QDMC OF DISTILLATION COLUMNS

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree of

MASTER OF TECHNOLOGY

in

CHEMICAL ENGINEERING

(With Specialization in Computer Aided Process Plant Design)

By

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CANDIDATE'S DECLARATION

I hereby declare that the work which is being presented in the dissertation entitled "**QDMC OF DISTILLATION COLUMNS**", in partial fulfillment of the requirements for the award of the degree of Master of technology in Chemical Engineering with specialization in "**Computer Aided Process Plant Design**", and submitted to the **Department of Chemical Engineering, Indian Institute of Technology, Roorkee**, is an authentic record of the work carried out by me during the period June 2007 to June 2008, under the guidance of **Dr. RAVINDRA BHARGAVA.** The matter embodied in this work has not been submitted for the award of any other degree.

Date: 30 - 06 - 08
Place: IIT, Roorkee

S. Prakasa Rao
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CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

R Bhargava 30.6.08
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(PRAKASARAO SINGARU)

ABSTRACT

Many industrial control problems are nonlinear and multivariable in nature. It is common for dynamic models of industrial processes to have strong interactions between the loops. Distillation columns also exhibit elegantly complex dynamics which include strông interactions and large dead times. Though product quality control of simple binary distillation columns somewhat easy, it is challenging job for control engineer to control product quality of complex distillation columns like crude distillation columns. This is due to strong interactions among sidestream product quality control loops and large input-output delays.

Significant economic benefits can result from improved control of crude distillation towers because of their large throughput. Present work is about control of crude tower product quality and it is a 4 x 4 control problem which include strong interactions and large dead times. It is common for crude towers to change products quality on market specifications. So controller should maintain product quality on specification. Leo Hsie and McAvoy (1991) worked on product quality control of crude distillation tower. Both conventional PI control and model based QDMC control were applied to crude tower product quality variables. They had used old guide lines in tuning QDMC controller. This tuning involves trial and error procedure in selecting move suppression coefficients.

Present work includes redesign of conventional PI controller, redesign of QDMC with old tuning guidelines and design of QDMC with Novel tuning strategy for product quality control of crude distillation column. Present study considers the transfer function models and operating conditions (i.e. constraints on manipulated and controlled variables) given by Leo Hsie and McAvoy (1991). We have followed multiloop BLT tuning method proposed by Luyben (1986) in redesigning conventional PI controller and old tuning guidelines given in Cutler and Ramaker (1980) in redesigning QDMC for product quality control. Present work also followed tuning strategy proposed by Shridhar and Cooper (1998) in designing QDMC with novel tuning strategy. MATLAB simulink and MPC Toolbox are used for simulating results for PI and QDMC respectively. Finally performance of QDMC with Novel tuning strategy is compared with results of conventional PI and QDMC with old tuning guidelines. It was found that the QDMC with Novel tuning strategy performs better than other two control structures.

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NOMENCLATURE

Symbol

A	Dynamic Matrix of system
C_i	Condition number
E	Prediction Error
H	Hessian Matrix
K	Process Gain
M	Control Horizon
N	Model length
P	Prediction Horizon
R	Number of Controlled variables
S	Number of Manipulated variables
T	Sample time
T_S	Settling Time
X	Vector of Control Moves
Y	Vector of Control variable outputs

Greek Letters

Ø	Objective function
γ_i^2	Weights on controlled variables
λ_i^2	Move Suppression Coefficients
θ	Dead time
τ	Process time constant

Sub scripts

i	Manipulated variable
j	Controlled variable

Acronyms

CV	Control Variable
DMC	Dynamic Matrix Control

EP	End Point
FCCU	Fluid Catalytic Cracking Unit
FOPDT	First Order Plus Dead Time
HGO	Heavy gas oil
LGO	Light gas oil
LP	Linear Programming
LPG	Liquefied Petroleum Gas
MIMO	Multi Input Multi Output
MPC	Model Predictive Control
MV	Manipulated Variable
NDMC	Non-linear Dynamic Matrix Control
NQDMC	Non-linear Quadratic Dynamic Matrix Control
PI	Proportional Integral
PID	Proportional Integral Derivative
QDMC	Quadratic Dynamic Matrix Control
QP	Quadratic Programming
RGA	Relative Gain Array
SISO	Single Input Single Output
TBP	Total Boiling Point

Chapter-1

INTRODUCTION

The model-based control strategy that has been most widely applied in the process industries is Model Predictive Control (MPC). It is a general method that is especially well suited for difficult Multi-Input, Multi-Output (MIMO) control problems where there are significant interactions between the manipulated inputs and the controlled outputs. Unlike other model-based control strategies, MPC can easily accommodate inequality constraints on input and output variables. In the last decades several model predictive control algorithms have been proposed. Dynamic Matrix Control (DMC) is the most popular Model Predictive Control (MPC) Algorithm currently used in the chemical process industry. Although one of the earliest formulations of MPC, DMC represents the industry's standard for MPC today. The technique was developed in Shell as part of its process computer control activities. The objective of a DMC controller is to drive the output as close to the set point as possible in a least-squares sense with a penalty term on the manipulated variable moves and this technique provides a degree of robustness to model error. DMC algorithm has been used extensively in the process industry mainly because of its ability to handle input and output constraints, process delays and variable interactions encountered in many multivariable systems.

Control techniques such as dynamic matrix control, model algorithmic control, internal model control and inferential controls explicitly use a process model. Of these, undoubtedly the most popular with the process industry is dynamic matrix control (DMC). This algorithm has been successfully applied in many cases where the conventional control is unsuitable for various reasons. The modelling philosophy and the ability of DMC in handling complex control problems commonly encountered in multivariable systems have made it a very popular control algorithm. One major contributor to the success of DMC is the ability to handle constraints in an optimal fashion. The optimization-based procedure is intuitive and is also a natural way of handling multi variable systems. A key feature of DMC is that future process behaviour is predicted using a dynamic model and available measurements. The controller outputs are calculated so as to minimize the difference between the predicted process response and the desired response. At each sampling instant, the control calculations are repeated and the predictions updated based on current measurements. Constraints on the controlled and manipulated variables can be routinely included in both the DMC and optimization calculations.

1.1 ADVANTAGES OF DMC

Dynamic Matrix Control offers a number of important advantages:

- It is a general control strategy for MIMO processes with inequality constraints on input and output variables.
- It can easily accommodate difficult or unusual dynamic behaviour such as large time delays and inverse responses.
- Since the control calculations are based on optimizing control system performance, MPC can be readily integrated with on-line optimization strategies to optimize plant performance.
- The control strategy can be easily updated on-line to compensate for changes in process conditions, constraints, or performance criteria

Crude distillation units are the first separation units in any petroleum refinery. They are used to separate the crude oil into various fractions. These fractions can be products or feed stocks to the following processing units. These are high volume, high energy-consuming distillation columns in which any upset will propagate to downstream processing units and raise the total cost of refining. As a result, it is desirable to maintain crude tower operation as steady as possible. Control of crude tower product qualities represents a control problem with the characteristics of long dead times and strong interaction. The fundamental difference between the design of a multivariable control system and a single-input single-output (SISO) control system is the interaction caused by the closed control loops. In a multivariable feedback control system, each manipulated variable will affect more than one controlled variable when the loops are closed.

1.2 OBJECTIVE OF THESIS

- To redesign conventional PI controller and QDMC with old tuning guidelines for product quality control of crude distillation column.
- To design QDMC with Novel tuning for product quality control of same crude distillation column.

- To compare the performance of QDMC with Novel tuning strategy with the conventional PI controller and QDMC with old tuning guidelines for the system of crude distillation end point control of four products.

1.3 ORGANISATION OF THESIS

The thesis has been organised in seven chapters. Chapter-2 describes literature review on DMC and its application for product quality control of distillation columns. Chapter-3 presents process description and process models identification. Chapter-4 describes basic DMC and QDMC algorithms. Chapter-5 describes tuning of DMC and tuning by Novel tuning strategy. Results and discussion have been given in chapter-6. Finally chapter-7 highlights the main conclusions of the thesis and provides the recommendations for future work.

Chapter-2

LITERATURE REVIEW

Dynamic Matrix Control (DMC) is the most popular Model Predictive Control (MPC) Algorithm currently used in the chemical process industry. Although one of the earliest formulations of MPC, DMC represents the industry's standard for MPC today. The technique was developed by Shell Oil Company as part of its process computer control activities. Engineers at Shell Oil developed their own independent MPC technology in the early 1970's, with an initial application in 1973. Cutler and Ramaker (1980) presented details of an unconstrained multivariable control algorithm, which they named Dynamic Matrix Control (DMC) at the 1980 Joint Automatic Control Conference.

In a companion paper at the 1980 meeting Prett and Gillette (1980) described an application of DMC technology to an FCCU reactor/regenerator in which the algorithm was modified to handle non-linearities and constraints. The objective of a DMC controller is to drive the output as close to the set point as possible in a least-squares sense with a penalty term on the manipulated variable moves. Prett and Gillette formalized this concept mathematically by defining move suppression factors designed to penalize excessive input movement. Move suppression factors also provide an important numerical benefit in that they can be used to directly improve the conditioning of the numerical solution. Prett and Gillette described additional modifications to the DMC algorithm to prevent violation of absolute input constraints. When a predicted future input came sufficiently close to an absolute constraint, an extra equation was added to the process model that would drive the input back into the feasible region. These were referred to as time variant constraints.

The original DMC algorithms provided excellent control of unconstrained multivariable processes. Constraint handling, however, was still somewhat ad-hoc. Engineers at Shell Oil addressed this weakness by posing the DMC algorithm as a Quadratic Program (QP) in which input and output constraints appear explicitly. Garcia and Morshedi (1986) first published a more comprehensive description on QDMC. Garcia and Morshedi began with a clear and concise presentation of the unconstrained DMC algorithm, including an interesting discussion of tuning. Their experience showed that the DMC algorithm was closed loop stable when the prediction horizon was set long enough to include the steady-state effect of all computed input moves. This is supported by a rigorous proof presented by Garcia and Morari (1989), which shows that the DMC algorithm is nominally stabilizing for a sufficiently large prediction horizon. Garcia and Morshedi then showed that how the DMC objective function can be re-written in the form of a standard QP. Future projected outputs can be related directly back to the input move vector through the dynamic matrix; this allows all input and output constraints to be collected into a matrix inequality involving the input move vector. Although the QDMC algorithm is a somewhat advanced control algorithm, the QP itself is one of the simplest possible optimization problems that one could pose. The Hessian of the QP is positive definite for any reasonable problem and so the resulting optimization problem is convex. This means that a solution can be found readily using standard commercial optimization codes.

Garcia and Morshedi wrapped up their paper by presenting results from a Pyrolysis furnace application. The QDMC controller adjusted fuel gas pressure in three burners in order to control stream temperature at three locations in the furnace. Their test results demonstrated dynamic enforcement of input constraints and decoupling of the temperature dynamics. They reported good results on many applications within Shell on problems as large as 12x12 (12 process outputs and 12 process inputs). They stated that above all, the QDMC algorithm had proven particularly profitable in an on-line optimization environment, providing a smooth transition from one constrained operating point to another. The QDMC algorithm can be regarded as representing a second generation of MPC technology, comprised of algorithms, which provide a systematic way to implement input and output constraints. This was accomplished by posing the MPC problem as a QP, with the solution provided by standard QP codes.

Wood and Berry (1973) proposed use of the ratio control system for product quality of distillation column in which the overhead composition is controlled by manipulation of the reflux flow to adjust the overhead vapor rate to reflux flow ratio resulted in excellent control performance. The significant improvement in the control behaviour compared to that obtained using conventional two-point control, particularly in the case of the overhead composition, since this scheme provides an effective means of reducing the interaction effect of the steam flow on the overhead composition.

Marchetti et al (1983) presented a detailed sensitivity analysis of adjustable parameters and their effect on DMC performance. Maurath et al (1988) Proposed the M=1 controller configuration of DMC, it worked well for simple SISO systems but not for MIMO systems. Sigurd Skogestad and Manfred Morari (1988a) studied dynamic modelling of distillation columns. The dynamic behavior of a distillation column was approximated with a two time constant model. The response to changes in the external flows was approximately first order. This dominant time constant can be estimated by using a simple mixing tank model for the column. Skogestad and Morari (1988b) also worked on LV control of high purity distillation column. They concluded that, a single linear controller was able to give satisfactory control of high-purity column at widely different operating conditions. One reason for this was the use of logarithmic compositions, which effectively counteracts the non-linearity in the plant. However, even if absolute compositions were used, a single linear controller performs satisfactory if the deviations from steady state are reasonably small. Using the composition in the overhead vapor, as a controlled output makes the system less sensitive to variations in the condenser hold up. A simple diagonal controller was found to be robust with respect to model-plant mismatch, but gives a sluggish return to steady state. This particular part of the response was improved using the p-optimal controller. Inverse-based controllers, and in particular those based on a steady-state decoupler, are very sensitive to model-plant mismatch and should not be used with the LV-configuration for this high-purity column.

A mathematical model for the rigorous, non-linear dynamic simulation of a crude tower was presented by Leo Hsie and McAvoy (1990). The modeling equations of the crude tower form a very large set of stiff ordinary differential and algebraic equations. The large dimension and stiffness make the simulation very time consuming. A new approach, which is based on a "separated component" concept, was shown to reduce the dimension and stiffness of the system. Hence the computation cost was considerably reduced. It was found that the bubble point distillation algorithm (BPA) is extremely sensitive to error in liquid compositions of the light components in a crude tower system. This sensitivity causes numerical problems with the algorithm. The sum of rates algorithm was shown to be more suitable for computing the steady state conditions of a crude tower than the bubble point algorithm. Once an initial steady-state is reached, the transient responses of the crude tower can be obtained by the bubble point approach. The dynamic crude tower simulation predicted the expected strong,one-way interaction among the product quality control loops. Through dynamic simulation, it was shown that the interaction can be eliminated by a simple, steady state decoupler.

Leo Hsie and Thomas J. McAvoy (1991) presented a comparison of single loop PI and QDMC based control of crude oil distillation towers. A detailed, non-linear, dynamic tower simulation was used to test control approaches. To tune the various controllers used, a linearized dynamic model was developed from step testing the non-linear model. Traditional thinking on crude tower control has held that interactions propagate only down the tower. Their results indicated that significant two-way dynamic interaction occurs. This interaction required that the PI controllers be detuned substantially from Ziegler-Nichols settings. At steady state the interaction is essentially one way, i.e. down the column. The BLT tuning method was found to give unsatisfactory results for the 4 x 4 problem treated. When compared with the best PI tuning that they could find, QDMC produced better transient performance. When a decoupler was added to their best PI controller, it improved the response. However, QDMC again gave faster setpoint responses but at the expense of increased loop interaction. Their work is used in present study for comparison.

Lee and Yu (1994) integrated the latest developments in MPC with the frequency-domain robust control to develop a set of tuning guidelines for MPC controllers applied to both SISO and MIMO systems. It was shown that, for SISO systems and MIMO systems with output uncertainty, quantitative tuning rules based on robust performance analysis can be developed using the parameters of the state observer only. In addition to the precise knowledge of their effects on the closed-loop robustness, these parameters offer an additional advantage over the traditional tuning parameters in that the robustness is maintained even in the presence of active output constraints. It was also demonstrated through analysis and a numerical example that simple SISO tuning rules do not lead to robust controllers in general for MIMO systems with input uncertainty. It was suggested that, in the presence of significant input uncertainty, the input weight instead of the observer parameters are used to achieve robustness. A one-parameter tuning rule was proposed, which should work adequately for most problems.

Charos and Arkun (1993) had presented a decentralized version of the quadratic dynamic matrix control algorithm. It was shown that under a certain assumption the original quadratic programming can be decomposed to smaller QPs, which can be solved independently and in parallel. Simulations have shown performances comparable to the centralized QDMC with less demanding CPU times. However, it was not obvious how to determine a priori the dynamic performance of the proposed algorithm, as this is very much problem dependent. One should weigh the computational benefits against the performance loss carefully before accepting this algorithm for a particular problem in hand. More research in quantifying the performance differences between centralized QDMC, decentralized QDMC and fully decentralized IMC and additional computational experience with larger problems are needed.

Lundstrom and Skogestad (1995) applied MPC controller for 5×5 distillation control. The main advantages with 5×5 distillation control were the improved disturbance detection by indirect use of the level and pressure measurements, and the explicit input constraint handling. One difficulty was the tuning of the controller, but in their example they were able to tune the MPC scheme quite easily to get acceptable robustness. Meziou et al (1995) applied the servo and regulatory performance of DMC to an industrial steam gas reformer. Simulation results indicated the potential improvement of the closed-loop responses, compared with the multiloop design.

Balachandran and Chidambaram (1997) designed decentralized PI controllers by the method of inequalities. It gave lesser interactions among the four control loops of a crude distillation tower. The interactions were lesser than that of BLT method. Since the desired specifications of the closed loop responses and interactions can be easily incorporated in the method of inequalities, it is easier to get the diagonal settings by this method than by the BLT method. Hovd. et al (1997) worked on the project of designing and implementing model based predictive control on the vacuum distillation column at the Nynashamn Refinery of Nynas AB. They described in detail the modeling for the model based control, covered the controller implementation, and documented the benefits gained from the model based controller.

A novel tuning strategy for multivariable DMC, with a novel expression that computes the move suppression coefficients was presented by Shridhar and Cooper (1998). The application of easy to use and reliable tuning strategy was demonstrated both for constrained SISO and MIMO processes. The compact form for the analytical expression that computes the move suppression coefficients was derived as a function of a first order plus dead time (FOPDT) model approximation of the process dynamics. This tuning strategy was validated for 2 x 2 and 3 x 3 distillation product quality control problem and proven to be getting good performance than old tuning.

Abou Jayab et al (2001) applied constrained model predictive control to distillation column. They used a simplified model predictive control algorithm using Linear Programming for control of industrial distillation column to solve problem without decomposition. Their approach involved very small size optimization problem and required very modest computational resources. The control algorithm eliminated the large cycling in the product composition. This resulted in a 2.5% increase in production rate, a 0.5% increase in product recovery and a significant increase in profit.

Wojsznis et al (2003) presented the results of a heuristic approach for developing model predictive control tuning rules. The tuning has been applied and tested in easy-to-use MPC. Process modeling in this MPC uses normalized input/ output range. As a result there was no need for tuning outputs, a procedure known as adjusting equal concern error. Penalties on moves are set as a function of process dead time as the primary factor, with some correction from process gain. The default calculation delivers robust control, which tolerates up to triple increase in process static gain. If control is too aggressive, further on-line adjustment can be done by setpoint reference trajectory. Test results showed that this tuning was robust for process gain change; however, it was much less efficient in compensating for process dead-time changes. It was found that dead-time mismatch is much better compensated with the model correction filter. Combining the three handles, i.e., penalties on moves, reference trajectory, and model filter, easy and intuitively understandable MPC tuning was achieved. The findings were illustrated by numerous MPC simulated tests.

Qin and Badgwell (2003) presented excellent review on development of MPC. Their survey data show that the number of MPC applications has approximately doubled in 4 years from 1995 to 1999. MPC applications showed a solid foundation in refining and petrochemicals, and significant penetration into a wide range of application areas from chemicals to food processing. The MPC technology landscape has changed dramatically in recent years, making it difficult for us to keep track of the swift progress in academic research and industrial applications.

Chapter-3

PROCESS DESCRIPTION AND TRANSFER FUNCTION MODELS IDENTIFICATION

The Crude distillation unit is the mother unit of any refinery. They are used to separate the crude oil into various fractions. These fractions can be products or feed stocks to the following processing units. Typically, the crude distillation system involves a main tower linked to several side strippers.

3.1 PROCESS DESCRIPTION

The desalted crude feedstock is preheated using recovered process heat. The feedstock then flows to a direct-fired crude charge heater. Then it is fed into the vertical distillation column just above the bottom, at pressures slightly above atmospheric and at temperatures ranging from 343.4 to 371.1° C (above these temperatures undesirable thermal cracking may occur). The crude oil fractionator does not produce products having a single boiling point, rather, it produces fractions having boiling ranges. All but the heaviest fractions flash into vapor. As the hot vapor rises in the tower, its temperature is reduced. Heavy fuel oil or asphalt residue is taken from the bottom. At successively higher points on the tower, the various major products including heavy gas oil, light gas oil, kerosene, naphtha, gasoline and uncondensed gases (which condense at lower temperatures) are drawn off. Then, side streams from certain trays are taken off to obtain the desired fractions. Products ranging from uncondensed fixed gases at the top to heavy gas oils at the bottom can be taken continuously from a fractionating tower. Steam is often used in towers to lower the vapor pressure and create a partial vacuum. The distillation process separates the major constituents of crude oil into so-called straight-run products. Schematic diagram for process involved in atmospheric distillation of crude oil is shown below figure 3.1.

Crude distillation towers are high capacity, side stream distillation columns consuming large amounts of energy in which any upset will propagate to downstream processing units disturbing the quality and quantity of final products. Hence, it is desirable to maintain crude distillation tower operation very close to steady state. For this reason, operators may attempt to control the tower with large safety margin between actual and specified end points. This conservative operation results in a loss of more valuable material into a lower valued stream,

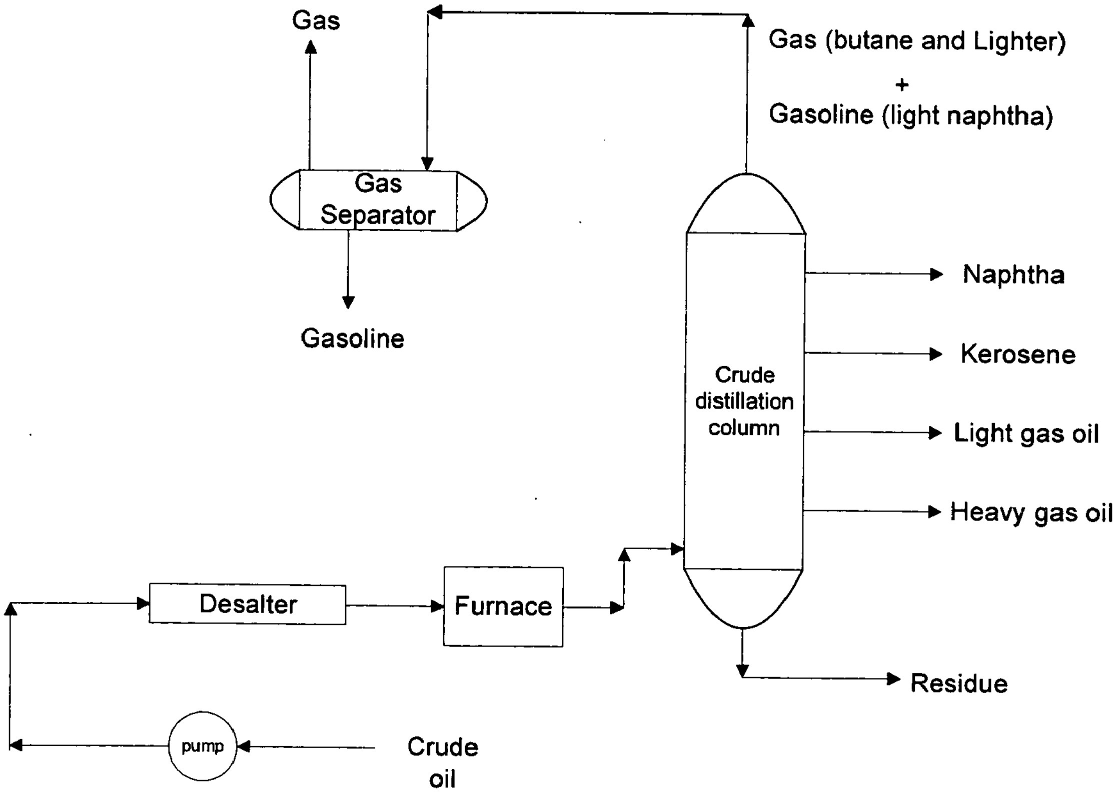

Figure 3.1: Schematic diagram for process involved in atmospheric distillation of crude oil.

and it thus conflicts with the company's profit objective. Side stream product quality is normally represented by a total boiling point (TBP) temperature curve or an ASTM distillation curve. For control purposes, a 90% TBP distilled point, or so-called 'end point' (EP) is usually chosen as the product specification and control variable of a side stream quality control loop. The 90% TBP point is the temperature at which 90% of a sample has distilled under heat.

Schematic product quality diagram for a crude tower is shown in figure 3.2. Product quality control is characterized by strong interaction among the sidestream control loops. Thus, adjusting a sidestream withdrawal rate for the purpose of affecting a change in the sidestream EP can bring undesired changes in the other product qualities. This adjustment requires subsequent adjustments of the other sidestream flow rates. Since the operator often makes these changes sequentially, it can take considerable time to bring the tower to steady state after a process upset or a crude switch. Near steady state interaction tends to be one-way, with disturbances propagating mainly downward. Based on a simplified crude tower model

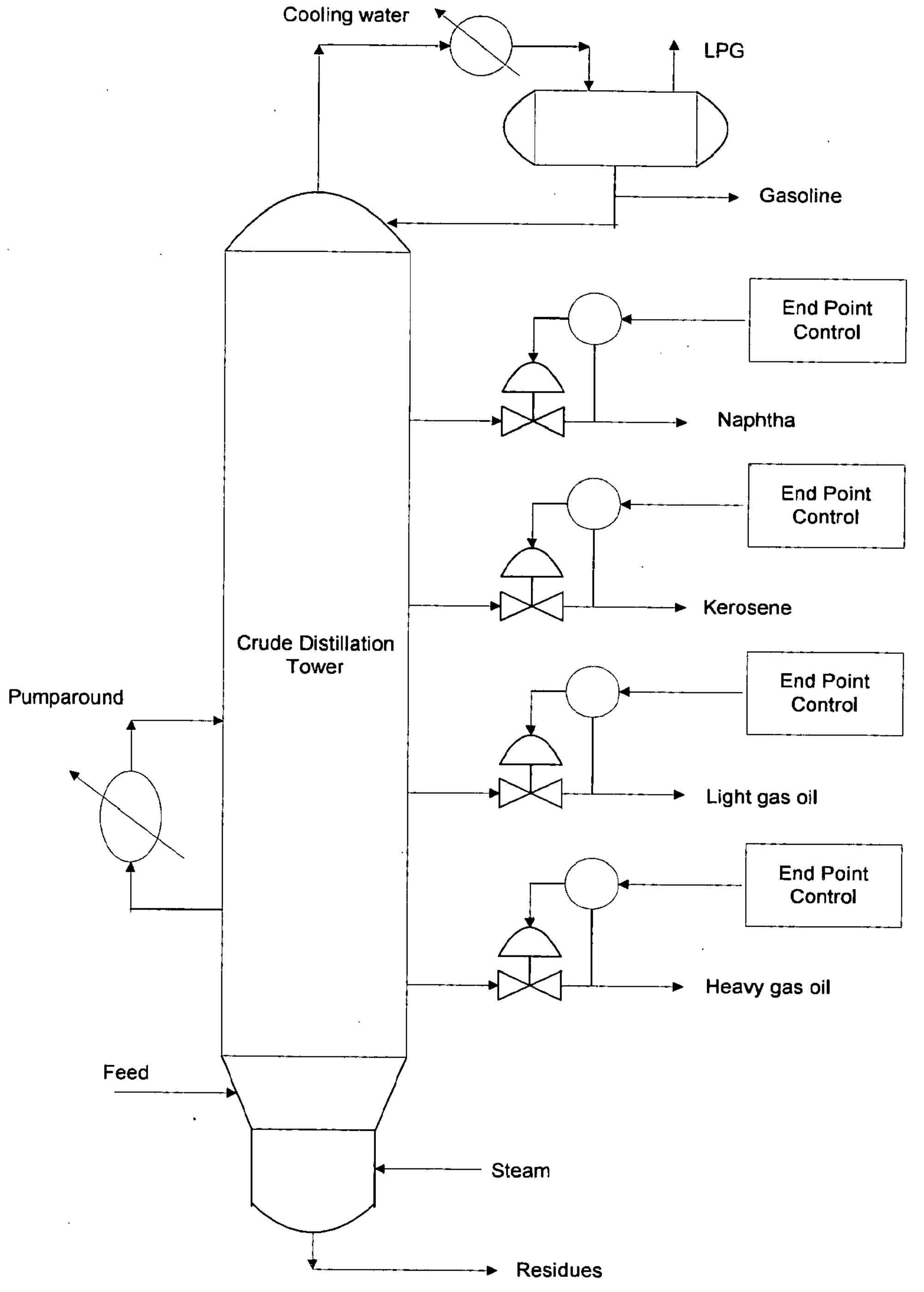

Figure 3.2: Diagram of product quality control scheme.

that assumed perfect stream separation, it has been shown that the steady gain matrix for a crude tower has a triangular form indicative of one way interaction. The primary control objectives for a crude tower can be summarized as follows:

- Maintain product quality on specification.

- Maximize the yield of every product by controlling the pumparounds to remove heat from the tower under the operating constraints and equipment limits. These constraints include tray flooding, minimum flow rate of pumparounds, and maximum heat duty of pumparounds.

Product quality control is usually applied only to the side streams of a crude tower. The overhead distillate is normally fed to a stabilizer and a splitter to further process this stream to liquefied petroleum gas (LPG), light naphtha, and medium naphtha. It is not necessary to control the end point of the distillate stream. At the tower bottom, the crude residue has no end point specification. The naphtha side stream is treated further to make jet fuel, which is a valuable product. The flash point of the naphtha is related to its initial boiling point, and it is usually controlled by adjusting the overhead temperature of the crude tower. The cloud point of the light gas oil and pour point of the heavy gas oil are useful in estimating the relative amount of wax in these product streams, and they can be controlled by controlling the streams EP. Therefore, each side draw product stream must meet an EP specification. The EP of a sidestream is typically controlled by manipulating its own flow.

3.2 TRANSFER FUNCTION MODELS IDENTIFICATION

This model, which is used here, involves a large number of differential equations and algebraic equations. These equations, based on fundamental physical and thermodynamical principles, represent the time-dependent behaviour of the system. In control system analysis and design where complicated sets of subsystems must be analysed and tested, the use of a differential equation model is rather inconvenient and time consuming. To overcome this problem, transfer function approximations are used to design controllers. These controllers are then tested on the complete dynamic model. These transfer function models are taken from Leo Hsie and McAvoy (1991). As the system involves four products namely, naphtha, kerosene, light gas oil (LGO) and heavy gas oil (HGO) as controlled variables and their respective flows as manipulated variables, hence the control system is a 4 x 4 MIMO system and sixteen transfer functions required are given below.

Transfer Functions:

$$g_{11} = \frac{1.064e^{-0.4s}}{40.5s^2 + 7.94s + 1.0}$$

$$g_{21} = \frac{0.627e^{-2.7s}}{48.0s^2 + 16.9s + 1.0}$$

$$g_{31} = \frac{0.695e^{-1.8s}}{45.0s + 1.0}$$

$$g_{41} = \frac{1.556e^{-6.66s}}{46.1s^2 + 14.9s + 1.0}$$

$$g_{12} = \frac{-0.2806(-57.5s + 1)e^{-5.94s}}{182.7s^2 + 27.7s + 1.0}$$

$$g_{22} = \frac{0.441e^{-4.68s}}{30.2s^2 + 14.1s + 1.0}$$

$$g_{32} = \frac{0.649e^{-1.98s}}{41.9s + 1.0}$$

$$g_{42} = \frac{1.556e^{-6.66s}}{36.1s^2 + 14.9s + 1.0}$$

$$g_{13} = \frac{-0.1593(-98.7s + 1)e^{-7.68s}}{173.0s^2 + 33.1s + 1.0}$$

$$g_{23} = \frac{-(22.9s^2 - 1.39s + 0.04)}{1539.5s^3 + 365s^2 + 34.9s + 1.0}$$

$$g_{33} = \frac{0.541e^{-3.84s}}{2.38s^2 + 37.4s + 1.0}$$

$$g_{43} = \frac{1.591e^{-6.84s}}{28.2s^2 + 14.2s + 1.0}$$

$$g_{14} = \frac{-(38.7s^2 - 6.48s + 0.217)}{893.6s^3 + 243.5s^2 + 30.84s + 1.0}$$

$$g_{24} = \frac{-(18.5s^2 - 0.338s + 0.066)}{1260s^3 + 308.6s^2 + 31.58s + 1.0}$$

$$g_{34} = \frac{-0.0324(25.2s + 1.0)e^{-1.0s}}{19.1s^2 + 8.88s + 1.0}$$

$$g_{44} = \frac{0.969(-4.31s + 1.0)e^{-2.6s}}{27.6s^2 + 12.4s + 1.0}$$

Process gain units are °C/ (kmol h).

In transfer function g_{ij}, subscripts i and j correspondence to variables is given in table 3.1.

Table 3.1: Correspondence of i and j to variables.

Subscripts		Variable
i	1	Naphtha flow
	2	Kerosene flow
	3	Light gas oil flow
	4	Heavy gas oil flow
j	1	Naphtha EP
	2	Kerosene EP
	3	Light gas oil EP
	4	Heavy gas oil EP

3.3 CONSTRAINTS VARIABLES

The constraints for the manipulated variables are summarized in table 3.2. The lower limits are set to avoid negative side draw rates. The upper limits are used for preventing dry out of the side draw trays. Draw rate is the rate of change of flow. QDMC controller takes these constraints into consideration and takes the control action without violating these constraints using Quadratic Programming. Where, this consideration is not there in case of standard DMC controller. The constraints in the table 3.2 are taken from Leo Hsie and McAvoy (1991). Negative sign on draw rate signifies down rate and positive sign for up rate. There are constraints on manipulated variables and manipulated rate variable and not for the controlled variables for product quality control of crude distillation tower.

Table 3.2: Constraints on the manipulated variables manipulated variable rates

Variable	High limit (draw: kmol/min) (draw rate: kmol/min^2)	Low limit (draw: kmol/min) (draw rate: kmol/min^2)
S_1 draw	1.512	0
S_2 draw	1.512	0
S_3 draw	1.512	0
S_4 draw	1.512	0
S_1 draw rate	0.00315	-0.00315
S_2 draw rate	0.00315	-0.00315
S_3 draw rate	0.00315	-0.00315
S_4 draw rate	0.00315	-0.00315

Chapter-4

CONTROL ALGORITHM

4.1 STANDARD DMC ALGORITHM

Let $\alpha = [a_1, a_2, a_3 \ldots a_P]$ α represent the unit step response function of a dynamical system, i.e., the elements of α represent the change observed in the system output, at P, consecutive, equally spaced, discrete time instants after implementing a unit change in the input variable. Now, let x_i represent the change in the input variable at time instant i. Initially, before the implementation of any control moves, let the predicted system output be $Y^0 = [Y^0{}_1, Y^0{}_2, Y^0{}_3 \ldots Y^0{}_P]^T$ where $Y^0{}_i$ need not be equal to $Y^0{}_j$ for i, j = 1, 2,......,P.

Let an arbitrary sequence of m control moves be $x = [x_1, x_2. \ldots . x_M]^T$. It will cause the system to change from the initial Y^0 to some new state Y. Linearity is assumed and principle of superposition is applied, the new state $Y= [Y_1, Y_2. \ldots Y_P]^T$ i given by the following equations:

$$Y_1 = Y_1^0 + a_1 x_1$$

$$Y_2 = Y_2^0 + a_2 x_1 + a_1 x_2$$

.

.

$$Y_M = Y_M^0 + a_M x_1 + a_{M-1} x_2 + \ldots\ldots\ldots\ldots\ldots\ldots + a_1 x_M$$

$$Y_{M+1} = Y_{M+1}^0 + a_{M+1} x_1 + a_M x_2 + \ldots\ldots\ldots\ldots\ldots\ldots + a_2 x_M$$

$$Y_P = Y_P^0 + a_P x_1 + a_{P-1} x_2 + \ldots\ldots\ldots\ldots\ldots\ldots + a_{P-M+1} x_M$$

This may be rewritten as

$$y = Ax$$

Where $y = Y - Y^0$ is system output in deviation variable form and

$$A = \begin{bmatrix} a_1 & 0 & 0 & \cdots\cdots\cdots & 0 \\ a_2 & a_1 & 0 & \cdots\cdots\cdots & 0 \\ \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & & \cdot \\ a_M & a_{M-1} & a_{M-2} & \cdots\cdots\cdots & a_1 \\ a_{M+1} & a_M & a_{M-1} & \cdots\cdots\cdots & a_2 \\ \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & & \cdot \\ a_P & a_{P-1} & a_{P-2} & \cdots\cdots & a_{P-M+1} \end{bmatrix}$$

is a P x M matrix and is called the system's "dynamic matrix".

Assuming that system dynamics are adequately represented by y = Ax, the control problem then becomes that of judiciously choosing, and implementing the sequence of control moves (x_1, x_2. . . x_M) such that the system output is as close as possible to the desired value Y*.

The DMC approach to the above stated control problem is outlined as given below;

- In the absence of control moves, the system output is predicted to remain as ($Y^0{}_1$, $Y^0{}_2$, $Y^0{}_3$....$Y^0{}_p$) over the prediction horizon of P time intervals. However, the desired situation is Y_i to be Y* for all i. The difference between the desired and currently predicted outputs (in the absence of control action) is termed E, the "error prediction vector", i.e., E = [e_1, e_2, . . . , e_p], with

$$e_i = Y^* - Y_i$$

- Given E, if x is chosen such that, Ax = E holds exactly, the system output would be transformed from Y^0 to Y*, since Y becomes Y^0 + E, which by definition of E is Y*.
- However, Ax = E usually contains an over determined set of equations (since M<P, usually), i.e., has fewer unknowns than equations, so that no unique solution exists. nevertheless vector x is determined to minimize the vector norm Φ

$$\min_x \Phi = [Ax - E]^T [Ax - E]$$

- A control sequence x thus chosen minimizes the sum of squared deviations of the system output from the desired state over the P-interval, prediction horizon.
- In practice, penalty against excessive control action is often incorporated into the optimization objective to reach min:

$$\min_x S = [Ax - E]^T \gamma^T \gamma [Ax - E] + x^T \lambda^T \lambda x$$

Thus for given A, the system model, E, information about the system state, γ, weights on controlled variables, and λ, move suppression coefficients represents the "control law" utilized by the DMC scheme.

4.2 QUADRATIC DMC ALGORITHM

The dynamic matrix control technique presented in the previous section is based on an unconstrained optimization of current and future control moves. The combination of a linear model and quadratic objective function lead to an analytical solution for the control moves. In practice, constraints on manipulated inputs (control moves) can be very important. Fortunately, dynamic matrix control is easily formulated to explicitly handle constraints by using Quadratic Programming (QP); the method is known as Quadratic Dynamic Matrix Control (QDMC).

Key features of the QDMC algorithm include:

- Linear step response model for the plant
- Quadratic performance objective over a finite prediction horizon
- Future plant output behaviour specified by trying to follow the setpoint as closely as possible subject to a move suppression term
- Solution to Quadratic Programming problem gives the optimal inputs

QP Solution of the DMC Equations (QDMC)

Three types of process constraints are usually encountered: Manipulated variable constraints: valve saturation. Controlled variable constraints: overshoots in the controlled variables past allowable limits must be avoided. Associated variables constraints: key process variables which are not directly controlled but that must be kept within bounds. The controller must be able to predict future violations and prescribe moves that would keep these variables within bounds. Constraints on controlled variables can be expressed mathematically as a system of linear inequalities:

$$y_{min} \leq y \leq y_{max}$$

The matrix y contains dynamic information on the constraints. Also, in practice, limits on individual moves are usually needed:

$$x_{min} \leq x \leq x_{max}$$

One can express the least-squares solution of the DMC equations as the following quadratic minimization problem:

$$\min_{x} S = \frac{1}{2}[Ax - E]^T \gamma^T \gamma [Ax - E] + \frac{1}{2} x^T \lambda^T \lambda x$$

Subjecting this problem to the linear inequality constraints, the following QP problem results:

Determine X, so as to

$$\min_{x} \ F = \frac{1}{2} x^T Hx - g^T x$$

Subjected to

$$y_{min} \leq y \leq y_{max}$$

$$x_{min} \leq x \leq x_{max}$$

Where:

$$H = A^T \gamma^T \gamma A + \gamma^T \gamma \qquad \text{(The QP Hessian matrix)}$$

And,

$$g = A^T \gamma^T \gamma E \qquad \text{(The QP gradient vector)}$$

Solution by a QP algorithm at each sampling interval k produces an optimal set of moves x(k) which satisfies the constraints. Any commercially available QP algorithm could be used for solving the above problem.

4.3 BASIC DESCRIPTION OF DMC

At each time step, k, an optimization problem is solved by linear or quadratic programming (depend on nature of objective function and constraints). An objective function (usually quadratic) based on output predictions over a prediction horizon of P time steps is minimized by a selection of manipulated variable moves over a control horizon of M control moves. Although M moves are optimized, only the first move is implemented. After x(k) is implemented, the measurement at the next time step, y_{k+1} is obtained. A correction for model error is performed, since the measured output will, in general, not be equal to the model predicted value. A new optimization problem is then solved, again, over a prediction horizon of P steps by adjusting M control moves. This approach is also known as receding horizon control. Block diagram for DMC is given in the following figure 4.1.

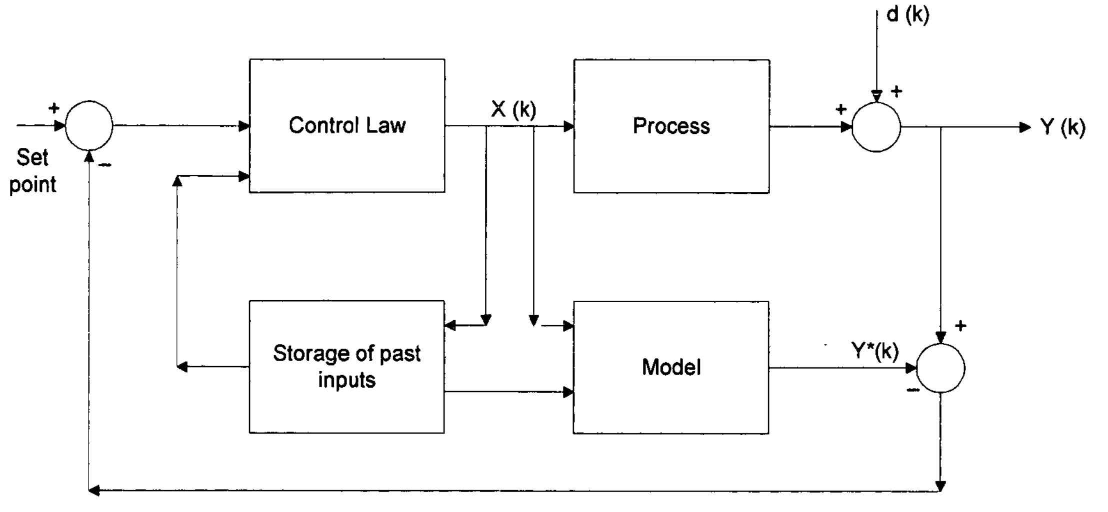

Figure 4.1: Block diagram for DMC controller.

Chapter-5

TUNING OF DMC

The adjustable parameters that affect closed loop performance of DMC include the prediction horizon, P; control horizon, M; sample time, T; controlled variable weights, γ; and move suppression coefficients, λ. Practical limitations often restrict the availability of sample time, T, as a tuning parameter. Model horizon, N; is number of time instants required for the response of model to reach steady state. Model horizon is also not an appropriate tuning parameter since truncation of model horizon misrepresents the effect of past moves in the predicted output and leads to unpredictable closed loop performance. The choice of prediction horizon, P, is dependent on the sample time, T. Although a large P does not significantly improve performance, it does improve nominal stability of the closed loop. For this reason, P Should be selected such that it includes the steady state effect of all past computed manipulated input moves, i.e., it should be fixed as the open loop settling time of the process. Hence, P should not be used as the primary DMC tuning parameter. M is also not well suited as the primary DMC tuning parameter. The controlled variable weights, serve a dual purpose in multivariable DMC. These weights can be appropriately chosen by the user to scale measurements of the R number of measured outputs to comparable units. Also, it is possible to achieve tighter control of a particular measured output by selectively increasing the relative weight of the corresponding least square residual. Hence, controlled variable weights are usually specified by the user for a certain application and should not be employed as the primary tuning parameters for multivariable DMC. For a control horizon (M) of 1, the set point step response is sluggish and move suppression coefficients, greater than 0 will only further slow the process response. With $M > 1$, the lack of move suppression results in aggressive control effort and a significantly under damped measured output response. An intermediate response can be achieved by an appropriate choice of suppression coefficient. However, further increasing suppression coefficient can lead to an undesirable sluggish response for most applications. Consequently, suppression coefficient is a continuous parameter that has a significant impact on closed loop performance. Furthermore, its choice is critical to the performance achieved by DMC. Therefore, the move suppression coefficients are the best suited for primary multivariable DMC tuning parameters.

5.1 OLD TUNING GUIDELINES FOR TUNING DMC [Cutler and Ramaker (1980)]

- The sampling time should be chosen as small as possible based on practical limitations. (0.1τ Or 0.5θ whichever is smaller). Where τ and θ are the time constant and dead time of system.
- The sampling period T and prediction horizon P should be chosen so that PT= T_S where T_S is the open loop settling time. This choice ensures that the model reflects the full effect of a change in an input variable over time required to reach steady state.
- As control horizon increases, the DMC controller tends to become more aggressive from 2 to 6, beyond 6, there is no significant effect of control horizon on DMC performance.
- The output variables to be weighted individually, with the most important variables having the largest weights.
- Input variables to be weighted according to their relative importance, these provide convenient tuning parameters because increasing the value of move suppression coefficients tends to make the DMC controller more conservative by reducing the magnitude of input moves. We have to follow trial error procedure in selecting move suppression coefficients.

5.2 NOVEL TUNING STRATEGY

Novel tuning strategy is proposed by Shridhar and Cooper (1998). Its step wise implementation is as follows:

- Approximate the process dynamics of all manipulated input-measured output pairs with first order plus dead time (FOPDT) models:

$$\frac{y_j(s)}{u_j(s)} = \frac{K_{ij}e^{-\theta_{ij}S}}{\tau_{ij}s+1} \quad (i = 1,2,.....S \; ; \; j = 1,2,....R)$$

- Select the sample time as close as possible to:

$$T = 0.1\tau_{ij} \text{ Or } T = 0.5\theta_{ij} \text{ whichever is smaller } (i = 1,2,...., S; j = 1,2,....., R)$$

- Compute the prediction horizon, *P,* and the model horizon, *N,* as the process settling time in samples (rounded to the next integer):

$$P = N = \mathrm{Max}\left(\frac{5\tau_{ij}}{T} + k_{ij}\right) \text{where } k_{ij} = \left(\frac{\theta_{ij}}{T} + 1\right) \quad (i = 1,2,....,S;\ j = 1,2,....,R)$$

- Select the control horizon, *M,* as an integer (usually in the range 1 to 6).
- Select the controlled variable weights, to scale measurements to similar magnitudes.
- Compute the move suppression coefficients

$$\lambda_i^2 = \frac{M}{C_i}\sum_{j=1}^{R}\left[\gamma_j^2 K_{ij}^2\left(P - k_{ij} - \frac{3}{2}\frac{\tau_{ij}}{T} + 2 - \frac{(M-1)}{2}\right)\right] \quad (i = 1,2,....,S)$$

Where C_i is the condition number of i th diagonal matrix.

An approximation of the multivariable DMC system matrix, ($A^T\gamma^T\gamma A$), is obtained using a FOPDT model approximation of the process. This (M. S x M. S) matrix is comprised of S^2 matrix blocks, each of dimensions (M x M). Interestingly, all the diagonal blocks are Hankel matrices (Hankel matrices are square matrices with constant skew-diagonals) with the additional feature that the elements of each row decrease from left to right by a constant quantity. Hence, the i th diagonal block in $A^T\gamma^T\gamma A$ has the form:

i th.Diagonal Block in $A^T\gamma^T\gamma A$

$$= \begin{bmatrix} \beta_i & \beta_i - \alpha_i & \beta_i - 2\alpha_i & .... \\ \beta_i - \alpha_i & \beta_i - 2\alpha_i & \beta_i - 3\alpha_i & .... \\ \beta_i - 2\alpha_i & \beta_i - 3\alpha_i & \beta_i - 4\alpha_i & .... \\ . & . & . & . \\ . & . & . & . \end{bmatrix}$$

Where

$$\beta_i = \sum_{j=1}^{R}\gamma_j^2 K_{ij}\left(P - k_{ij} - \frac{3}{2}\frac{\tau_{ij}}{T} + 2\right) \text{ and } \alpha_i = \frac{\sum_{j=1}^{R}\gamma_j^2 K_{ij}}{2}$$

Condition number is then obtained as the ratio of maximum to minimum Eigen values of diagonal block.

Chapter-6

RESULTS AND DISCUSSION

The transfer function models and operating conditions (i.e. constraints on manipulated and controlled variables) given in Chapter-3 are used after minor modification. The models given in chapter-3 are having gain units of °C / (kmol h). Those units are converted to °C / (kmol min) to get the simulation time in minute. By using these models and operating conditions, a Quadratic Dynamic Matrix Controller is designed for the atmospheric crude distillation column sidestream product quality control. Novel tuning strategy proposed by Shridhar and Cooper (1998) is used in calculating tuning parameters for DMC. This tuning strategy requires models in the form of First Order Plus Dead Time (FOPDT) transfer functions. Models given in chapter-3 have been approximated to FOPDT by two methods, half rule and Process reaction curve fitting using sigma plot. The FOPDT models from two methods are compared using sum of square of errors in response to unit step. Error is in comparison to models given by Leo Hsie and McAvoy (1991). Finally process reaction curve fitting approximations are chosen as they give lesser sum of square errors as reported in table A1 in appendix-A. FOPDT approximate models by both techniques are given in Appendix-A. Proportional integral (PI) controller and QDMC with old tuning guidelines are also redesigned for this product quality control. Substantial improvement in the performance of QDMC with Novel tuning strategy is observed when compared with conventional PI controller and QDMC with old tuning strategy for step change in setpoints.

6.1 RELATIVE GAIN ARRAY

As a first step of a multiloop control system design paring of controlled variable with which manipulated variable is performed. The relative gain array (RGA) has been widely accepted as a useful tool to solve this pairing problem. From the definition of the relative gain, it is clear that the steady state interaction is minimized for those pairs of variables with relative gains are close to unity. The process transfer functions that relate the sidestream flow rates (S) to the sidestream end points of the simulated tower are given in Chapter-3. The steady state gain matrix of the tower's product quality control system as obtained from the transfer functions as is given below form which we can obtain Relative Gain Array for product quality control of crude distillation column.

$$P(0)=\begin{bmatrix} 1.064 & -0.2806 & -0.1593 & -0.217 \\ 0.627 & 0.441 & -0.04 & -0.066 \\ 0.695 & 0.649 & 0.541 & -0.0324 \\ 1.556 & 1.556 & 1.591 & 0.969 \end{bmatrix}$$

The RGA is computed by multiplying the corresponding elements in the P (0) and $(P^{-1}(0))^T$ matrices to give

$$RGA=\begin{bmatrix} 0.769 & 0.279 & -0.0422 & -0.0055 \\ 0.151 & 0.776 & 0.116 & -0.0437 \\ -0.242 & 0.130 & 1.023 & 0.0888 \\ 0.322 & -0.185 & -0.0968 & 0.960 \end{bmatrix}$$

This RGA indicates that a sidestream flow rate should be used to control its own product end point.

6.2 REDESIGN OF PI CONTROLLER

Luyben proposed the biggest log modulus tuning (BLT) method for the design of multiloop PID control systems. The method is an extension of the SISO Nyquist stability criterion method. Time domain simulations were carried out on the full non-linear model by Leo Hsie and McAvoy [1991] to test the performance of the BLT settings. The transient responses of the sidestream end point to a + 10 °F step change of the setpoint in the naphtha sidestream were presented. They got unsatisfactory performance with BLT factor four for all control loops. Later they tried with different BLT factor for each loop. By trial and error and dynamic simulation, they determined controller settings given in table-A2 with somewhat satisfactory performance. These detuned Z-N settings are used in redesigning conventional PI controller for product quality control.

Time domain simulations are carried out on the full non-linear model to test the performance of conventional PI controller. MATLAB Simulink is used in simulating results for multiloop PI controller. Simulink diagram is shown in figure 6.1 for PI controller and in figure 6.2 for QDMC controller. The transient responses of the sidestream end point to a +10 °C step change of the set point in the naphtha and kerosene sidestream are presented in Figure 6.3 to 6.10. From figure 6.3 to 6.10, settling times and peak responses for each EP are tabulated in table 6.1. This simulation shows that the conventional PI controller give stable but somewhat unsatisfactory responses. The settings for the PI controller of the naphtha EP loop are tight,

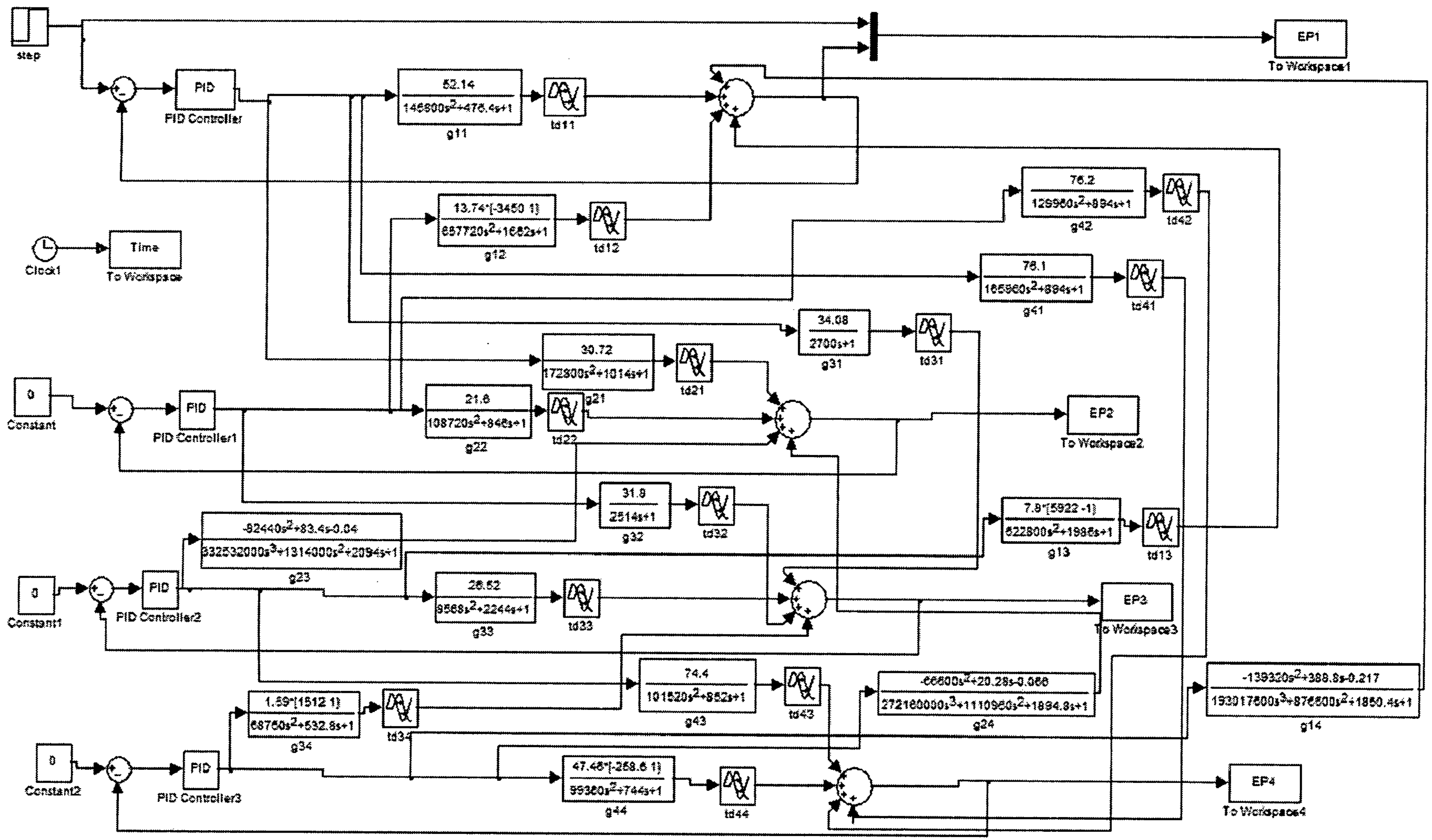

Figure 6.1: Simulink diagram of conventional PI controller for product quality control of crude distillation tower.

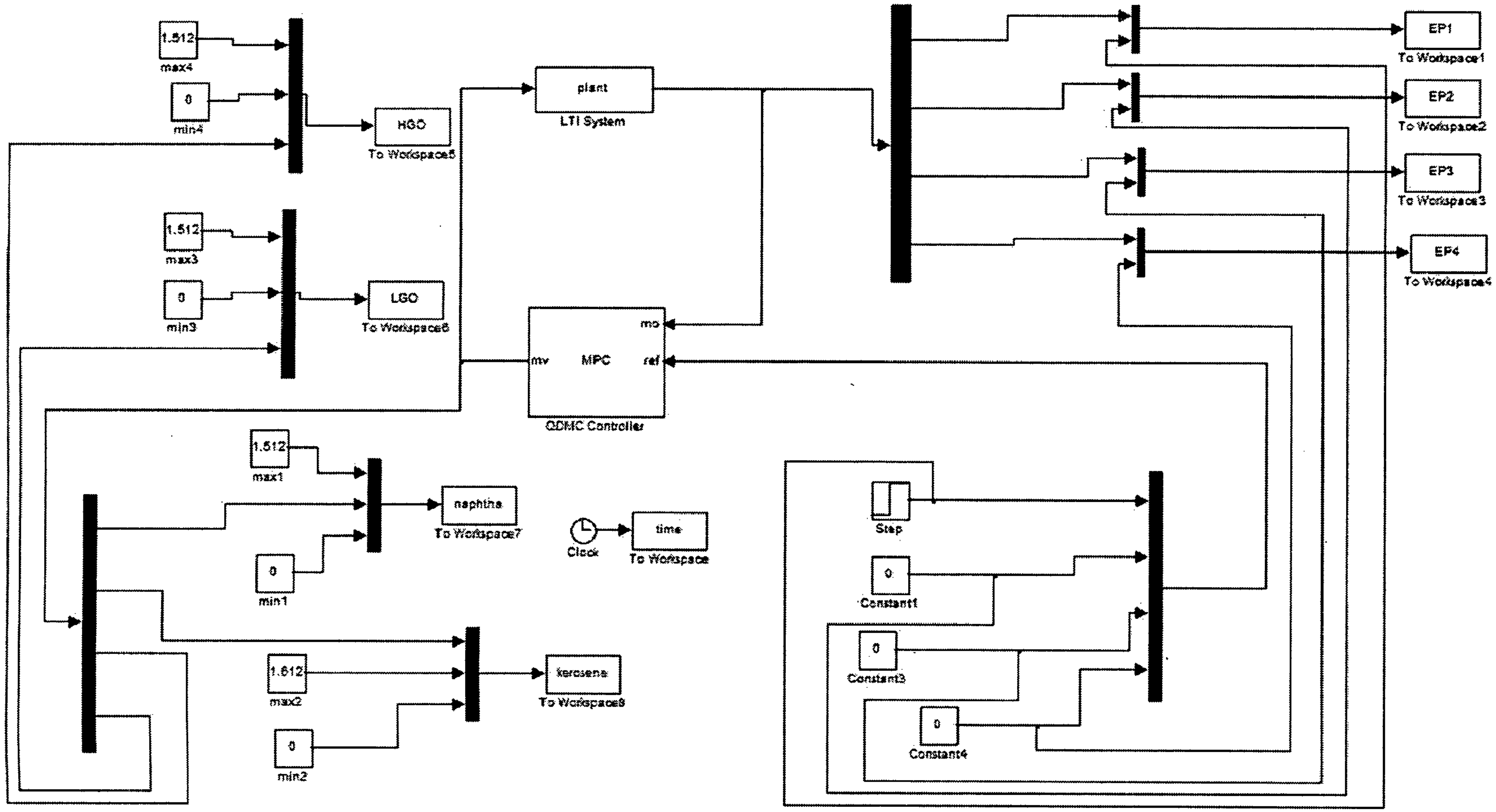

Figure 6.2: Simulink Diagram of QDMC controller for product quality control of crude distillation tower.

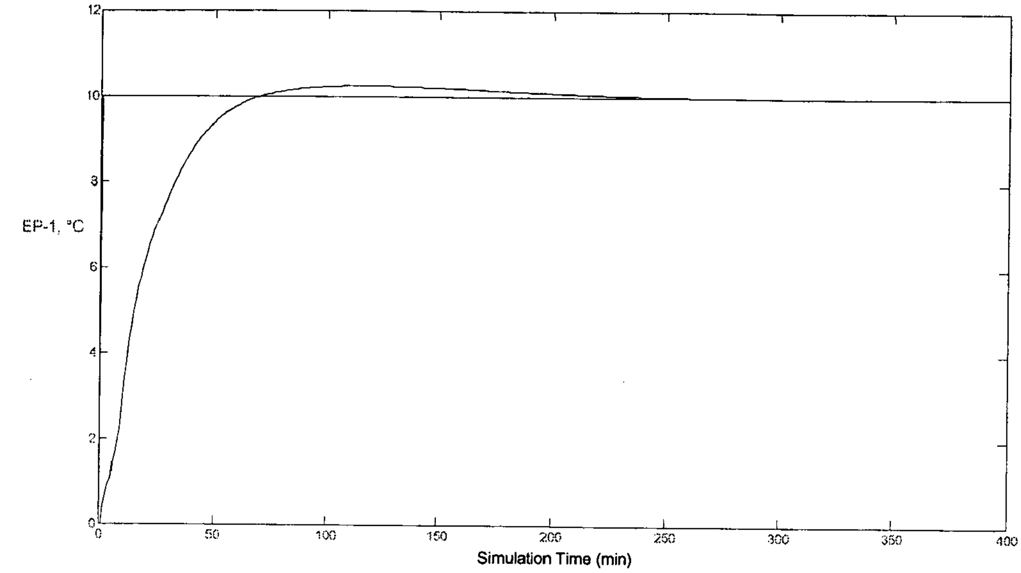

Figure 6.3: Response of Naphtha EP to +10 °C step change in Naphtha EP setpoint using PI controller.

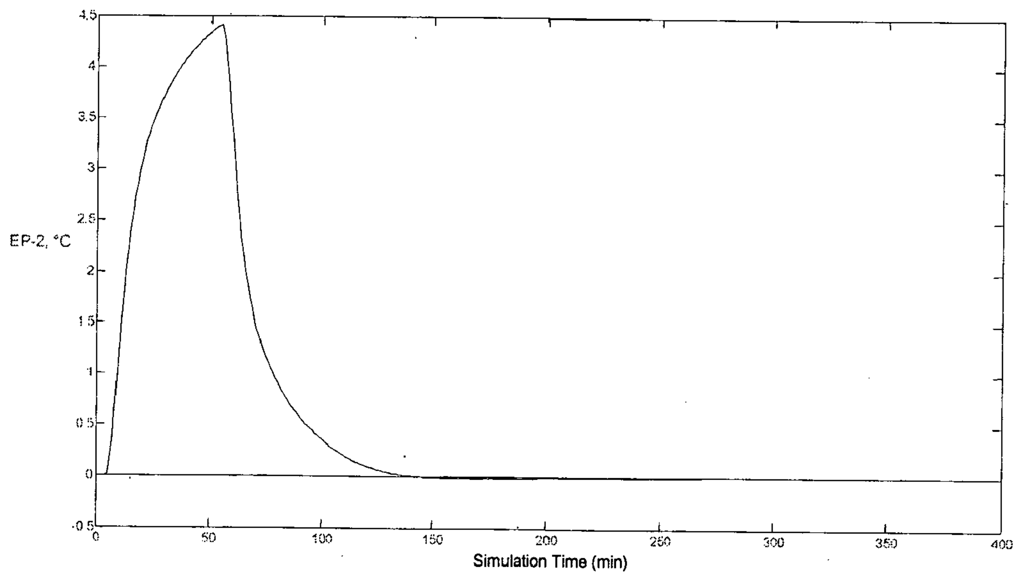

Figure 6.4: Response of Kerosene EP to +10 °C step change in Naphtha EP setpoint using PI controller.

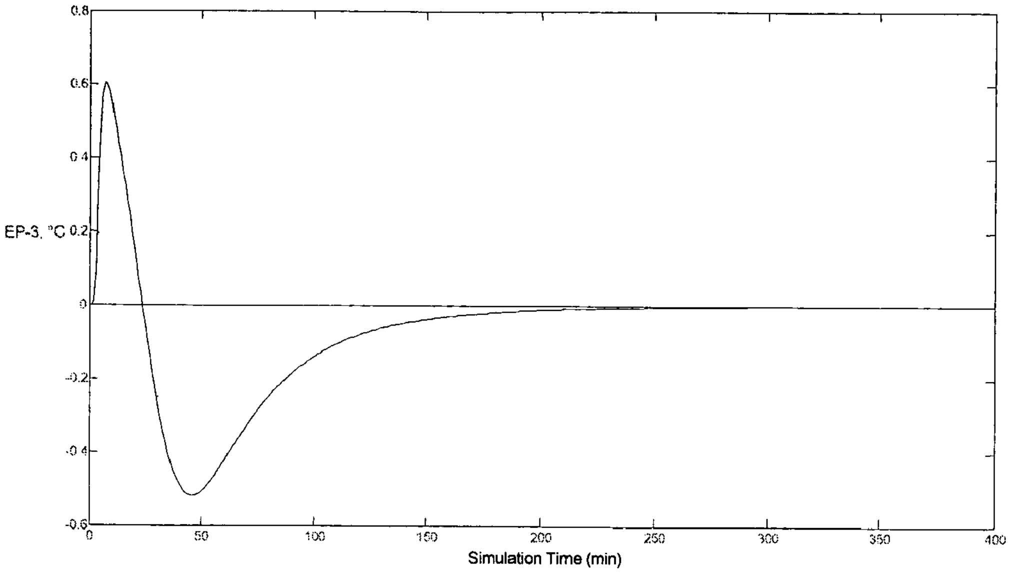

Figure 6.5: Response of Light gas oil EP to +10 °C step change in Naphtha EP setpoint using PI controller.

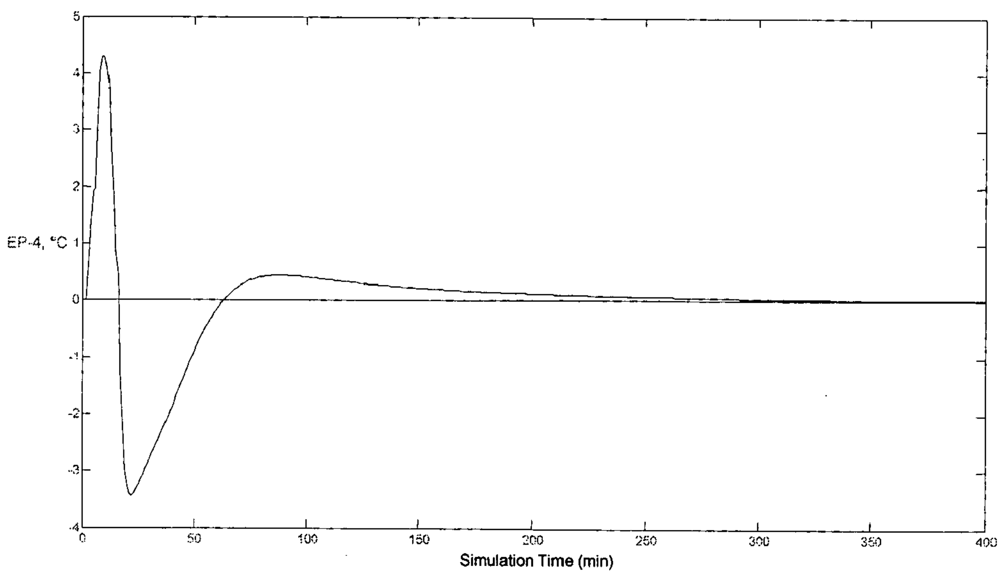

Figure 6.6: Response of Heavy gas oil EP to +10 °C step change in Naphtha EP setpoint using PI controller.

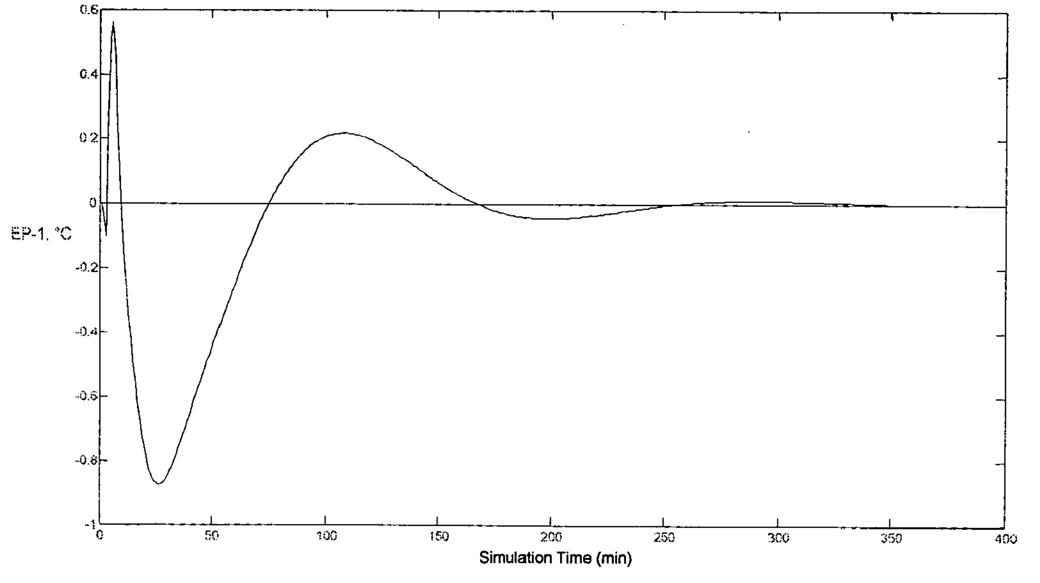

Figure 6.7: Response of Naphtha EP to +10 °C step change in Kerosene EP setpoint using PI controller.

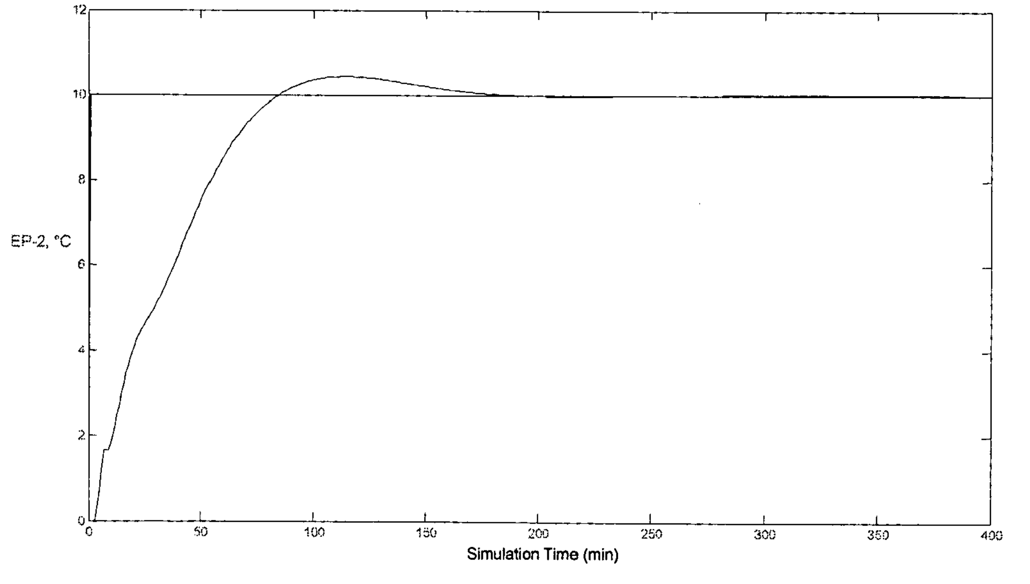

Figure 6.8: Response of Kerosene EP to +10 °C step change in Kerosene EP setpoint using PI controller

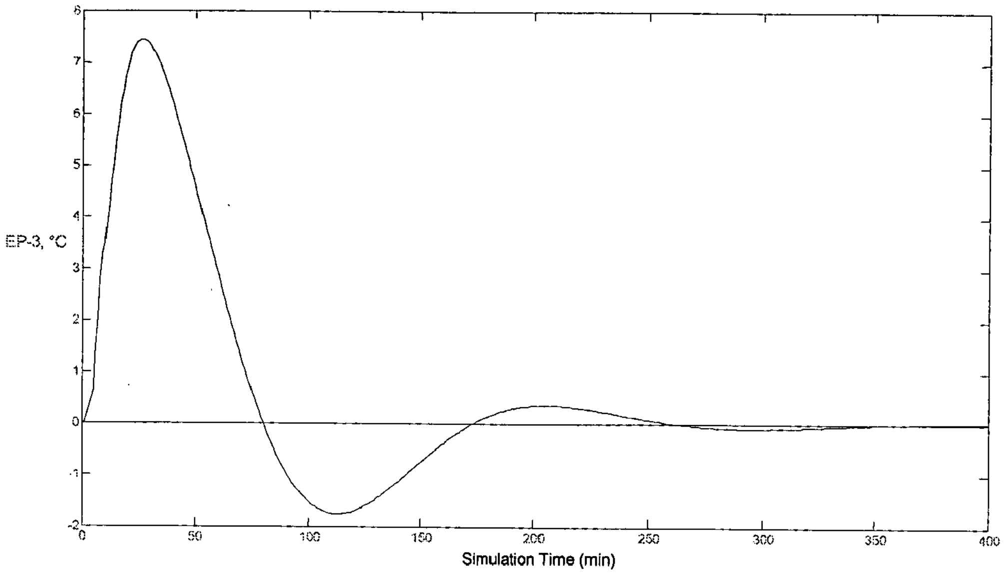

Figure 6.9: Response of Light gas oil EP to +10 °C step change in Kerosene EP setpoint using PI controller.

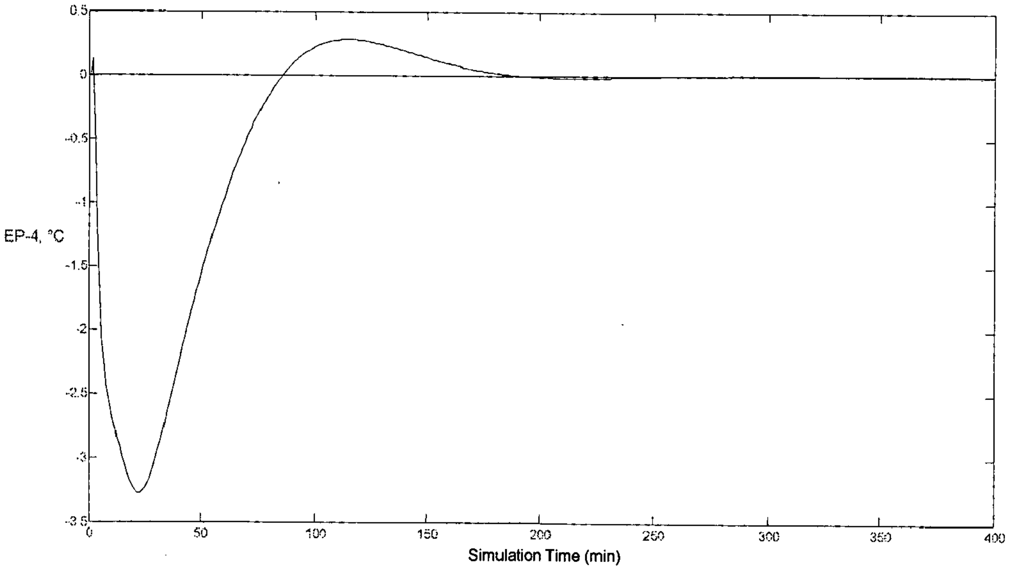

Figure 10: Response of Heavy gas oil EP to +10 °C step change in Kerosene EP setpoint using PI controller.

which causes undesired overshoot and oscillation in this loop. Furthermore, the oscillation is propagated down to all other loops. However, the settings for the other three PI controllers resulted in transient responses that approached steady state very slowly. The reset times of these three controllers can be decreased to improve the sluggish responses. From the results given in figure 6.3 to figure-6.10, it can be said that, there is two-way interaction among the control loops. Though interaction is more from naphtha loop to heavy gas oil loop to the downwards, there is significant interaction in the upward direction also. This interaction is more between the upper loops. A substantial reduction in control action of loop 1 and 2 is necessary to prevent the control system from being overly affected by dynamic interaction. Therefore, there is margin for improving the performance achieved by conventional PI controller with proper tuning.

Table 6.1: Settling times and peak amplitudes of conventional PI controller for product quality control of crude tower.

Response	Step change in Naphtha EP setpoint		Step change in Kerosene EP setpoint	
	Settling time (min)	Peak amplitude	Settling time(min)	Peak amplitude
EP-1	170	10.4	250	-0.9
EP-2	140	4.4	160	10.6
EP-3	200	0.6	255	7
EP-4	250	-3.5	175	-3.5

6.3 REDESIGN OF QDMC WITH OLD TUNING GUIDELINES

Design of QDMC requires constraints on variables and tuning parameters. The upper and lower boundaries of all variables are specified in chapter-3. Several parameters of the QDMC controller require tuning. These tuning parameters include: sample time, input horizon, output horizon, control move suppression factors, output weighting factors. Literature (cutler) presents guidelines for selecting DMC parameters for an SISO system. These guidelines can be applied to MIMO systems. These tuning guidelines are followed in redesigning QDMC. The tuning parameters obtained are shown in Appendix-C.

The simulated EP responses for QDMC are shown in Figure 6.11 to 6.14 for a 10 °C step change in the naphtha EP and Figure 6.15 to 6.18 for a 10 °C step change in the kerosene

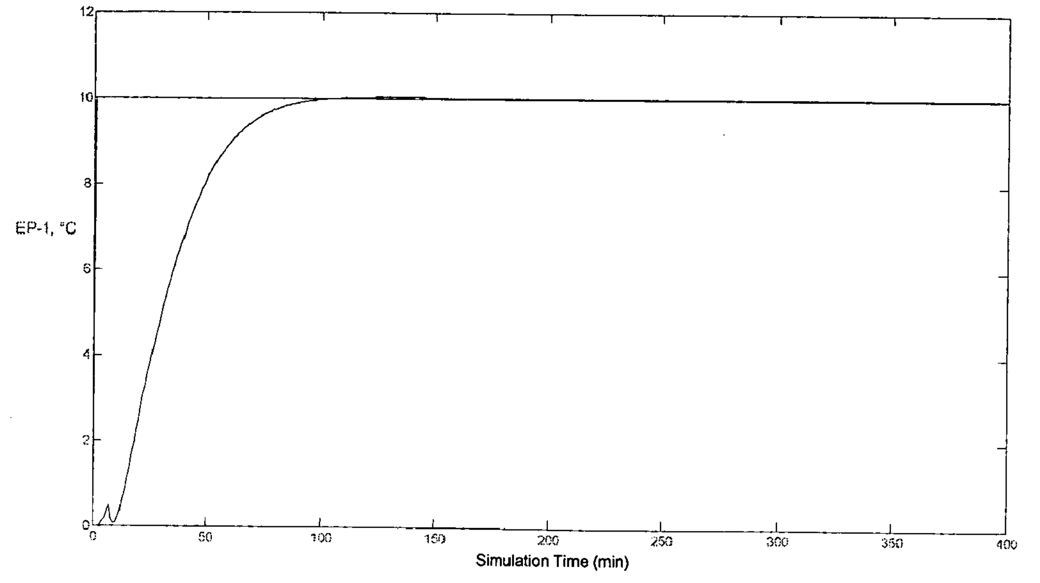

Figure 6.11: Response of Naphtha EP to +10 °C step change in Naphtha EP setpoint using QDMC with old tuning guidelines.

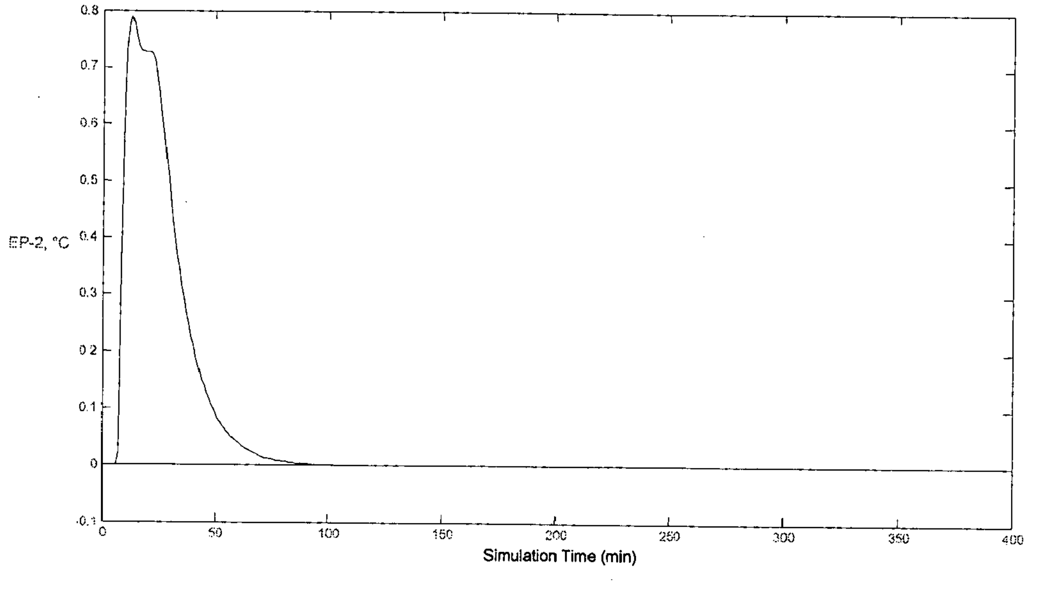

Figure 6.12: Response of Kerosene EP to +10 °C step change in Naphtha EP setpoint using QDMC with old tuning guidelines.

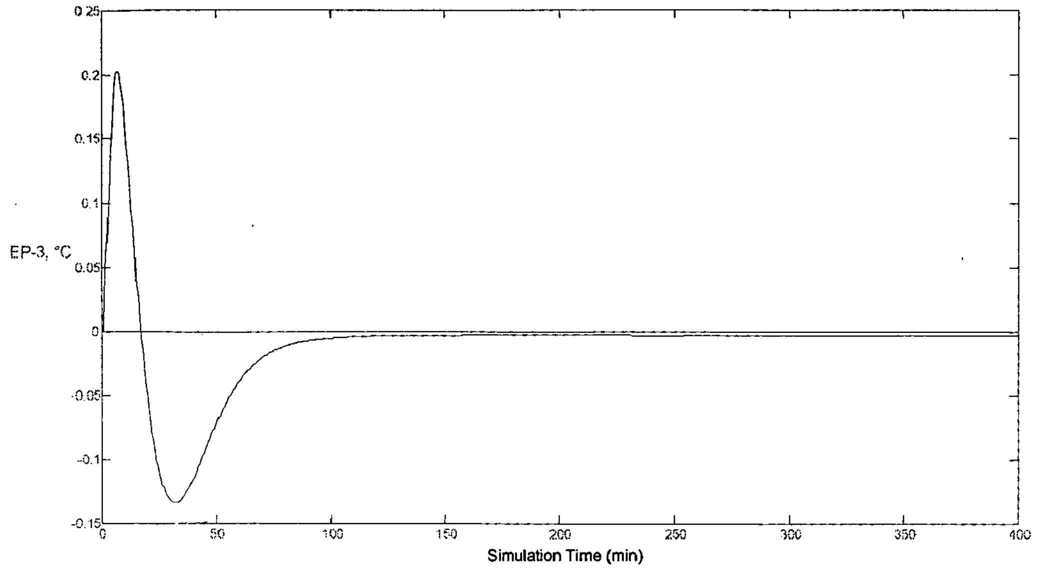

Figure 6.13: Response of Light gas oil EP to +10 °C step change in Naphtha EP setpoint using QDMC with old tuning guidelines.

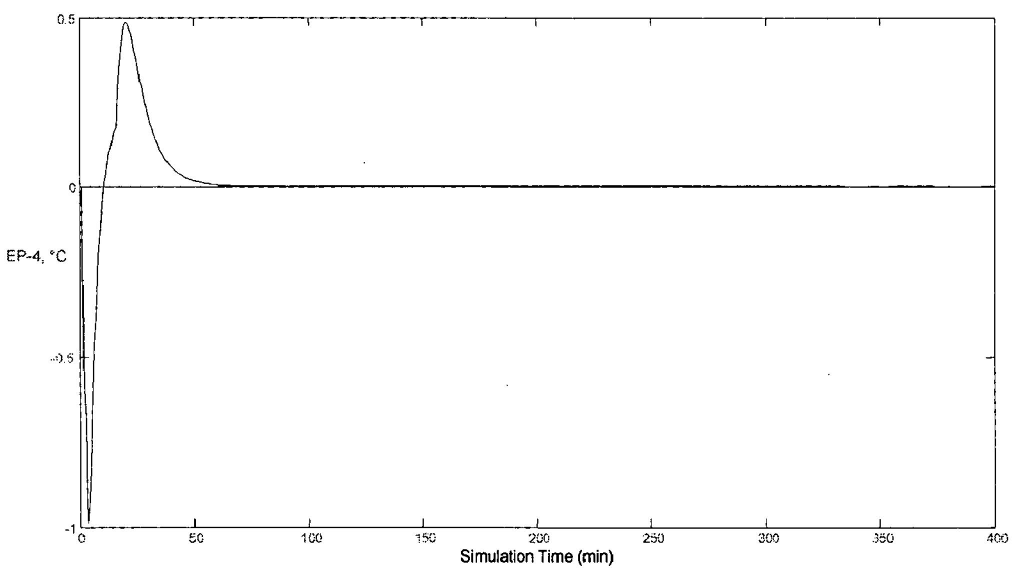

Figure 6.14: Response of Heavy gas oil EP to +10 °C step change in Naphtha EP setpoint using QDMC with old tuning guidelines.

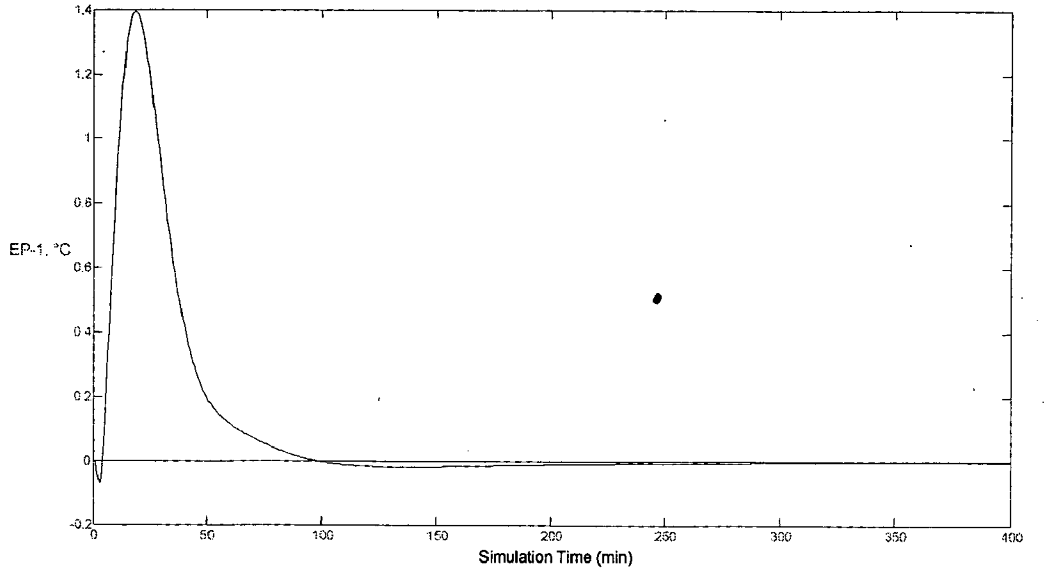

Figure 6.15: Response of Naphtha EP to +10 °C step change in Kerosene EP setpoint using QDMC with old tuning guidelines.

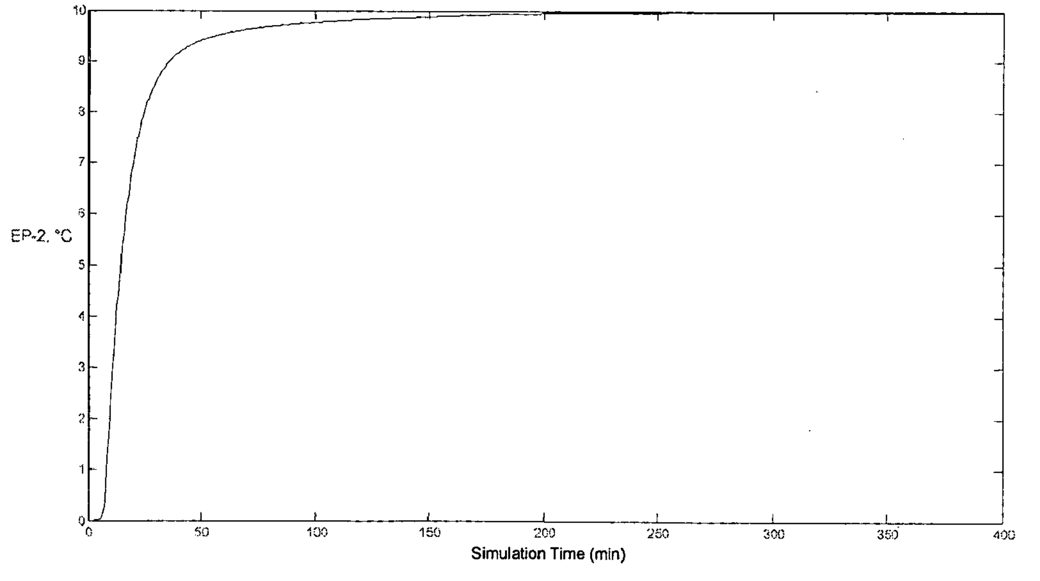

Figure 6.16: Response of Kerosene EP to +10 °C step change in Kerosene EP setpoint using QDMC with old tuning guidelines.

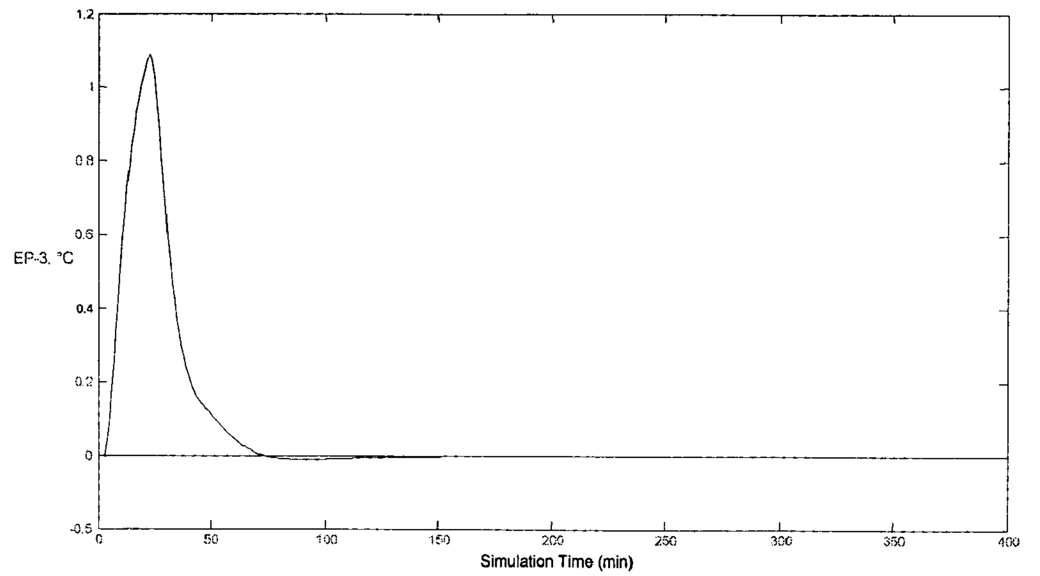

Figure 6.17: Response of Light gas oil EP to +10 °C step change in Kerosene EP setpoint using QDMC with old tuning guidelines.

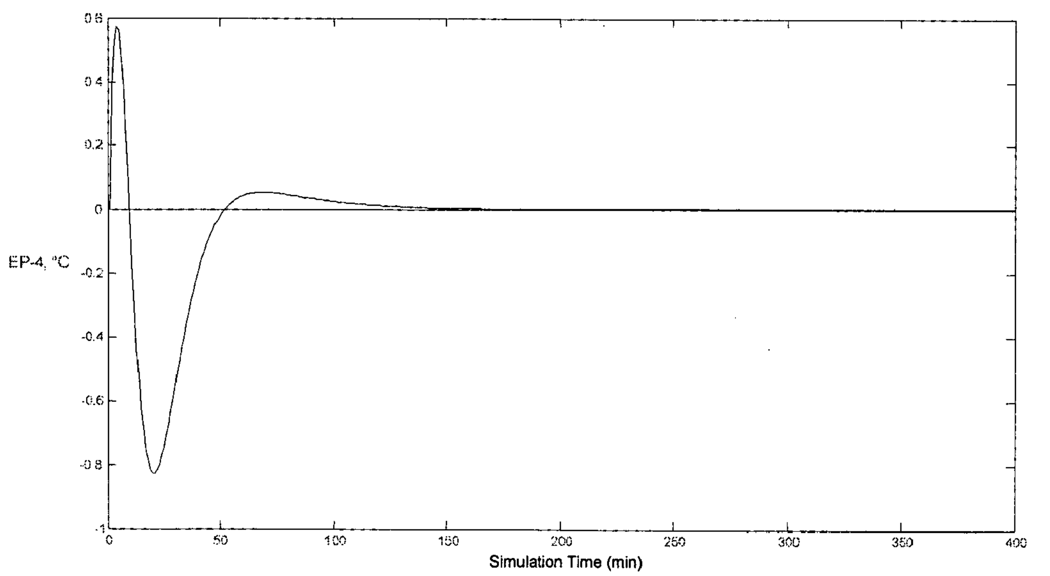

Figure 6.18: Response of Heavy gas oil EP to +10 °C step change in Kerosene EP setpoint using QDMC with old tuning guidelines.

EP. Significant two-way interaction is there in this case also. A comparison of Figure 6.11 to 6.18 with Figure 6.3 to 6.10 shows the following. QDMC control brings the EPs to their new setpoints faster than the conventional PI controller. There is no overshoot in Naphtha control loop but there is overshoot in case of conventional PI controller. From peak responses given in table 6.1 and table 6.2, one can say that interaction is more with conventional controller than with QDMC. It also can be concluded that IAE, ISE and ITAE are more in case conventional PI controller than QDMC with old tuning guidelines from their figures.

Table 6.2: Settling times and peak amplitudes of QDMC with old tuning guidelines for product quality control of crude tower.

	Step change in Naphtha EP setpoint		Step change in Kerosene EP setpoint	
Response	Settling time (min)	Peak amplitude	Settling time (min)	Peak amplitude
EP-1	90	10	90	1.4
EP-2	75	0.8	120	10
EP-3	100	0.2	75	1.1
EP-4	50	-1	105	-0.8

6.4 DESIGN OF QDMC WITH NOVEL TUNING STRATEGY

Now Novel tuning strategy proposed by Shridhar and Cooper (1998) is used in calculating tuning parameters for DMC instead of old tuning guidelines. This tuning strategy requires models of form First Order Plus Dead Time (FOPDT). They have been approximated to FOPDT by two methods, half rule and Process reaction curve fitting using Sigma Plot. Finally process reaction curve fitting approximations have been selected as they have lesser sum of square errors as given in Table A1. Approximated FOPDT models by process reaction curve fitting with Sigma Plot are given in Appendix-A. Calculation of tuning parameters is given in Appendix-B.

The simulated EP responses for QDMC are shown in Figure 6.19 to 6.22 for a 10 °C step change in the naphtha EP and Figure 23 to 26 for a 10 °C step change in the kerosene EP. Settling times and peak responses for each EP are tabulated in Table 6.3 from figure 6.19 to 6.26. Interaction among the control loops is two-way and more in case of this controller than conventional PI and QDMC with old tuning guidelines. A comparison of Figure 6.11 to 6.18

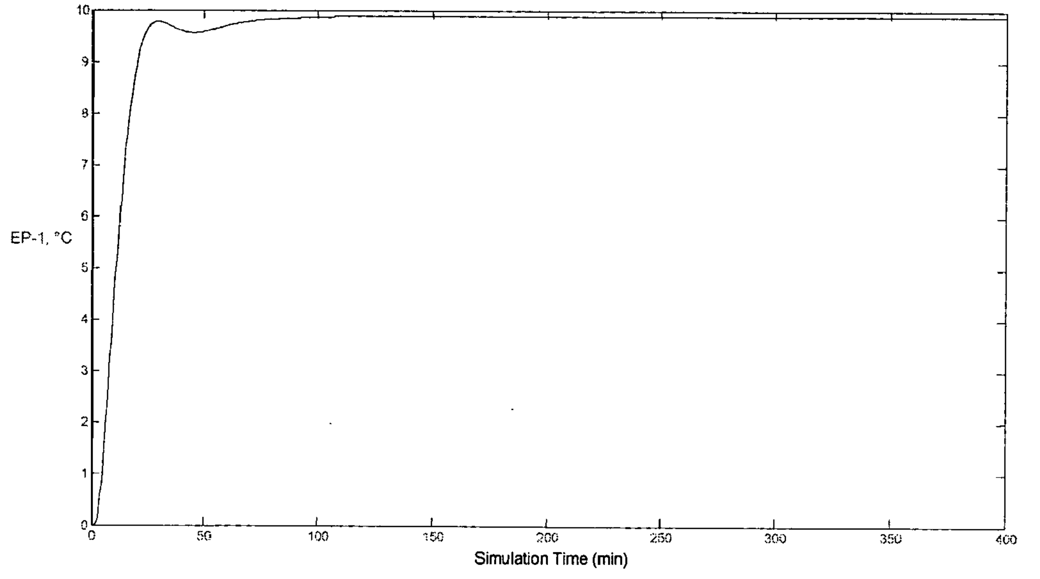

Figure 6.19: Response of Naphtha EP to +10 °C step change in Naphtha EP setpoint using QDMC with Novel tuning strategy.

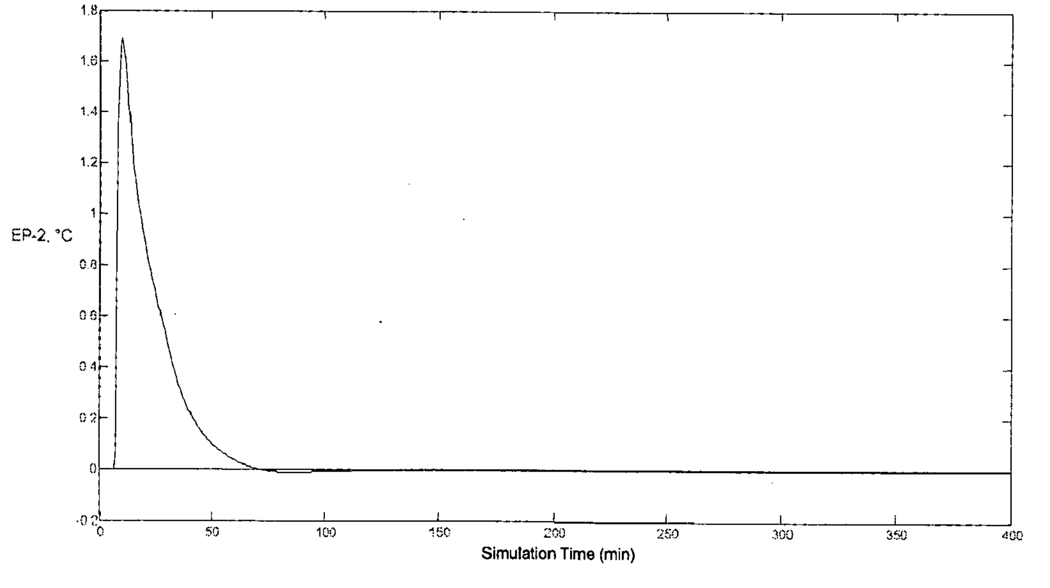

Figure 6.20: Response of Kerosene EP to +10 °C step change in Naphtha EP setpoint using QDMC with Novel tuning strategy.

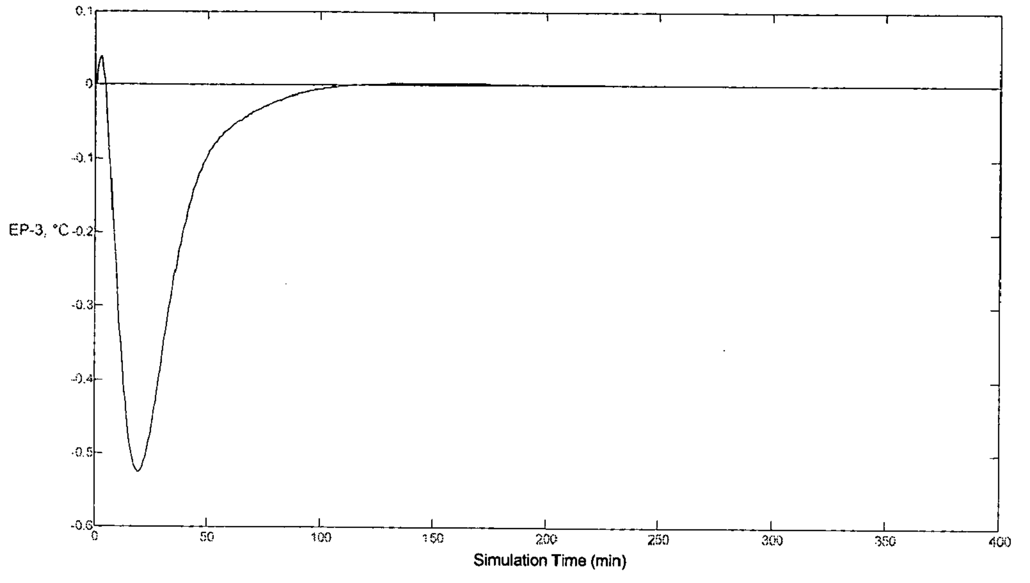

Figure 6.21: Response of Light gas oil EP to +10 °C step change in Naphtha EP setpoint using QDMC with Novel tuning strategy.

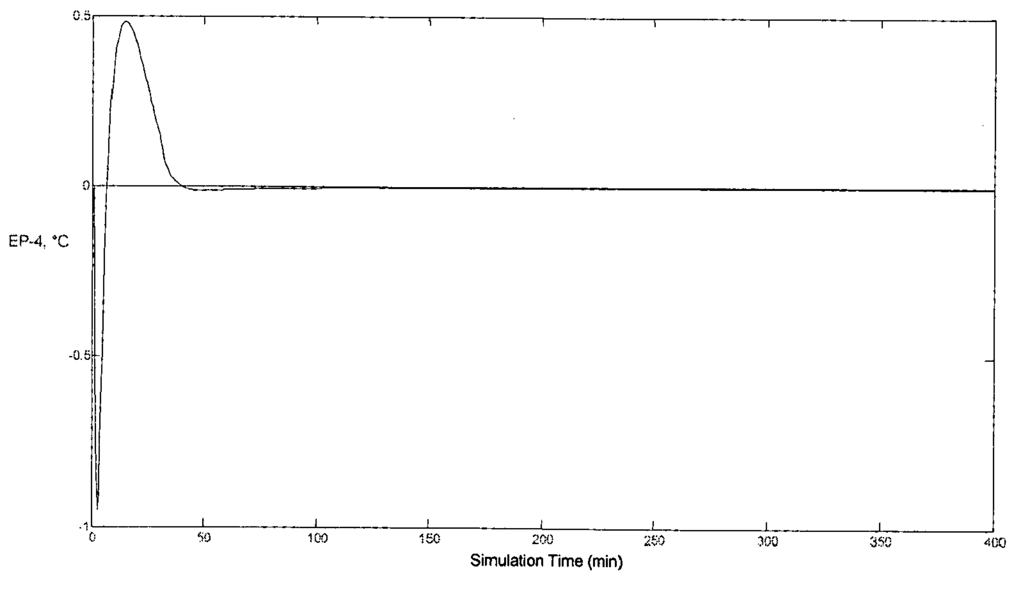

Figure 6.22: Response of Heavy gas oil to +10 °C step change in Naphtha EP setpoint using QDMC with Novel tuning strategy.

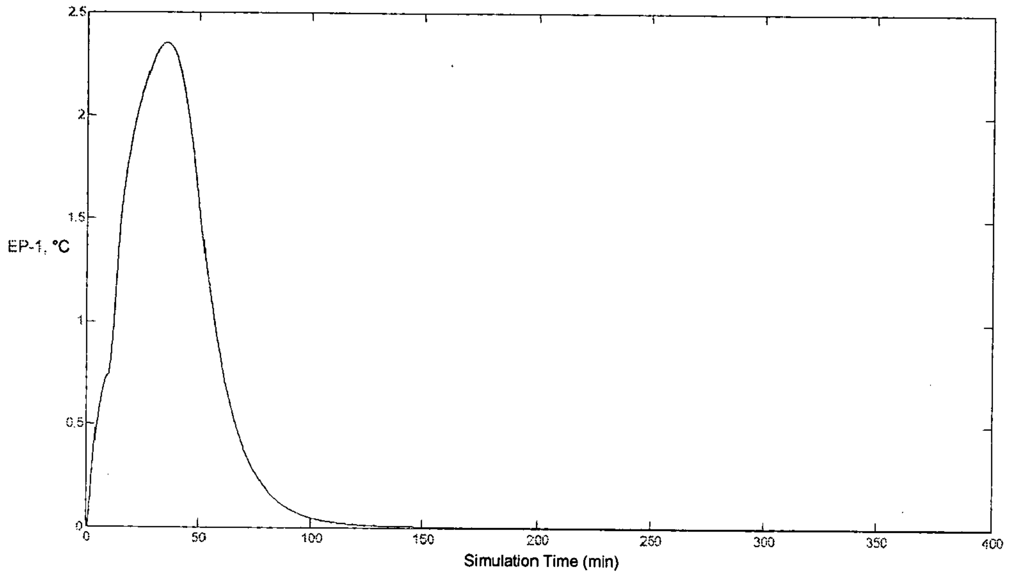

Figure 6.23: Response of Naphtha EP to +10 °C step change in Kerosene EP setpoint using QDMC with Novel tuning strategy.

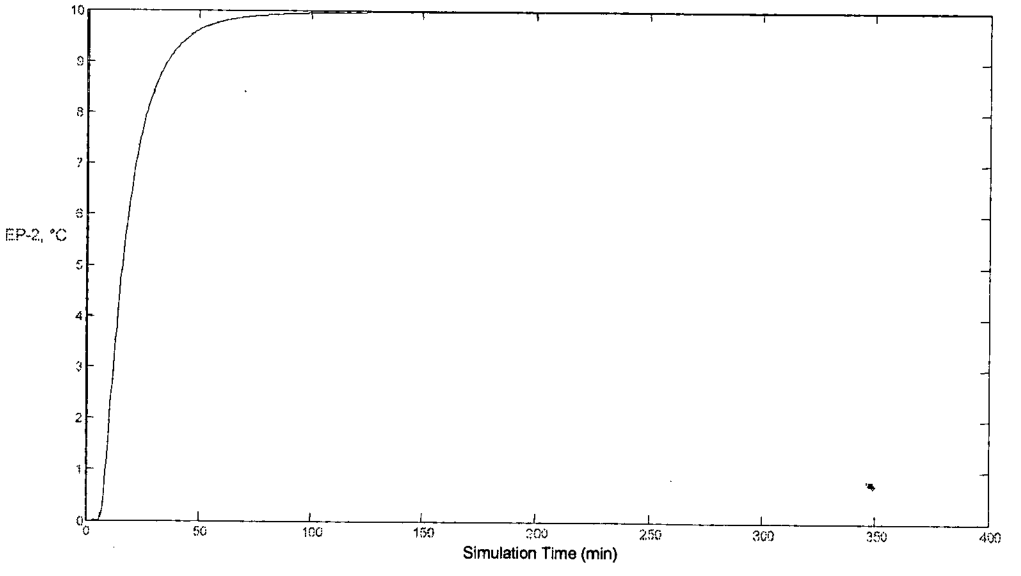

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Figure 6.24: Response of Kerosene EP to +10 °C step change in Kerosene EP setpoint using QDMC with Novel tuning strategy.

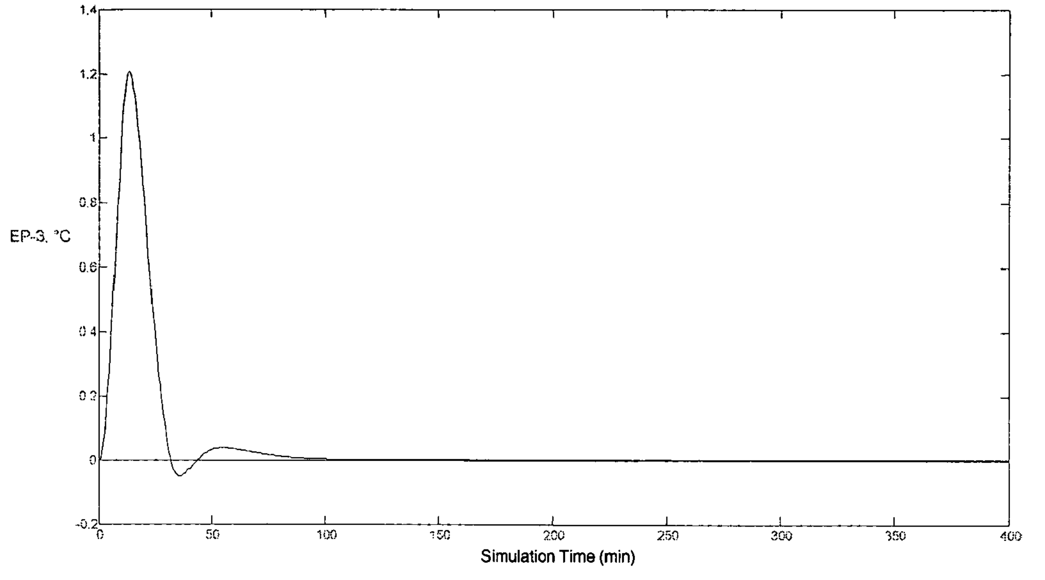

Figure 6.25: Response of Light gas oil EP to +10 °C step change in Kerosene EP setpoint using QDMC with Novel tuning strategy.

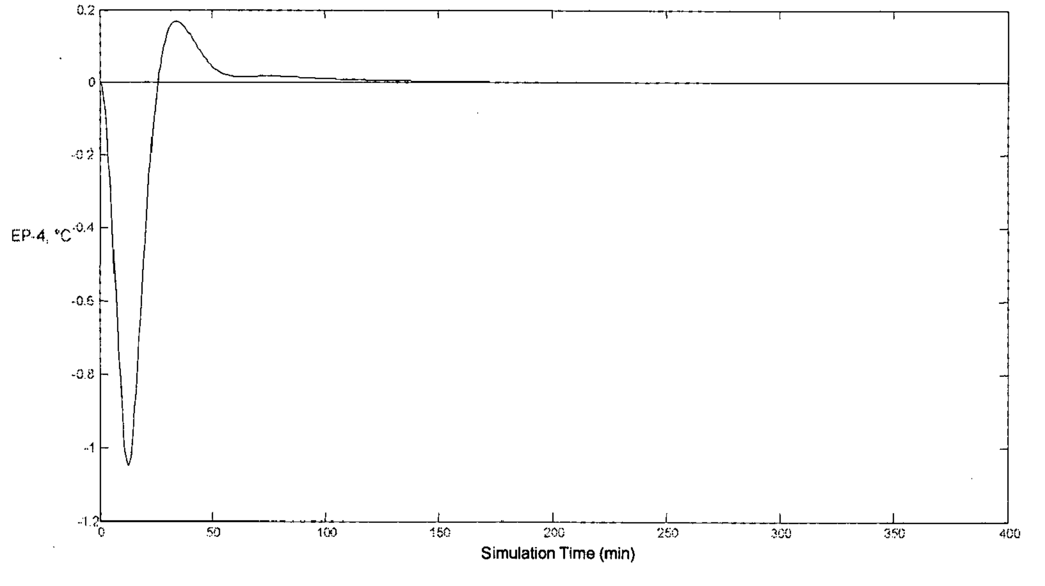

Figure 6.26: Response of Heavy gas oil EP to +10 °C step change in Kerosene EP setpoint using QDMC with Novel tuning strategy.

with Figure 6.19 to 6.26 shows the following. Naphtha EP has taken 90 min to reach steady state for 10 C step change in Naphtha EP setpoint where it is 65 min in the present case. IAE, ISE and ITAE are also more in case of QDMC with old tuning guidelines than the present case. But there is negligible offset in present case. Similarly, there are substantial improvements in settling times in the present case with expense of interaction. Settling times and peak amplitudes are tabulated in Table 6.3. Though ITAE is less for all responses in the present case, ISE and IAE are more for some responses. In case of responses of Naphtha and Light gas oil to step change in kerosene EP, QDMC with old tuning guidelines is given better response than present case with less peak amplitude and small IAE, ISE and ITAEs. Finally overall performance of QDMC with novel tuning strategy is better than that of QDMC with old tuning guidelines.

Table 6.3: Settling times and peak amplitudes for QDMC with Novel tuning strategy for product quality control.

Response	Step change in Naphtha EP setpoint		Step change in Kerosene EP setpoint	
	Settling time (min)	Peak amplitude	Settling time (min)	Peak amplitude
EP-1	65	9.9	90	2.3
EP-2	60	1.7	120	10
EP-3	90	0.53	75	1.2
EP-4	40	-0.9	105	-1

Chapter-7

CONCLUSIONS AND RECOMMENDATIONS

7.1 CONCLUSIONS

- There exists significant two-way interaction among the control loops of the crude distillation column treated. This interaction is more between the upper loops.
- This interaction is one way at steady state i.e. down the column.
- Conventional PI controller gives unsatisfactory performance for systems having strong interactions like crude distillation columns. They should be detuned properly for satisfactory performance.
- QDMC gives better performance than traditional PI controller for control problems having strong interactions like crude distillation columns.
- Performance of QDMC is purely depending on tuning parameters.
- QDMC with Novel tuning strategy is giving better performance than QDMC with old tuning strategy.

7.2 RECOMMENDATIONS

- Yield of every product can be maximized by controlling the pumparounds to remove heat from the tower under the operating constraints and equipment limits. These constraints include tray flooding, minimum flow rate of pumparounds, and maximum heat duty of pumparounds.
- The effect of feed rate on product quality has not been considered. The feed rate can be treated as a disturbance to product quality control.
- These will require more modelling in addition to present available models.
- Interaction can be reduced by using PI controller with decoupers, so that performance of conventional PI controller can be improved.

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APPENDIX-A

APPROXIMATION OF PROCESS TRANSFER FUNCTION MODELS GIVEN IN CHAPTER-3 TO FOPDT MODELS

Half Rule Approximation [Skogestad (2003)]:

$$g_{11} = \frac{1.064e^{-0.4s}}{7.94s+1}$$

$$g_{21} = \frac{0.627e^{-4.505s}}{15.08s+1}$$

$$g_{31} = \frac{0.695e^{-1.8s}}{45s+1}$$

$$g_{41} = \frac{1.556e^{-8.85s}}{12.71s+1}$$

$$g_{12} = \frac{-0.229e^{-68.85s}}{22.28s+1}$$

$$g_{22} = \frac{0.441e^{-5.99s}}{12.78s+1}$$

$$g_{32} = \frac{0.649e^{-1.98s}}{41.9s+1}$$

$$g_{42} = \frac{1.556e^{-8.18s}}{13.37s+1}$$

$$g_{13} = \frac{-0.1593e^{-109.63s}}{29.85s+1}$$

$$g_{23} = \frac{0.049e^{-48.63s}}{21s+1}$$

$$g_{33} = \frac{0.541e^{-3.87s}}{37.37s+1}$$

$$g_{43} = \frac{1.519e^{-8.03s}}{13s+1}$$

$$g_{14} = \frac{-0.265e^{-39.31s}}{21.41s+1}$$

$$g_{24} = \frac{-0.066e^{-18.04s}}{18.66s+1}$$

$$g_{34} = \frac{-0.1568e^{-1s}}{3.66s+1}$$

$$g_{44} = \frac{0.969e^{-8.36s}}{10.95s+1}$$

Process Reaction Curve Approximation:

$$g_{11} = \frac{1.1196e^{-1.87s}}{8.739s+1}$$

$$g_{21} = \frac{0.6512e^{-2.99s}}{18.8s+1}$$

$$g_{31} = \frac{0.695e^{-1.8s}}{45s+1}$$

$$g_{41} = \frac{1.752e^{-4.46s}}{23.42s+1}$$

$$g_{12} = \frac{-0.2677e^{-32.2s}}{18.93s+1}$$

$$g_{22} = \frac{0.4683e^{-3.41s}}{18.41s+1}$$

$$g_{32} = \frac{0.649e^{-1.98s}}{41.9s+1}$$

$$g_{42} = \frac{1.67e^{-4.3s}}{21.35s+1}$$

$$g_{13} = \frac{-0.1558e^{-46.9s}}{25.55s+1}$$

$$g_{23} = \frac{-0.0476e^{-24.7s}}{24.08s+1}$$

$$g_{33} = \frac{0.5425e^{-2.89s}}{38.69s+1}$$

$$g_{43} = \frac{1.623e^{-4.2s}}{20.56s+1}$$

$$g_{14} = \frac{-0.2614e^{-25.7s}}{19.04s+1}$$

$$g_{24} = \frac{-0.0802e^{-16.7s}}{18.75s+1}$$

$$g_{34} = \frac{-0.034e^{-0.4s}}{1.39s+1}$$

$$g_{44} = \frac{1.092e^{-4.73s}}{19.63s+1}$$

Table A1: Sum of Square Errors in approximating process transfer function models to FOPDT models.

	Half Rule	Process Reaction Curve
g_{11}	0.8332	0.4701
g_{21}	0.0857	0.0398
g_{31}	-	-
g_{41}	7.8556	0.9866
g_{12}	14.189	0.6283
g_{22}	0.1573	0.0412
g_{32}	-	-
g_{42}	4.7301	0.8339
g_{13}	23.390	2.3158
g_{23}	1.1714	0.0767
g_{33}	0.0028	0.0019
g_{43}	3.5474	0.7954
g_{14}	5.1810	1.2531
g_{24}	0.1225	0.0996
g_{34}	0.6210	0.0378
g_{44}	3.6502	0.5785

Table: A2 the detuned Z-N settings for product quality control system (Leo Hsie and Thomas J. McAvoy [1991]).

Loop no	K_C	τ_I
1	0.52	14.8
2	1.16	19.4
3	0.73	12.5
4	0.15	22.4

APPENDIX-B

CALCULATION OF TUNING PARAMETERS USING NOVEL TUNING STRATEGY

Table B1: Calculation of sampling time and Prediction horizon

	$0.1\ \tau_{ij}$ (h)	$0.5\,\theta_{ij}$ (h)	Max (h)	k_{ij}	Prediction Horizon
g_{11}	0.8739	0.9350	0.9350	10.35	228.82
g_{12}	1.8930	16.100	16.100	162.0	635.25
g_{13}	2.5550	23.450	23.450	235.5	874.25
g_{14}	1.9040	12.850	12.850	129.5	605.50
g_{21}	1.8800	1.4950	1.8800	15.95	485.90
g_{22}	1.8410	1.7050	1.8410	18.05	478.30
g_{23}	2.4080	12.350	12.350	124.7	726.70
g_{24}	1.8700	8.3500	8.3500	84.50	553.25
g_{31}	4.5000	0.9000	4.5000	10.00	1135.0
g_{32}	4.1900	0.9900	4.1900	10.90	1058.4
g_{33}	3.8690	1.4450	3.8690	15.45	982.70
g_{34}	0.1390	0.2000	0.2000	3.000	57.750
g_{41}	2.3420	2.2300	2.3420	23.30	608.80
g_{42}	2.1350	2.1500	2.1500	22.50	556.25
g_{43}	2.0560	2.1000	2.1000	22.00	536.00
g_{44}	1.9630	2.3650	2.3650	24.65	515.40

Diagonal blocks of crude tower Dynamic matrix:

$$[1] = \begin{bmatrix} 34946 & 34933 & 34920 & 34907 \\ 34933 & 34920 & 34907 & 34894 \\ 34920 & 34907 & 34894 & 34881 \\ 34907 & 34894 & 34881 & 34868 \end{bmatrix}$$

$$[2]=\begin{bmatrix} 59086 & 59032 & 58978 & 58924 \\ 59032 & 58978 & 58924 & 58870 \\ 58978 & 58924 & 58870 & 58816 \\ 58924 & 58870 & 58816 & 58762 \end{bmatrix}$$

$$[3]=\begin{bmatrix} 88900 & 88870 & 88840 & 88810 \\ 88870 & 88840 & 88810 & 88780 \\ 88840 & 88810 & 88780 & 88750 \\ 88810 & 88780 & 88750 & 88720 \end{bmatrix}$$

$$[4]=\begin{bmatrix} 351149 & 350965 & 350781 & 350597 \\ 350965 & 350781 & 350597 & 350413 \\ 350781 & 350597 & 350413 & 350229 \\ 350597 & 350413 & 350229 & 350045 \end{bmatrix}$$

Table B2: Calculation of condition number for each loop.

Diagonal matrix no:	Eigen values		Condition number (C_i)
	min	max	
1	3.5	139600	39885
2	4	235700	58925
3	3.7	355240	96011
4	4	1402400	350600

From the above **Table B1**, **Table B2** and tuning formulas given in chapter-5:

Sampling Time (T) = 12 min

Prediction Horizon (P) = 1135

Control Horizon (M) = 6

Controlled Variable Weights = [1 1 1 1]

Move Suppression Coefficients = [0.956 1.405 1.312 0.749]

APPENDIX-C

CALCULATION OF TUNING PARAMETERS OF DMC USING OLD TUNING GUIDELINES

Sampling time (T) = 12 min (same as novel tuning)

Table C1: Open loop settling times for each system transfer functions.

system	Settling time (min)	system	Settling time (min)
g_{11}	2300	g_{31}	10666
g_{12}	5952	g_{32}	9950
g_{13}	7800	g_{33}	9000
g_{14}	6333	g_{34}	1950
g_{21}	3533	g_{41}	3216
g_{22}	3150	g_{42}	3400
g_{23}	6933	g_{43}	3350
g_{24}	5950	g_{44}	2733

Form the above **Table C1:**

Maximum settling time (T_S) = 10666 min (for g_{31})

Prediction horizon (P) = 10666/12 = 889

Control Horizon (M) = 6

Weights on controlled variables = [1 1 1 1]

Weights on manipulated variables = [1.5 2.4 3.2 1.5]

APPENDIX-D

MATLAB PROGRAM FOR PLANT MODEL OF CRUDE DISTILLATION TOWER

```
num11=52.14;
den11=[145800, 476.4, 1];
g11=tf(num11,den11,'iodelay',24);
num21=30.72;
den21=[172800, 1014, 1];
g21=tf(num21,den21,'iodelay',162);
num31=34.08;
den31=[2700, 1];
g31=tf(num31,den31,'iodelay',108);
num41=76.2;
den41=[165960, 894, 1];
g41=tf(num41,den41,'iodelay',399.6);
num12=-13.74*[-3450, 1];
den12=[657720, 1662, 1];
g12=tf(num12,den12,'iodelay',356.4);
num22=21.6;
den22=[108720, 846, 1];
g22=tf(num22,den22,'iodelay',280.8);
num32=31.8;
den32=[2514, 1];
g32=tf(num32,den32,'iodelay',118.8);
num42=76.2;
den42=[129960, 894, 1];
g42=tf(num42,den42,'iodelay',399.6);
```

```
num13=-7.8*[-5922, 1];
den13 = [622800, 1986, 1];
g13 = tf(num13,den13,'iodelay',460.8);
num23=[-82440, 83.4, -0.04];
den23=[332532000, 1314000, 2094, 1];
g23=tf(num23,den23);
num33=26.52;
den33=[8568, 2244, 1];
g33=tf(num33,den33,'iodelay',230.4);
num43=74.4;
den43=[101520, 852, 1];
g43=tf(num43,den43,'iodelay',410.4);
num14=[-139320, 388.8, -0.217];
den14=[193017600, 876600, 1850.4, 1];
g14=tf(num14,den14);
num24=[-66600, 20.28, -0.066];
den24=[272160000, 1110960, 1894.8, 1];
g24=tf(num24,den24);
num34=-1.59*[1512, 1];
den34=[68760, 532.8, 1];
g34=tf(num34,den34,'iodelay',60);
num44=47.46*[-258.6, 1];
den44=[99360, 744, 1];
g44=tf(num44,den44,'iodelay',156);
model=[g11 g21 g31 g41;g12 g22 g32 g42;g13 g23 g33 g43;g14 g24 g34 g44]
```