DEVELOPMENT OF MODEL BASED DECOUPLER FOR MULTI INPUT MULTI OUTPUT DISTILLATION COLUMN

by

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TABLE OF CONTENTS

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ARX	Autoregressive with exogenous input
BP	Back propagation
FANN	Feedforward Artificial Neural Network
IAE	Integral absolute error
ISE	Integral squared error
ITAE	Integral time absolute error
MIMO	Multi input multi output
mv	Manipulated variable
mv_1	1st manipulated variable
mv_2	2nd manipulated variable
PID	Proportional integral derivative
SSE	Sum squared error
y_1	Top composition
y_2	Bottom composition

PEMBANGUNAN NYAHPASANGAN BERASASKAN MODEL BAGI BERBILANG MASUKAN BERBILANG KELUARAN TURUS PENYULINGAN

ABSTRAK

Turus penyulingan adalah sistem pembolehubah yang kompleks dan mempamerkan tingkah laku dinamik yang tak linear kerana tatarajah pemprosesan yang kompleks dan ketulenan produk yang tinggi. Gandingan merupakan fenomena yang sangat umum dalam berbilang masukan berbilang keluaran (MIMO) sistem. Dalam industri, pengawalan pelbagai direka untuk kilang pemprosesan bagi memastikan penghasilan produk yang berkualiti. Gandingan mempengaruhi gelungan disebabkan interaksi antara gelungan, ia juga mempengaruhi kestabilan dan kualiti.

Kajian thesis ini bertumpu pada cara untuk mengurangkan interaksi gandingan dalam proses pembolehubah tak linear dalam turus penyulingan. Dinamik nyahpasangan PID-ARX (Autoregresi eksogen) dan PID-FANN (Rangkaian Neural) telah diperkenalkan di dalam sistem pengawalan turus penyulingan dan dibandingkan dengan nyahpasangan PID konvensional. Dalam kajian ini, tiga kajian kes yang berbeza telah digunakan : Shell fractionators, Turus penyulingan Skogestad dan turus penyulingan metanol /air digunakan untuk pengawalan nyahpasangan. Semua turus penyulingan ini adalah MIMO (berbilangmasukan berbilang keluaran) sistem.

Berdasarkan keputusan dalam kajian ini, didapati nyahpasangan berasaskan model PID-FANN adalah lebih baik daripada PID-ARX dan nyahpasangan PID Konvensional. PID-ARX menghasilkan keputusan yang lebih baik daripada nyahpasangan PID konvensional dalam setiap kajian kes. PID-ARX dan PID-FANN menunjukkan keputusan yang baik dalam kajian ini, PID-FANN lebih baik dalam mengatasi interaksi gelung dalam MIMO sistem untuk setiap kajian kes. Ia jelas menunjukkan dalam Kajian Kes 3 komposisi metanol (y_1) dengan menggunakan PID konvensional decoupler mempunyai lebih kenaikan dan interaksi gelung dan mencapai nilai baru 0.9942 daripada nilai asal 0.9953 berbanding dengan PID-FANN decoupler, manakala metanol komposisi (y_1) di PID-FANN decoupler berjalan dengan lancar untuk mencapai output keinginan apabila titik set baru telah ditetapkan sebagai perbandingan dengan PID-ARX dan PID Konvensional.

Analisis statistik digunakan di mana jumlah ralat kuasa dua (SSE), kesilapan masa mutlak wajaran (ITAE) dan ralat kuasa dua (ISE), menunjukkan hasil yang konsisten terhadap sambutan proses keluaran. Kajian Kes 3 telah menunjukkan bahawa SSE 1 dengan menggunakan PID-FANN adalah 0.006923 manakala dengan menggunakan PID Konvensional dan PID ARX, nilai SSE adalah 0.007591 dan 0.0073.

Kesimpulannya ialah nyahpasangan berasaskan model mempunyai keupayaan dari segi menguasai dinamik sistem dan seterusnya berjaya mengurangkan interaksi gelung dalam sistem.

DEVELOPMENT OF MODEL BASED DECOUPLER FOR MULTI INPUT MULTI OUTPUT DISTILLATION COLUMN

ABSTRACT

Distillation column is a complex multivariable system and exhibits nonlinear dynamic behaviour due to the complex processing configurations and high product purities. The strong coupling among control loops often invalidates conventional loop controllers. Coupling is a very common phenomenon in multiple input multiple output (MIMO) systems. During processes, multiple control loops are designed for a process plant to control and guarantee the product quality. However, the control loops interact with other significantly. Due to the interaction between the loops, the stability and the product quality of the process may be compromised. Therefore, decoupling control was introduced to reduce the coupling problem in the nonlinear system.

This research focuses on finding the way to reduce the coupling interaction in the nonlinear multivariable process in distillation column. Dynamic decoupler PID-ARX (AutoRegressive eXogenous) and PID-FANN (Feedforward Artificial Neural Network) was introduced in the distillation control system and compared with the PID-conventional decoupler. In this research, three different case studies: Shell heavy oil fractionators, Skogestad column and methanol/water column were used to

develop decoupling control. All these distillation columns are MIMO (multi input-multi output) system.

Based on result, it was observed that PID-FANN was better than PID-ARX and PID Conventional Decoupler for all three case studies. PID-ARX performs better than PID conventional decoupler in all case studies. The overall performance of PID-ARX and PID-FANN were found to be consistent throughout all case studies, where PID-FANN is superior in handling the loop interaction in MIMO control strategy. Case Study 3 shown the composition of methanol (y_1) by using PID-conventional decoupler have more spike and loop interaction and reach the new set point 0.9942 from original set point 0.9953 slowly compare to PID-FANN decoupler, while composition methanol (y_1) in PID-FANN decoupler reduce spike and run smoothly to reach the desire output when new set point was set as compared with PID-ARX and PID-Conventional.

In statistical analysis, the Sum square error (SSE), integral of the time weighted absolute error (ITAE) and integral of the square error (ISE) shows the consistent result of the response of the process output. Case Study 3 was shown that SSE 1 by using PID-FANN was 0.006923 while by using PID Conventional and PID ARX, SSE value were 0.007591 and 0.0073 respectively.

This concluded that model based decoupler has high capability in terms of capturing the dynamics of the systems especially the time delays which cannot be inversed in conventional decoupler and consequently managed or be able to reduce or eliminate the loop interaction in the system.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Distillation is a method of separating a mixture of liquids. The basic requirements for distillation are that the liquids have different boiling points and different latent heats of evaporation, and their boiling points lie inside the range of operating temperatures. Within USA there are an estimated 40000 columns which consume 3% of the total US energy usage (Ramchandran and Russell Rhinehart, 1995). For these reasons, distillation has been studied for many years to improve distillation control which can have a significant impact on reducing energy consumption, improving product quality and protecting environmental resources (Coffey *et al.*, 2000).

The main difficulty with this control strategy is related to the strong interactions among the individual control loops (Bettoni *et al.*, 2000). The integration gives rise to a complex and nonlinear behavior, and it is difficult to control the system. The strong coupling among control loops often invalidates conventional loop controllers (Zhai *et al.*, 2005). Decoupling control was introduced to reduce the coupling problem in the nonlinear system.

Model based decouplers are widely used in chemical processes (Huaillin *et al.*, 2000). Proportional Integral Derivative (PID) conventional decoupler controller is the most common control algorithm used widely in chemical process as could be seen in Desbourough *et al.* (2002) and also Astrom *et al.* (2001) due to the simple structure provided that it can be tuned well. By now, a lot of tuning schemes have been devised by researcher namely Atherton *et al.* (1999) and Martins *et al.* (2000). Rivera and Jun (2000) presented a way to take advantage of Proportional Integral Derivative AutoRegressive eXogenous (PID-ARX) decoupler to develop an integrated methodology for identification and controller design for multivariable process plants. PID-ARX serves as a suitable intermediate model for the design and analysis of multi input multi output (MIMO) distillation control systems.

Proportional Integral Derivative Feedforward Artificial Neural Network (PID FANN) decoupler were widely used in temperature control system , time delay system (Shu and Pi, 2000) and power system generation. In recent years, artificial neural networks have progressed a lot. Martins *et al.* (2000), Junghui *et al.* (2004), Andrasik *et al.* (2004), use PID-neural networks to modify PID controllers. PID-FANN which is a new kind of networks and its hidden layer neurons simply work as PID controller terms through their activation functions thus it simultaneously utilizes advantages of both PID controller and neural structure.

Model based decoupler was applied in this research on finding the way to reduce the coupling interaction in the nonlinear multivariable process in distillation column. Dynamic decoupler PID-ARX and PID-FANN was introduced in distillation control system and compared with the PID-conventional decoupler. Three case studies were carried out: Skogestad distillation column (Skogestad, 1997), shell heavy oil fractionators (Maciejowski, 2002) and methanol/water column (Ramesh *et al*; 2008). These case studies were carried out due to different degree of nonlinearities.

1.2 Problem Statement

Distillation columns are the most widely used unit operation in the petroleum and petrochemical industries, which present a wide range of operation and control difficulties (Freitas *et al.*, 1994; Fisher, 1994). The modeling and control of distillation column form a challenging problem for both control engineers and theorists for several reasons.

Due to the couple, nonlinear, constrained and nonstationary process behaviour of distillation column, it limits the effectiveness of linear controllers (Dutta and Rhinehart, 1999, Ravi Sriniwas *et al.*, 1995).

Coupling of variables in multivariable processes can be problematic and often requires the use of predictive modeling for robust process controllability (Hay *et al.*, 2005). Interaction between control loops frequently introduces some complexity in process control (Freitas *et al.*, 1994). Due to the interaction among the loops, it will affect the stability and the product quality of the process. Therefore reducing the effect of coupling in multi loops control is essential to gain a better control of the process.

Nonlinearities and variation with time reduce the robustness of controller. The performance of controller is limited by the degree of nonlinearities and frequency of process variations in distillation column. Coupling is a very common phenomenon in multiple input multiple output (MIMO) systems (Ding *et al.*, 2007, El-Garhy and El-Shimy, 2007). Proper input output pairing is required in order to control MIMO processes. During industrial processes, multiple control loops are designed for a process plant to guarantee the product quality. Usually, there are coupling influences among these loops. If the influences cannot be eliminated successfully, these loops will not able to be auto controlled. As such, it will affect the stability of the process and the product quality. Hence, it is of great importance to eliminate the coupling influence.

Decoupling control is one of the most critical and effective methods to solve this problem besides model predictive control approach. It is due to decoupling control can eliminate interaction easily between control loops. As a consequence, the stability of the closed loop system is determined solely by the stability characteristics of the individual feedback control loops. When a set point is changed for one controlled variables it has no effect on the other controlled variable. The conventional decoupling control methods include diagonal matrix decoupling, identification matrix decoupling, feedforward compensation decoupling and pole assignment decoupling but recently it has been receiving partially justified criticism, once it reduces loop capacity for load disturbance rejection. An improved control strategy, using decouplers, was implemented by mid-1992. Satisfactory performances have been achieved with stable product composition in the column by using decoupler.

However, conventional decoupler may provide good performance, but the decoupling may be non-robust (Gjasater and Foss, 1997). Conventional decouplers may be particularly non-robust when applied to ill conditioned plants. Beside that the existing decoupling methods may be a little complicated or decoupling effectiveness is not very satisfactory, and most of them are based on the mathematical model, which is more or less impractical for industrial control. In order to make some decoupling algorithms more practical, the estimated parameter of the mathematical model should be obtained automatically via system identification. Furthermore, most of the PID decoupler ignore the dynamics term of the system while developing the decoupler.

1.3 Objectives of the Research

The primary objective of this research is to develop a nonlinear decoupling feedforward artificial neural network and decoupling ARX for three different case studies distillation column. The objectives of this research are as follows:

1. To develop model based decoupler (feedforward artificial neural network (FANN) and AutoRegressive eXogenous model (ARX)) for distillation column
2. To simulate and validate all case studies for distillation column with various scenario for loop interaction study
3. To analyse the effectiveness of the proposed decoupler based on the statistical tools analysis.

4. To evaluate and propose the suitable model based decoupler for the proposed distillation column.

1.4 Organization of Thesis

This thesis is divided into five chapters.

Chapter 1 describes the existence of nonlinear behaviors in chemical processes particularly in the distillation process. It also discusses the importance of developing decoupling conventional, ARX and decoupling FANN controller in distillation control. In addition, this chapter also outlines the problem statement and the objectives of the research.

Chapter 2 describes an overview of the distillation column. It also gives details about the need of a nonlinear model in advanced control strategies. Several reviews which applied in the development of nonlinear decoupler of distillation column were stated. This is followed by a discussion on the development of conventional, ARX and feedforward artificial neural network decoupling. Finally, the advantages of the feedforward artificial neural network decoupler approach are highlighted.

Chapter 3 outlines the methodology of this work. This chapter explains the methodology used in developing conventional decoupling, ARX decoupling and feedforward artificial neural network (FANN) decoupling for three case studies.

Chapter 4 presents the results and discussions obtained from simulation in Matlab. It covers the simulation results obtained from three different case studies of distillation column. The chapter also discusses the results of the PID-ARX and PID-FANN decoupling for all case studies.

Chapter 5 contains the conclusions of the present work. Some recommendations for future research are also proposed in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Distillation Column

Distillation columns designed to separate an input stream of chemical species into two or more output streams into useful chemical species. Distillation column has become a favourite research subject in the process systems engineering fields, including the areas of process synthesis, process dynamics and process control.

2.1.1 Operation

Distillation process is to separate a mixture of two or more liquids with different boiling points by heating the mixture to a temperature between their respective boiling points. The basic principle is the preferential vaporization of low boiling point components away from high boiling point components when heat is applied to the mixture. The low boiling point component will boil and transforms into vapor while the high boiling point component will remain as a liquid. This phenomenon is usually quantified by the relative volatility of the components.

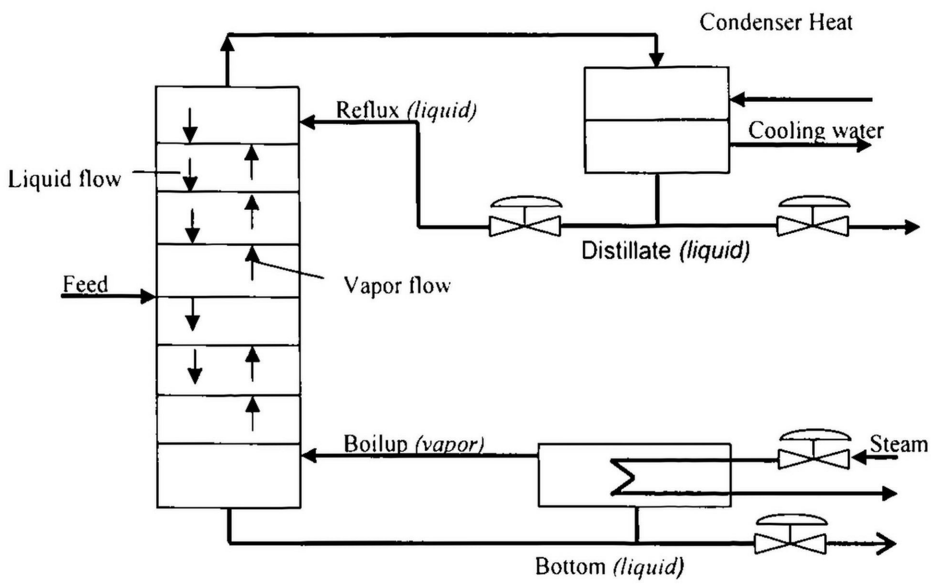

Figure 2.1: A schematic diagram of a distillation column

Figure 2.1 shows a schematic diagram of a distillation column. In the distillation column, the mixture of components enters the column at one or more points. The liquid flows over the plates and vapour bubbles up through the liquid via holes in the plates. As the liquid flows down the column, vapour will contact with it. Liquid and vapour are kept in contact for certain period to ensure chemical components are transferred between phases until equilibrium is reached. All compositions stop changing phases at equilibrium stage. As the system moves toward equilibrium, each species establishes a different concentration in each zone and the new liquid and vapor phases are separated.

Liquid with the high boiling point component remain in the base of distillation column. Boil up product is the liquid that was heated in the reboiler and returned to the column while the remaining liquid is removed as a bottom product. The vapor follows its way to the top of the column and enters a reflux drum. Vapor is cooled until it becomes a liquid in the drum. Part of the product is returned to the column as reflux and the remainder of the product leaves the column as distillate.

2.1.2 Sensitivity

The sensitivity of the process shows the influences of various variables on the system behaviour in the distillation process. The variables are feed rate, vapor rate, heat input, pressure, temperature and reflux (Felder and Garrett, 2003; Abdullah, 2007). The effect of variables to distillation column behaviors are given below.

i. Feed rate

Changes of feed composition and deviates from the feed stage concentration will affect the composition of the overhead and bottom products. Amount of feed rate will affect the vapour-liquid contact on the trays which consequently affect the separation process. In addition, change of the feed rate will affect column temperature and pressure.

ii. Vapor rate

The velocity of vapour in the distillation column must be sufficient to overcome the pressure drop across each tray. Vapor velocity can be stabilized by reducing the reflux at high feed rates but if reduced too much on reflux will cause the separation of high boiling component will become unsatisfactory.

iii. Heat input

A portion of the liquid which converted into vapour in the reboiler which serves as the major hear input to the column. Latent heat energy added into the reboiler cause the vapour flow move upwards till the top of the column. Amount of liquid vaporized determine by the amount of heat added which corresponds to the vapour flow rate rising up the column.

iv. Pressure

Pressure has two effects on the column operation:

a) Operating temperature will be affected with the increase and decrease of the pressure.
b) Vapor-liquid contact will be affected due to pressure changed.

In order to maintain temperature, the columns are designed to operate at a fixed head pressure which are the boiling point of the top and bottom streams. Pressure drop play an important role to measure the vapour flow in order to indicate possible interior problems of the columns.

v. Temperature

A profile of the temperature is measured across the column between the top and bottom. Concentration of high boiling point component increases as temperature increases while concentrations of low boiling point component increase as temperature decrease.

Base temperature is measured at or very near to the bottom of the column. Changes in pressures drop and composition profile will affect the changes of base temperature. Excessive pressure drop inside the column could be detected when base temperature was high thus it could affect thermal stability of bottom product stream.

Temperature on the trays will increase as vapour rate increase. Therefore, the liquid contains more of the high boiling point component. As reflux rate increases, the temperature on tray decreases. Therefore, the liquid contains more of the low boiling point component.

vi. Reflux

Increase of reflux flow rate can be used to control the component of the vapour in top of the column when product contain higher boiling point component. Top column temperature can indicate high boiling point component content in the condensate.

Temperature profile in the column can be controlled by reflux. As the reflux flow rate increases the temperature profile decreases and vice versa. Changing the temperature with the reflux flow rate change is the consequence of changing the concentration of components.

2.2 Distillation Column Control

The challenge in model based decoupler development is to construct a model that can be utilized to describe the process and this issue has been noted by several researchers (Qin and Badgewell, 1998; Pearson, 2003). Distillation control and nonlinearity effect of each loop are the main issue in distillation column (Abdullah, 2007).

Linear process model such as the first-order-plus-dead-time model or the pure-integrator-plus-dead-time model was used as controller in industrial. The linear model is applied to the estimation of the linearity and dynamic range of the process. However, the satisfactory performance of this linear controller is limited. This is due to the reason that controller cannot overcome the process operation with highly nonlinearities and consequently becomes more critical and control performance is sacrificed (Mahfouf *et al.*, 2002).

Since many of the processes are nonlinear, linear models are incapable to perform well within an enourmous range of dynamic phenomena when the process industries require operating systems which are closer to the boundary of the admissible operating region (Pearson, 2003; Abdullah, 2007).

The facts that model utility can be measured in general, in a conflicting way and the class of nonlinear models does not exhibit unity are the difficulty in developing the nonlinear model. There are four important criteria of model utility (Pearson, 2003; Abdullah, 2007):

i. approximation accuracy

ii. physical interpretation

iii. suitability for control

iv. ease of development

There are many reasons for developing process models in order to improve chemical process operation. These models are often used for (i) operator training, (ii) process design, (iii) safety system analysis, or (iv) process control.

Operator training: the people responsible for the operation of a chemical manufacturing process are known as process operators. A dynamic process model can be used to perform simulations to train process operators. Process operators can learn the proper response to upset conditions, before having to experience them on the actual process.

Process design: A dynamic process model can be used to properly design chemical process equipment for a desired production rate. For example, a model of a batch chemical reactor can be used to determine the appropriate size of the reactor to produce a certain product at a desired rate.

Safety: Dynamic process models can also be used to design safety systems. For example, they can be used to determine how long it will take, after a valve fails, for a system to reach a certain pressure.

Process control: Feedback control systems are used to maintain process variables at desirable values. For complex systems, particularly those with many inputs and outputs, it is necessary to base the control system design on a process model. Also, before a complex control system is implemented on a process, it is normally tested by simulation.

It should be noted that no single model of a process exists, since a model only approximates the process behavior. The desired accuracy and resulting complexity of a process model depends on the final use of the model. Usually more complex models will require much more data and effort to develop than simplified models, since more model parameters will need to be determined.

2.2.1 Nonlinearities

Distillation columns are fairly complex units with highly nonlinear dynamics. Their dynamics are mixture of very fast vapour flow rate changes, moderately fast liquid flow rate changes, slow temperature changes and very slow composition changes (Kapilakarn and Luyben, 2003; Muhammad *et al.*; 2011). The motivation to explore nonlinear models comes from the unavoidable nonlinearity of the dynamics of distillation column. Pearson (2003) explained that the observation of anyone of the following phenomenon implies the need for a nonlinear dynamic model.

1. Asymmetric responses to symmetric input changes
2. Generation of harmonics in response to a sinusoidal input.

3. Observation of input multiplicity
4. Observation of output multiplicity
5. Generation of sub-harmonics in response to any periodic input
6. Highly irregular response to simple inputs.
7. Input dependent stability.

The first stage of any practical identification procedure should be to perform some calculations on the input/output data to indicate whether the relationship between input and output is linear or nonlinear, that is, to make a decision as to whether it would be worthwhile attempting to identify a nonlinear model of the process. Any one of the above mentioned phenomenon needs to be verified to validate the necessity of the nonlinear model.

There are four types of responses that are used to identify the degree of the nonlinearity for the process (Muhammad *et al.;* 2011). Degree of nonlinearity can be determined by the asymmetric behavior, harmonic response, input multiplicity and output multiplicity. Symmetrical input that results in asymmetrical response was asymmetric behavior. Step test method that giving positive and negative step change was applied in this research. Harmonic response is a system which periodic input is used to determine the nonlinearity of the system. Existences of several steady states input for a fixed set of output are input multiplicity method which considered as mild nonlinearity behavior. Output multiplicity is a strong nonlinearity behavior with existence of several steady state output for a fixed input.

2.2.2. Loop Interaction

Control of distillation columns is usually a multivariable and interactive control (Masoumi and Zarandi, 2011). Correct pairs of inputs and outputs guarantee performance and robustness of controllers. Relative Gain Array (RGA) matrix is the most commonly used method for this purpose. Most of industrial processes are naturally multi input multi output (MIMO) systems. MIMO systems are more difficult to control due to existence of interaction among input and output variables. Although considerable effort has been dedicated to this problem and many design techniques have been proposed over the decades, but design of control system for MIMO processes is still a big challenge for practical control engineers. Relative Gain Array (RGA) highlights the fact that its use in interaction analysis is inherently bound to the concept of the "perfect" controller, a controller whose action prevents the appearance of any deviation from set point in its controlled condition following a disturbance (Shinskey, 2009).

The interactive multivariable systems can be either controlled by a multivariable or centralized MIMO controller or by a set of SISO decentralized controllers (Masoumi and Zarandi, 2011). Decoupling methods or optimal multivariable control theory is usually applied to obtain centralized MIMO controllers.

Decoupling control is one of the most critical and effective methods to solve this problem beside model predictive control approach. Decoupling control can eliminate interaction between control loops. As a consequence, the stability of the closed loop system is determined solely by the stability characteristics of the individual feedback control loops.

The most important and easiest way to evaluate the performance of decoupler is by checking the settling time, Integral of the Absolute value of the Error (IAE) when set point changed in order to eliminate the loop interaction and increase the disturbance rejection. There are three popular integral error criteria such as Integral of the absolute value of the error (IAE), Integral of squared error (ISE) and Integral of the time-weighted absolute error (ITAE). In this research IAE was used to determine the performance of the decoupler. IAE was defined as equation 2.1 below:

$$\int_0^{\infty} e(t)dt \qquad (2.1)$$

Where the error signal e(t) is the difference between the set point and the measurement.

2.3 Static Decoupler

One of the early approaches to multivariable control is decoupling control (Seborg *et al.*, 2003). By adding additional controllers called decouplers to a conventional multiloop configuration, the design objective of reducing control loop interactions can be realized. Decoupling control provide two important advantages: control loop interactions are eliminated or reduced. As a consequence, the stability of the closed loop system is determined solely by the stability characteristics of the individual feedback control loops. A set point change for one controlled variable has no effect on the other controlled variables.

There are three decoupling control schemes studies are shown in Figure 2.2 to 2.4. These schemes are simplified, ideal and partial decoupling (Hadisupadmo *et al.*, 2001). Tham *et al.* (2010) has discussed the difference between simplified and ideal decoupling. To explain this difference as well as to determine the D_{ij}'s, the P_{ij}'s are taken as transfer functions. It should be emphasized, however, that the simulation results presented here are for the cases where the linear decouplers are applied to the nonlinear column models discussed above. The D_{ij}'s in Figures 2.2 to 2.4 are given by the expression in Equation 2.2

$$D_{ij} = -\frac{P_{ij}}{P_{ii}} \tag{2.2}$$

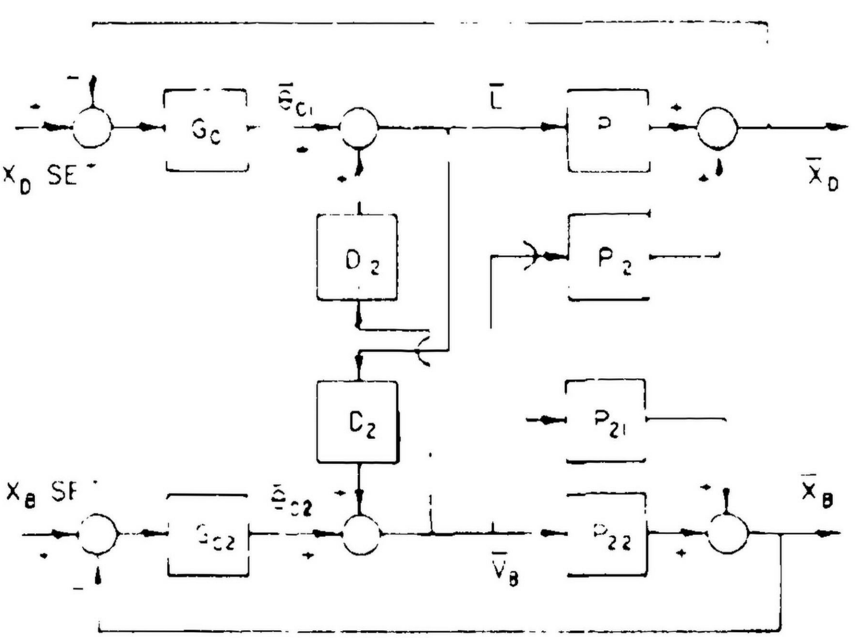

Figure 2.2: Ideal decoupling (Weischedel and McAvoy, 1980; Waller *et al.*, 2003)

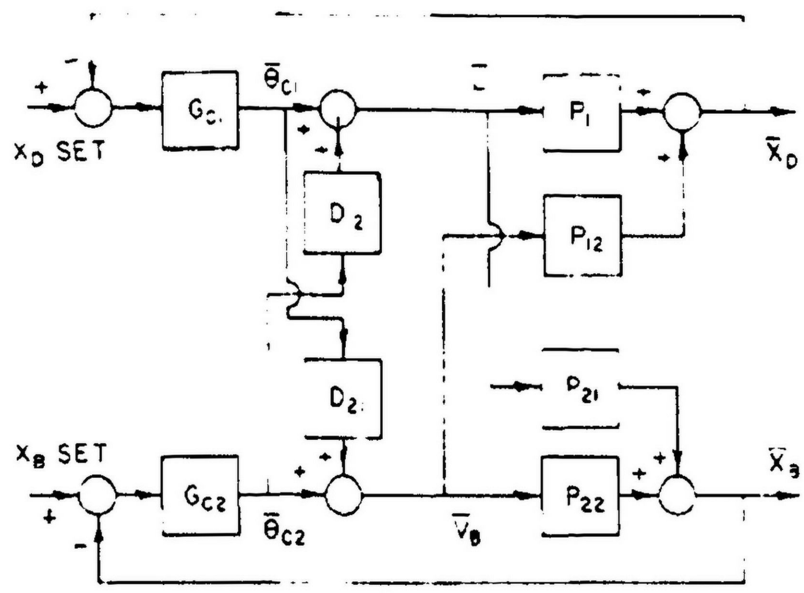

Figure 2.3: Simplified decoupling (Weischedel and McAvoy, 1980; Waller *et al.*, 2003)

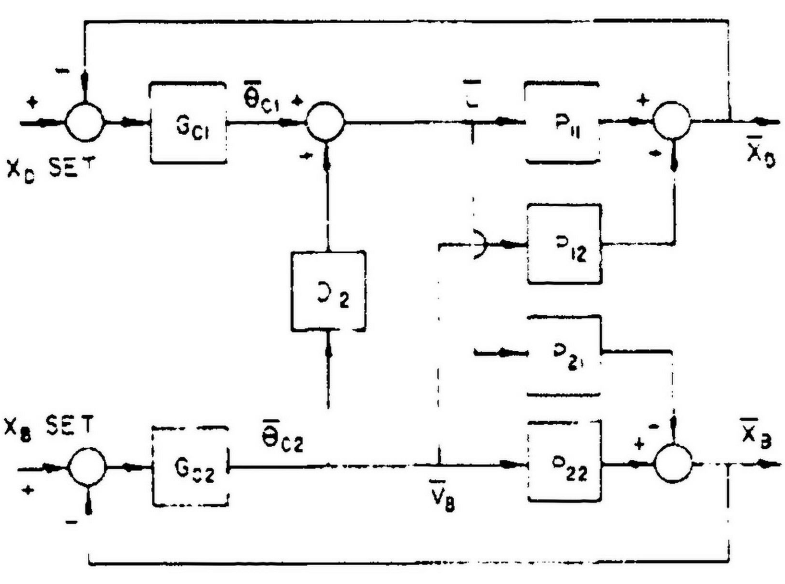

Figure 2.4: One way decoupling (Weischedel and McAvoy, 1980; Waller *et al.*, 2003)

The difference between simplified and ideal decoupling can be seen by deriving the open loop transfer functions relating $\tilde{x}_D$ and $\tilde{\theta}_{c1}$ for both cases. These transfer functions are shown in Equation 2.3 and 2.4.

$$\frac{x_D}{\tilde{\theta}_{c1}} = \mathrm{P}_{11} \text{ (ideal)} \tag{2.3}$$

$$\frac{\tilde{x}_D}{\tilde{\theta}_{c1}} = \mathrm{P}_{11}\left(1 - \frac{P_{12}P_{21}}{P_{11}P_{22}}\right) \tag{2.4}$$

Similar expressions can be derived for the transfer function relating $\tilde{x}_B$ and $\tilde{\theta}_{c2}$. In the discussion that follows only the distillate loop is considered. As Equation 2.3 and 2.4 shows, $\tilde{\theta}_{c2}$ has no effect on x_D and thus the distillate composition loop is decoupled from the bottoms composition loop. For ideal decoupling the effective process transfer function is identical with that obtained if the bottoms composition loop is on manual. For simplified decoupling the factor $[\![1 - (P_{12}P_{21}/P_{11}P_{22})]\!]$ complicated the problem of designing G_{c1}. This factor contains both steady state and dynamic elements. A less general approach which only considers the steady state value of this factor will be taken in order to give a simple explanation of decoupling. The steady state value of $[\![1 - (P_{12}P_{21}/P_{11}P_{22})]\!]$ can be related to λ as shown in the Equation 2.5 (Witcher and McAvoy, 1977; Waller *et al.*, 2003)

$$\lambda = \frac{1}{\left(1 - \frac{K_{12}K_{21}}{K_{11}K_{22}}\right)} \tag{2.5}$$

Then the effective process gain shown by Equation 2.6

$$\frac{\tilde{x}_D}{\tilde{\theta}c1} = \frac{K_{11}}{\lambda} \tag{2.6}$$

Equation above shows that simplified decoupling of columns with large relative gains will result in a large reduction in the effective process gain relative to K_{11}. If a single loop approach is used to design G_{c1} then the resulting distillate loop will be extremely sluggish. Alternatively, one can increase the controller gain to compensate for the reduction in effective process gain and thereby achieve a fast control system response. Decoupler failure could produce instability. In addition, it was found that increasing the feedback gains for column actually resulted in deterioration in control system performance. Thus, in the simulations on simplified decoupling the single loop tuning parameters were used.

Partial decoupling, shown in Figure 2.5, is halfway between simplified and ideal decoupling. The effective open loop process transfer functions for both the distillate and bottoms loops for this case are different in form from one another and are given by the expression in Equation 2.7 and 2.8:

$$\tilde{x}_D = P_{11}\theta_{c1} \tag{2.7}$$

$$\tilde{x}_B = P_{21}\tilde{\theta}c1 + \tilde{\theta}c2P_{22}[\![1 - (P_{12}P_{21}/P_{11}P_{22})]\!] \tag{2.8}$$

As can be seen from above, the distillate loop is unaffected by changes in the bottoms loop. However, that θ_{c1} does affect x_B. For the x_B loop the factor $[\![1 - (P_{12}P_{21}/P_{11}P_{22})]\!]$ again appears in the effective transfer function. Thus, the discussion given above for designing feedback controllers for simplified decoupling applies to the x_B loop.

Processes with only one output being controlled by a single manipulated variable are classified as single input single output (SISO) systems (Lasheen *et al.*, 2009). Many processes, however, do not conform to such a simple control configuration, where in the process industries for example, any unit operation capable of manufacturing or refining a product cannot do so with only a single control loop, and in most cases, the control system has more than one manipulated variable and more than one control input, and the interactions between these loops are such that the model cannot be further reduced. A system with multiple inputs and multiple outputs (MIMO), sometimes also called a multivariable system.

One of the most challenging aspects of the control of MIMO systems is the interaction between different inputs and outputs. This loop interaction naturally causes instability in the control system. This problem can be alleviated by a proper choice of input output pairings to minimize the effect of each inputs on the outputs.

Dorrah *et al.* (2012) implemented decoupler into a group of independent loops and a conventional PID controller in highly interacted MIMO distillation column. Tuning of conventional PID controller is very difficult. Sum square errors (SSEs) are used to minimize the optimal values of different PID controller parameters. The simulation of the proposed proved their excellence in improving the transient and steady state characteristics of conventional PID decoupler.

Castellano and Alvarez (2006) addressed the two point composition control problem of binary distillation column. The combination of inventory control, observability, feedforward, feedback and IMC ideas led to a linear output feedback two way decoupling control scheme. The associated controller consisted of two PI feedback components and a static interaction compensator. The application of singular perturbation theory yield closed loop stability conditions coupled with conventional like tuning rules. It was found that the two-way PID decoupling structure yielded the best overall behaviour.

Castellano *et al.*, (2005) designed a two point linear temperature controller for the regulation of the product compositions in binary distillation columns. The two-point linear temperature feedforward feedback decoupling control of binary distillation columns has been addressed. The controller consisted of a static interaction compensator with a pair of PID conventional decoupled control loops, including feed-temperature-based setpoint adjusters built from the static output temperature dependencies on the feed temperature. It was established that the proposed linear controller recovered the behavior of the underlying exact model-based feedforward- feedback material balance controller. The approach was tested with two binary columns through simulations with ideal and non-ideal thermodynamics. It was found that the one-way PID decoupling structure yielded the best overall behavior, with offsetless composition response about 2 times faster than the ones yielded, with offsets, by the previous conventional and two-point temperature controllers.