg/l. Tracking of the effluent ammonia setpoint is easily achieved, as will be shown next.

Figure 4-14 is a plot of the input variables and the output variables after a -25% setpoint change in ammonia (loop 2) at time, t=10 days, for the PI controlled system. The system remains stable for a limited time span, and then it proceeds to instability. This is due to the "nasty" characteristics of the system dynamics, such as inverse response in loop 2 and dead time in both loops. A more conservative tuning of the system would make it more robust, thus stabilizing it for a longer time period. However, without the addition of compensating filters, it will eventually become unstable. Figure 4-15 is a time simulation plot of the input variables and the output variables after a -25% setpoint change in ammonia at time, t=10 days, for the IMC controlled system. The output graph is displayed as a deviation from normal steady state in mg/l in order to better display the -25% change in effluent ammonia. In contrast to the PI controlled system, the IMC controlled system is stable in the long term. Figure 4-16 is a time simulation plot of the PI controlled system with added first order lag filters undergoing a setpoint change in effluent ammonia (loop 2). The system is now stable (in contrast to that shown in Figure 4-13) and, as can be seen, corresponds similarly with the response to the same setpoint change in the IMC controlled system. Again, this illustrates that when the process dynamics exhibit dead time and inverse response characteristics, the intrinsic IMC controller designed for it is equivalent to a PID controller with an additional filter added. The IMC still has just one tuning parameter, whereas the PID would have four parameters per loop to be tuned in accordance with each other.

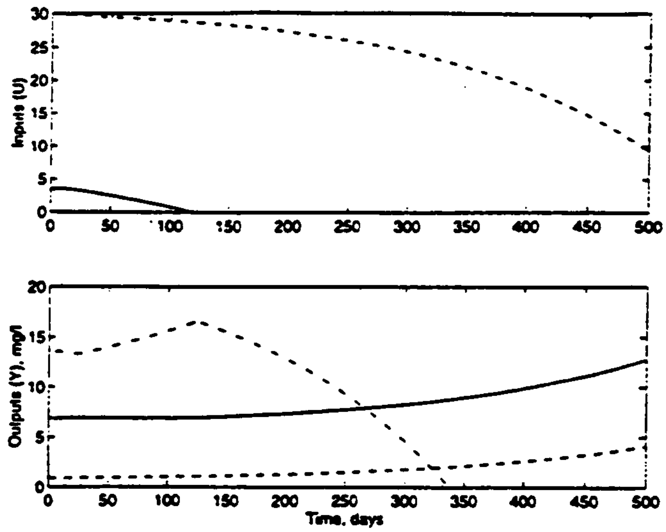

Figure 4-14. PI Based Servo Control for a Setpoint Change in Effluent Ammonia (I);

(a) Inputs: recirculation ratio, — ; sludge age, - - - ;

(b) Outputs: BOD, — ; $[NH_4^+]$, - - -; $[NO_3^-]$, -·-·

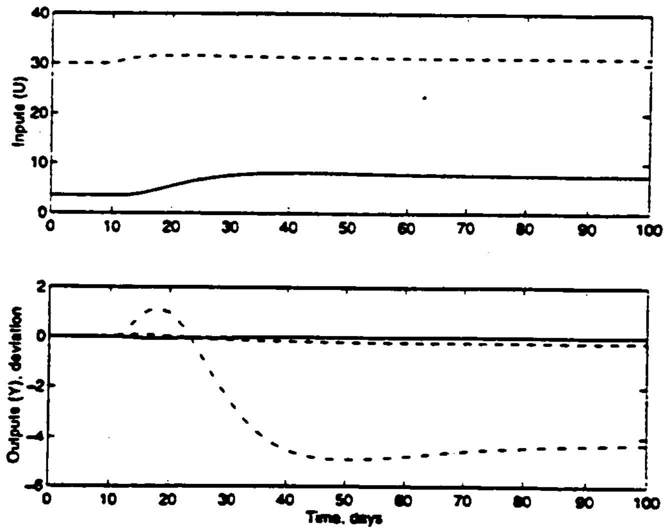

Figure 4-15. IMC Based Servo Control for a Setpoint Change in Effluent Ammonia (I);

(a) Inputs: recirculation ratio, — ; sludge age, - - -;

(b) Outputs: BOD, — ; $[NH_4^+]$, - - -; $[NO_3^-]$, -·-·

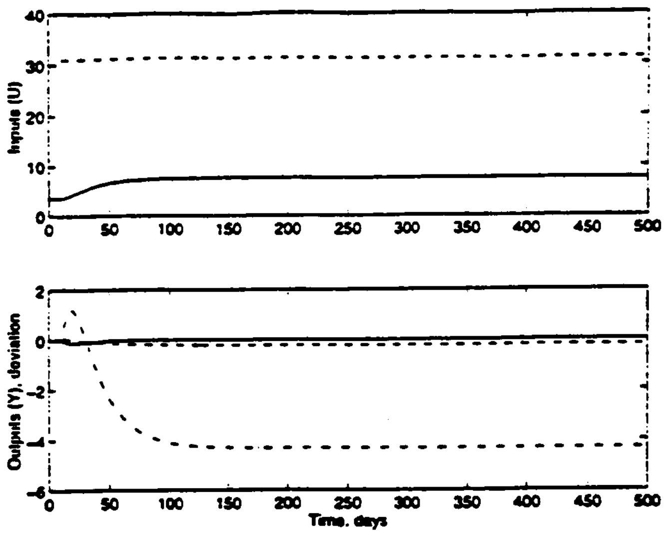

Figure 4-16. PI Based with Additional Filters Servo Control for a Setpoint Change in Effluent Ammonia (I);
(a) Inputs: recirculation ratio, — ; sludge age, - - -;
(b) Outputs: BOD, — ; $[NH_4^+]$, - - -; $[NO_3^-]$, -•-•

b. Case II

This is the case where recirculation ratio and sludge age are used to control effluent BOD and effluent nitrate, respectively, and effluent ammonia is the free variable. Once again, a 5% reduction in the steady state effluent BOD value should lower the setpoint from 6.90 mg/l to 5.56 mg/l. Figure 4-17 is a plot of the input variables u_i, and the output variables y_i, after a -5% setpoint change in BOD (loop 1) introduced at time, t=10 days, for the PI control system. The system remains stable for a lengthy time span because there is no inverse response exhibited in the closed-loop process dynamics. The "nasty" characteristics consist of only dead time in both loops and a lead response in loop 2. A more conservative tuning of the system would make it more robust, thus stabilizing it for an even longer time period, but still, without the addition of compensating filters, it may eventually go unstable under certain circumstances. Figure 4-18 is a plot of the input and output variables after a -5% setpoint change in BOD (loop 1) introduced at time, t=10 days, for the IMC controlled system. This is a stable but sluggish system.

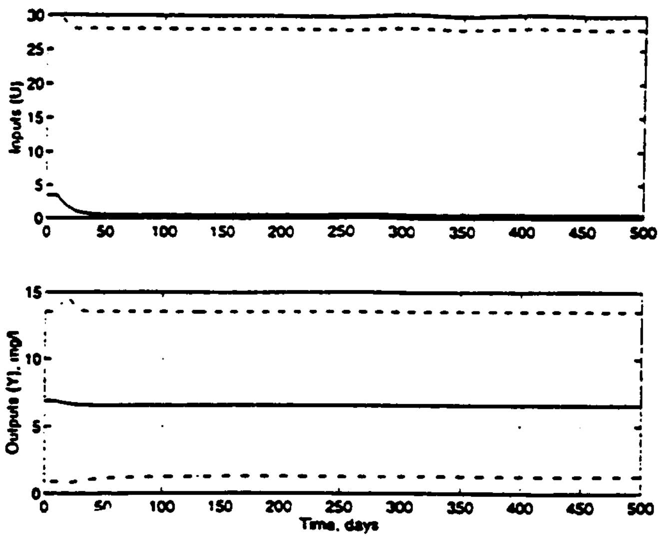

Figure 4-17. PI Based Servo Control for a Setpoint Change in Effluent BOD (II);
(a) Inputs: recirculation ratio, — ; sludge age, - - -;
(b) Outputs: BOD,— ; [NO_3^-],- - -; [NH_4^+], -·-

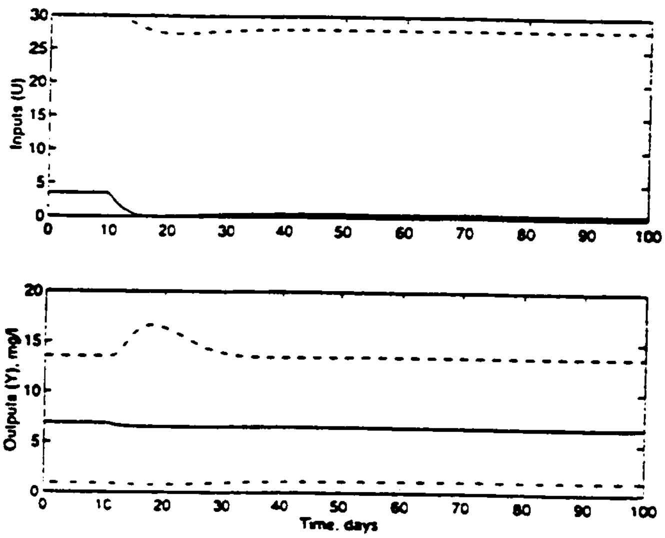

Figure 4-18. IMC Based Servo Control for a Setpoint Change in Effluent BOD (II);
(a) Inputs: recirculation ratio, — ; sludge age, - - -;
(b) Outputs: BOD,— ; [NO_3^-],- - -; [NH_4^+], -·-

Figure 4-19 is a plot of the input variables and the output variables after a -25% setpoint change in nitrate (loop 2) at time, t=10 days, for the PI controlled system. As seen in Figure 4-17, the system remains stable for a very lengthy time span because there is no inverse response exhibited in the closed-loop process dynamics. The "nasty" characteristics consist of only dead time in both loops and a lead response in loop 2. A more conservative tuning of the system would make it more robust, thus stabilizing it for an even longer time period, but still, without the addition of compensating filters, it may eventually go unstable under certain circumstances as depicted earlier from the μ-Interaction Measure test (see Figure 4-8). Figure 4-20 is a plot of the input and output variables after a -25% setpoint change in effluent nitrate (loop 2) introduced at time, t=10 days, for the IMC controlled system. Unlike the plot of the PI controlled system, this plot has long term stability.

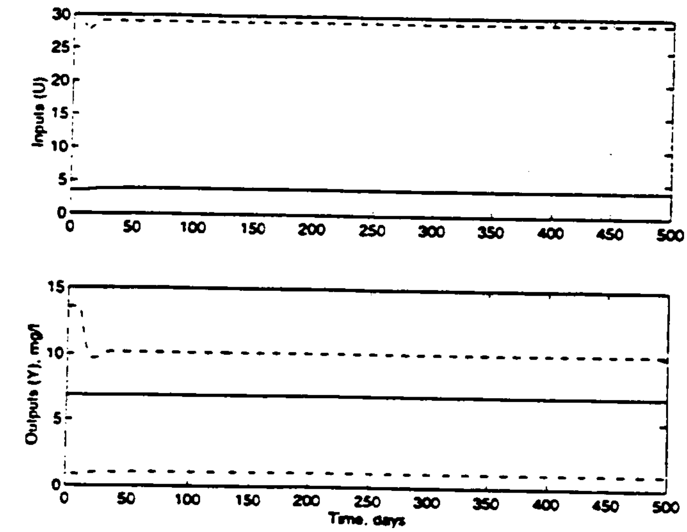

Figure 4-19. PI Based Servo Control for a Setpoint Change in Effluent Nitrate (II);
(a) Inputs: recirculation ratio, — ; sludge age, – – –;
(b) Outputs: BOD,— ; $[NO_3^-]$,– – –; $[NH_4^+]$, –•–

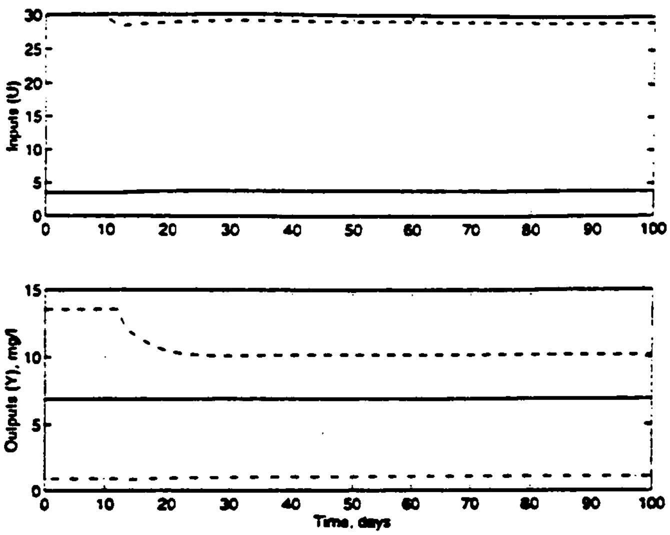

Figure 4-20. IMC Based Servo Control for a Setpoint Change in Effluent Nitrate (II);
(a) Inputs: recirculation ratio, — ; sludge age, – – –;
(b) Outputs: BOD,— ; [NO3⁻],– – –; [NH4⁺], –·–·

c. Case III

This case involves using sludge age and recirculation ratio to control effluent ammonia and effluent nitrate, respectively, with effluent BOD as the free variable. Figure 4-21 is a plot of the input variables u_i, and the output variables y_i, after a -25% setpoint change in ammonia (loop 1) introduced at time, t=10 days, for the PI controlled system. The overall long term stability of the system is compromised by the inclusion of inverse response and dead time in the system process dynamics. Additional lag filters would be needed along with the PI controller in order to remedy the situation. Figure 4-22 is a plot of the input and output responses after the same -25% setpoint change in ammonia is introduced at time, t=10 days, for the IMC controlled system. The ouput graph is in deviation from steady state in mg/l. As opposed to the PI controlled system, this clearly is a stable system.

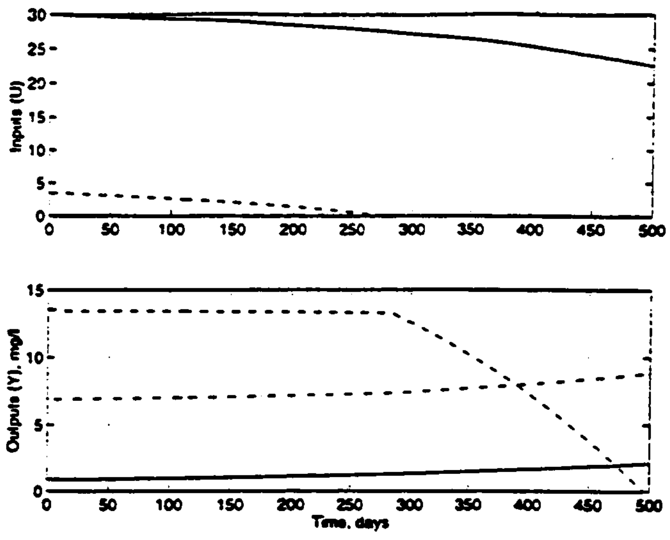

Figure 4-21. PI Based Servo Control for a Setpoint Change in Effluent Ammonia (III);

(a) Inputs: sludge age, — ; recirculation ratio, – – –;

(b) Outputs: $[NH_4^+]$,— ; $[NO_3^-]$,– – –; BOD, -·-·

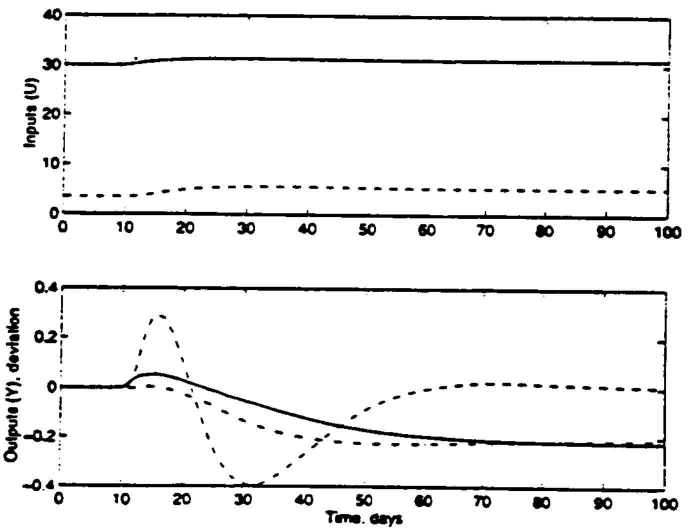

Figure 4-22. IMC Based Servo Control for a Setpoint Change in Effluent Ammonia (III);

(a) Inputs: sludge age, — ; recirculation ratio, – – –;

(b) Outputs: $[NH_4^+]$,— ; $[NO_3^-]$,– – –; BOD, -·-·

Figure 4-23 is a plot of the input variables and the output variables after a -25% setpoint change in nitrate (loop 2) at time, t=10, for the PI controlled system. As in the other cases, the PI controlled system remains stable for a limited time span, and then it begins to proceed to go unstable after a lengthy time period. This is because of the introduction of an inverse response in the first loop (sludge age-effluent ammonia) in addition to the dead time in both loops. In contrast, Figures 4-24 is a plot of the input and output variables after setpoint changes in nitrate, for the IMC control system. This clearly is a stable system, but sluggish.

2. Regulator Control (Disturbance Rejection)

Contrary to servo control, regulator control is very common in the chemical industry (Coughanowr, 1991), and it is a major concern for the wastewater treatment plant. Since several parameters in the chemical industry, such as flow rate and inlet concentrations, are expected to vary depending on up stream conditions. Inputs can also vary when the nature of the waste vary from batch to batch and process to process. It is highly desirable for the control system to have the ability to compensate for these disturbances and to still maintain outputs at the desired setpoint values. Studies reported here also include results of introducing percentage increases in the nominal steady state inlet values of feed flow rate, ammonia concentration, and nitrate concentration for each of the three pairing cases. Only a small disturbance in the feed flow rate was introduced in all three cases (about 6%) in order to try and keep zero recirculation from occurring. There tends to be a small mathematical anomaly in the outputs when this disturbance is introduced. The outputs tend to display small little spikes periodically throughout the simulation. This is most likely due to the inter-loop interactions and the mathematical calculations used in the Simulink package of Matlab.

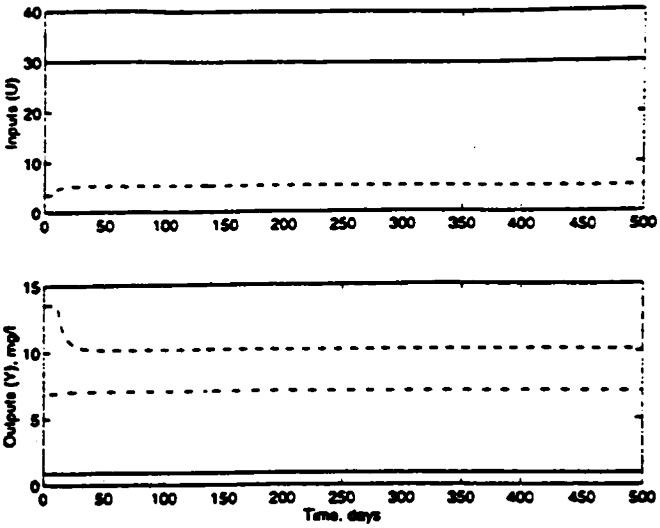

Figure 4-23. PI Based Servo Control for a Setpoint Change in Effluent Nitrate (III);
(a) Inputs: sludge age, — ; recirculation ratio, – – –;
(b) Outputs: [NH_4^+],— ; [NO_3^-],– – –; BOD, –•–•

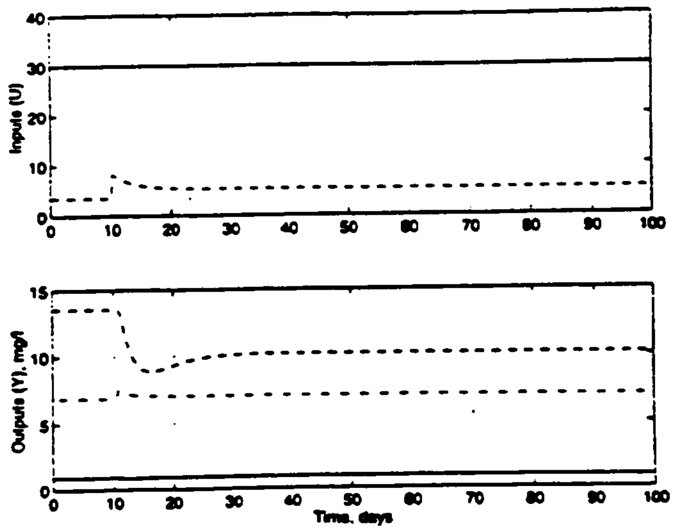

Figure 4-24. IMC Based Servo Control for a Setpoint Change in Effluent Nitrate (III);
(a) Inputs: sludge age, — ; recirculation ratio, – – – ;
(b) Outputs: [NH_4^+],— ; [NO_3^-],– – –; BOD, –•–•

a. Case I

In this case, recirculation ratio and sludge age are used to control effluent BOD and effluent ammonia, respectively, and effluent nitrate is a free variable. The nominal steady state value of influent flow rate is 5,450,000 liters/day and a 6% increase in this value would result in a feed flow rate of 5,777,000 liters/day. Any disturbance significantly higher results in zero recirculation, thus a higher new steady state value of effluent BOD, along with a greater display of the aforementioned anomaly. Figure 4-25 is a plot of the input variables u_i, and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with PI controllers. As with servo control with the PI control systems, the system is initially stable, but begins to go unstable after a lengthy period of time. Figure 4-26 is a plot of the input variables u_i, and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with IMC controllers. The system is stable as guaranteed by the μ-Interaction Measure. The BOD effluent is controlled rather well, though a drastic change is not expected because of the small disturbance. The ammonia effluent at first deviates from its original steady state, but eventually returns to it. The "free" effluent nitrate increases to a higher steady state. This is due to the opposing action between recirculation ratio and nitrate.

The second disturbance introduced was that of a 15% step increase in influent ammonia. The nominal inlet concentration of ammonia is 300 mg/l and a 15% increase would step this value to 345 mg/l. Figure 4-27 is a plot of the input variables and the output variables after a 15% disturbance perturbation in ammonia introduced at time, t=10 days, for the PI control system. As it can be seen, the system remains stable for a limited time span, and then it proceeds to become unstable. This is due to the "nasty" characteristics of the system, such as inverse response in the first loop and dead time in both loops. A more conservative tuning of the system would make it more robust, thus stabilizing it for a longer time period, but without the addition of compensating filters, it

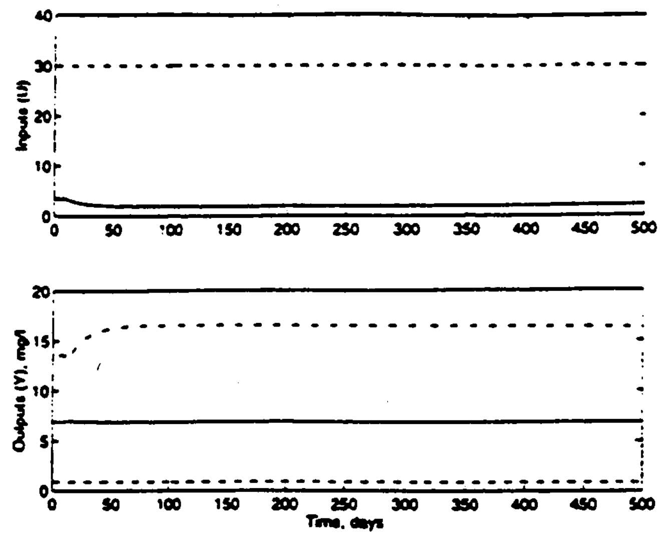

Figure 4-25. PI Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case I;

(a) Inputs: recirculation ratio, — ; sludge age, - - -;

(b) Outputs: BOD,— ; $[NH_4^+]$, - - - ; $[NO_3^-]$, -•-•

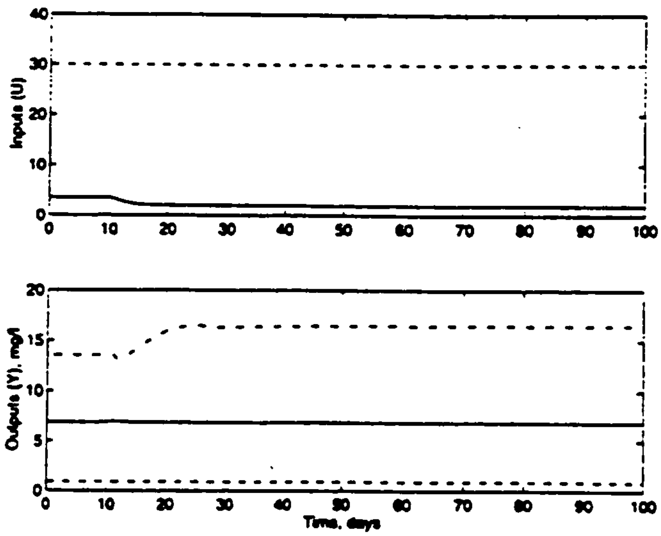

Figure 4-26. IMC Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case I;

(a) Inputs: recirculation ratio, — ; sludge age, - - -;

(b) Outputs: BOD,— ; $[NH_4^+]$, - - - ; $[NO_3^-]$, -•-•

will eventually go unstable. Figure 4-28 is that of the same system under the same disturbance perturbation and having the same PI controller tuning, but compensatory filters have been added. As you can see, the system is now stable. However, the nitrate level settles toward a much higher steady state, because the first step in ammonia degradation is conversion to nitrate and the nitrate is uncontrolled. This compensated PI controlled system is similar to that of the IMC controlled system, whose response to the same ammonia disturbance introduced at time, t=10 days, is shown in Figure 4-29. Once again, the two controlled variables, effluent BOD and effluent ammonia, are regulated by the controllers at their original steady state value, but nitrate emissions increase to a higher steady state value.

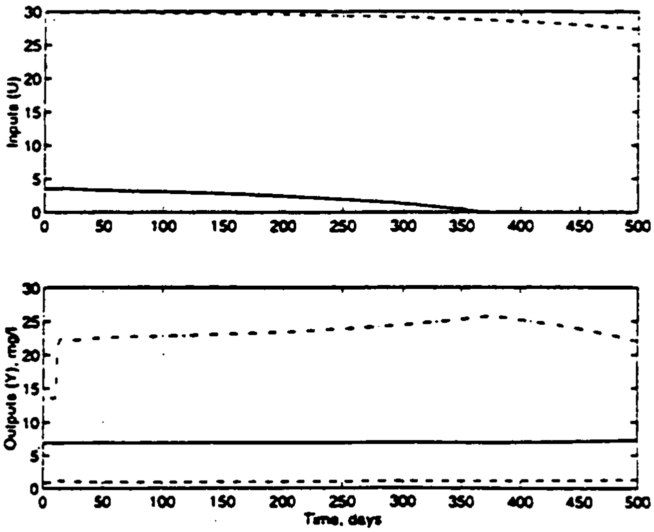

Figure 4-27. PI Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case I;
(a) Inputs: recirculation ratio, —; sludge age, - - -;
(b) Outputs: BOD,—; [NH_4^+], - - -; [NO_3^-], -·-

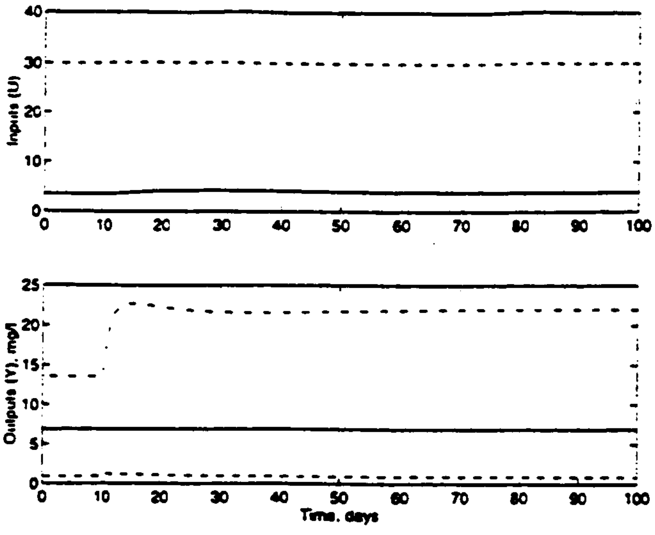

Figure 4-28. IMC Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case I;

(a) Inputs: recirculation ratio, — ; sludge age, - - -;

(b) Outputs: BOD,— ; $[NH_4^+]$, - - - ; $[NO_3^-]$, -·-

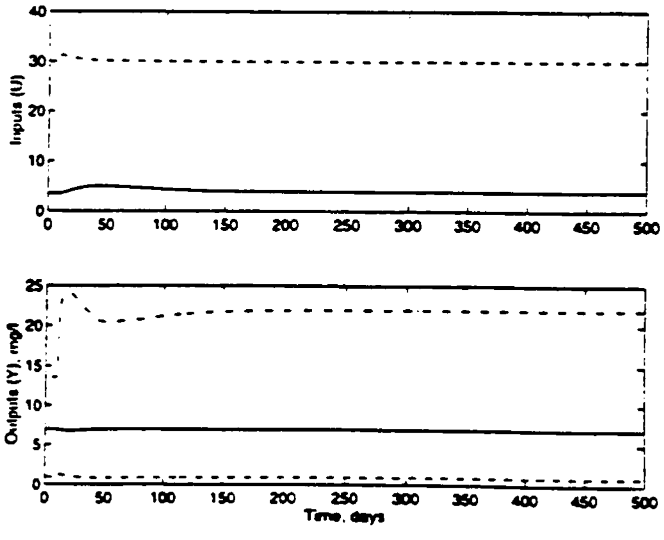

Figure 4-29. PI Based with Compensating Filters Regulator Control for a 15% Disturbance in Influent Ammonia for Case I;

(a) Inputs: recirculation ratio, — ; sludge age, - - -;

(b) Outputs: BOD,— ; $[NH_4^+]$, - - - ; $[NO_3^-]$, -·-

Figure 4-30 is that of the input and output variables in response to a 10% disturbance in the influent nitrate concentration introduced at time, t=10 days, for the PI controlled system. The nominal value of the influent nitrate is 1000 mg/l. This pairing configuration of the plant is such that this disturbance leads to a more stable response than the other two disturbances; but it still eventually goes unstable. This supports the claim that when the μ-Interaction criteria is violated, then PI control alone for the plant may cause severe instability in the long run, for some configurations, while other configurations may only lead to moderate instability or may even maintain stability. However, there always will be the potential for instability when the μ-Interaction criteria is violated by the presence of inverse and significant dead time process kinetics. In contrast, Figure 4-31 is that of the input and output variables in response to a 10% disturbance in the influent nitrate concentration for the IMC controlled system. As with the case of the ammonia disturbance for the IMC controlled system, and contrary to the PI controlled system, the two controlled variables are regulated to their original steady state values and the "free" effluent nitrate approaches a lower steady state value, because the recirculation ratio increases.

b. Case II

This case involves using recirculation ratio and sludge age to control effluent BOD and effluent nitrate, respectively, and effluent ammonia is the free variable. Figure 4-32 is a plot of the input variables u_i and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with PI controllers. The system is fairly stable, because there is no inverse response in either of the control loops, but over time, and/or under certain disturbance, it may become unstable. This demonstrates how the μ-Interaction Measure test allows one to see if a system has the potential to become unstable, without informing when or under what circumstances the system will become unstable. However, the potential for instability is always there. Figure 4-33 is a plot of

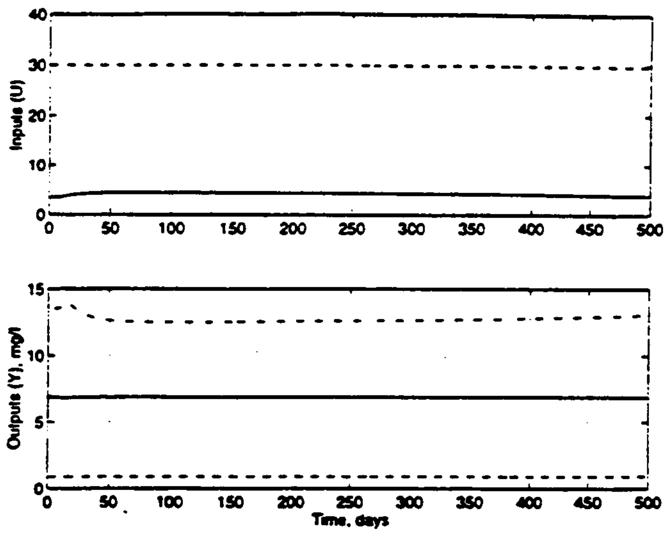

Figure 4-30. PI Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case I;

(a) Inputs: recirculation ratio, — ; sludge age, - - -;

(b) Outputs: BOD,— ; [NH_4^+], - - - ; [NO_3^-], -·-

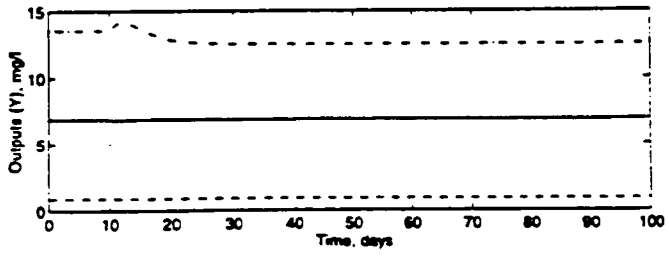

Figure 4-31. IMC Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case I;

(a) Inputs: recirculation ratio, — ; sludge age, - - -;

(b) Outputs: BOD,— ; [NH_4^+], - - - ; [NO_3^-], -·-

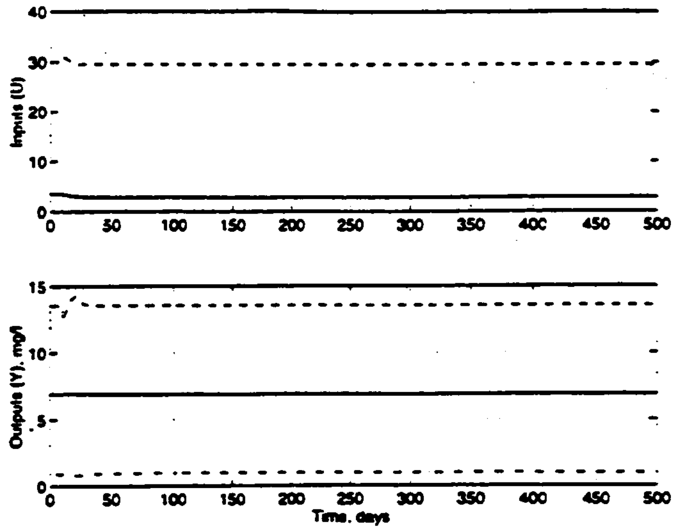

Figure 4-32. PI Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case II;

(a) Inputs: recirculation ratio, — ; sludge age, - - - ;

(b) Outputs: BOD, — ; $[NO_3^-]$, - - - ; $[NH_4^+]$, -•-•

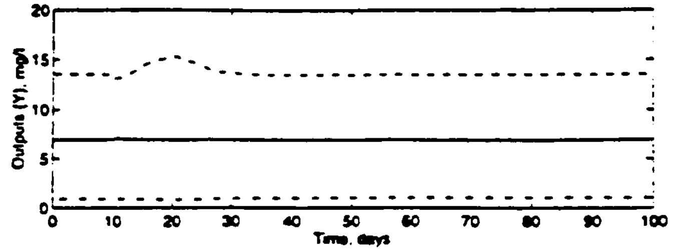

Figure 4-33. IMC Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case II;

(a) Inputs: recirculation ratio, — ; sludge age, - - - ;

(b) Outputs: BOD, — ; $[NO_3^-]$, - - - ; $[NH_4^+]$, -•-•

the input variables u_i, and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with IMC controllers. The system is stable as guaranteed by the μ-Interaction Measure. The BOD effluent is controlled rather well, though a drastic change is not expected because of the small disturbance. The nitrate in the PI controlled case never quite reaches its original steady state value after a brief deviation. In the IMC controlled system it does. In contrast to Case I, the free variable (nitrate in Case I and ammonia in this Case II) in Case II the free variable is not affected by this disturbance.

Figure 4-34 is a plot of the input variables and the output variables after a 15% disturbance perturbation in ammonia for the PI control system. Once again the sludge age control action is initially too aggressive, but it eventually regulates the effluent nitrate to its original steady state. The other control variable, effluent BOD, is also regulated to its original steady state. As seen in the servo control simulations, Case II tends to be the most stable of the three cases. Figure 4-35 is a plot of the input variables and the output variables after a 15% disturbance perturbation in influent ammonia introduced at time, t=10 days, for the IMC control system. The two control variables, effluent BOD and effluent nitrate, are regulated by the controller to their original steady state values.

Figure 4-36 is that of the input and output variables due to a 10% disturbance introduced at time, t=10 days, in the influent nitrate concentration. Once again, this configuration of the plant seems to be more stable than the other two disturbances. The control actions are significantly less aggressive; even though the tuning is the same. This supports the notion that when the μ-Interaction criteria is violated, then certain configurations of the plant may cause severe instability; other configurations may cause moderate instability; and some confiigurations may maintain stability. There will always be the potential for instability when the μ-Interaction criteria is violated. Figure 4-37 is that of the input and output variables due to a 10% disturbance in the influent nitrate

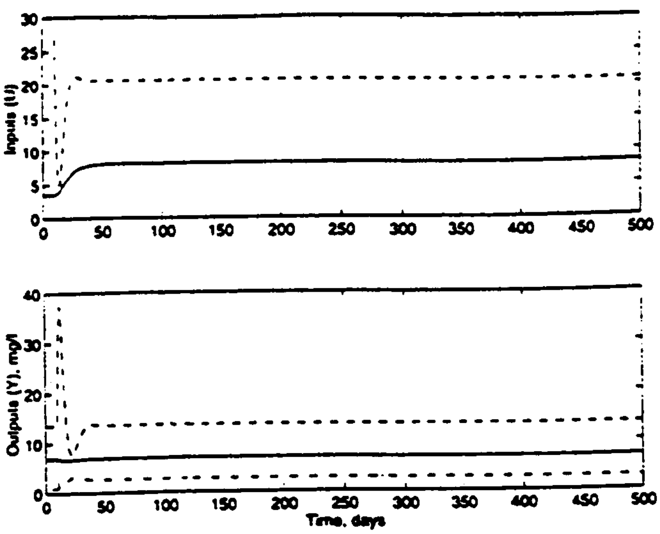

Figure 4-34. PI Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case II;

(a) Inputs: recirculation ratio, —; sludge age, - - - ;

(b) Outputs: BOD, —; [NO_3^-], - - - ; [NH_4^+], -·-

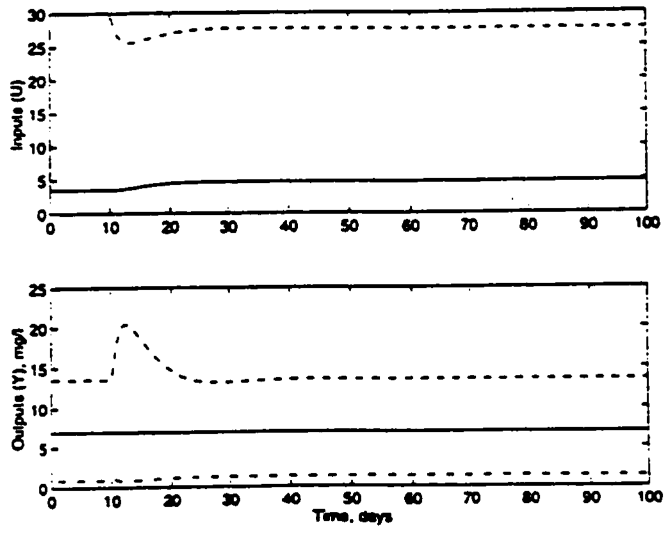

Figure 4-35. IMC Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case II;

(a) Inputs: recirculation ratio, —; sludge age, - - - ;

(b) Outputs: BOD, —; [NO_3^-], - - - ; [NH_4^+], -·-

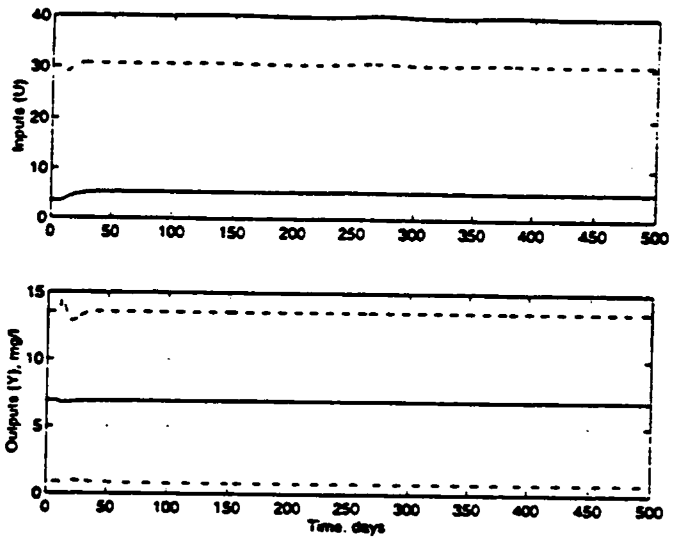

Figure 4-36. PI Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case II;

(a) Inputs: recirculation ratio, —; sludge age, - - - ;

(b) Outputs: BOD, —; $[NO_3^-]$, - - - ; $[NH_4^+]$, -•-•

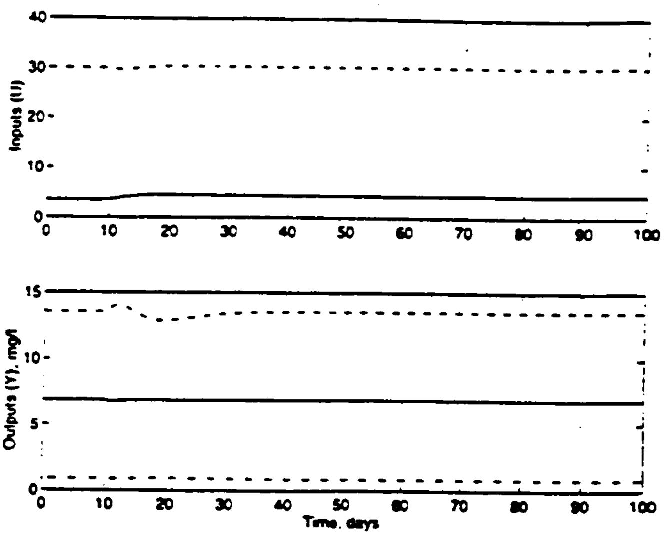

Figure 4-37. IMC Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case II;

(a) Inputs: recirculation ratio, —; sludge age, - - - ;

(b) Outputs: BOD, —; $[NO_3^-]$, - - - ; $[NH_4^+]$, -•-•

concentration for the IMC controlled system. This is very similar to the PI controlled system, but according to the μ-Interaction Measure test, the IMC controlled system is guaranteed long term stability. Both control variables, effluent BOD and effluent nitrate, eventually return to their original steady state. The free variable, effluent ammonia, is once again barely affected.

c. Case III

Case III has the pairings of sludge age-effluent ammonia and recirculation ratio-effluent nitrate. The free variable is effluent BOD. Figure 4-38 is a plot of the input variables u_i, and the output variables y_i, after a 6% disturbance perturbation in the feed flow rate at time, t=10 days, for the PI controlled system. This control scheme completely fails for PI control. Not only is inverse response and dead time involved, but added complications occur in the inter-loop interactions due to the choice of pairings. Though the RGA for this system (see Table 4-3) depicts nearly complete decoupling of the loops (represented by the near λ values of the corresponding pairings), the inter-action of the other loop has an opposite effect (represented by the negative numbers in the RGA in Table 4-3). This is an undesirable characteristic of decentralized controlled systems. Figure 4-39 is the response of an IMC controlled system after a 6% disturbance in the feed flow rate. The controller is able to return the system back to its desired steady state values, but only after large initial deviations, such as that in the nitrate. The free BOD is hardly affected, because it is a minute change in the feed flow rate.

Figure 4-40 is a plot of the input variables and the output variables after a 15% disturbance perturbation in ammonia introduced at time, t=10 days, for the PI controlled system. In the long term, the control variables undergo unrealistic changes, such as an extremely high recirculation ratio and the steady decline of the sludge age. The IMC controlled system, whose response is seen in Figure 4-41, has the same problem with the recirculation ratio, but the problem with the declining sludge age in the long run is

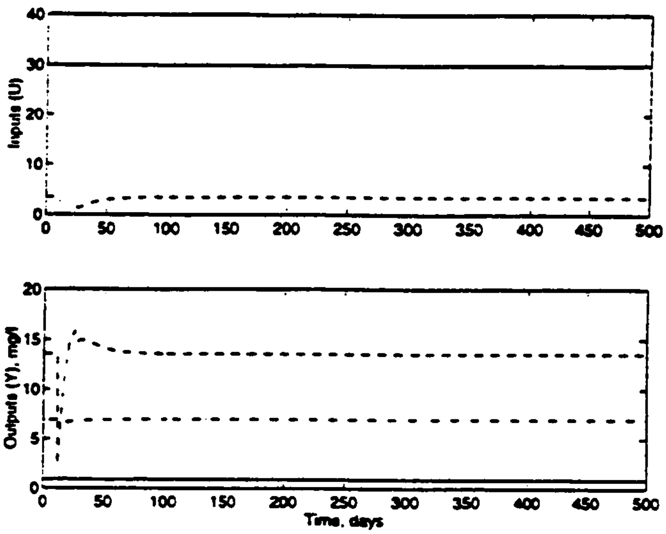

Figure 4-38. PI Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case III;

(a) Inputs: sludge age, — ; recirculation ratio, – – – ;

(b) Outputs: $[NH_4^+]$, — ; $[NO_3^-]$, – – – ; BOD, -·-·

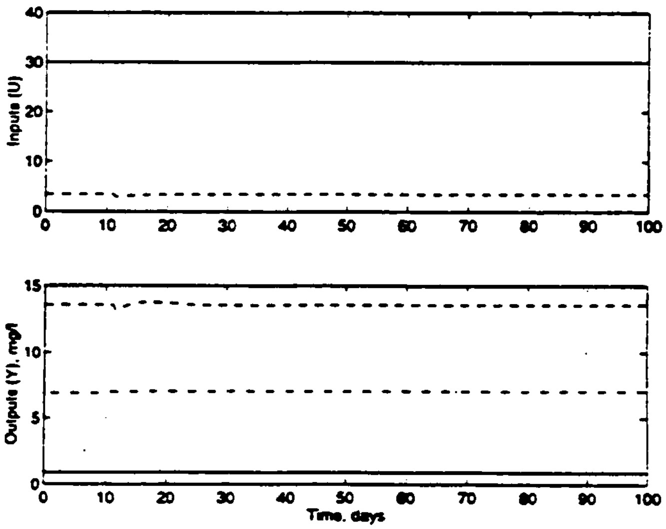

Figure 4-39. IMC Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case III;

(a) Inputs: sludge age, — ; recirculation ratio, – – – ;

(b) Outputs: $[NH_4^+]$, — ; $[NO_3^-]$, – – – ; BOD, -·-·

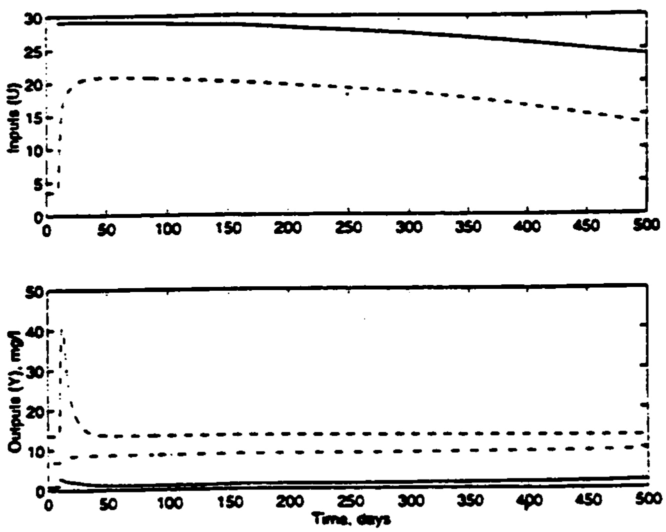

Figure 4-40. PI Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case III;
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -·-

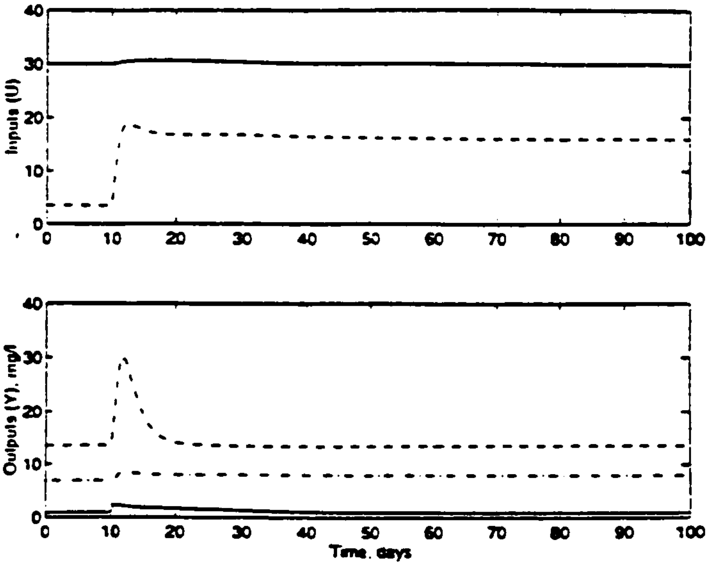

Figure 4-41. IMC Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case III;
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -·-

remedied. This is due to the inherent ability to compensate for inverse responses. The high recirculation ratio must be due to the opposing inter-loop interactions as demonstrated by the RGA shown in Table 4-3, because the controller has to counteract the opposing effect of the other loop.

Figure 4-42 is that of the input and output variables due to a 10% disturbance in the influent nitrate concentration for the PI controlled case. The system is stable for a limited time period, but in the long term it becomes unstable. In contrast, the response of the IMC controlled system is able to handle the inverse responses, as seen in Figure 4-43. This is because the IMC controlled system has inherent filters that will compensate for the inverse response and dead time that are inherent to the system. It is necessary to add additional lag filters to the PID controlled system, which in turn would add addtional tuing constants.

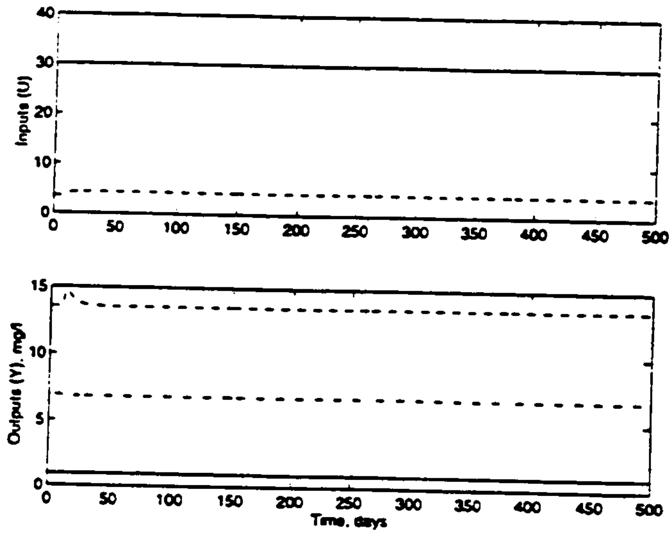

Figure 4-42. PI Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case III;
(a) Inputs: sludge age, — ; recirculation ratio, – – – ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], – – – ; BOD, —·—.

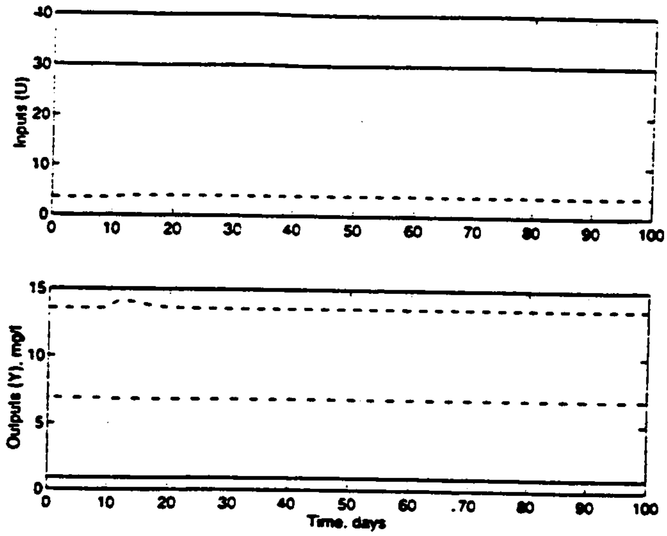

Figure 4-43. IMC Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case III;
(a) Inputs: sludge age, — ; recirculation ratio, – – – ;
(b) Outputs: $[NH_4^+]$, — ; $[NO_3^-]$, – – – ; BOD, –•–

I. Plant/Model Mismatch

One of the issues that always arises in control system design is how sensitive the controlled system is to expected variations in the process parameters. For example, if the controller is tuned for a particular loop, how will this control loop behave if the process gain changes, by say, 20% or the time delay changes, by say, 30%? This is a question of process sensitivity and the robustness of the control design. A highly desired feature of a controller design is the ability to render the closed-loop stable at all times, even when the process has changed somewhat. At the same time, the controller is expected to deliver a given minimum amount of controller performance

As discussed in Chapter Three, there are two practical situations that lead to problems with robustness: process variability and inadequate modeling, both leading to plant/model mismatch. Inadequate modeling is an important concern whenever a linear controller is designed for the linearized model of an originally nonlinear plant model, as is the case in this study. Using linear models to represent the nonlinear wastewater treatment is a prime example of inadequate modeling that will lead to plant/model mismatch.

Plant/model mismatch may cause the closed-loop process to become unstable under certain conditions, because the controllers are no longer able to maintain a stable system due to their sometimes severe over tuning. The problem is usually remedied by conservatively tuning the controller in the first place. Conservative tuning renders the process response more sluggish, although more robust. Hopefully, this will be adequate to tolerate plant/model mismatch. For a nonlinear process, conservative tuning of the PID based controller usually only achieves stability over a given time span. This may be sufficient, depending on one's needs. To completely rectify the situation, additional lag filters must be added to the PID based controller to make it less aggressive and to increase its stability margin (how close to the point of instability). Model based controllers need no added filters. This eliminates the need for additional tuning parameters because model based controllers inherently contain necessary filters. Their coordinated tuning is included in the tuning of the single parameter, λ, of IMC. It is only necessary to increase the λ value to make the IMC controller more robust.

For this study, a maximum of either positive or negative error was considered for each parameter of the plant transfer function. Fifty percent is rather large. A conservative approach will insure stability, if the actual error is less. The worst possible scenario for overall plant error for each parameter can be determined by engineering judgment and trial and error. A tendency toward larger process gains, K, and smaller process time constants, τ, larger dead times, leads, and longer inverses all contribute to lower the μ-Interaction boundary, μ^{-1}. This forces the operator to tune the controllers more conservatively so that they are more robust and do not violate the boundary.

Figures 4-44, 4-45, and 4-46 are frequency plots of the μ-Interaction parameter and the nominal closed-loop transfer function for each of the loops, for the PI based

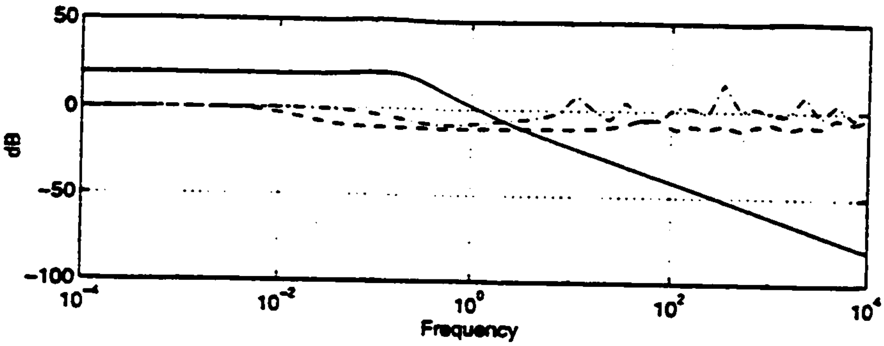

Figure 4-44. Frequency Response of μ-Interaction for Case I with PI Controllers and Incorporating Plant/Model Mismatch; μ^{-1}, — ; loop 1, -•- ; loop 2, - - -

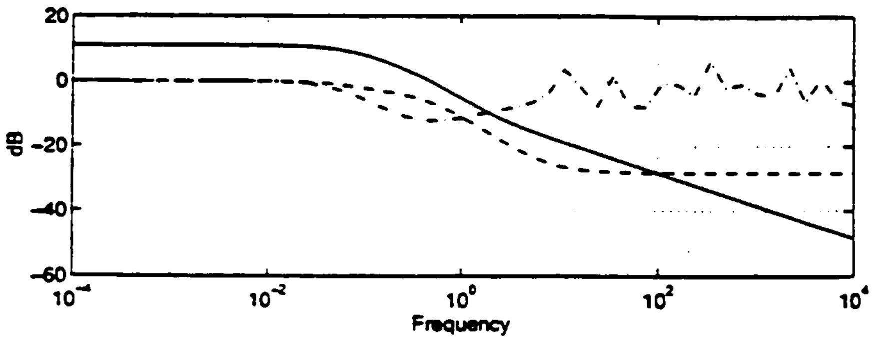

Figure 4-45. Frequency Response of μ-Interaction for Case II with PI Controllers and Incorporating Plant/Model Mismatch; μ^{-1}, — ; loop 1, -•- ; loop 2, - - -

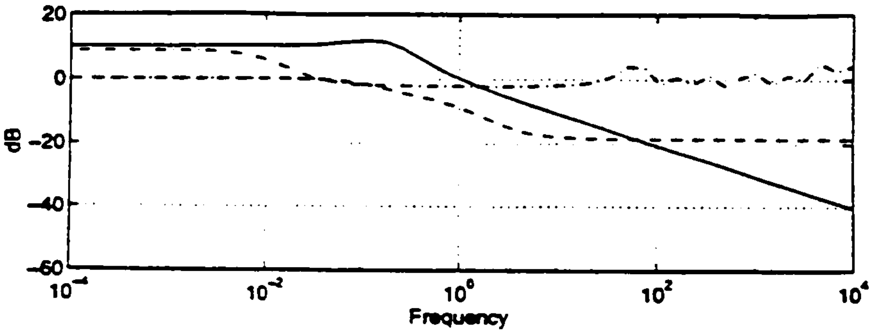

Figure 4-46. Frequency Response of μ-Interaction for Case III with PI Controllers and Incorporating Plant/Model Mismatch; μ^{-1}, — ; loop 1, -•- ; loop 2, - - -

control systems of Case I, Case II, and Case III. Plant/model mismatch is incorporated into all of the parameters as an average percentage drift. This slightly lowered the μ^{-1} boundary. It is difficult to determine how much conservative fine tuning is needed because of the systems inability to "roll off" at high frequencies, a necessary event for the closed-loop system to remain stable. A reduction in the controller gain K_C, by five times tended to bring most of the system below the μ^{-1} boundary.

The addition of lag filters are needed to guarantee stability of the system in the presence of plant/model mismatch. Figure 4-47 is the μ-Interaction plot for Case I with added filters derived form the equivalent IMC controller, taking into consideration the plant/model mismatch. It is evident that the addition of a filter allows the closed-loop transfer function to "roll off" in the high frequency region.

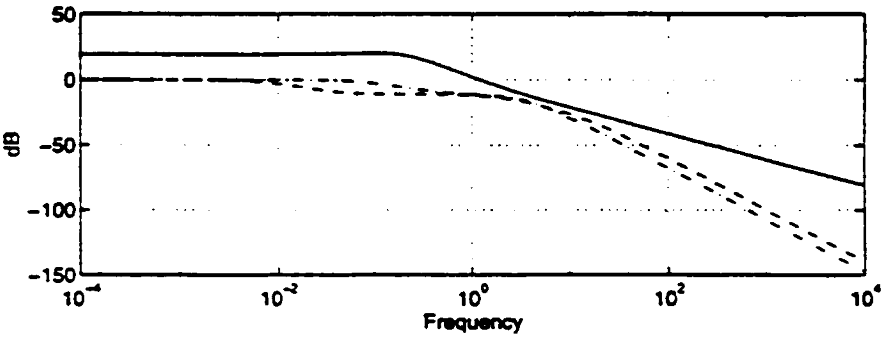

Figure 4-47. Frequency Response of μ-Interaction for Case I with PI Controllers with Compensating Filters and Incorporating Plant/Model Mismatch;
μ^{-1}, — ; loop 1, -·-· ; loop 2, - - -

The three cases with IMC based control systems are simple to retune when plant/model mismatch is considered. There is only one tuning parameter, λ, to manipulate. IMC controllers inherently incorporate all of the added filters. The greater the value of λ, the more robust the system. Increased robustness is at the expense of more sluggish response. The smaller the value of λ, the less robust the system. However, the corresponding response is more aggressive. This exemplifies the simplicity and directness of tuning an IMC controller.

Figure 4-48 is the μ-Interaction plot for Case I with IMC controllers and roughly 50% plant/model mismatch from each parameter's original nominal value. In order to meet stability criteria, the controllers must be re-tuned more conservatively. This is acheived by increasing the single tuning parameter, λ. The first loop had to have its nominal λ doubled and the second loop did not need to be retuned. Figure 4-49 is the μ-Interaction plot for Case II with IMC controllers and 50% plant/model mismatch. The first loop had to have its nominal λ increased to 2.5 times and the second loop to 1.5 times. Figure 4-50 is the μ-Interaction plot for Case III with IMC control and 50% plant/model mismatch. The first loop had to be manipulated to 2.5 times and the second loop to 1.5 times in order to meet stability criteria. All three IMC control systems do not violate the μ-Interaction boundary. This guarantees stability under all perturbations, within the boundary of the plant/model mismatch considered.

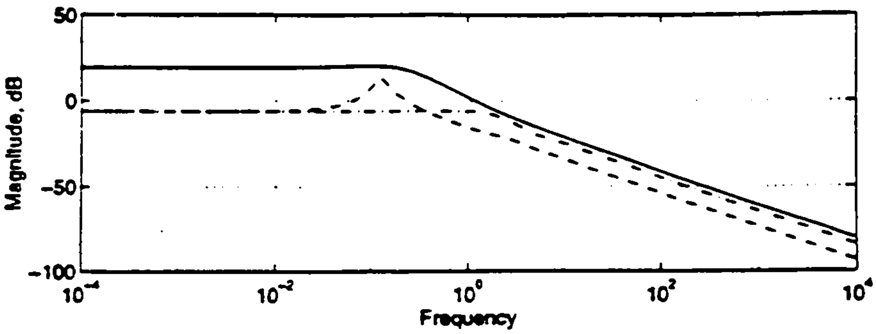

Figure 4-48. Frequency Response of μ-Interaction for Case I with IMC Controllers and Incorporating Plant/Model Mismatch; μ^{-1}, — ; loop 1, —•— ; loop 2, - - -

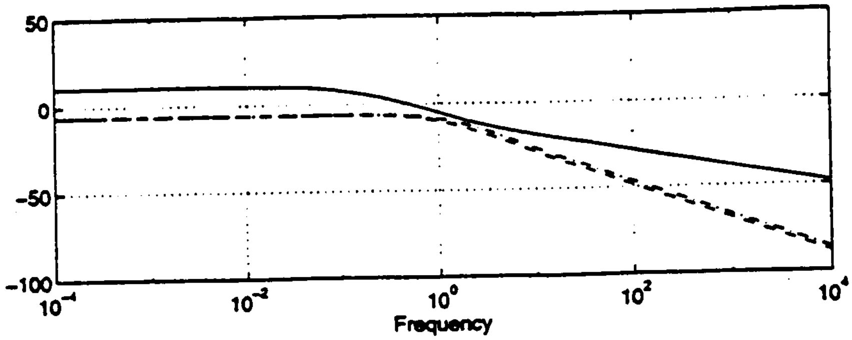

Figure 4-49. Frequency Response of μ-Interaction for Case II with IMC Controllers and Incorporating Plant/Model Mismatch; μ^{-1}, — ; loop 1, —•— ; loop 2, - - -

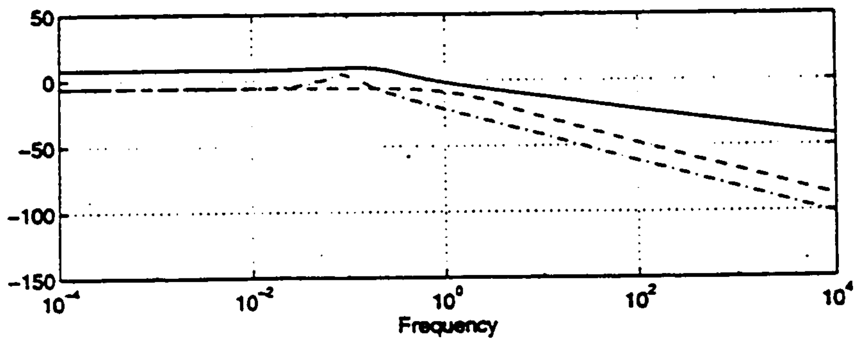

Figure 4-50. Frequency Response of μ-Interaction for Case III with IMC Controllers and Incorporating Plant/Model Mismatch;
μ^{-1}, — ; loop 1, —•— ; loop 2, - - -

J. Servo Control and Regulator Control with Plant/Model Mismatch

Since the systems now have plant/model mismatch incorporated into them the behavior of the system due to setpoint changes and disturbance perturbations will be different from that of the nominal cases without plant/model mismatch. Trying to simulate servo and regulator control using the controllers not retuned to the new mismatched system will render almost all simulations unstable, even for the IMC control systems. It is necessary to retune the controllers using the mismatched m-Interaction Measure defined for the mismatched model and apply them to the system that is also mismatched. The same setpoint changes and disturbance perturbations will be initiated and the results will then be compared between the PI controlled systems and the IMC controlled systems, as well as, compared to the simulation results where no mismatch was incorporated.

1. Servo Control (Setpoint Tracking)

This section of the study individually simulates a 25% reduction from the nominal steady state value in the setpoints of all three output variables for each of the three pairing cases. Even though the system now has plant/model mismatch, the controllers have been retuned to compensate for this. The trend of the results should be similar to those without plant/model mismatch.

a. Case I

Effluent BOD and effluent ammonia concentrations are controlled by recirculation ratio and sludge age, respectively, and effluent nitrate concentration is the free variable. The nominal steady state value of effluent ammonia is 0.89 mg/l (reported by Grove, 1995) and a 25% setpoint reduction in this value would ideally bring the new steady state value to 0.67 mg/l. A 5% reduction in the steady state effluent BOD value lowers the setpoint from 6.90 mg/l to 5.56 mg/l. Figure 4-51 is a plot of the input variables u_i, and the output variables y_i, after a setpoint change in BOD (loop 1) at time, t=10 days, for the PI controlled system. Figure 4-52 is a plot of a setpoint change in BOD at time, t=10 days, for the IMC controlled system. Where the IMC controlled system is stable, the PI controlled system becomes unstable in the long term. These mismatched simulation results are similar to the non-mismatched simulations, because the controllers have been retuned taking into consideration the plant/model mismatch.

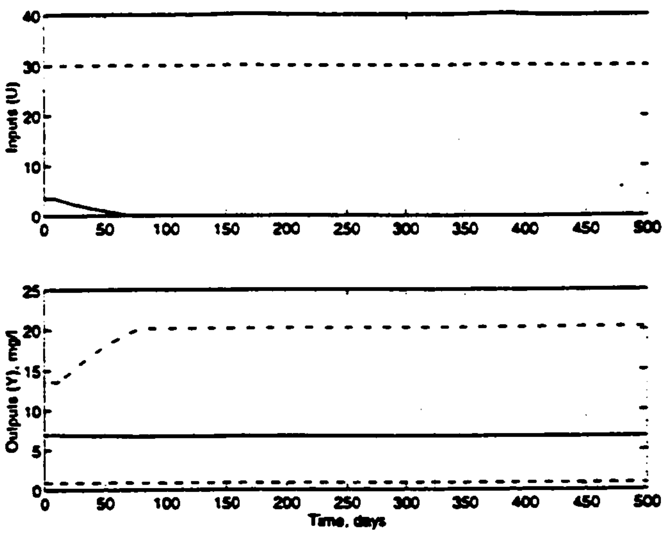

Figure 4-51. PI Based Servo Control for a Setpoint Change in Effluent BOD Incorporating Plant/Model Mismatch (I);
(a) Inputs: recirculation ratio, — ; sludge age, – – –;
(b) Outputs: BOD,— ; [NH_4^+], – – – ; [NO_3^-], -·-

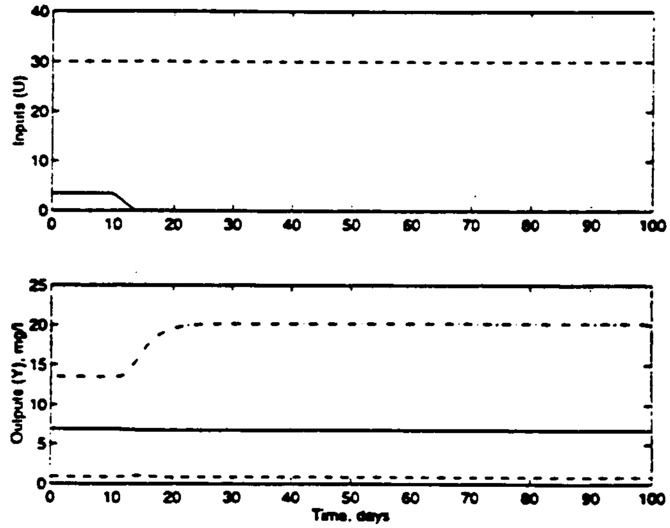

Figure 4-52. IMC Based Servo Control for a Setpoint Change in Effluent BOD Incorporating Plant/Model Mismatch (I);
(a) Inputs: recirculation ratio, — ; sludge age, – – –;
(b) Outputs: BOD,— ; [NH_4^+], – – – ; [NO_3^-], -·-

Figure 4-53 is a plot of the input variables and the output variables after a -25% setpoint change in ammonia (loop 2) at time, t=10 days, for the PI controlled system. The system remains stable for a limited time span, and then it proceeds to instability, just like the non-mismatched simulation. This is due to the "nasty" characteristics of the system dynamics, such as inverse response in loop 2 and dead time in both loops. A more conservative tuning of the system would make it more robust, thus stabilizing it for a longer time period; but without the addition of compensating filters, it will eventually become unstable. Figure 4-54 is a time simulation plot of the input variables and the output variables after a -25% setpoint change in ammonia at time, t=10 days, for the IMC controlled system. This output graph is a deviation from the nominal steady state values in mg/l. This was done in order to better display the -25% change in effluent ammonia (from 0.89 mg/l to about 0.67 mg/l). In contrast to the PI controlled system, the IMC controlled system is stable in the long term. Figure 4-55 is a time simulation plot of the PI controlled system with added first order lag filters undergoing a setpoint change in effluent ammonia (loop 2). The system is now stable (in contrast to that shown in Figure 4-54) and corresponds with the response to the same setpoint change in the IMC controlled system. Again, this illustrates that when the process dynamics exhibit dead time and inverse response characteristics, the intrinsic IMC controller designed for it is equivalent to a PID controller with an additional filter added. The IMC still has just one tuning parameter. The PID needs four parameters per loop, tuned in accordance with each other

b. Case II

In this case recirculation ratio and sludge age are used to control effluent BOD and effluent nitrate, respectively, and effluent ammonia is the free variable. The nominal steady state value of effluent nitrate is 13.55 mg/l and a 25% setpoint reduction in this value would ideally bring the new steady state value to 10.16 mg/l. Once again, a 25%

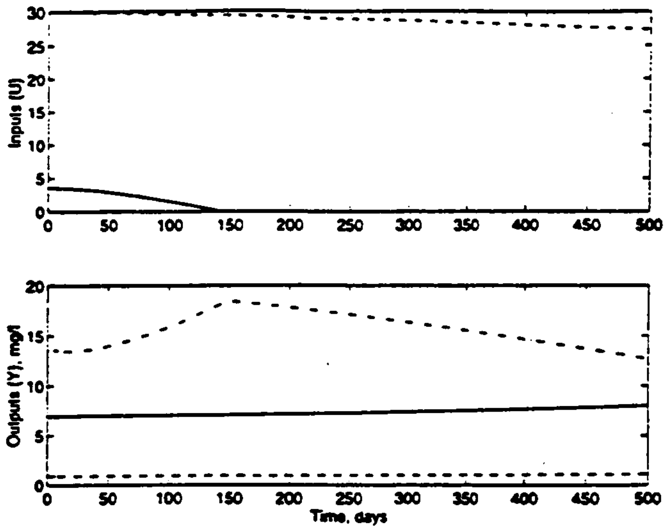

Figure 4-53. PI Based Servo Control for a Setpoint Change in Effluent Ammonia Incorporating Plant/Model Mismatch (I);
(a) Inputs: recirculation ratio, — ; sludge age, – – –;
(b) Outputs: BOD,— ; [NH_4^+], – – – ; [NO_3^-], -•-•

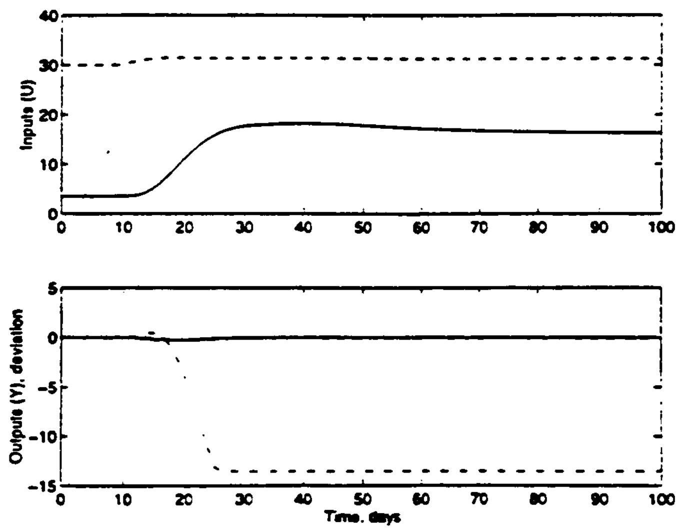

Figure 4-54. IMC Based Servo Control for a Setpoint Change in Effluent Ammonia Incorporating Plant/Model Mismatch (I);
(a) Inputs: recirculation ratio, — ; sludge age, – – –;
(b) Outputs: BOD,— ; [NH_4^+], – – – ; [NO_3^-], -•-•

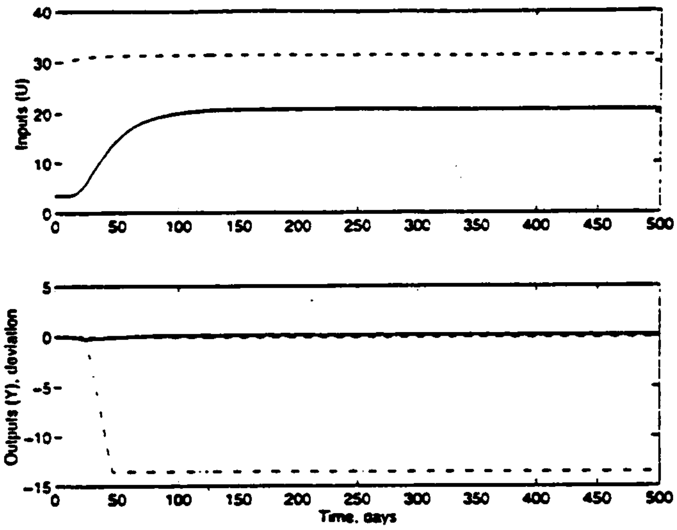

Figure 4-55. PI Based with Compensating Filters Servo Control for a Setpoint Change in Effluent Ammonia Incorporating Plant/Model Mismatch (I); (a) Inputs: recirculation ratio, — ; sludge age, - - -; **(b) Outputs:** BOD,— ; [NH_4^+], - - - ; [NO_3^-], —•—

reduction in the steady state effluent BOD value should lower the setpoint from 6.90 mg/l to 5.56 mg/l. Figure 4-56 is a plot of the input variables u_i, and the output variables y_i, after a -5% setpoint change in BOD (loop 1) introduced at time, t=10 days, for the PI control system. The system remains stable for a lengthy time span because there is no inverse response exhibited in the closed-loop process dynamics. The "nasty" characteristics consist of only dead time in both loops and a lead response in loop 2. A more conservative tuning of the system would make it more robust, thus stabilizing it for an even longer time period. Without the addition of compensating filters, it may eventually go unstable under certain circumstances as depicted earlier from the μ-Interaction Measure test (see Figure 4-44). Figure 4-57 is a plot of the input and output variables after a -5% setpoint change in BOD (loop 1) introduced at time, t=10 days, for the IMC controlled system. In contrast to the PI controlled system, this clearly is a stable system. In this case, the mismatched simulation responses are slightly more oscillatory than those of the non-mismatched simulations (even more so than the other two

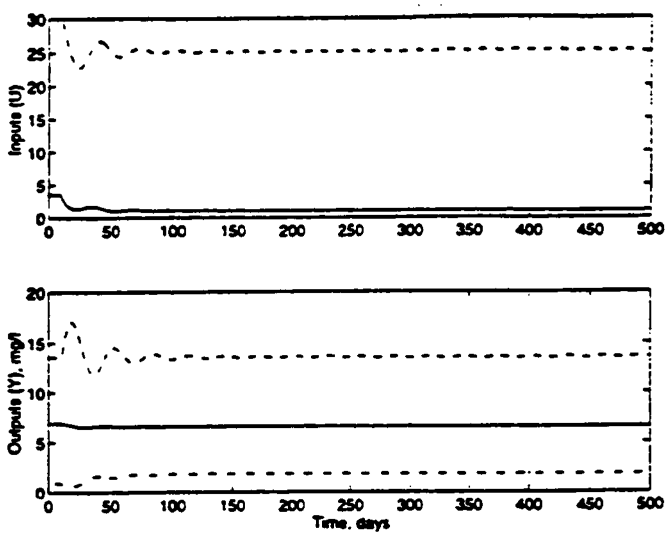

Figure 4-56. PI Based Servo Control for a Setpoint Change in Effluent BOD Incorporating Plant/Model Mismatch (II);

(a) Inputs: recirculation ratio, — ; sludge age, - - - ;

(b) Outputs: BOD, — ; [NO_3^-], - - - ; [NH_4^+], -·-

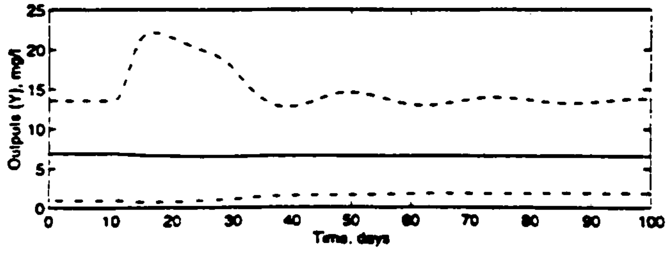

Figure 4-57. IMC Based Servo Control for a Setpoint Change in Effluent BOD Incorporating Plant/Model Mismatch (II);

(a) Inputs: recirculation ratio, — ; sludge age, - - - ;

(b) Outputs: BOD, — ; [NO_3^-], - - - ; [NH_4^+], -·-

mismatched cases). This is a result of Case II being slightly more inter-loop interactive than the other two cases, as shown in the RGA analysis (see Table 4-3). The benefit of being able to regulate nitrate emissions, and not having to worry about the free variable, ammonia, reaching much higher steady state values, greatly outweighs the sacrifice of this slight increase in inter-loop interaction.

Figure 4-58 is a plot of the input variables and the output variables after a -25% setpoint change in nitrate (loop 2) at time, t=10 days, for the PI controlled system. As seen in Figure 4-56, the system remains stable for a lengthy time span because there is no inverse response exhibited in the closed-loop process dynamics. The "nasty" characteristics consist of dead time in both loops and a lead response in loop 2. A more conservative tuning of the system would make it more robust, thus stabilizing it for an even longer time period. Without the addition of compensating filters, it may eventually go unstable under certain circumstances as depicted earlier from the μ-Interaction Measure test (see Figure 4-44). Figure 4-59 is a plot of the input and output variables after a -25% setpoint change in effluent nitrate (loop 2) introduced at time, t=10 days, for the IMC controlled system. Unlike the plot of the PI controlled system, this plot has long term stability. Once again, the system is slightly more oscillatory.

c. Case III

This case involves using sludge age and recirculation ratio to control effluent ammonia and effluent nitrate, respectively, with effluent BOD as the free variable. Figure 4-60 is a plot of the input variables u_i, and the output variables y_i, after a -25% setpoint change in ammonia (loop 1) introduced at time, t=10 days, for the PI controlled system. The overall long term stability of the system is compromised by the inclusion of inverse response and dead time in the system process dynamics, plus the undesirable inter-loop interaction. Additional lag filters would be needed along with the PI controller in order to remedy the situation. Figure 4-61 is a plot of the input and output responses after the

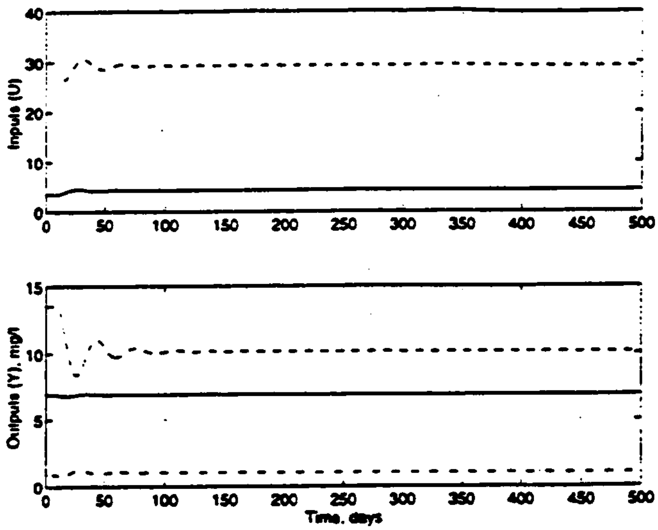

Figure 4-58. PI Based Servo Control for a Setpoint Change in Effluent Nitrate Incorporating Plant/Model Mismatch (II);

(a) Inputs: recirculation ratio, — ; sludge age, - - - ;

(b) Outputs: BOD, — ; [NO_3^-], - - - ; [NH_4^+], -•-

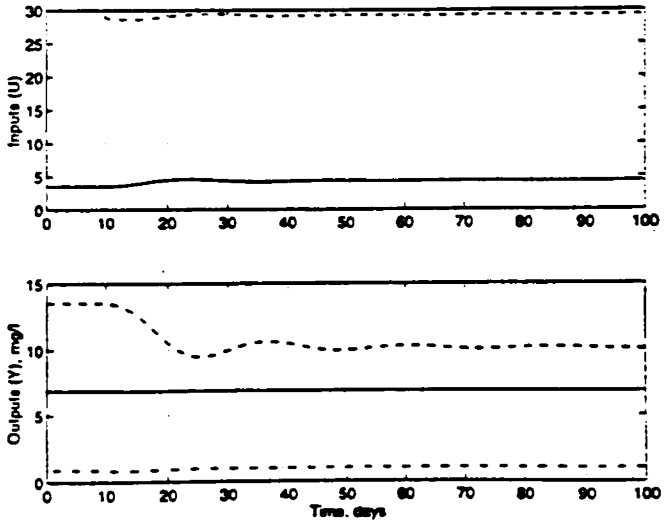

Figure 4-59. IMC Based Servo Control for a Setpoint Change in Effluent Nitrate Incorporating Plant/Model Mismatch (II);

(a) Inputs: recirculation ratio, — ; sludge age, - - - ;

(b) Outputs: BOD, — ; [NO_3^-], - - - ; [NH_4^+], -•-

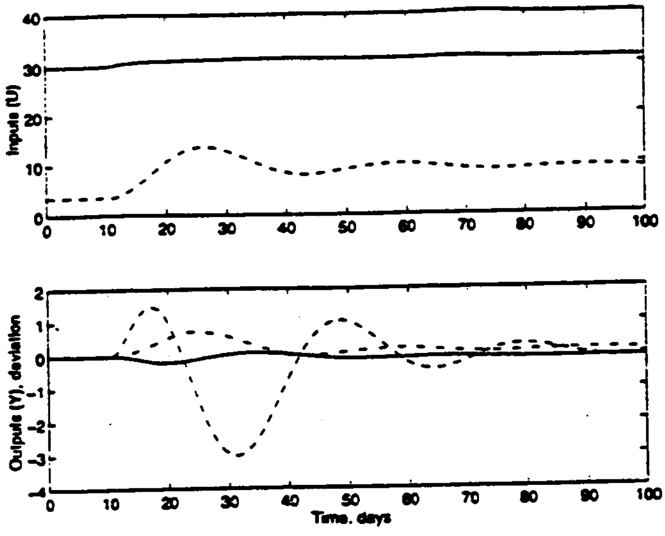

Figure 4-60. PI Based Servo Control for a Setpoint Change in Effluent Ammonia Incorporating Plant/Model Mismatch (III);

(a) Inputs: sludge age, — ; recirculation ratio, - - - ;

(b) Outputs: $[NH_4^+]$, — ; $[NO_3^-]$, - - - ; BOD, -•-

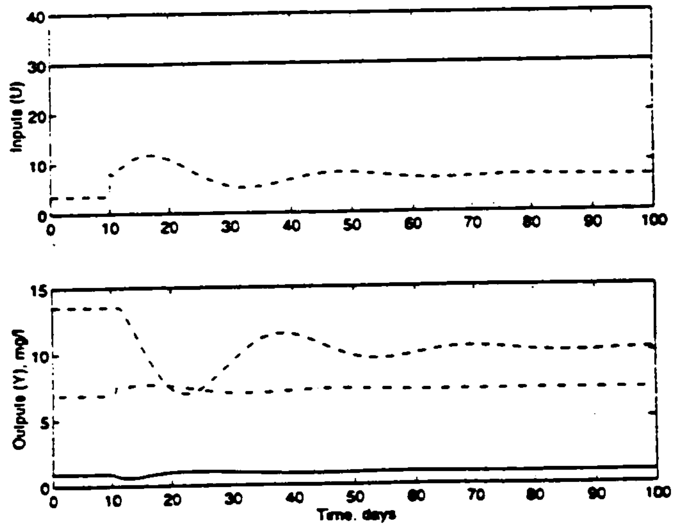

Figure 4-61. IMC Based Servo Control for a Setpoint Change in Effluent Ammonia Incorporating Plant/Model Mismatch (III);

(a) Inputs: sludge age, — ; recirculation ratio, - - - ;

(b) Outputs: $[NH_4^+]$, — ; $[NO_3^-]$, - - - ; BOD, -•-

same -25% setpoint change in ammonia is introduced at time, t=10 days, for the IMC controlled system. Once again, the output graph is of the deviation in mg/l from the nominal steady state values.

Figure 4-62 is a plot of the input variables and the output variables after a -25% setpoint change in nitrate (loop 2) at time, t=10, for the PI controlled system. As in the other cases, the PI controlled system remains stable for a limited time span, and then it proceeds to go unstable. This is because of the introduction of an inverse response in the first loop (sludge age-effluent ammonia), in addition to the dead time in both loops. In contrast, Figures 4-63 is a plot of the input and output variables after setpoint changes in nitrate, for the IMC control system. This clearly is a stable system, but sluggish.

2. Regulator Control (Disturbance Rejection)

Once again, regulator control is very common in the chemical industry (Coughanowr, 1991), and it is a major concern for the wastewater treatment plant. Since several parameters in the chemical industry, such as flow rate and inlet concentrations, are expected to vary depending on up stream conditions. Input characteristics can also vary when the nature of the waste varies from batch to batch and process to process. It is highly desirable for the control system to have the ability to compensate for these disturbances and to still maintain outputs at the desired setpoint values. Studies reported here also include results of introducing percentage increases in the nominal steady state inlet values of feed flow rate, ammonia concentration, and nitrate concentration for each of the three pairing cases. Only a small disturbance in the feed flow rate was introduced into all three cases (about 6%) in order to try and keep zero recirculation from occurring. There tends to be a small mathematical anomaly in the outputs when this disturbance is introduced. The outputs tend to display small little spikes periodically throughout the simulation. This is most likely due to the inter-loop interactions and the mathematical calculations used in the Simulink package of Matlab. The plant/model mismatch results in

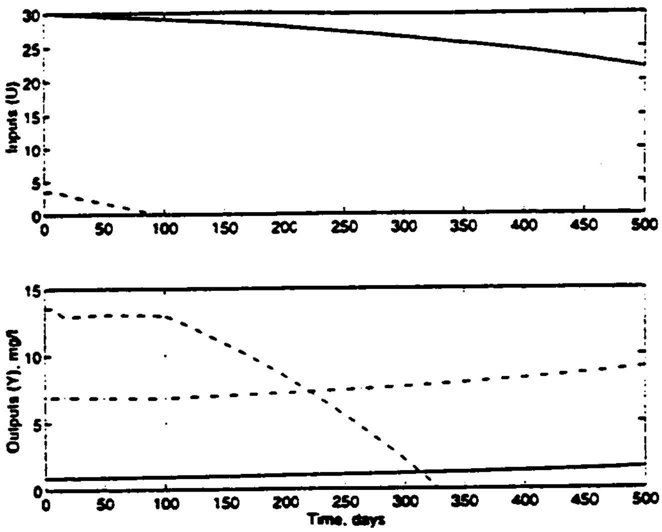

Figure 4-62. PI Based Servo Control for a Setpoint Change in Effluent Nitrate Incorporating Plant/Model Mismatch (III);
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -·-·

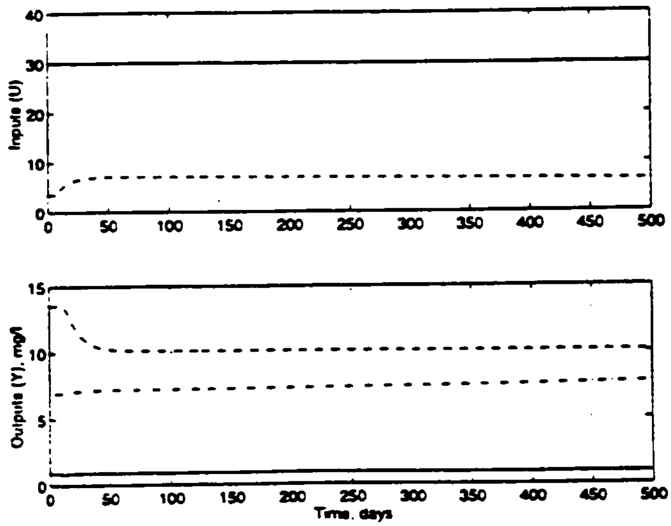

Figure 4-63. IMC Based Servo Control for a Setpoint Change in Effluent Nitrate Incorporating Plant/Model Mismatch (III);
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -·-·

a more sensitive system that would more easily go unstable under disturbance perturbations. The control parameters needed to be fine tuned more conservatively in order to insure plant stability.

a. Case I

In this case, recirculation ratio and sludge age are used to control effluent BOD and effluent ammonia, respectively, and effluent nitrate is a free variable. The nominal steady state value of influent flow rate is 5,450,000 liters/day and a 6% increase in this value would result in a feed flow rate of 5,777,000 liters/day. Any disturbance significantly higher results in zero recirculation, thus a higher new steady state value of effluent BOD, along with a greater display of the aforementioned anomaly. Figure 4-64 is a plot of the input variables u_i, and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with PI controllers. As with the non-mismatched case, the system is initially stable. In the long term, it becomes unstable, as seen by the slow decline of the sludge age. Figure 4-65 is a plot of the input variables u_i, and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with IMC controllers. The system is stable as guaranteed by the μ-Interaction Measure. The BOD effluent is controlled rather well, though a drastic change is not expected because of the small disturbance. The ammonia effluent at first deviates from its original steady state, but eventually returns to it. The "free" effluent nitrate increases to a higher steady state. This is due to the opposing action between recirculation ratio and nitrate.

The second disturbance introduced was that of a 15% step increase in influent ammonia. The nominal inlet concentration of ammonia is 300 mg/l and a 15% increase would step this value to 345 mg/l. Figure 4-66 is a plot of the input variables and the output variables after a 15% disturbance perturbation in ammonia introduced at time, t=10 days, for the PI control system. The system remains stable for a limited time span, and

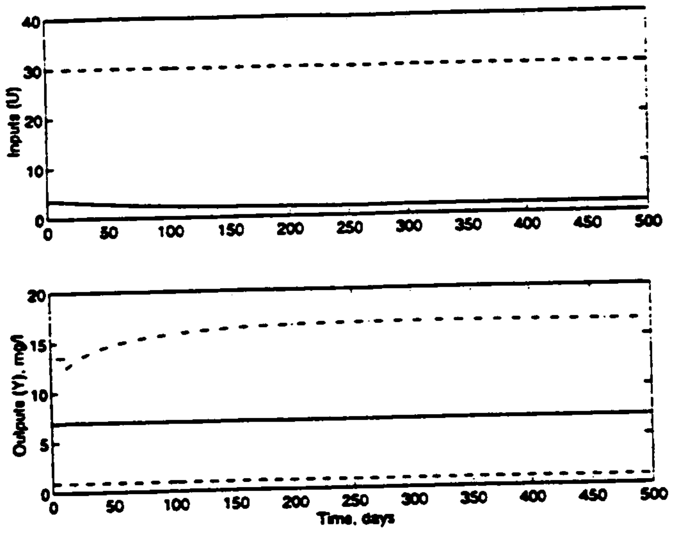

Figure 4-64. PI Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case I Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NH_4^+], - - -; [NO_3^-], -•-•

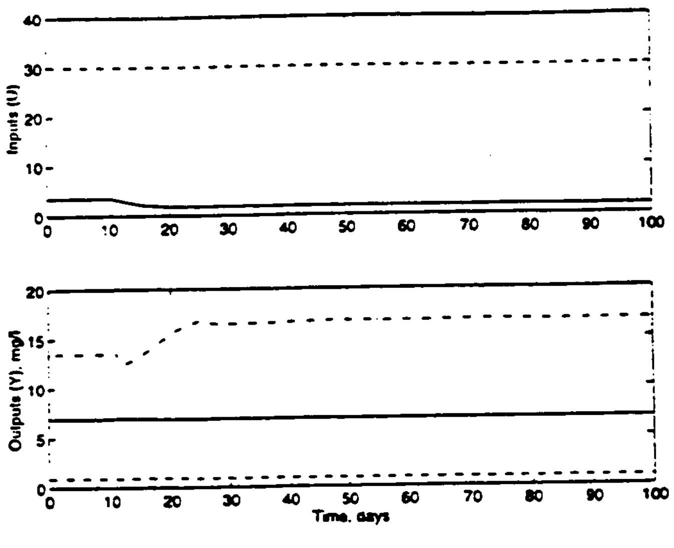

Figure 4-65. IMC Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case I Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NH_4^+], - - -; [NO_3^-], -•-•

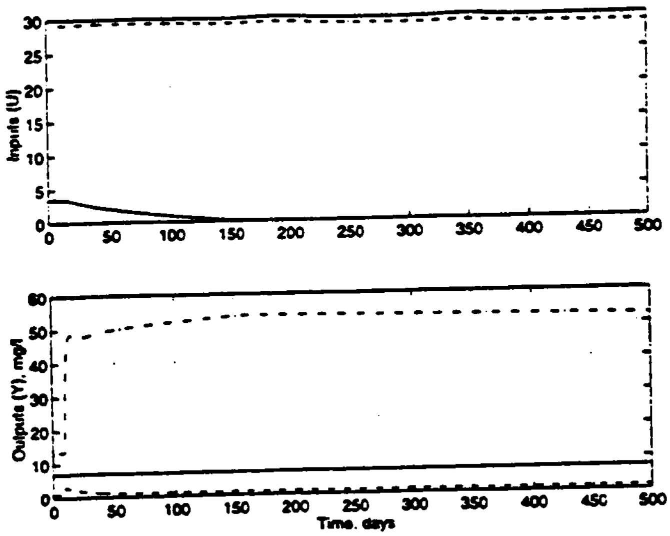

Figure 4-66. PI Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case I Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NH_4^+], - - -; [NO_3^-], -•-•

then it proceeds to become unstable. This is due to the "nasty" characteristics of the system, such as inverse response in the first loop and dead time in both loops. A more conservative tuning of the system would make it more robust, thus stabilizing it for a longer time period. Without the addition of compensating filters, it will eventually go unstable. Figure 4-67 is that of the same system under the same disturbance perturbation and having the same PI controller tuning, but with the addition of compensatory filters. The system is now stable. However, the nitrate level settles toward a much higher steady state, because the first step in ammonia degradation is conversion to nitrate and the nitrate is uncontrolled. This compensated PI controlled system is similar to that of the IMC controlled system, whose response to the same ammonia disturbance introduced at time, t=10 days, is shown in Figure 4-68. Once again, the two controlled variables, effluent BOD and effluent ammonia, are regulated by the controllers at their original steady state value, but nitrate emissions increase to a higher steady state value.

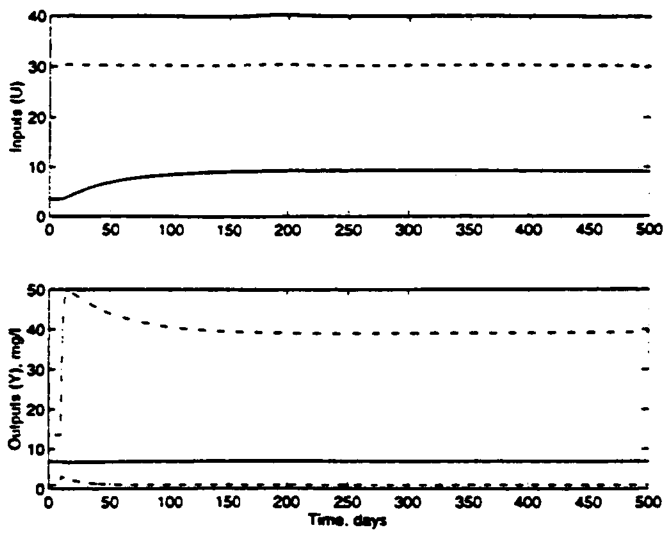

Figure 4-67. PI Based with Additional Filters Regulator Control for a 15% Disturbance in Influent Ammonia for Case I Incorporating Plant Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NH_4^+], - - -; [NO_3^-], -·-·

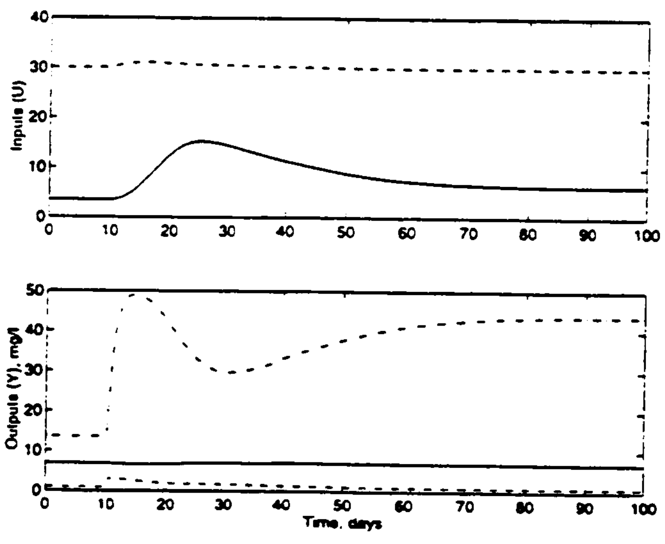

Figure 4-68. IMC Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case I Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NH_4^+], - - -; [NO_3^-], -·-·

Figure 4-69 is that of the input and output variables in response to a 10% disturbance in the influent nitrate concentration introduced at time, t=10 days, for the PI controlled system. The nominal value of the influent nitrate is 1000 mg/l. This pairing configuration of the plant is such that this disturbance leads to a more stable response than the other two disturbances, but it still eventually goes unstable. This supports the claim that when the μ-Interaction criteria is violated, then PI control alone for the plant may cause severe instability in the long run, for some configurations, while other configurations may only lead to moderate instability or may even maintain stability. There always will be the potential for instability when the μ-Interaction criteria is violated by the presence of inverse and significant dead time process kinetics. In contrast, Figure 4-70 is that of the input and output variables in response to a 10% disturbance in the influent nitrate concentration for the IMC controlled system. As with the case of the ammonia disturbance for the IMC controlled system, and contrary to the PI controlled system, the two controlled variables are regulated to their original steady state values and the "free" effluent nitrate approaches a lower steady state value, because the recirculation ratio increases.

b. Case II

This case involves using recirculation ratio and sludge age to control effluent BOD and effluent nitrate, respectively, and effluent ammonia is the free variable. Figure 4-71 is a plot of the input variables u_i, and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with PI controllers. The system is fairly stable, because there is no inverse response in either of the control loops. However, over time, and/or under disturbance, it may become unstable. This demonstrates how the μ-Interaction Measure test allows one to see if a system has the potential to become unstable, without informing when or under what circumstances the system will become unstable. The potential for instability is always there. Note how the system is slightly

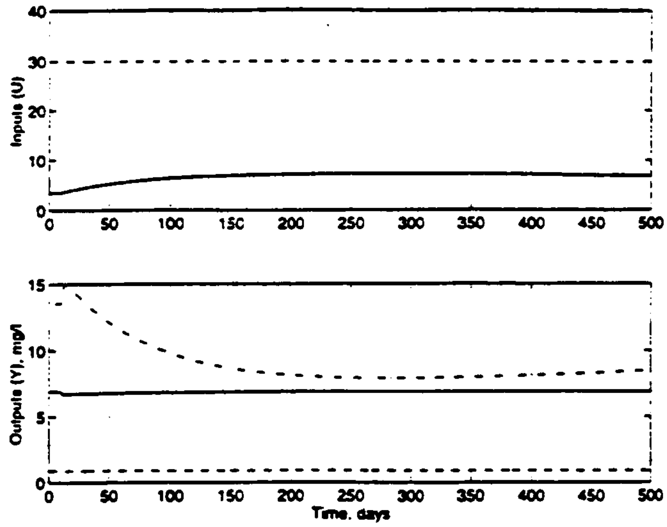

Figure 4-69. PI Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case I Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NH_4^+], - - -; [NO_3^-], -·-·

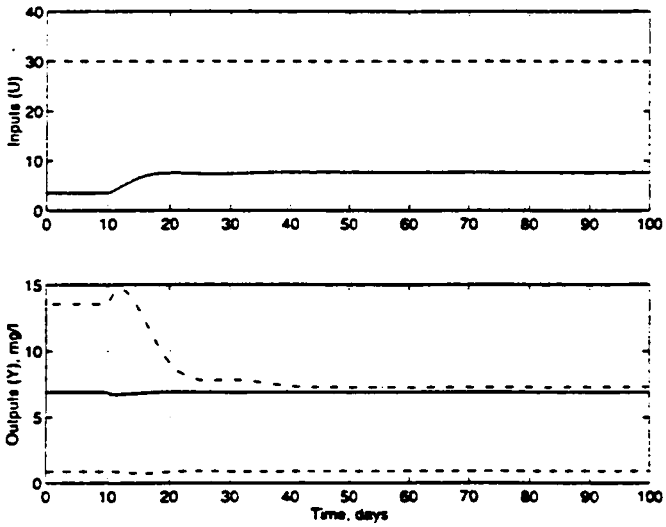

Figure 4-70. IMC Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case I Incorporating Plan/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NH_4^+], - - -; [NO_3^-], -·-·

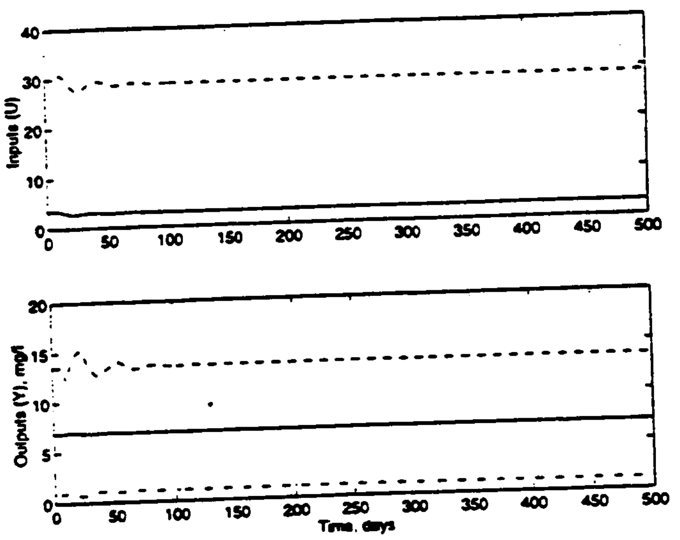

Figure 4-71. PI Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case II Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; $[NO_3^-]$, - - - ; $[NH_4^+]$, -•-•

more oscillatory than the non-mismatched simulations. This is due to the plant/model mismatch, causing the system to be more sensitive to perturbations.

Figure 4-72 is a plot of the input variables u_i, and the output variables y_i, after 6% disturbance perturbation in the feed flow rate for the system with IMC controllers. The system is slightly more oscillatory, but stable as guaranteed by the μ-Interaction Measure. The BOD effluent is controlled rather well, though a drastic change is not expected because of the small disturbance. The nitrate in the PI controlled case never quite reaches its original steady state value after a brief deviation, whereas in the IMC controlled system it does. In contrast to Case I, the free variable (nitrate in Case I and ammonia in Case II) is not affected by this disturbance. This supports the notion that the system is adept at maintaining a low level of ammonia emissions.

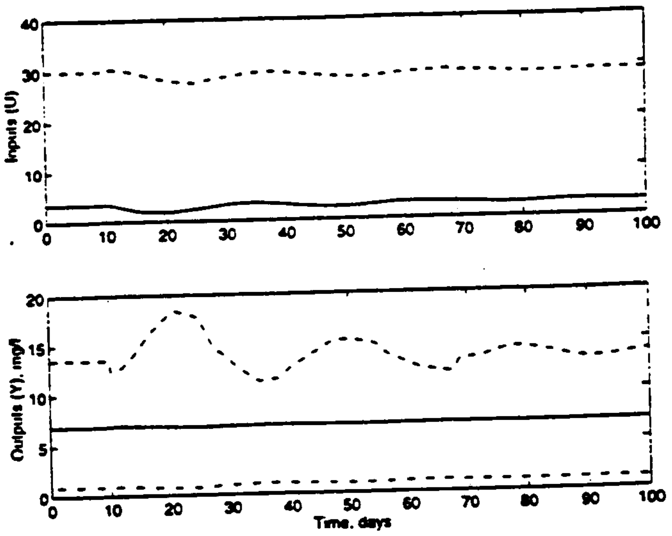

Figure 4-72. IMC Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case II Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NO_3^-], - - - ; [NH_4^+], -·-

Figure 4-73 is a plot of the input variables and the output variables after a 15% disturbance perturbation in ammonia introduced at time, t=10 days, for the PI control system. Once again, the sludge age control action is initially too aggressive, but it eventually regulates the effluent nitrate to its original steady state. The other control variable, effluent BOD, is also regulated to its original steady state. As seen in the servo control simulations, Case II tends to be the most stable of the three cases. This is due to the lack of an inverse response in either of the loops. Figure 4-74 is a plot of the input variables and the output variables after a 15% disturbance perturbation in influent ammonia introduced at time, t=10 days, for the IMC control system. The two control variables, effluent BOD and effluent nitrate, are regulated by the controller to their original steady state values. However, the system, using either type of controller, is significantly more oscillatory for the ammonia disturbance. Tuning the parameters of the controllers more conservatively will reduce this oscillation, but a more sluggish performance will also result (i.e. a longer settling time).

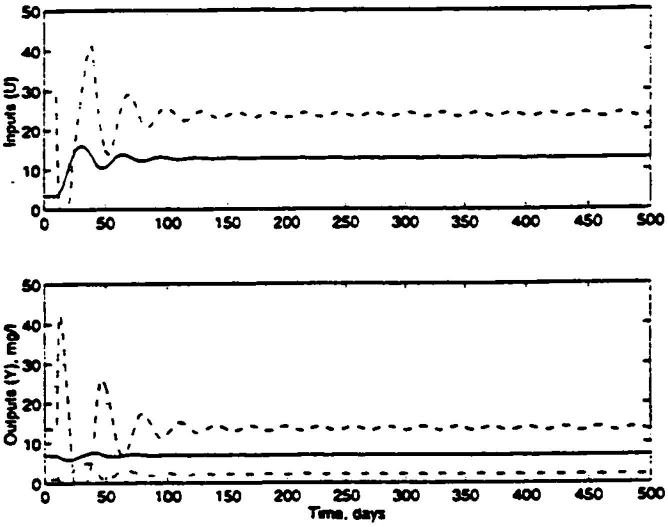

Figure 4-73. PI Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case II Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; $[NO_3^-]$, - - - ; $[NH_4^+]$, -•-•

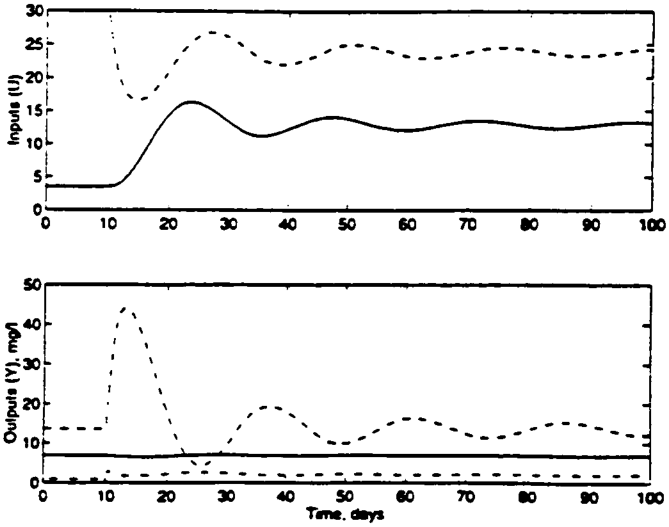

Figure 4-74. IMC Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case II Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; $[NO_3^-]$, - - - ; $[NH_4^+]$, -•-•

Figure 4-75 is that of the input and output variables due to a 10% disturbance introduced at time, t=10 days, in the influent nitrate concentration. Figure 4-76 is that of the input and output variables due to a 10% disturbance in the influent nitrate concentration for the IMC controlled system. This is very similar to the PI controlled system, but according to the μ-Interaction Measure test, the IMC controlled system is guaranteed long term stability. Both control variables, effluent BOD and effluent nitrate eventually return to their original steady state, while the free variable, effluent ammonia, is once again barely affected. Though the oscillation of the output is reduced, when compared to the responses to an ammonia disturbance, the destabilizing effect of plant/model mismatch can be seen in the increased sensitivity to perturbations of the system.

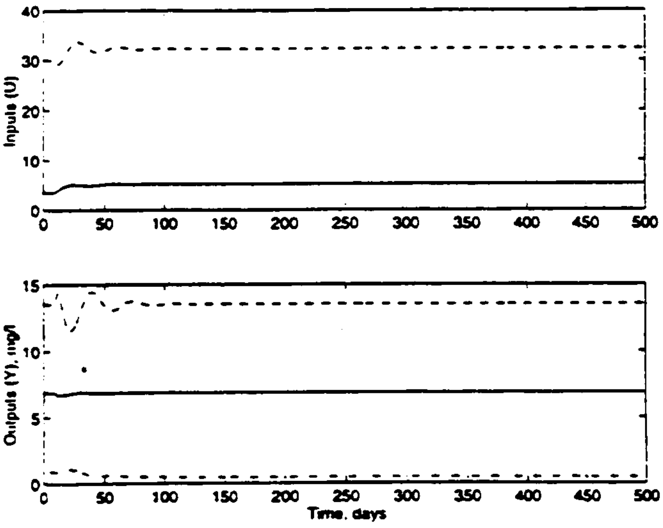

Figure 4-75. PI Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case II Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; [NO_3^-], - - - ; [NH_4^+], -•-

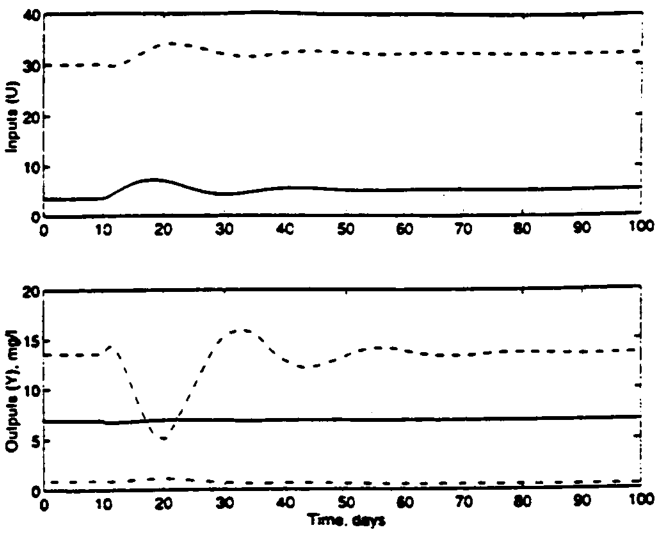

Figure 4-76. IMC Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case II Incorporating Plant/Model Mismatch;
(a) Inputs: recirculation ratio, — ; sludge age, - - - ;
(b) Outputs: BOD, — ; $[NO_3^-]$, - - - ; $[NH_4^+]$, -·-

c. Case III

Case III has the pairings of sludge age-effluent ammonia and recirculation ratio-effluent nitrate. The free variable is effluent BOD. Figure 4-77 is a plot of the input variables u_i, and the output variables y_i, after a 6% disturbance perturbation in the feed flow rate at time, t=10 days, for the PI controlled system. Just as in the non-mismatched simulations, this control scheme fails terribly for PI control because, not only is inverse response and dead time involved, but added complications occur in the inter-loop interactions due to the choice of pairings. The two loops have opposing effects on each other, which is an undesirable effect in decentralized control. Figure 4-78 is the response of an IMC controlled system after a 6% disturbance in the feed flow rate. The controller is able to return the system back to its desired steady state values, but only after large initial deviations, such as that in the nitrate. The free BOD is hardly affected, because it is a minute change in the feed flow rate.

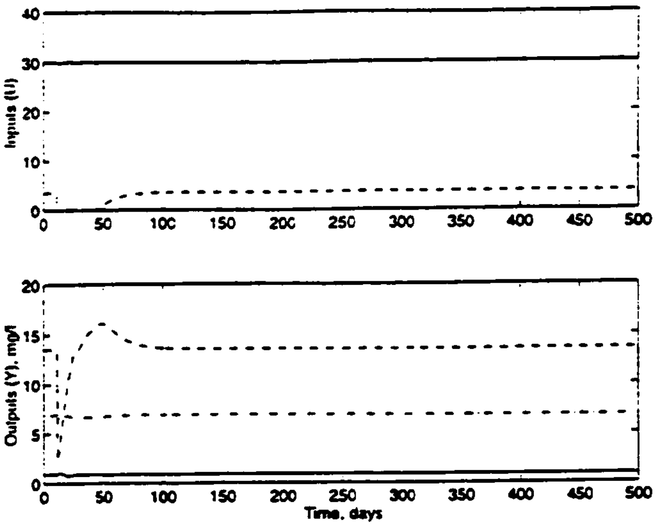

Figure 4-77. **PI Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case III Incorporating Plant/Model Mismatch;**
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -•-•.

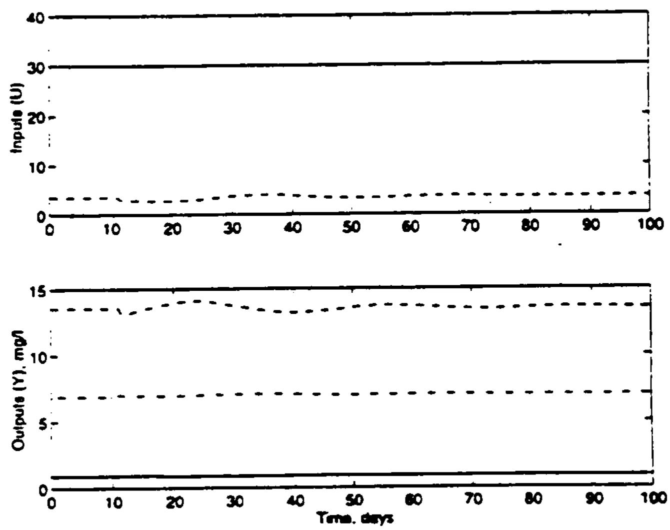

Figure 4-78. **IMC Based Regulator Control for a 6% Disturbance in Feed Flow Rate for Case III Incorporating Plant/Model Mismatch;**
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -•-•.

Figure 4-79 is a plot of the input variables and the output variables after a 15% disturbance perturbation in ammonia introduced at time, t=10 days, for the PI controlled system. In the long term, the control variables undergo unrealistic changes, such as an extremely high recirculation ratio and the steady decline of the sludge age. The IMC controlled system, whose response is seen in Figure 4-80, has the same problem with the recirculation ratio (almost double that of the similar non-mismatched simulation), but the problem with the declining sludge age in the long run is remedied. This is due to the IMC's inherent ability to compensate for inverse responses. The high recirculation ratio must be due to the opposing inter-loop interactions as demonstrated by the RGA shown in Table 4-3, because the controller has to counteract the opposing effect of the other loop.

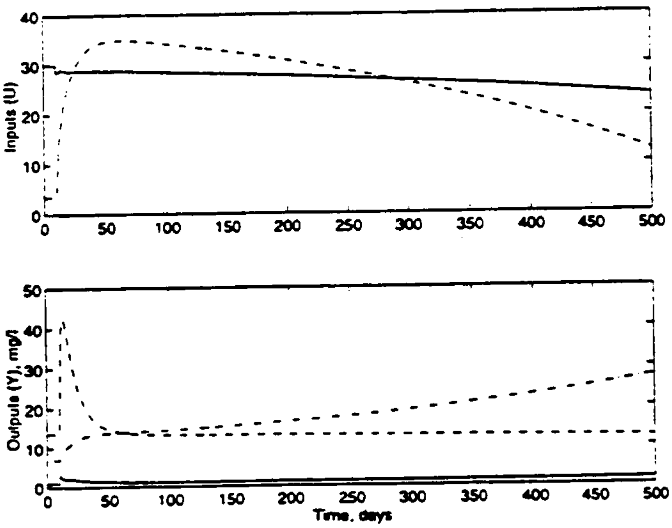

Figure 4-79. PI Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case III Incorporating Plant/Model Mismatch;
(a) Inputs: sludge age, — ; recirculation ratio, – – – ;
(b) Outputs: $[NH_4^+]$, — ; $[NO_3^-]$, – – – ; BOD, -•-.

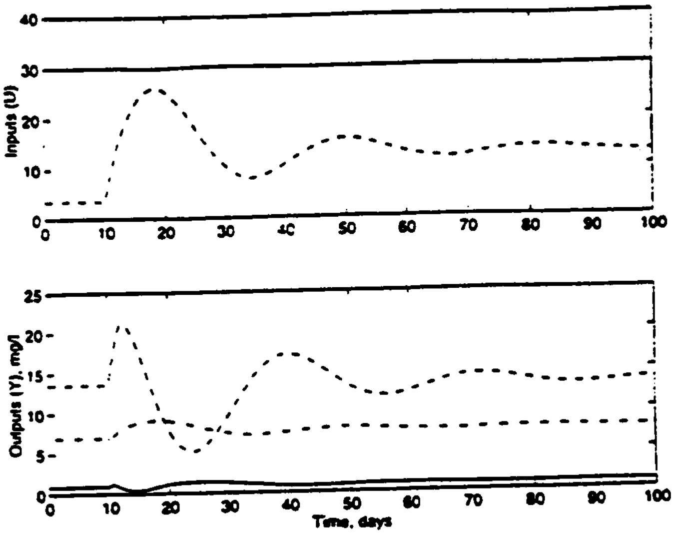

Figure 4-80. IMC Based Regulator Control for a 15% Disturbance in Influent Ammonia for Case III Incorporating Plant/Model Mismatch;
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -•-•.

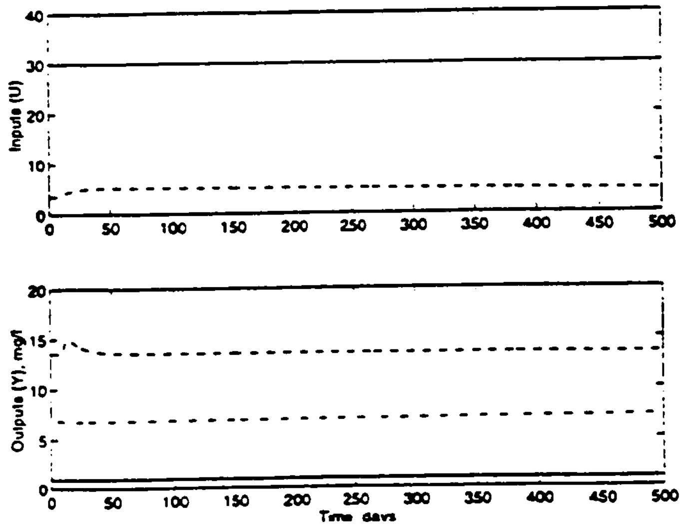

Figure 4-81. PI Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case III Incorporating Plant/Model Mismatch;
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -•-•.

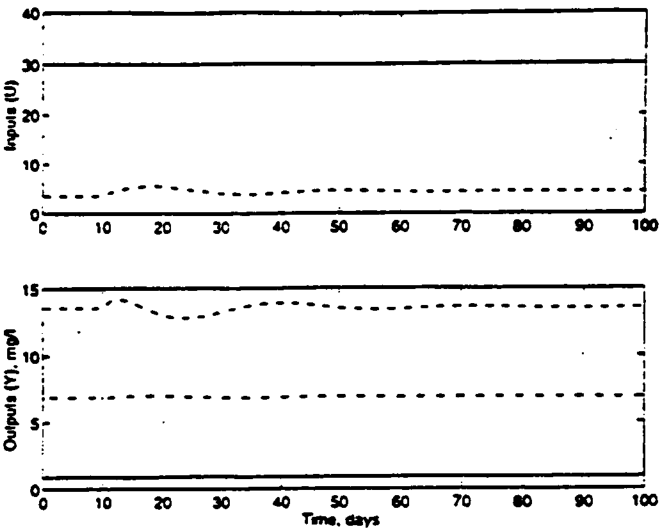

Figure 4-82. IMC Based Regulator Control for a 10% Disturbance in Influent Nitrate for Case III Incorporating Plant/Model Mismatch;
(a) Inputs: sludge age, — ; recirculation ratio, - - - ;
(b) Outputs: [NH_4^+], — ; [NO_3^-], - - - ; BOD, -·-·.

K. Random Disturbance Perturbations for Case II

The wastewater treatment plant has the ability to minimize the amount of ammonia in the discharge, even when perturbations are present. This was shown in Case II where ammonia was the free variable, but its effluent concentration fluctuated only slightly during the setpoint and disturbance simulations. Contrarily, the effluent nitrate was very sensitive to perturbations, especially ammonia perturbations, because of the chemical breakdown of ammonia into nitrate. This was shown in Case I where the effluent nitrate was the free variable. Leaving BOD as the free variable is also undesirable. It can be sensitive to large fluctuations in the feed flow rate, and the use of recirculation ratio and sludge age to control ammonia and nitrate, respectively, is an undesirable choice due to their opposing inter-loop interactions.

Taking this into consideration, one more test on Case II was studied. Case II uses recirculation ratio and sludge age to control BOD and effluent nitrate, respectively, and effluent ammonia is the free variable. In the chemical industry, it is more realistic to have perturbations that are more random and more frequent than that of a single step input. Therefore, perturbations in the feed flow rate, the influent ammonia, and the influent nitrate of roughly -50% to +50% were individually introduced to the closed-loop IMC controlled systems.

The results for feed flow rate disturbances is shown in Figure 4-83. The BOD is easily controlled by the recirculation ratio, but control of the nitrate is slightly more erratic, due to the interaction between the two loops. For the most part, the nitrate level tends to oscillate around its steady state value of 13.5 mg/l, though there are a few exceptions due to large disturbances in the feed flow rate. The input graph is displayed as percent deviation from normal steady state. A concern may be the frequent changing of the sludge age. This is not a realistic option (Reich, 1996).

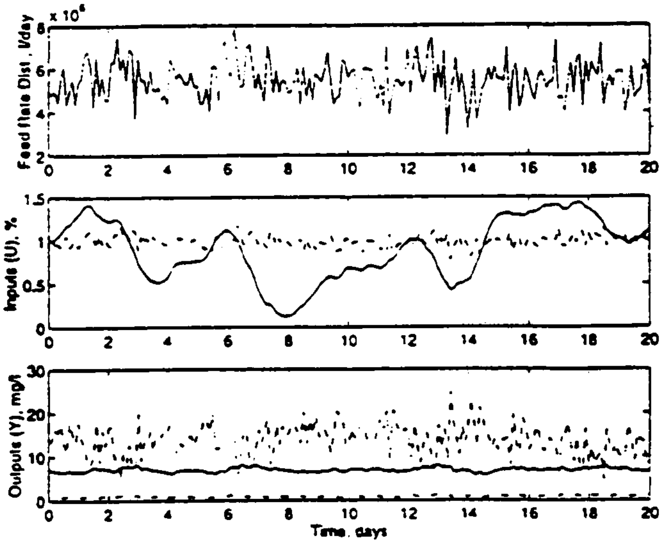

Figure 4-83. IMC Based Regulator Control for Random Disturbances in Feed Flow Rate (II);
(a) Disturbance: feed flow rate;
(b) Inputs: recirculation ratio, — ; sludge age, - - - ;
(c) Outputs: BOD, — ; [NO_3^-], - - - ; [NH_4^+], -•-

Figure 4-84 is that of the IMC controlled system for Case II with disturbances in the influent ammonia. As can be seen, the effluent nitrate is very sensitive to disturbances in the influent ammonia, thus requiring the need to control it. Leaving it as a free variable would result in unsatisfactory discharge levels of nitrate. Once again, the input graph is displayed in percentage change and the sludge age change rate may be too frequent.

Figure 4-85 is that of the same system with disturbances in the influent nitrate. The IMC controlled system, regulates the two controlled variables (BOD and nitrate) very well, with minimal control action. The free ammonia is barely affected. The input graph is shown as percentage change, and the change in sludge age is considerably less frequent than for the other two disturbances.

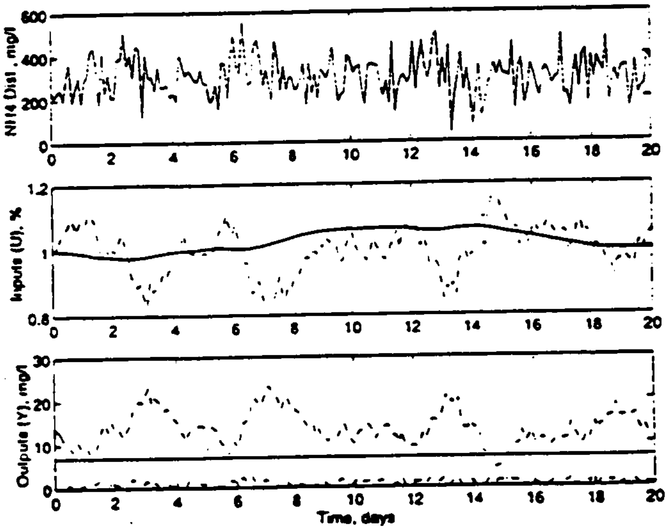

Figure 4-84. IMC Based Regulator Control for Random Disturbances in Influent Ammonia (II);
(a) Disturbance: influent ammonia;
(b) Inputs: recirculation ratio, —; sludge age, - - - ;
(c) Outputs: BOD, —; [NO_3^-], - - - ; [NH_4^+], -•-•

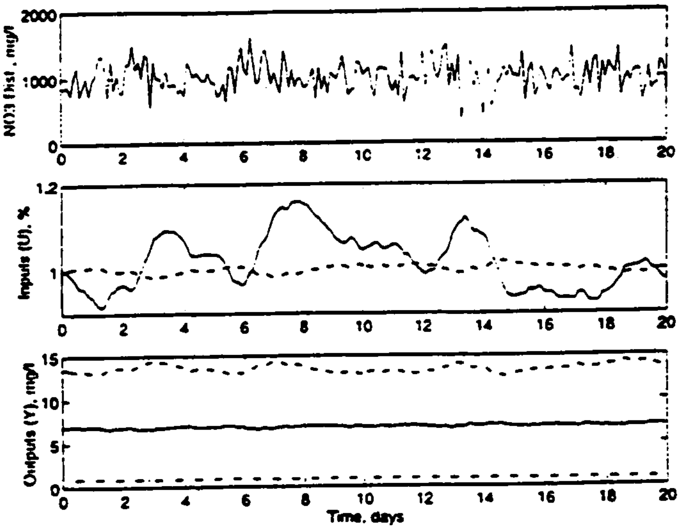

Figure 4-85. IMC Based Regulator Control for Random Disturbances in Influent Nitrate (II);
(a) Disturbance: influent nitrate;
(b) Inputs: recirculation ratio, —; sludge age, - - - ;
(c) Outputs: BOD, —; [NO_3^-], - - - ; [NH_4^+], -•-•

L. Effects of Biochemical Oxygen Demand (BOD) Disturbances

An additional concern for the DuPont Corporation is the effect of changes in the level of concentration of biochemical oxygen demand (BOD) in the influent stream (Reich, 1996). BOD influent is not a separate inlet stream to the wastewater treatment plant, but it is a component of the wastage stream that is to be treated by the plant.

Depending on the conditions in the process generating the wastewater stream that is in need of treating, the concentration of BOD in this stream will vary. This variation of BOD concentration in the inlet stream will impose disturbances on the wastewater plant, thus affecting the concentrations in the effluent. This study examined how step disturbances in BOD concentration affects the effluent of the wastewater treatment plant for both the PI and IMC controlled systems. Also, the effects of a more realistic random disturbance of BOD influent was studied for Case II with IMC control. This is the same situation where other random responses were examined. The results for these simulations are presented below.

1. Step Disturbance on Case I

This is the case where recirculation ratio and sludge age are used to control BOD effluent and ammonia effluent, respectively, with effluent nitrate as the free variable. As in the simulations for other disturbances, the long term stability of the PI controlled system is compromised when a 5% disturbance of BOD is introduced at a time of t=10 days. This is shown in Figure 4-86. Although this disturbance is small, the recirculation ratio is greatly affected by the increased level of BOD. Figure of 4-87 is the same disturbance on the IMC controlled system. The problem of long term instability is corrected, but the free variable (nitrate) reaches a new, higher steady state value.

2. Step Disturbance on Case II

This is the case where recirculation ratio and sludge age are used to control BOD and nitrate, respectively, with effluent ammonia as the free variable. As seen previously, for Case II, the PI and IMC controlled systems have similar responses, due to the lack of inverse response in the system. Figure 4-88 is a graph of the response of the PI controlled system after a 5% disturbance in influent BOD. The effluent nitrate is now controlled back to its original steady state. The free ammonia only increases slightly. Figure 4-89 is the response of the IMC controlled system after a 5% disturbance in the influent BOD. The result is similar to the PI controlled system, but unlike the PI controlled system, the μ-

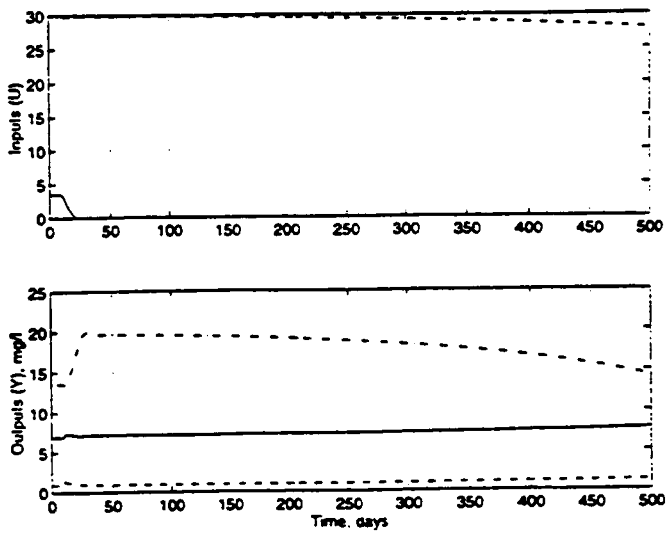

Figure 4-86. PI Based Regulator Control for a 5% Disturbance in Influent BOD for Case I

(a) Inputs: recirculation ratio, —; sludge age, - - - ;

(b) Outputs: BOD, —; [NH4+], - - - ; [NO3-], -•-•

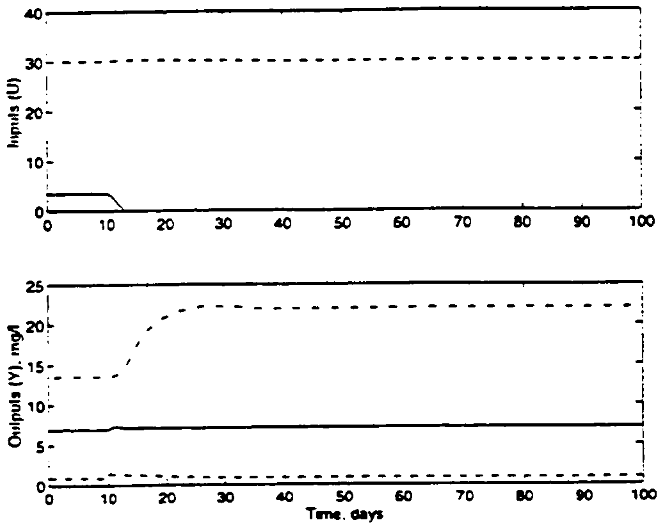

Figure 4-87. IMC Based Regulator Control for a 5% Disturbance in Influent BOD for Case I

(a) Inputs: recirculation ratio, —; sludge age, - - - ;

(b) Outputs: BOD, —; [NH4+], - - - ; [NO3-], -•-•

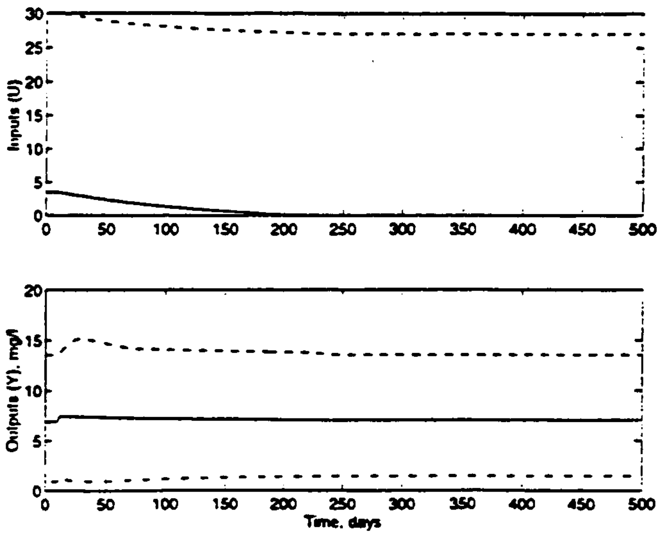

Figure 4-88. PI Based Regulator Control for a 5% Disturbance in Influent BOD for Case II

(a) **Inputs:** recirculation ratio, —; sludge age, - - - ;
(b) **Outputs:** BOD, —; [NO3-], - - - ; [NH4+], -•-•

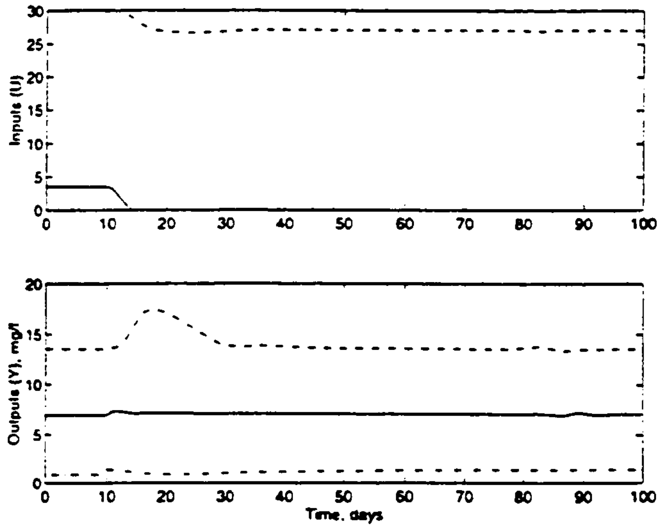

Figure 4-89. IMC Based Regulator Control for a 5% Disturbance in Influent BOD for Case II

(a) **Inputs:** recirculation ratio, —; sludge age, - - - ;
(b) **Outputs:** BOD, —; [NO3-], - - - ; [NH4+], -•-•

interaction test, discussed earlier, had no high frequency violation, which would indicate the possibility of instability.

3. Step Disturbance on Case III

This case utilizes the sludge age and the recirculation ratio to control effluent ammonia and effluent nitrate, respectively, with effluent BOD as the free variable. Figure 4-90 is a graph of the response of the PI controlled system after a 5% disturbance in influent BOD at time t=10 days. The system is stable for a lengthy period of time, but it eventually begins to go unstable. Figure 4-91 is a graph of the response of the IMC controlled system after a 5% disturbance in BOD. The IMC controller remedies the instability problem. However, the system is sluggish in its performance.

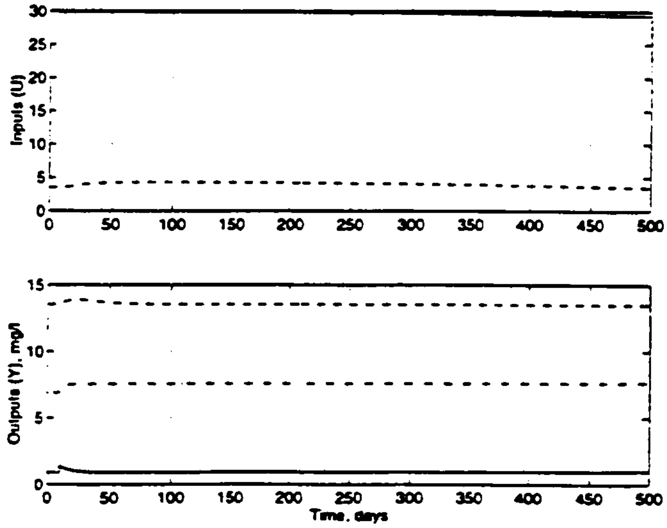

Figure 4-90. PI Based Regulator Control for a 5% Disturbance in Influent BOD for Case III

(a) Inputs: sludge age, —; recirculation ratio, - - - ;

(b) Outputs: [NH4+], —; [NO3-], - - - ; BOD, -·-

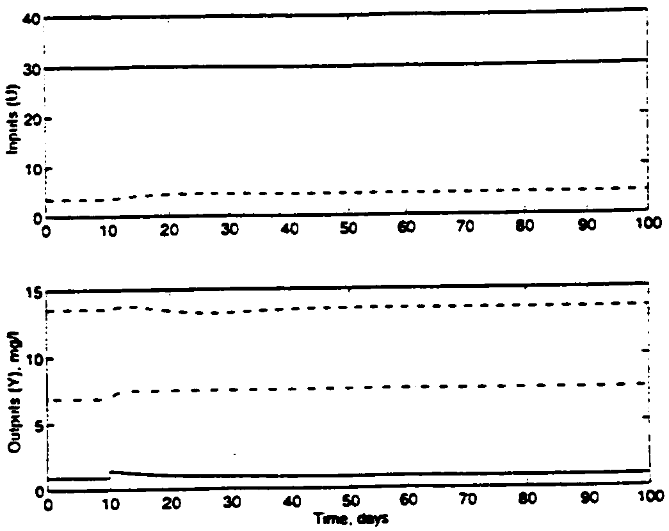

Figure 4-91. IMC Based Regulator Control for a 5% Disturbance in Influent BOD for Case III
(a) Inputs: sludge age, —; recirculation ratio, - - - ;
(b) Outputs: [NH4+], —; [NO3-], - - - ; BOD, -•-

4. Random Disturbances in Influent BOD

A more realistic representation of influent disturbance is that of a more frequent random disturbance, rather than a constant, single step disturbance. This was studied for Case II with IMC control, because it was found to be the most stable pairing and it has the ability to control effluent nitrate, a substance very sensitive to changes in ammonia. The BOD disturbance ranged from about -50% to +50% of the nominal steady state value. As can be seen in Figure 4-92, the recirculation ratio undergoes dramatic changes in order to maintain the effluent BOD concentration at the desired level. The change in sludge age is not as dramatic, because the effluent ammonia is not as affected by changes in influent BOD as the effluent BOD is. The input change is measured as a percent change from the nominal steady state level.

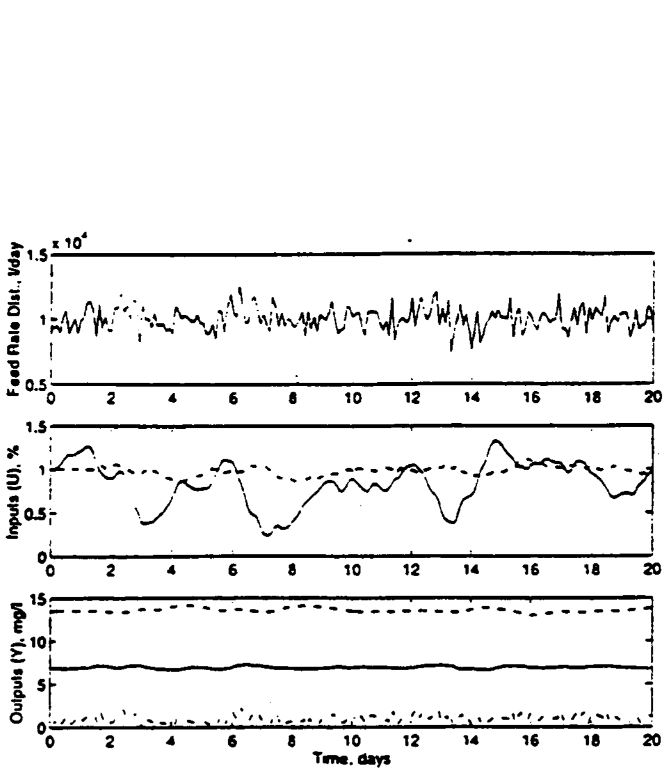

Figure 4-92. IMC Based Regulator Control for Random Disturbances in Influent BOD;
(a) Disturbance: Influent BOD
(b) Inputs: recirculation ratio, —; sludge age, - - - ;
(c) Outputs: BOD, —; [NO3-], - - - ; [NH4+], -•-•

M. Summary of Results and Discussion

The PI Based control strategy is not very adept at maintaining long term stability of the wastewater treatment plant. PI based control has several problems in handling dead time and, especially, inverse responses when no additional compensatory filters are added to the controller. This results in stability for only a limited period of time, and instability is usually inevitable when setpoint changes and disturbance perturbations are introduced to the system. However, it is noted that in most cases, trend toward instability is only very gradual, taking place over a period of about one hundred days or so. Contrary to the instability problems that were seen with PI control, model based control, such as Internal

Model Control (IMC), is very adept at handling the non-ideal characteristics of the wastewater treatment plant without additional filters, and thus additional tuning parameters to the controller. This makes the IMC controller much easier to tune than the multiparameter PI based controller plus compensators.

Though the stability of the system would be a major concern to the operator and the engineer, the sluggish performance of both the PI controlled system and the IMC controlled system must be noted. This may be a result of the interaction among the loops. There is always a trade off between robustness and performance. In this case, stability may be guaranteed with IMC, but the performance is too sluggish to be desirable. To increase the performance, the IMC controller must be retuned as to make the system more aggressive, but one risks the possibility of instability due to interaction. However, from the theory of IMC control (Morari and Zafiriou, 1989), IMC has the advantage that the stability of the IMC controller alone implies the stability of the overall closed-loop if there is negligible plant/model mismatch (provided the plant is inherently open-loop stable). Therefore, retuning of the stable IMC controller can be carried out without endangering the overall system stability, except for the consideration of the interaction effect. The μ-Interaction Measure needs to be used such that retuning individual loops of the IMC controlled system does not violate the overall multiloop closed-loop stability.

In contrast, the stability of the PI controller alone implies nothing about the overall closed-loop stability. The overall closed-loop stability has to be derived by calculating for the poles of the closed-loop transfer function, which is a chore each time the PI controller is retuned. Furthermore, calculating the overall stability at a particular PI tuning setting necessitates the knowledge of the plant's exact model, often an impossible task. On the other hand, no such knowledge is required for calculating for the stability of the IMC controller system, as long as the open-loop remains stable, because stability of the IMC controller is enough to imply the stability of the overall closed-loop. It can be shown (Morari and Zafiriou, 1989) that for each mode of IMC, an equivalent PID or PID plus additional lag-filters controllers can be derived. Because of the above argument concerning stability, it would be preferable to implement even a simple PID feedback controller in the framework of the IMC.

However, with PI based control alone, for the wastewater treatment system the closed-loop is inherently unstable. No amount of retuning will insure the long term closed-loop stability. Relative stability can only be maintained over a short period of time (days) before the PI controller has to be returned less aggressively to stave off instability. This detuning has to be repeated a short while later. After a series of detuning to stave off instability, the controller performance may have become so sluggish as to render any feedback control action useless. The loops would have to be decommissioned and a new start-up commissioned. A new round of PI control would then have to begin, accompanied by vigilant monitoring and periodic detuning to insure stability. If frequent retuning is necessary to insure stability while at the same time trying to maintain desired performance, then the automated PI control strategy may be no better than manual open-loop control by an experienced operator.

The ease of tuning of the controllers is an important factor when considering that the controllers may have to be periodically retuned in order to maintain stability while performing as desired. The single parameter of an IMC controller loop is much easier to retune than that for a multiparameter PI controller. This ease of tuning is also very apparent when plant/model mismatch is incorporated into the system. When the system changed and the original controllers were not suitable enough to guarantee stability, the parameters of each controller had to be made more conservative in order to guarantee stability. In the case of the PI controller, the perfect balance between the two different parameters in each loop and between the loops had to be found in order to stabilize the primary loops and to take into account the effects of the inter-loop interaction. The difficulty of the retuning increases as more parameters are incorporated when compensating filters are added to the PI controllers. For the IMC controllers there was only one parameter in each loop to retune to compensate for plant/model mismatch, which results in much easier and transparent retuning.

Simulation results for all three cases of input-output pairings, along with the advantages and disadvantages of PI and IMC controllers are summarized in the following tables. Table 4-4 is a summary for Case I, where recirculation ratio and sludge age are used to control BOD and ammonia, respectively, and nitrate is the free variable. Table 4-5 is a summary for Case II, where recirculation ratio and sludge age are used to control BOD and nitrate, respectively, and ammonia is the free variable. Table 4-6 is a summary for Case III, where sludge age and recirculation ratio are used to control ammonia and nitrate, respectively, and BOD is the free variable.

Table 4-4. Summary of Case I

Manipulative Variable	Controlled Variable	Free Variable
Recirculation Ratio Sludge Age	Effluent BOD Effluent Ammonia	Effluent Nitrate

Type of Simulation	PI Controlled Response	IMC Controlled Response
μ-Interaction Measure	Uncorrectable high frequency violation of the μ^{-1} boundary due to dead time and inverse Adding additional filters will correct the high frequency violation, but adds additional tuning parameters, thus making tuning more difficult	Any boundary violation can easily be corrected by conservative tuning of the single parameter Controller has intrinsic compensators, thus there is no need for additional filters
Servo Control (Setpoint Tracking)	Long term stability is a problem due to dead time and inverse response Performance is sluggish and improving the performance will decrease the robustness of the system	Maintains long term stability and achieves new setpoints (though BOD setpoint is limited) Performance is sluggish and improving the performance will decrease the robustness of the system
Regulator Control (Disturbance Rejection)	Long term stability is a problem due to dead time and inverse response Free variable (nitrate) is sensitive to ammonia input Performance is sluggish	Long term stability is maintained Free Variable (nitrate) is sensitive to ammonia input Performance is sluggish
Plant/Model Mismatch	Incorporation of 50% mismatch on plant transfer function parameters results in a more sensitive system that needs to be retuned to maintain stability	Incorporation of 50% mismatch on plant transfer function parameters results in a more sensitive system that needs to be retuned to maintain stability
μ-Interaction Measure with Plant/Model Mismatch	Controllers must be made more robust, but system becomes even more sluggish High frequency violation of μ^{-1} boundary Additional filters are needed to insure long term stability	Controllers must be made more robust, but system becomes even more sluggish Very easy to retune without having to add additional filters
Servo Control with Plant/Model Mismatch	Long term stability is a problem due to dead time and inverse response System is sluggish, which diminishes performance	Maintains long term stability and achieves new setpoints (though BOD change is limited) System is sluggish, which diminishes performance
Regulator Control with Plant/Model Mismatch	Long term stability is a problem due to dead time and inverse response System is sluggish, which diminishes performance	Able to maintain long term stability System is sluggish, which diminishes performance

Table 4-5. Summary of Case II

Manipulative Variable	Controlled Variable	Free Variable
Recirculation Ratio	Effluent BOD	Effluent Ammonia
Sludge Age	Effluent Nitrate	

Type of Simulation	PI Controlled Response	IMC Controlled Response
μ-Interaction Measure	Uncorrectable high frequency violation of the μ^{-1} boundary due to dead time and inverse Adding additional filters will correct the high frequency violation, but adds additional tuning parameters, thus making tuning more difficult	Any boundary violation can easily be corrected by conservative tuning of the single parameter Controller has intrinsic compensators, thus there is no need for additional filters
Servo Control (Setpoint Tracking)	Tends to be stable, but potential for instability exists due to dead time Performance is sluggish and improving the performance will decrease the robustness of the system	Maintains long term stability and achieves new setpoints (though BOD setpoint is limited) Performance is sluggish and improving the performance will decrease the robustness of the system
Regulator Control (Disturbance Rejection)	Long term stability is a problem due to dead time and inverse response Free variable (ammonia) is not very sensitive Performance is sluggish	Long term stability is maintained Free Variable (ammonia) is not very sensitive Performance is sluggish
Plant/Model Mismatch	Incorporation of 50% mismatch on plant transfer function parameters results in a more sensitive system that needs to be retuned to maintain stability	Incorporation of 50% mismatch on plant transfer function parameters results in a more sensitive system that needs to be retuned to maintain stability
μ-Interaction Measure with Plant/Model Mismatch	Controllers must be made more robust, but system becomes even more sluggish High frequency violation of μ^{-1} boundary Additional filters are needed to insure long term stability	Controllers must be made more robust, but system becomes even more sluggish Very easy to retune without having to add additional filters
Servo Control with Plant/Model Mismatch	Tends to be stable, but potential for instability exists due to dead time System is sluggish, which diminishes performance Response is more oscillatory due to increased sensitivity	Maintains long term stability and achieves new setpoints (though BOD change is limited) System is sluggish, which diminishes performance Response is more oscillatory due to increased sensitivity
Regulator Control with Plant/Model Mismatch	Tends to be stable, but potential for instability exists due to dead time System is sluggish, which diminishes performance	Able to maintain long term stability System is sluggish, which diminishes performance

Table 4-6. Summary of Case III

Manipulative Variable	Controlled Variable	Free Variable
Sludge Age Recirculation Ratio	Effluent Ammonia Effluent Nitrate	Effluent BOD

Type of Simulation	PI Controlled Response	IMC Controlled Response
μ-Interaction Measure	Uncorrectable high frequency violation of the μ^{-1} boundary due to dead time and inverse Adding additional filters will correct the high frequency violation, but adds additional tuning parameters, thus making tuning more difficult	Any boundary violation can easily be corrected by conservative tuning of the single parameter Controller has intrinsic compensators, thus there is no need for additional filters
Servo Control (Setpoint Tracking)	Long term stability is a problem due to dead time and inverse response Performance is sluggish and improving the performance will decrease the robustness of the system Opposing interaction between the loops may cause the controller to overcompensate	Maintains long term stability and achieves new setpoints (though BOD setpoint is limited) Performance is sluggish and improving the performance will decrease the robustness of the system Opposing interaction between the loops may cause the controller to overcompensate
Regulator Control (Disturbance Rejection)	Long term stability is a problem due to dead time and inverse response Performance is sluggish Opposing interaction between the loops may cause the controller to overcompensate	Long term stability is maintained Performance is sluggish Opposing interaction between the loops may cause the controller to overcompensate
Plant/Model Mismatch	Incorporation of 50% mismatch on plant transfer function parameters results in a more sensitive system that needs to be retuned to maintain stability	Incorporation of 50% mismatch on plant transfer function parameters results in a more sensitive system that needs to be retuned to maintain stability
μ-Interaction Measure with Plant/Model Mismatch	Controllers must be made more robust, system is more sluggish High frequency violation of μ^{-1} boundary Additional filters are needed to insure long term stability	Controllers must be made more robust, system is sluggish Very easy to retune without having to add additional filters
Servo Control with Plant/Model Mismatch	Long term stability is a problem due to dead time and inverse response System is sluggish, which diminishes performance	Maintains long term stability and achieves new setpoints System is sluggish, which diminishes performance
Regulator Control with Plant/Model Mismatch	Long term stability is a problem due to dead time and inverse response System is sluggish, which diminishes performance	Able to maintain long term stability System is sluggish, which diminishes performance

N. Implications of Results in Application

One objective of this study is to help wastewater treatment plant personnel and control engineers to achieve a better understanding of what first level automated control will give them over and above that of manual open-loop control, and what its limitations are. With a first level PID as the automated control strategy, and for non-ideal systems, the operator is able to tune the controller in the short term such that the system gives good performance for a period of time, but has to detune the PI controllers when the onset of instability becomes apparent. If the PI controllers have to be frequently detuned to maintain stability then this labor intensive method offers no greater benefits in automation than open-loop manual control done by experienced personnel.

Retuning of the IMC controller to improve performance has a less likely chance of the system becoming unstable, because the controller has intrinsic properties to deal with large dead times and inverse response, and the stability of the IMC controller alone implies the stability of the overall closed loop system, except for the possible effect of inter-loop interaction. Then an interaction measure, such as the μ-Interaction Measure (Grosdidier and Morari, 1987) can be used to establish an upper bound for the retuning of the IMC control loops.

Granted, controller design strategies without taking explicit input or output constraints into considerations may not be feasible when control actions lead to violations of practical limits, such as a very large or negative (e.g., negative recirculation ratio) control action, a very rapid control action, or a very large output response. If constraint violation is to be strictly avoided, then an advanced full multivariable control design strategy that takes into explicit account constraints would be the choice. However, this approach usually requires a dedicated body of control personnel versed in the knowledge of advanced control theory and design procedures as well as in the follow-up maintenance expertise. Extensive modeling and simulation would need to be done upfront before closed-loop controller commissioning. This approach would usually involve a considerable level of expert personnel and financial commitment. It would be the last resort to be taken, only after a first lever controller design strategy, such as the two presented in this study (classical PID and model based IMC), have failed to meet the desired criteria. Of the two, the latter would be a preferred controller framework to implement because of the stability features discussed previously.

Chapter Five

Conclusions and Recommendations

A. Conclusions

During the design stage for a plant, the type of and effectiveness of the control scheme to be used should be part of the consideration leading to the selection of the final design. This study presents a theoretical analysis of two alternate control strategies for a multistage wastewater treatment plant. Specification for the plant is based upon DuPont's Victoria, Texas plant under consideration.

The alternate control schemes considered were multiple, decentralized single-input single-output (SISO) PID based and model based systems (Internal Model Control (IMC)). The former was chosen because it is the most common approach taken by most control engineers. The latter was selected because model based control has many advantages that a PID controller does not have and is only the next level up in design complexity. The evaluation and comparison of these two control strategies was based upon the ability of each control system to maintain stability over the long term and to meet plant treatment performance criteria in the face of setpoint and disturbance perturbations. The ease of controller tuning was also an important part of the evaluation and comparison considerations.

From the analysis of the relative gain arrays between the two input variables and the three output variables, the optimum control pairings for the wastewater plant were arrived at based on the measure of interaction between the proposed control loops. Three of the six possible pairing combinations were found to be highly interactive. The less interactive pairings are shown in Table 5-1, Table 5-2, and Table 5-3.

Table 5-1. Optimum Control Pairing Case I

Manipulated Variable	Control Variable	Free Variable
Recirculation Ratio	Effluent BOD	Effluent Nitrate
Sludge Age	Effluent Ammonia	

Table 5-2. Optimum Control Pairing Case II

Manipulated Variable	Control Variable	Free Variable
Recirculation Ratio	Effluent BOD	Effluent Ammonia
Sludge Age	Effluent Nitrate	

Table 5-3. Optimum Control Pairing Case III

Manipulated Variable	Control Variable	Free Variable
Sludge Age	Effluent Ammonia	Effluent BOD
Recirculation Ratio	Effluent Nitrate	

The complexity of the wastewater treatment plant's nonlinear characteristics, such as process dead time and inverse response, are present to a higher degree in Cases I and III. In Case II, dead time and lead response were present.

The PI controller proves to be inadequate in maintaining long term stability, especially for the systems involving inverse response (Case I and III). The performance of the PI control system becomes extremely inadequate (too sluggish) when the controller is tuned to increase the margin of stability. More aggressive tuning of the PI controller to improve the performance to a desired level decreases the margin of stability. In this situation, after the controller is initially tuned to give acceptable speed of response, it would have to be detuned after a certain time period in order to stave off instability. If this detuning is frequent, then implementing an automated feedback control would appear to be no more beneficial than an open-loop manual control mode done regularly by an experienced operator.

On the other hand, model based control offered stability advantage when compared to PID based control. Tuning was much simpler and more intuitive because IMC has only one tuning parameter. It also has the built-in capability for compensating for process dead time and inverse response. Therefore, no additional filters or tuning parameters are necessary. Though the IMC controller can assure stability for the long term, its performance while doing so is rather poor at times. The controller can be retuned to increase the performance. Retuning of the IMC has the advantage over the PID controller in that the stability of the IMC controller alone implies the stability of the overall closed-loop system; whereas the stability of a PID controller is not necessarily indicative of the overall closed-loop system. However, more aggressive tuning of an IMC controller in the decentralized control scheme is limited by consideration of the inter-loop interaction.

The linear representation of the nonlinear system limits the accuracy of the calculation of the true interactions between the many parameters, when more than one variable is changing at a time. This may skew the results simulated with the linear representation of the system. The accuracy of the linear representation of the system tends to agree with the open-loop non-linear system only when the multiple changes in the manipulative variables are well below 50% of their nominal values.

B. Recommendations

This study examined two alternative control strategies for a wastewater treatment plant. These strategies are not recommended strongly for the final control scheme for the Victoria, Texas plant, mainly because of the sluggishness in response, even though IMC is able to maintain long term stability of the closed-loop system. The fact that the 2 x 2 controller is a decentralized controller whose design does not take into explicit consideration the inter-loop interaction, limits severely the maximum allowable tuning of the controllers in order to improve the speed of process response to control actions. Furthermore, IMC control actions, even though stable, frequently result in too big or too rapid control moves that are not feasible to be implemented. It appears that the application of a much more advanced model based controller, such as Quadratic Dynamic Matrix Control (QDMC), which has a better ability to handle constraints on the process inputs and outputs or a full multivariable robust controller, need to be considered for the wastewater treatment system. Both of these advanced control strategies would require much more specialized personnel in its design, implementation, and maintenance. The many non-ideal characteristics of the plant kinetics, as well as the interactive nature among the loops, are too complex for the first level decentralized PID and unconstrained model based (IMC) controllers to handle.

It has also been noted that a better manipulated variable for controlling the effluent BOD might be that of the sludge age, rather than the recirculation ratio (Arthur, 1983). However, this may not be feasible if the change in the sludge age needed for control is more than once per day. It is unrealistic to implement frequent changes in the sludge age (Reich, 1996), when its change is dependent on the elapse of time.

Further, during simulation, the application of the desired control strategy directly to the original non-linear model would be more revealing of its effect than its application to the linearized model of the system.

In conclusion, simulation of the effectiveness of various control strategies upfront during the process design stage would aid greatly in the selection of an acceptable final control strategy.

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Appendices

Appendix A

Mathematical Equivalencies of IMC and PID Controllers

A. Theoretical Basis

Morari, *et al.* (1989) derived the general relationship between the classic PID based feedback controller c and the IMC controller q when the process model is $\bar{p}$. This is shown in equation A-1.

$$c = \frac{q}{1 - \bar{p}q} \tag{A-1}$$

Using this relationship, along with the general equation for a PID controller with added compensating filters (equation A-2), and assuming a step input to the process, one can calculate and demonstrate how the one parameter, λ, IMC based controller contains all of the PID based parameters (Kc, τ_I, and τ_D), plus any and all additional filters, τ_{F1} and τ_{F2}, needed to compensate for "nasty" characteristics, such as large dead time and inverse response.

$$c = \left(1 + \frac{1}{\tau_I s} + \tau_D s\right)\left(\frac{1}{\tau_{F1}s^2 + \tau_{F2}s + 1}\right) \tag{A-2}$$

Rearranging yields:

$$c = \left(\frac{K_c\tau_D\tau_I s^2}{\tau_I s} + \frac{K_c\tau_I s}{\tau_I s} + \frac{K_c}{\tau_I s}\right)\left(\frac{1}{\tau_{F1}s^2 + \tau_{F2}s + 1}\right) \tag{A-3}$$

In order to simplify the design of the controller, the dead time is approximated by a first order Pade expression shown below in equation A-4. The dead time is given by θ.

$$e^{-\theta s} = \frac{-\frac{\theta}{2}s + 1}{\frac{\theta}{2}s + 1} \tag{A-4}$$

Substituting $\beta=\theta/2$ into equation A-4 results in equation A-5

$$e^{-\theta s} = \frac{-\beta s+1}{\beta s+1} \tag{A-5}$$

B. First Order Lag Plus Dead Time

The plant $\bar{p}$ is represented by equation A-6, where K is the gain, θ is the dead time, and τ is the time constant.

$$p = \frac{Ke^{-\theta s}}{\tau s+1} \tag{A-6}$$

Following the procedure to calculate the internal model controller (IMC) q from $\bar{p}$ results in equation A-7, where λ is the IMC tuning parameter.

$$q = \frac{\tau s+1}{K(\lambda s+1)} \tag{A-7}$$

Multiplying $\bar{p}$ and q yields equation A-8

$$pq = \frac{e^{-\theta s}}{\lambda s+1} \tag{A-8}$$

Combining equations A-1, A-7, and A-8 yields the PID with filter equivalent of an IMC controller for a first order lag system plus dead time, shown in equation A-9.

$$c = \frac{\tau s+1}{K\left(\lambda s+1-e^{-\theta s}\right)} \tag{A-9}$$

After applying equation A-5 to the dead time, equation A-9 can then be rearranged to have the similar structure as equation A-3.

$$c = \frac{\tau\beta s^2+(\tau+\beta)s+1}{K(\lambda+2\beta)s\left(\frac{\lambda\beta}{\lambda+2\beta}s+1\right)} \tag{A-10}$$

After equivocating like terms, the following relationships between the parameters is deduced.

$$K_cK = \frac{\tau+\beta}{\lambda+2\beta} \tag{A-11}$$

$$\tau_I = \tau+\beta \tag{A-12}$$

$$\tau_D = \frac{\tau\beta}{\tau+\beta} \qquad \text{(A-13)}$$

$$\tau_{F1} = 0 \qquad \text{(A-14)}$$

$$\tau_{F2} = \frac{\lambda\beta}{\lambda+2\beta} \qquad \text{(A-15)}$$

C. First Order Lead-Lag Plus Dead Time

The plant $\tilde{p}$ is represented by equation A-16, where K is the gain, θ is the dead time, τ is the time constant, and z is the lead time constant (or left half plane zero).

$$\tilde{p} = \frac{K(zs+1)e^{-\theta s}}{\tau s+1} \qquad \text{(A-16)}$$

Following the procedure to calculate the internal model controller (IMC) q from $\tilde{p}$ results in equation A-17, where λ is the IMC tuning parameter.

$$q = \frac{\tau s+1}{K(zs+1)(\lambda s+1)} \qquad \text{(A-17)}$$

Multiplying $\tilde{p}$ and q yields equation A-18

$$\tilde{p}q = \frac{e^{-\theta s}}{\lambda s+1} \qquad \text{(A-18)}$$

Combining equations A-1, A-17, and A-18 yields the PID with filter equivalent of an IMC controller for a first order lag system plus dead time, shown in equation A-19.

$$c = \frac{\tau s+1}{K(zs+1)\left(\lambda s+1-e^{-\theta s}\right)} \qquad \text{(A-19)}$$

After applying equation A-5 to the dead time, equation A-19 can then be rearranged to have the similar structure as equation A-3.

$$c = \frac{\tau\beta s^2+(\tau+\beta)s+1}{K(\lambda+2\beta)s\left(\frac{\lambda\beta z}{\lambda+2\beta}s^2+\frac{\lambda\beta+2z\beta+\lambda z}{\lambda+2\beta}s+1\right)} \qquad \text{(A-20)}$$

After equivocating like terms, the following relationships between the parameters is deduced.

$$K_cK = \frac{\tau+\beta}{\lambda+2\beta} \qquad \text{(A-21)}$$

$$\tau_I = \tau + \beta \qquad \text{(A-22)}$$

$$\tau_D = \frac{\tau\beta}{\tau + \beta} \qquad \text{(A-23)}$$

$$\tau_{F1} = \frac{\lambda\beta z}{\lambda + 2\beta} \qquad \text{(A-24)}$$

$$\tau_{F2} = \frac{\lambda\beta + 2z\beta + \lambda z}{\lambda + 2\beta} \qquad \text{(A-25)}$$

D. First Order Lag Plus Dead Time and Inverse Response

The plant $\bar{p}$ is represented by equation A-26, where K is the gain, θ is the dead time, τ is the time constant, and z is the inverse time constant (or right half plane zero).

$$p = \frac{K(-zs+1)e^{-\theta s}}{\tau s + 1} \qquad \text{(A-26)}$$

Following the procedure to calculate the internal model controller (IMC) q from $\bar{p}$ results in equation A-27, where λ is the IMC tuning parameter.

$$q = \frac{\tau s + 1}{K(\lambda s + 1)} \qquad \text{(A-27)}$$

Multiplying $\bar{p}$ and q yields equation A-28

$$pq = \frac{(-zs+1)e^{-\theta s}}{(zs+1)(\lambda s + 1)} \qquad \text{(A-28)}$$

Combining equations A-1, A-27, and A-28 yields the PID with filter equivalent of an IMC controller for a first order lag system plus dead time, shown in equation A-29.

$$c = \frac{\tau s + 1}{K\left((zs+1)(\lambda s+1) - (-zs+1)e^{-\theta s}\right)} \qquad \text{(A-29)}$$

After applying equation A-5 to the dead time, equation A-29 can then be rearranged to have the similar structure as equation A-3.

$$c = \frac{\tau\beta s^2 + (\tau + \beta)s + 1}{K(\lambda + 2z + 2\beta)s\left(\frac{\lambda\beta z}{\lambda + 2z + 2\beta}s^2 + \frac{\lambda(z+\beta)}{\lambda + 2z + 2\beta}s + 1\right)} \qquad \text{(A-30)}$$

After equivocating like terms, the following relationships between the parameters is deduced.

$$K_cK = \frac{\tau+\beta}{\lambda+2z+2\beta} \tag{A-31}$$

$$\tau_I = \tau+\beta \tag{A-32}$$

$$\tau_D = \frac{\tau\beta}{\tau+\beta} \tag{A-33}$$

$$\tau_{F1} = \frac{\lambda\beta z}{\lambda+2z+2\beta} \tag{A-34}$$

$$\tau_{F2} = \frac{\lambda(z+\beta)}{\lambda+2z+2\beta} \tag{A-35}$$

Vita

Brandon Thomas Schmidt was born in Warren, Michigan on March 8, 1971. He graduated from Warren DeLaSalle Collegiate High School in 1989. He entered the University of Michigan, Ann Arbor during August, 1989 where in May, 1994 he received the Bachelor of Science in Chemical Engineering. While at the University of Michigan, he joined Theta Chi Fraternity, Alpha Gamma Chapter, where he held many leadership positions such as: Executive Council Secretary, OX Roast Chairman, and Editor of the Jon Journal.

Being a philomathic person, he entered the Master's program in Chemical Engineering at the University of Tennessee, Knoxville in August, 1994, officially receiving the Master's degree in December, 1996. Upon graduation, he accepted a job as a Process Automation Engineer with the Information Technology Division of Union Carbide Corporation in Houston, Texas.

The hardest earned triumphs are crucial helpers in making gains over blockades; leaving us every possible opportunity, with promises of winning.