Design and Implementation of Multivariable Control System in Refinery

I simply picked a bunch of flowers
and added nothing
but the thread that binds them

-Michel De Montaigne

Design and Implementation of Multivariable Control System in Refinery

A Thesis

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

Master of Engineering
in
Electronic Instrumentation & Control Engineering

Submitted by

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CERTIFICATE

This is to certify that my work presented in this thesis entitled **"Design and Implementation of Multivariable Control System in Refinery"** in partial fulfillment of the requirements for the award of the degree of **Master of Engineering** in **Electronic Instrumentation and Control Engineering** at **Thapar University, Patiala,** is an original record under supervision and guidance of **Mr. Sunil Singla** and **Mr. Sudhanshu Shekhar**.

The matter embodied in this report has not been submitted anywhere for the award of any other degree of this or any other university.

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To Mom and Dad

ABSTRACT

In a high margin environment, it is essential for refiners to take advantage of the favourable economic conditions while achieving reliable operations at maximum throughput. While the processes & systems are getting complex, higher-performance catalysts have been studied, Advance Control Systems that can handle ever-restricting multivariable reaction conditions have also been sought. Advanced Process Control (APC) systems are applied almost universally on major process units to identify the optimum operating point and to maintain stable operations within multiple constraints. The purpose of advanced process control (APC) is to improve profitability by applying strategies which coordinate the regulatory control systems on the plant. APC benefits come from smoother operation of plants (reducing impacts of process disturbances) and providing consistent operation at optimal constraints.

The objective of the present work is to describe the application of Advanced Multivariable Control System on Diesel Hydrotreater unit of IOCL, Panipat Refinery, Panipat and compares its performance to the previous conventional control system. The purpose of multivariable controller is to provide a control on Diesel quality, minimization of power loss by recovering more power and maximization of throughput while operating within all constraints and hence achieve economic benefits from the smoother operation of the plant.

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Chapter 1
Introduction

A chemical plant is an arrangement of processing units (reactors, heat exchangers, pumps, distillation columns, absorbers, evaporators, tanks, etc.), integrated with each other in a systematic and rational manner. The plant's overall objective is to convert certain raw materials (input feedstock) into desired products using available sources of energy, in the most economic way.

During its operation, a chemical plant must satisfy several requirements imposed by its designers and the general technical, economic and social conditions in the presence of ever-changing external influences (disturbances). Among such requirements are the following:

- ***Safety***: The safe operation of a chemical process is a primary requirement, for the well being of the people in the plant and its continued contribution to the economic development. Thus, the operating pressures, temperatures, concentration of chemicals, etc. should always be within allowable limits. For example, if a reactor has been designed to operate at a pressure up to 100 psig, we should have a control system that will maintain the pressure below this value.

- ***Production specifications***: The plant should produce the desired amounts and quality of the final products. For example, we may require the production of two million pounds of ethylene per day, of 99.5% purity, from an ethylene plant. Therefore, a control system is needed to ensure that the production level (2 million pounds per day) and the purity specifications (99.5% ethylene) are satisfied.

- ***Environmental regulations***: Various central and state laws may specify that the temperatures, concentrations of chemicals and flowrates of the effluents from a plant be within certain limits. Such regulations for example exist on the amounts of SO_2 that a plant can eject to the atmosphere, and the quality of water returned to a river or a lake.

- ***Operational constraints***: The various types of equipments used in a chemical plant have constraints inherent to their operation. Such constraints should be satisfied throughout the operation of a plant. For example, pumps must maintain a certain net positive suction head; tanks should not overflow or go dry; distillation columns should *not* be flooded: the temperature in a catalytic reactor should not exceed an upper limit since the catalyst will be destroyed. Control systems are needed to satisfy all these operational constraints.

- ***Economics***: The operation of a plant must conform with the market conditions, i.e. the availability of raw materials and the demand of the final products. Furthermore, it should be as economic as possible in its utilization of raw materials, energy, capital and human labor. Thus, it is required that the operating conditions are controlled at given optimum levels of minimum operating cost, or maximum profit; etc.

All the above requirements dictate the need for a continuous monitoring of the operation of a chemical plant and an external intervention (control) to guarantee the satisfaction of the operational objectives. This is accomplished through a rational arrangement of various equipment (measuring devices, valves, controllers, computers) and human intervention (plant designers, plant operators), which constitutes the control system.

The variables (flow rates, temperatures, pressures, concentrations, etc) associated with a chemical plant are divided into two groups:

i. *Input* Variables; denote the effect of the surroundings on the chemical process.

ii. *Output* Variables, denote the effect of the process on the surroundings

The input variables can be further classified into the following categories:

i. *Manipulated* (or adjustable) variables, if their values can be adjusted freely by the human operator or a control mechanism and

ii. *Disturbances*, if their values are not the result of adjustment by an operator or a control system.

The output variables are also classified into the following categories:

i. *Measured* output variables, if their values are known by directly measuring them, and

ii. *Unmeasured* output variables, if they are not or cannot be measured directly.

Figure 1.1 summarizes all the classes of variables that we have around a chemical process.

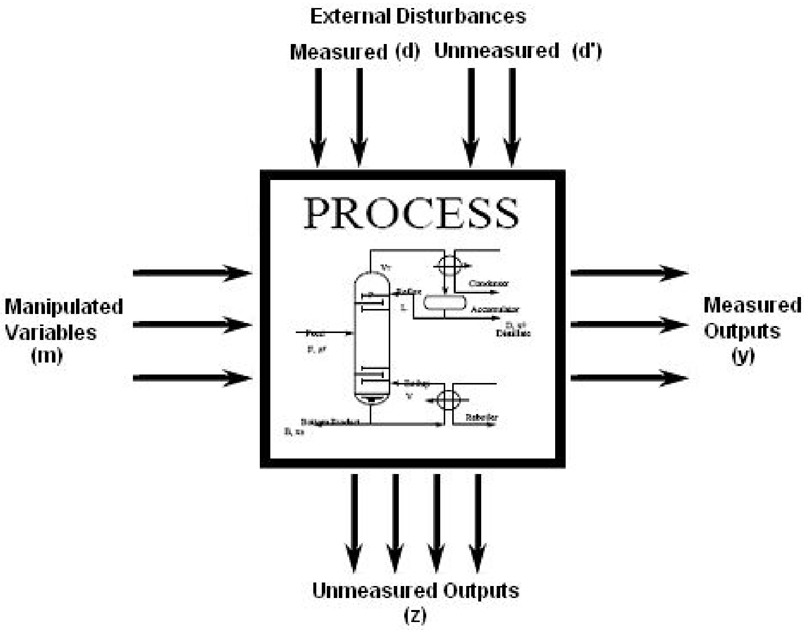


Figure 1.1 Input and output variables around a chemical process

The objective of a control system is to make the output y behave in a desired way by manipulating the plant input m. The **regulator problem** is to manipulate m to counteract the effect of a disturbance d and d'. The **servo problem** is to manipulate m to keep the output close to a given reference input r. Thus, in both cases we want the **control error** $e=y-r$ to be small. This is achieved by manipulating the MV's using a control algorithm.

Depending on how many controlled outputs and manipulated inputs there are in a chemical process, the control configurations can be distinguish into: ***single-input, single-output*** (SISO) or ***multiple-input, multiple-output*** (MIMO) control systems.

For example, for the tank heater system:

- If the control objective (controlled output) is to keep the liquid level at a desired value by manipulating the effluent flowrate, then we have a SISO system.
- On the contrary, if our control objectives are (more than one) to keep the level and the temperature of the liquid at desired values, by manipulating (more than one) the steam flowrate and the effluent flowrate, then we have a MIMO system.

1.1. Control Configurations

The various control configurations available in a control system and their Hierarchy is shown in Figure 1.2.

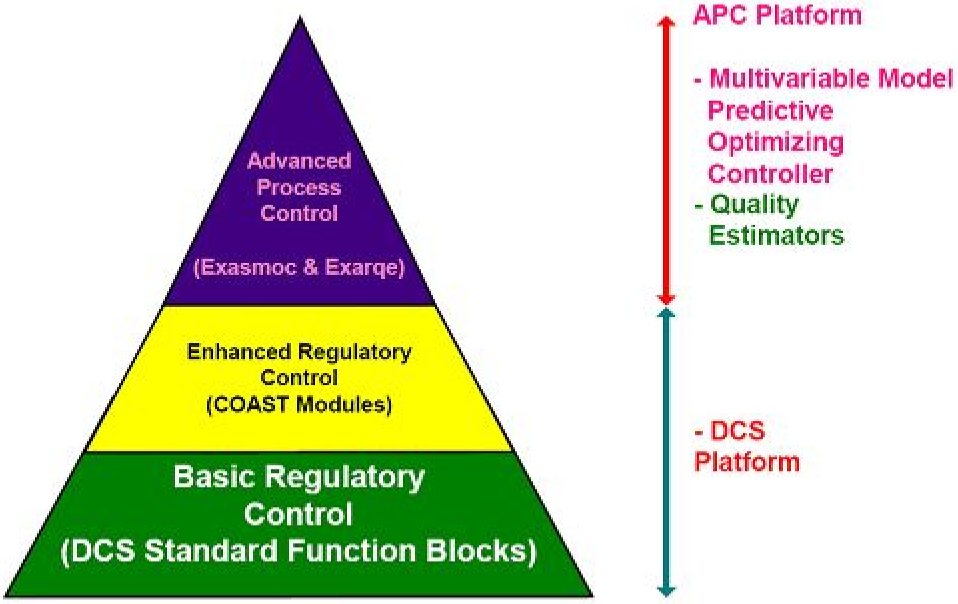


Figure 1.2 Hierarchy of control levels

1.1.1. First Level - Basic Regulatory Control (BRC)

This level covers Feedback Control, Cascade Control, and Ratio Control etc., which are executed in control stations of Distributed Control System (DCS). Operator and Engineers access these controllers through operator stations for changing

Auto/Manual, Set Point, and Tuning Parameters etc. The entire plant in most of the process control application needs BRC. The various basic regulatory controls available are:

1.1.1.1. Feedback Control

A general block diagram for the feedback control system is shown in Figure 1.3,

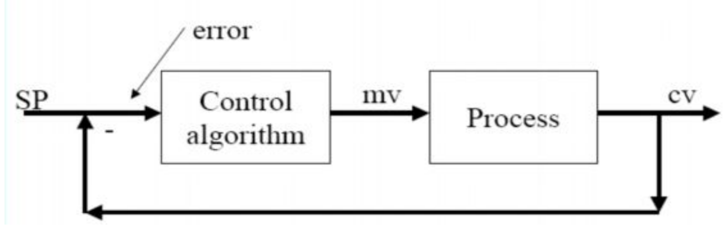


Figure 1.3 Block diagram representation of Feedback Control system

The feedback controller is 'driven' by the error between the actual process output and the setpoint. The feedback controller generally, is of the Proportional-Integral-Derivative (PID) type.

A basic feedback control system is shown in Figure 1.4. The objective is to control the temperature of the outlet stream of the shell and tube heat exchanger. The temperature is therefore the Control Variable (CV). The Manipulated Variable (MV) is coolant flow. Typical Disturbance Variable (DV) would include inlet temperature, inlet flow, ambient temperature, etc.

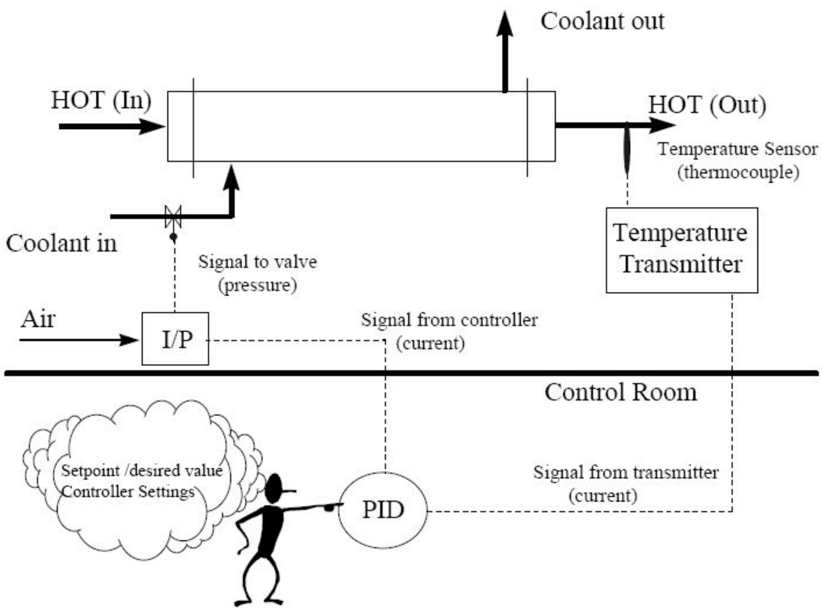


Figure 1.4 Feedback Control Scheme

If the CV is not at setpoint then the objective of the controller is to adjust the MV to ensure that the desired level of operation is obtained.

1.1.1.2. Cascade Control

Cascade control is widely used within the process industries. Conventional cascade schemes have two distinct features:

- There are two nested feedback control loops. There is a secondary control loop located inside a primary control loop.
- The primary loop controller is used to calculate the setpoint for the inner (secondary) control loop.

Cascade control is used to improve the response of a single feedback strategy. The idea is similar to that of feed forward control: to take corrective action in response to dv's before the CV deviates from setpoint. The secondary control loop is located so that it recognizes the upset condition sooner than the primary loops.

A General block diagram representation of a cascade control loop is shown below in Figure 1.5,

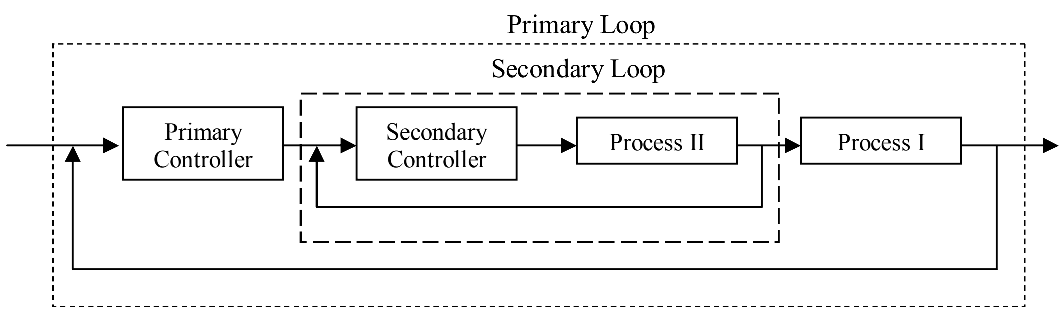


Figure 1.5 Block Diagram representation of Cascade control system

The block diagram demonstrates very clearly the major benefits to be gained by cascade control i.e. “Disturbances arising within the secondary loops are corrected by the secondary controller before they can affect the value of the primary controller output”.

1.1.1.3. Ratio Control

The objective of a ratio control scheme is to keep the ratio of two variables at a specified value. Thus, the ratio (R) of two variables (A and B),

$$R = A / B$$

is controlled rather than controlling the individual variables. Typical ratio control schemes includes:

- Maintaining the reflux ratio for a distillation column.
- Maintaining the stochiometric ratio of reactants to a reactor.
- Maintaining air/fuel ratio to a furnace.

1.1.1.3.1. Implementation: method I

The flow rate of the two streams is measured and their ratio calculated using a 'divider'. The output of the divider is sent to the ratio controller (usually a standard PI controller). The controller compares the actual ratio with that of the desired ratio and computes any necessary change in the manipulated variable.

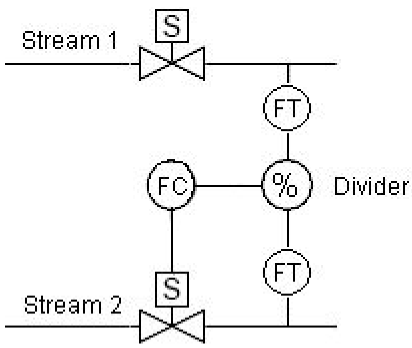


Figure 1.6 Ratio Control Systems Configuration

1.1.1.3.2. Implementation: method II

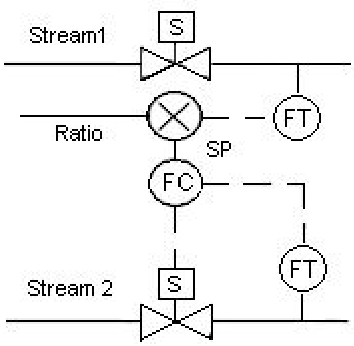


Figure 1.7 Alternative Configuration of Ratio Control Systems

Here one stream is under standard feedback control. The flow of the second stream is measured and sent to a 'multiplier', which multiplies the signal, by the desired ratio yielding the setpoint for the feedback control law.

1.1.1.4. Summary of BRC

Summarizing the Basic Regulatory Controls:

- SISO Type.
- Load Variation not addressed.
- Interacting loops difficult to tune.
- No optimization features.
- Constraints may not be handled.

1.1.2. Second Level - Enhanced Regulatory Control (ERC).

This level is one level above BRC and covers a bit complex situation in the process such as Feed Forward control, De-coupler, Delay Compensation, Gap control, Calculation based control, **SEBOL** program function block based control etc. Even though it is second level the execution of the ERC scheme is still under the control station of a DCS. Some of the COAST (Control Application Standards) modules work as an ERC for some typical process units such as Furnace coil balancing, Surge volume control etc. The various Enhanced Regulatory Controls available are:

1.1.2.1. Feedforward Control

A Feedforward control law is used to compensate for the effect that measured dv's may have on the CV. The basic idea is to measure a disturbance directly and take control action to eliminate its impact on the process output. How well the scheme will work depends on the accuracy of the process and disturbance models used to describe the system dynamics. Feedforward control actually offers the potential for perfect control. However, because of Plant Model Mismatch (PMM) and unmeasured / unknown disturbances this is rarely achieved in practice. Consequently, Feedforward control is normally used in conjunction with feedback control. The feedback controller is used to compensate for any model errors; unmeasured disturbances etc. and ensure offset free control.

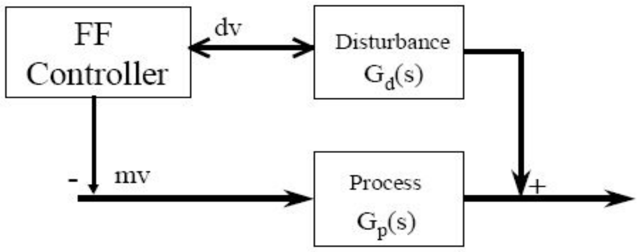


Figure 1.8 Block Diagram of Feed Froward Control System

Figure 1.8 shows the block diagram representation of Feed Forward Control system. $G_p(s)$ is a symbol used to represent the process dynamics. This is the relationship between the *MV* and the *CV*. This could be a 1st order plus dead-time transfer function. $G_d(s)$ is a symbol used to describe the mathematical relationship between inlet concentration and reactor temperature. The Feedforward controller calculates the appropriate *MV* to ensure the *CV* remains at SP.

The Figure 1.9 shows the FeedForward control of a Continuous Stirred Tank Reactor. The reactor is fed by a stream rich in reactant A, of concentration CA (in) and flow rate F(in). Within the system the following exothermic reaction take place, A→ B → C. Reactant A is converted to product B, but at high temperatures B undergoes further reaction and is transformed to undesired by-product C. The reactor is cooled by means of a heat exchanger.

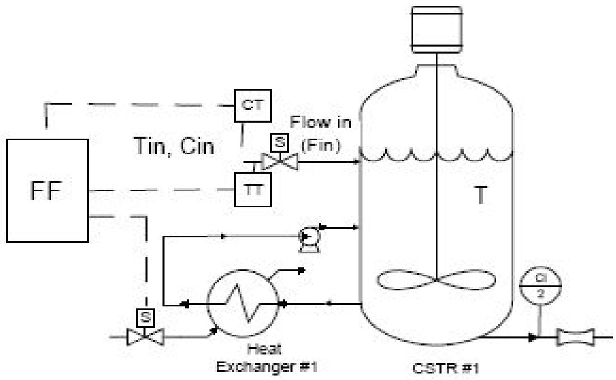


Figure 1.9 Example of FeeedForward Control for Continuous Stirred Tank Heater

The objective is to maintain the temperature of the reaction mass at the desired value when subjected to changes in inlet concentration (C_{in}) and temperature (T_{in}). Thus, the CV is reactor liquid temperature, the MV is the coolant flow rate to the heat exchanger and the DV's are inlet concentration and inlet stream temperature. The Feedforward control loop may be configured as shown in Figure 1.9.

Here, 'FF' represents the Feedforward control algorithm, 'CT' and 'TT' are symbols used to describe the composition and the temperature transmitters. So, the disturbances are measured and passed to a 'FF' device that calculates the necessary coolant flow rate to compensate for any CV moves when the measured DV deviates from it's nominal value.

1.1.2.2 Summarizing ERC

The control configurations discussed so far were confined to processes with a single controlled output, requiring a single manipulated input. Many Processes, however, do not conform to such simple control configuration. In the process industry for example, any unit operation capable of manufacturing or refining a product cannot do so with only one single control loop. In fact, each unit operation typically requires control over at least two variables, e.g. product rate and product quality. There are, therefore, usually at least two control loops to contend with. Systems with more than one control loop are known as multi-input multi-output (MIMO) or multivariable systems.

1.1.3. Third Level - Advanced Process Control (APC)

APC handles the most complex situation in the process. It has multivariable, model predictive and optimization features. The objective of APC is to maximize the plant throughput, power recovery and optimization subject to qualities and other limiting constraints while handling the multi-input multi-output (MIMO) system. To achieve this controller manipulate the process variable (PV) to push the unit to the optimum set of operating limits without compromising unit safety and reliability.

The predictive control algorithm uses dynamic models relating the CV to the MV. These models are generated during step testing of the unit and subsequent model identification and analysis. MV controller implementation stabilizes the process operation provides tighter control to operating targets and make it possible to operates closes to key constraints. Using MPC (Model Predictive Control) the MVC (Multivariable Controller) reduces the variability of the process. This reduction in process variability permits operating the unit closer to constraints. As a result unit profitability is improved.

Main Features of Multivariable Model Predictive Control (MVPC).

- Capability to handle multiple inputs.
- Plant actual model in-built.
- Prediction Capability.
- Optimization inbuilt.
- Inferential based control.

1.2 Problem Formulation

The objective of the present work is to

1. Study the process and existing control system strategy of Diesel Hydrotreater Unit of IOCL, Panipat Refinery, Panipat .
2. Designing of an Advanced Multivariable Control System for the same unit.
3. Implementation of the Proposed Scheme on the Diesel Hydrotreater Unit of IOCL, Panipat Refinery, Panipat.
4. Compare the results obtained from conventional and new proposed system.

The new proposed multivariable control system must have the following features

- Provide a control on Diesel quality.
- Minimization of power loss by recovering more power and maximization of throughput while operating within all constraints and hence achieve economic benefits from the smoother operation of the plant.

Chapter 2
Literature Survey

Model Predictive Control (MPC) is a widely spread technology in industry for control design of highly complex multivariable processes [1]–[3]. Model predictive control refers to a class of computer control algorithms that utilize an explicit process model to predict the future response of a plant [4]. MPC has been used in industry for more than 30 years, and has become an industry standard due to its intrinsic capability for dealing with constraints and with multivariable systems [5]. Originally developed to meet the specialized control needs of power plants and petroleum refineries, MPC technology can now be found in a wide variety of application areas including chemicals, food processing, automotive, and aerospace applications. Most commercially available MPC technologies are based on a linear model of the process [4]. Model Predictive Control (MPC), is also referred as Receding Horizon Control and Moving Horizon Optimal Control [6], [7]. What we today call MPC was conceived as a control algorithm that met a key requirement, not explicitly handled by other control algorithms i.e. the handling of inequality constraints [8].

The first description of MPC control applications was presented by [9] and was later summarized in "Model Predictive *Heuristic* Control: Applications to Industrial Processes" published in 1978 Automatica paper [10], whereas the idea of receding horizon control and Model Predictive Control can be traced back to 1960s [11]. A MPC algorithm with quadratic cost, linear constraints, and moving horizon of length one is described in [12]. The interest in this field started to surge in 1980s after the publication of the first paper on IDCOM [10] and Dynamic Matrix Control (DMC) [13], [14], and the first comprehensive exposition of Generalized Predictive Control (GPC) [15].

Various MPC techniques such as Dynamic Matrix Control [14], Model Algorithmic Control (MAC) [16], and Internal Model Control (IMC) [11] have demonstrated their effectiveness in industrial applications during the last two decades [4, 10, and 11]. An excellent introductory tutorial aimed at control practitioners is provided in [1]. A more comprehensive overview of nonlinear MPC and moving horizon estimation, including a summary of recent theoretical developments and numerical solution techniques is presented in [17]. Past reviews and survey of MPC theory include those of [11], [18], [19], [20], [21], [22], [6], [23], and [4].

[24] reviews the basic ideas of MPC design, from the traditional linear MPC setup based on quadratic programming to more advanced explicit and hybrid MPC, and highlights available software tools for the design, evaluation, code generation, and deployment of MPC controllers in real-time hardware platforms.

In [5] two chemical processes are simulated in HYSYS software as a more realistic environment that exhibits many properties of real plants. In this work two different chemical processes are simulated in HYSYS software and a complete procedure for applying MPC control is done for each one including pre tests, design of test signal, system identification, controller design, pre tuning, final tuning and dealing with low-level control loops.

A brief history of industrial available MPC

[4] provides a brief history of MPC technology development and is presented in the following section. Figure 2.1 shows an evolutionary tree for the most significant industrial MPC algorithms and illustrating their connections. The description on the MPC key algorithm shown in the evolutionary tree is as:

3.1. Linear Quadratic Gaussian (LQG)

In 1960, R.E. Kalman published his famous paper describing a recursive solution to the discrete-data linear filtering problem [25]. The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error.

The filter is very powerful in several aspects: it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown [26].

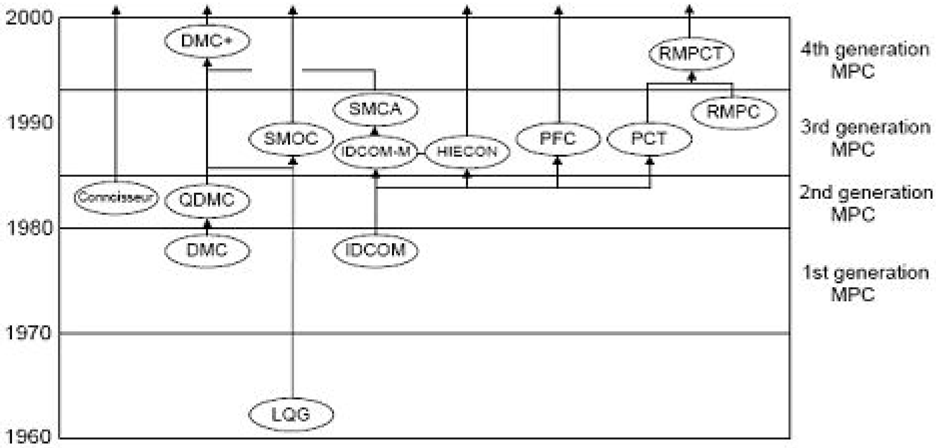


Figure 2.1 Genealogy of MPC Algorithm

The process considered by Kalman et al. can be described by a discrete-time, linear state-space model [3]:

$$x_{k+1} = Ax_k + Bu_k + Gw_k \qquad (2.1a)$$

$$y_k = Cx_k + \xi_k \qquad (2.1b)$$

The vector u represents process inputs, or manipulated variables, and vector y describes measured process outputs. The vector x represents process states to be controlled. The state disturbance w_k and measurement noise n_k are independent Gaussian noise with zero mean. The initial state x_0 is assumed to be Gaussian with non-zero mean.

The objective is to minimized the expected values of squared input and state deviations from the origin, shown by the Objective function Φ, which includes separate state and input weight matrices Q and R to allow for tuning trade-offs:

$$\phi = \mathcal{E}(J); \qquad J = \sum_{i=1}^{\infty} (\| x_{k+j} \|_Q^2 + \| u_{k+j} \|_R^2) \qquad (2.2)$$

The norm terms in the objective function are defined as follows:

$$\| x \|_Q^2 = x^T Q x \qquad (2.3)$$

The solution to this problem, known as the linear quadratic Gaussian (LQG) controller, involves two separate steps. At time interval k; the output measurement y_k is first used to obtain an optimal state estimate #xkjk:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_{k-1} \qquad (2.4a)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_f\left(y_k - C\hat{x}_{k|k-1}\right) \qquad (2.4b)$$

Then the optimal input u_k is computed using an optimal proportional state controller:

$$u_k = -K_c\hat{x}_{k|k} \qquad (2.5)$$

Here, the notation $\hat{x}_{i|j}$ refers to the state estimate at time i given information upto and including time j: The Kalman filter gain Kf is computed from the solution of a matrix Ricatti equation. The controller gain Kc can be found by constructing a dual Ricatti equation, so that the same numerical techniques and software can be used for both calculations.

The infinite prediction horizon of the LQG algorithm endows the algorithm with powerful stabilizing properties. For the case of a perfect model, it was shown to be stabilizing for any reasonable linear plant as long as Q is positive semidefinite and R is positive definite.

LQG theory became a standard approach to solve control problems in a wide range of application areas. [27] estimate that there may be thousands of real-world applications of LQG with roughly 400 patents per year based on the Kalman filter. However, it has had little impact on control technology development in the process industries. The most significant of the reasons cited for this failure include [9,11]:

- Constraints.
- Process nonlinearities.
- Model uncertainty (robustness).
- Unique performance criteria.
- Cultural reasons (people, education, etc.).

However, the most significant reasons that LQG theory failed to have a strong impact may have been related to the culture of the industrial process control community at the time, in which instrument technicians and control engineers either had no exposure to LQG concepts or regarded them as impractical [4].

2.2. Identification and Command (IDCOM)

The first description of MPC control applications was presented by [9]. They described their approach as model predictive heuristic control (MPHC). The solution software was referred to as IDCOM, an acronym for Identification and Command. The distinguishing features of the IDCOM approach are [4]:

- Impulse response model for the plant, linear in inputs or internal variables.
- Quadratic performance objective over a finite prediction horizon.
- Future plant output behavior specified by a reference trajectory.
- Input and Output constraints included in the formulation.
- Optimal inputs computed using a heuristic iterative algorithm, interpreted as the dual of identification.

Richalet et al. chose an input-output representation of the process in which the process inputs influence the process outputs directly. Process inputs are divided into manipulated variables (MVs), which the controller adjusts, and disturbance variables (DVS) which are not available for control. Process outputs are referred to as controlled variables (CVs). They chose to describe the relationship between process inputs and outputs using a discrete-time finite impulse response (FIR) model. For the single input, single output (SISO) case the FIR model looks like:

$$y_{k+j} = \sum_{i=1}^{N} h_i u_{k+j-i} \tag{2.6}$$

This model predicts that the output at a given time depends on a linear combination of past input values and summation weights h_i which are the impulse response coefficients. The sum is truncated at the point where past inputs no longer influence the output. Thus this representation is possible only for stable plants.

2.3. Dynamic Matrix Control (DMC)

Engineers at Shell Oil developed their own independent MPC technology in the early 1970s, with an initial application in 1973. Cutler and Ramaker presented details of an unconstrained multivariable control algorithm, which they named dynamic matrix control (DMC) at the 1979 National AIChE meeting [13] and at the 1980 Joint Automatic Control Conference [14]. Key features of the DMC control algorithm include [4]:

- Linear step response model for the plant.
- Quadratic performance objective over a finite prediction horizon.
- Future plant output behavior specified by trying to follow the setpoint as closely as possible.
- Optimal inputs computed as the solution to a leastsquares problem.

The linear step response model used by the DMC algorithm relates changes in a process output to a weighted sum of past input changes, referred to as input moves. For the SISO case the step response model looks like:

$$y_{k+j} = \sum_{i=1}^{N-1} s_i \Delta u_{k+j-i} + s_N u_{k+j-N} \qquad (2.7)$$

The move weights s_i are the step response coefficients.

The objective of a DMC controller is to drive the output as close to the setpoint as possible in a least-squares sense with a penalty term on the MV moves. This results in smaller computed input moves and a less aggressive output response. This technique provides a degree of robustness to model error, as with the IDCOM reference trajectory.

The initial IDCOM and DMC algorithms represent the first generation of MPC technology; they had an enormous impact on industrial process control and served to define the industrial MPC paradigm.

2.4. Quadratic Programming Solution of Dynamic Matrix Control (QDMC)

The original IDCOM and 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. Cutler et al. first described the QDMC algorithm in a 1983 AIChE conference paper [28]. [29] published a more comprehensive description several years later in 1986.

Key features of the QDMC algorithm include [4]:

- Linear step response model for the plant.
- Quadratic performance objective over a finite prediction horizon.
- Future plant output behavior specified by trying to follow the setpoint as closely as possible subject to a move suppression term.
- Optimal inputs computed as the solution to a quadratic program.

[29] show 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.

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.

2.5. Identification and Command-MultiVariable (IDCOM-M), Hierarchical Constraint Control (HIECON), Setpoint Multivariable Control Architecture (SMCA), and Shell Multivariable Optimizing Controller (SMOC)

The QDMC algorithm provided a systematic approach to incorporate hard input and output constraints, but second-generation MPC technology into practical problems. There was no clear way to handle an infeasible solution. The soft constraint formulation is not completely satisfactory because it means that all constraints will be violated to some extent, as determined by the relative weights. Fault tolerance is also another important practical issue. Rather than simply turning itself off as signals are lost, a practical MPC controller should remain online and try to make the best of the sub-plant under its control.

These issues motivated engineers to develop new versions of MPC algorithms. The version marketed by Setpoint was called IDCOM-M, while the nearly identical Adersa version was referred to as hierarchical constraint control (HIECON). The IDCOM- M controller was first described in a paper by [30]. A second paper presented at the 1990 AIChE conference describes an application of IDCOM-M to the Shell Fundamental Control Problem [31] and provides additional details concerning the constraint methodology. Distinguishing features of the IDCOM-M algorithm include:

- Linear impulse response model of plant.
- Controllability supervisor to screen out ill-conditioned plant subsets.
- Multi-objective function formulation; quadratic output objective followed by a quadratic input objective.
- Controls a subset of future points in time for each output, called the coincidence points, chosen from a reference trajectory.
- A single move is computed for each input.
- Constraints can be hard or soft, with hard constraints ranked in order of priority.

An important distinction of the IDCOM-M algorithm is that it uses *two separate objective functions*, one for the outputs and then, if there are extra degrees of freedom, one for the inputs. A quadratic output objective function is minimized first subject to hard input constraints. Each output is driven as closely as possible to a desired value at a single point in time known as the *coincidence point*. The name comes from the fact that this is where the desired and predicted values should coincide. The desired output value comes from a first order reference trajectory that starts at the current measured value and leads smoothly to the setpoint. Each output has two basic tuning parameters; a coincidence point and a closed-loop response time, used to define the reference trajectory.

Setpoint engineers continued to improve the IDCOM-M technology, and eventually combined their identification, simulation, configuration, and control products into a single integrated offering called SMCA, for Setpoint Multivariable Control Architecture. An improved numerical solution engine allowed them to solve a sequence of separate steady-state target optimizations, providing a natural way to incorporate multiple ranked control objectives and constraints.

In the late 1980's engineers at Shell Research in France developed the Shell Multivariable Optimizing Controller (SMOC) which they described as a bridge between state-space and MPC algorithms [32, 33]. They combine the constraint handling features of MPC with the richer framework for feedback offered by statespace methods.

The SMOC algorithm includes several features that are considered essential to a "modern" MPC formulation:

- State-space models are used so that the full range of linear dynamics can be represented (stable, unstable, and integrating). An explicit disturbance model describes the effect of unmeasured disturbances; the constant output disturbance is simply a special case.
- A Kalman filter is used to estimate the plant states and unmeasured disturbances from output measurements.
- A distinction is introduced between *controlled variables* appearing in the control objective and *feedback variables* that are used for state estimation.
- Input and output constraints are enforced via a QP formulation.

The IDCOM-M, HIECON, SMCA, and SMOC algorithms represent a third generation of MPC technology; others include the PCT algorithm by Profimatics, and the RMPC algorithm by Honeywell. This generation distinguishes between several levels of constraints (hard, soft, ranked), provides some mechanism to recover from an infeasible solution, addresses the issues resulting from a control structure that changes in real time, provides a richer set of options for feedback, and allows for a wider range of process dynamics (stable, integrating and unstable) and controller specifications.

2.6. DMC-plus and RMPCT

In the last 5 years, increased competition and the mergers of several MPC vendors which have led to significant changes in the industrial MPC landscape. In late 1995 Honeywell purchased Profimatics, Inc. and formed Honeywell Hi-Spec Solutions. The RMPC algorithm offered by Honeywell was merged with the Profimatics PCT controller to create their current offering called RMPCT. In early 1996, Aspen Technology Inc. purchased both Setpoint, Inc. and DMC Corporation. This was followed by acquisition of Treiber Controls in 1998. The SMCA and DMC technologies were subsequently merged to create Aspen Technology's current DMC-plus product. DMC-plus and RMPCT are representative of the fourth generation MPC technology sold today, with features such as [4]:

- Windows-based graphical user interfaces.
- Multiple optimization levels to address prioritized control objectives.
- Additional flexibility in the steady-state target optimization, including QP and economic objectives.
- Direct consideration of model uncertainty (robust control design).
- Improved identification technology based on prediction error method and sub-space ID methods.

Chapter 3

Model Predictive Control

The conceptual structure of MPC is depicted in Figure 3.1. The name MPC stems from the idea of employing an explicit model of the plant to be controlled which is used to predict the future output behavior. This prediction capability allows solving optimal control problems on line, where tracking error, namely the difference between the predicted output and the desired reference, is minimized over a future horizon, possibly subject to constraints on the manipulated inputs and outputs.

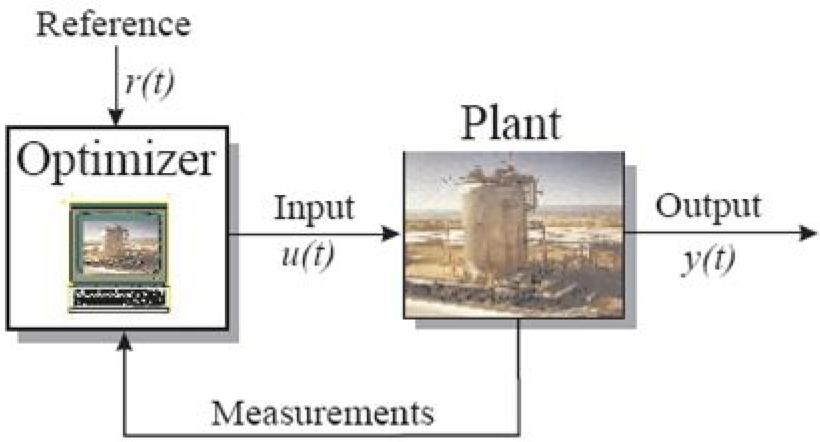


Figure 3.1 Basic Structure of Model Predictive Control [23]

Model Predictive Control (MPC) is conceptually a natural method for generating feedback control actions for linear and nonlinear plants. A human being, for instance, while driving a vehicle, generates steering-wheel commands by forecasting or *predicting* over a finite time-horizon the (possible) vehicle state-evolutions on the basis of vehicle current state and dynamics, and a *virtual* or potential steering-wheel command sequence. Then, one, among such sequences, is sorted out, which fulfills safety constraints and meets performance requirements. Only a short initial portion of such a sequence is applied by the driver to the steering-wheel, while its remaining part is discarded. After such an initial portion is applied, the driver repeats the whole operation by restarting predictions over a moved-ahead or *receded* time-horizon from the updated vehicle state as determined by the applied command. MPC complies with the same logical scheme: the control sequence is computed by solving on-line, over a finite control horizon, an open-loop optimal control problem, given the plant dynamical model and current state. Indeed, similarly to the driver behavior, in a discrete-time setting only the first control of the open-loop control sequence is applied to the plant, and, according to the *receding horizon control* philosophy, the whole optimization cycle is repeated at the subsequent time-instant based on the new plant-state.

The result of the optimization is applied according to a receding horizon philosophy: At time t only the first input of the optimal command sequence is actually applied to the plant. The remaining optimal inputs are discarded, and a new optimal control problem is solved at time t + 1. This idea is illustrated in Figure 3.2. As new measurements are collected from the plant at each time t, the receding horizon mechanism provides the controller with the desired feedback characteristics.

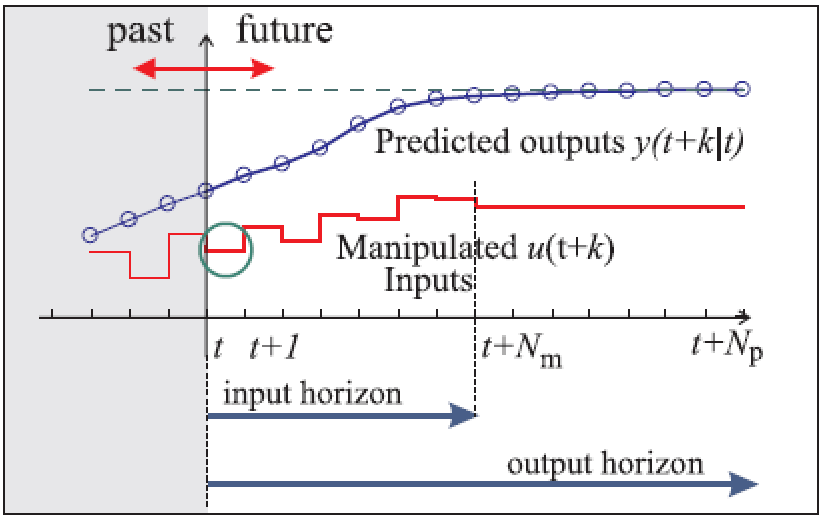


Figure 3.2 Receding horizon strategy: only the first one of the computed moves u(t) is implemented [23]

Figure 3.3 shows the structure of a typical MPC system. It makes it clear that a number of possibilities exist for

- Input-output model,
- disturbance prediction,

- objective,
- measurement,
- constraints and
- sampling period.

Regardless of the particular choice made for the above elements, on-line optimization is the common thread tying them together. Indeed, the possibilities for on-line optimization [34] are numerous.

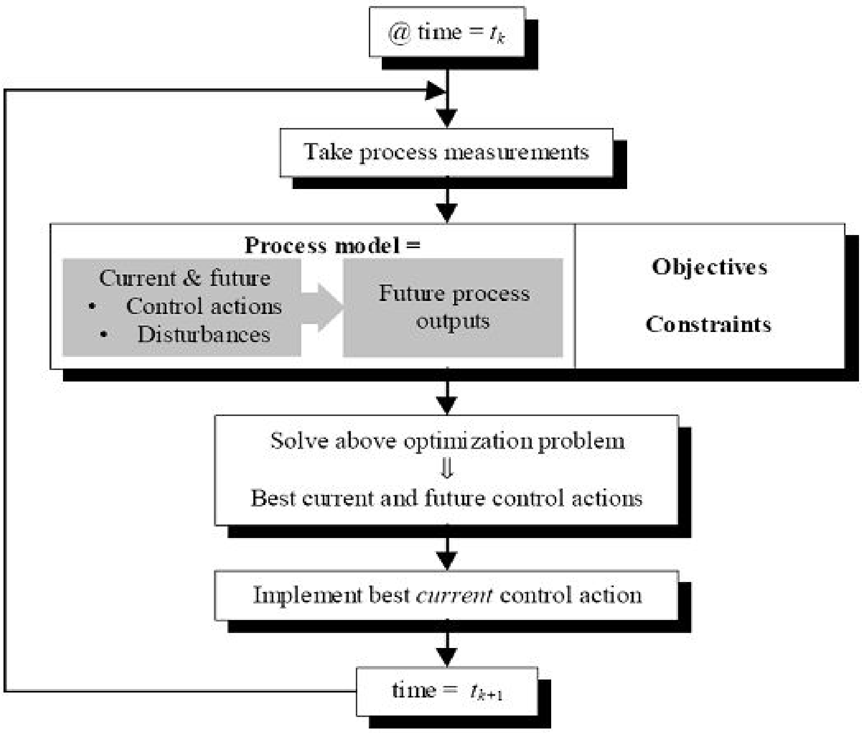


Figure 3.3 Model Predictive Control Scheme [8]

Figure 3.3 also makes it clear that the behavior of an MPC system can be quite complicated, because the control action is determined as the result of the on-line optimization problem.

3.1. MPC Formulation

The objective function is a "sum of squares" of the predictive errors (difference between the set points and the model-predictive outputs) and the control moves (change in control action from step to step). Consider a stable single-input-single-output (SISO) process with input u and output y. A formulation of the MPC on-line optimization problem can be as follows [3.8]: At time k find

$$\min_{u[k|k],\ldots,u[k+p-1|k]} \sum_{i=1}^{p} w_i (y[k+i|k] - y^{sp})^2 + \sum_{i=1}^{m} r_i \Delta u[k+i-1|k]^2 \quad (3.1)$$

subject to

$$u_{\max} \geq u[k+i-1|k] \geq u_{\min} \, , \, i = 1, \ldots , m \quad (3.2)$$

$$\Delta u_{\max} \geq \Delta u[k+i-1|k] \geq -\Delta u_{\max} \, , \, i = 1, \ldots , m \quad (3.3)$$

$$y_{\max} \geq y[k+i\,|k] \geq y_{\min} \, , \, i = 1, \ldots , p \quad (3.4)$$

where p and $m < p$ are the lengths of the process output prediction and manipulated process input horizons, respectively; $u[k+i-1k]$, $i = 1, \ldots , p$, is the set of future process input values with respect to which the optimization will be performed, where

$$u[k+i\;k] = u[k+m-1k] \, , \, i = m, \_ \, , p-1 \; ; \quad (3.5)$$

y_{sp} is the set-point; and Δ is the backward difference operator, i.e.`

$$\Delta u[k+i-1k] \hat{=} u[k+i-1k] - u[k+i-2\;k] \quad (3.6)$$

In typical MPC fashion [35] the above optimization problem is solved at time k, and the optimal input $u[k] = u_{opt}\,[k\;k]$ is applied to the process. This procedure is repeated at subsequent times k+1, k+2, etc.

Taking an example, assume that the following finite-impulse-response (FIR) model describes the dynamics of the controlled process:

$$y[k] = \sum_{j=1}^{n} h_i \, u[k-j] + d[k] \quad (3.7)$$

where h_i are the model coefficients (convolution kernel) and d is a disturbance. Then

$$y[k+i|k] = \sum_{j=1}^{n} h_j [k+i-j|k] + d[k+i|k] \quad (3.8)$$

where

$$u[k+i-j\;k] = u[k+i-j], \; i-j < 0 \quad (3.9)$$

The prediction of the future disturbance $d[k+i|\;k]$ clearly can be neither certain nor exact. An approximation or simplification has to be employed, such as

$$d[k+i|k] = d[k|k] - \sum_{j=1}^{n} h_j u[k-j] \qquad (3.10)$$

where $y[k]$ is the measured value of the process output y at sampling point k and $u[k-j]$ are past values of the process input u. Substitution of eqns. (3.8) to (3.10) into eqns. (3.1) to (3.4) yields

$$\min_{u[k|k],\dots,u[k+p-1|k]} \sum_{i=1}^{p} w_i \left[\sum_{j=1}^{n} h_j[k+i-j|k] - \sum_{j=1}^{n} h_j u[k-j] + y[k] - y^{sp} \right]^2 + \sum_{i=1}^{m} r_i \Delta u[k+i-1|k]^2 \qquad (3.11)$$

Subject to

$$u_{\max} \geq u[k+i-1|k] \geq u_{\min}\ ,\ i = 1, \dots, m \qquad (3.12)$$

$$\Delta u_{\max} \geq \Delta u[k+i-1|k] \geq -\Delta u_{\max}\ ,\ i = 1, \dots, m \qquad (3.13)$$

$$y_{max} \geq \sum_{i=1}^{n} h_j u[k=i-j|k] - \sum_{i=1}^{n} h_j u[k-j] + y[k] \geq y_{min}\ ,\ i = 1,2,\dots,p \qquad (3.14)$$

The above optimization problem is a quadratic programming problem, which can be easily solved at each time k.

The basic MPC law is described by the following algorithm:

1. Get the new state x (t)
2. Solve the optimization problem
3. Apply only u(t) = u(t + 0|t)
4. $t \leftarrow t+1$ Go to 1.

The Model Predictive Control algorithm used in the work is SMOC (Shell Multivariable Optimizing Controller), and hereon will use the acronym MVOC (MultiVariable Optimizing Controller) for the same.

3.2. MVOC Terminology and Functionality

The various technologies and functions used by MVOC are:

3.2.1. ***MV*** – The controller computes Manipulated Variables to keep the CV's at setpoint or within limit and to optimize the process behavior. The controller always keeps the MV's within their limits. The MV output from MVOC can be configured to go on to any set point or directly output control connection of a DCS PID controller block.

3.2.2 ***DV*** **–** Disturbance variables are measured variables not under the control of MVOC controller but they affect the CV's of the controller. The feed forward predictive action of the controller prevents the CV's to be changed from the set limits.

3.2.3 ***POV*** **–** Process Output Variables are those, which include Controlled Variables and Intermediate variables. E.g. In a distillation process product top quality is a Controlled Variable (which is directly controlled by MVOC), on other hand top tray temperature, which affects the top quality, is an intermediate variable not directly controlled by MVOC.

3.2.4 ***CV*** **–** Controlled Variables are the Process variables that must be maintained at some value or within limits, and/or are to be optimized. CV's are input by the controller and may be measured or calculated values. E.g. Top product Quality is the CV in a distillation process.

3.2.5 ***EF*** **–** Economic Functions are process function to be optimized. Economic Functions and Economic Coefficients define targets for optimization. EFs are effective only during MVOC controller's optimization mode of operation.

3.2.6 ***Compaction point*** **-** MVOC calculates the controller action not at every point in the future time, but only at some predefined points. These predefined points are specified during the off-line design of the controller and called compaction points. Compaction points must be specified for the inputs (control actions i.e. MVOC MV's) and the outputs (CV's,) and can be selected differently. Compaction points are used to reduce the computations of the control actions.

3.2.7 ***Action Model*** **–** This is the actual dynamic model of the process calculated from the series of manipulations of the MVOC. MVOC predicts control action by referring to this model. In other words Action Model relates changes in MV's (i.e. setpoints or direct valve positions) to POV's (i.e. Intermediate and Controlled Variables).

3.2.8 ***Measured Disturbance Model*** **–** This model is calculated from the measured disturbance from the past (e.g. feed rate change which is actual DV) assuming that this disturbance will remain constant in future. It supplements feed forward control to the predictions of the Action Model.

3.2.9 *Unmeasured Disturbance Model (or"Observer"Model) –*

This type of model is useful when effects of those disturbances that cannot be measured are present. This model includes:

- Stochastic/Noise Model
- Intermediate Variables Disturbances
- Model component for integrating process

Unexpected variations in POV's are used to adopt predictions (based on Kalman filtering) to provide another supplementary control to Action Model.

If MV and DV do not change Action and Measured Disturbance model will not predict any control; therefore it is the only unmeasured disturbance model, which predict control action to unexpected circumstance.

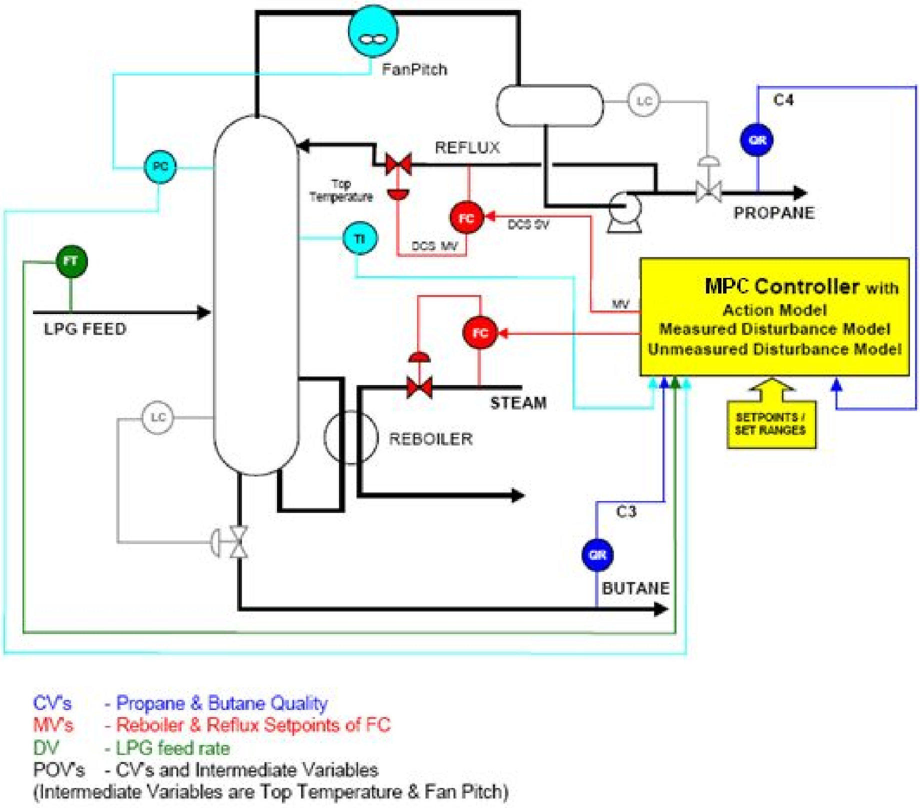


Figure 3.4 A generic Depropaniser process flow scheme with MPC controller

3.2.10 Optimization – It is important to understand economic optimization function of the main controller in order to run the process at most cost effective way while achieving the set point or the desire objectives. Economic Coefficients based on individual cost factor such as cost of Energy or the Feed maximization can be assigned to achieve most optimum economic benefits.

The economic function in is a bilinear function that the controller minimizes. It is made up of terms that are bilinear combinations of manipulated input and measured output variables. Economic coefficients appear in the bilinear combinations.

Multiple economic functions can be defined, but only a single economic function can be active at a time. The active economic function is selected on-line. The economic coefficients can also be changed on-line.

"Controlled Variables have always a higher priority than Economic Function"

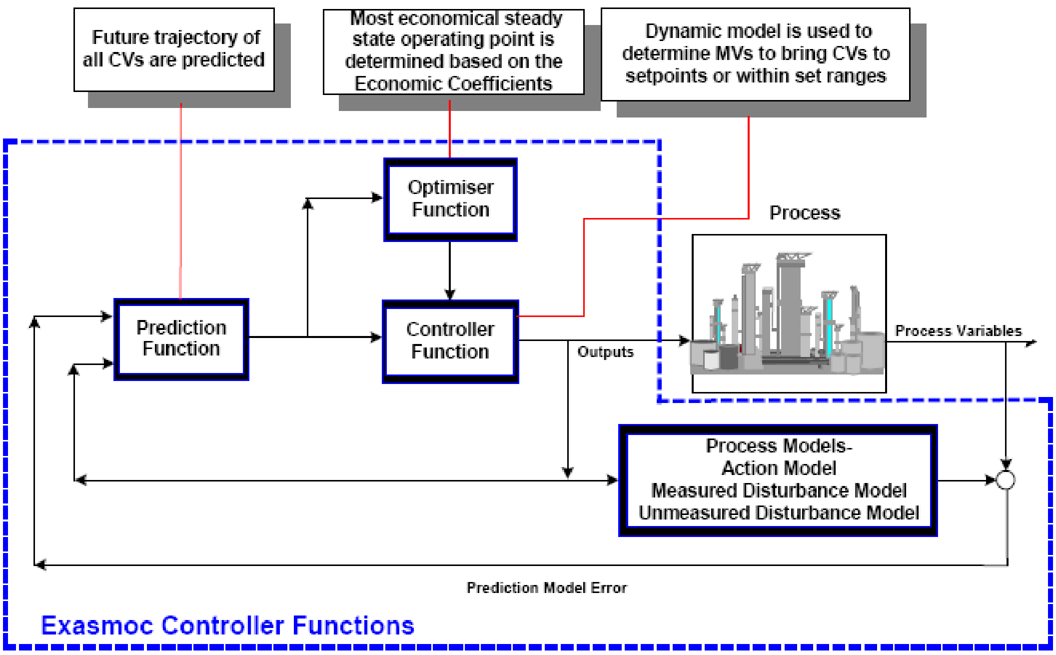


Figure 3.5 Optimization, Prediction & Control function [36]

3.3 System Configuration

The following is a typical system configuration which includes MPC (SMOC) station and OPC interface with CENTUM CS 3000/1000 DCS used in DHDT plant of IOCL,Panipat [36]

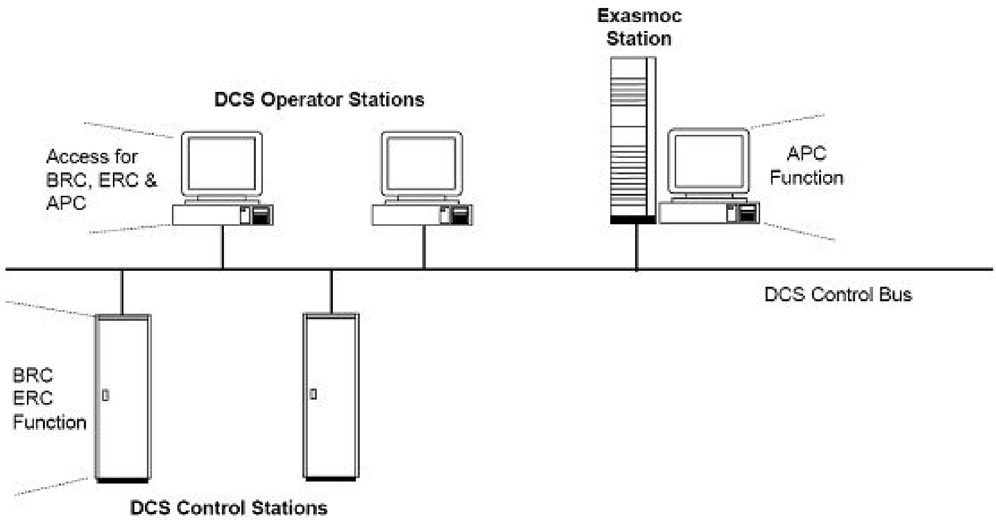


Figure 3.6 (a) General System Configuration[36]

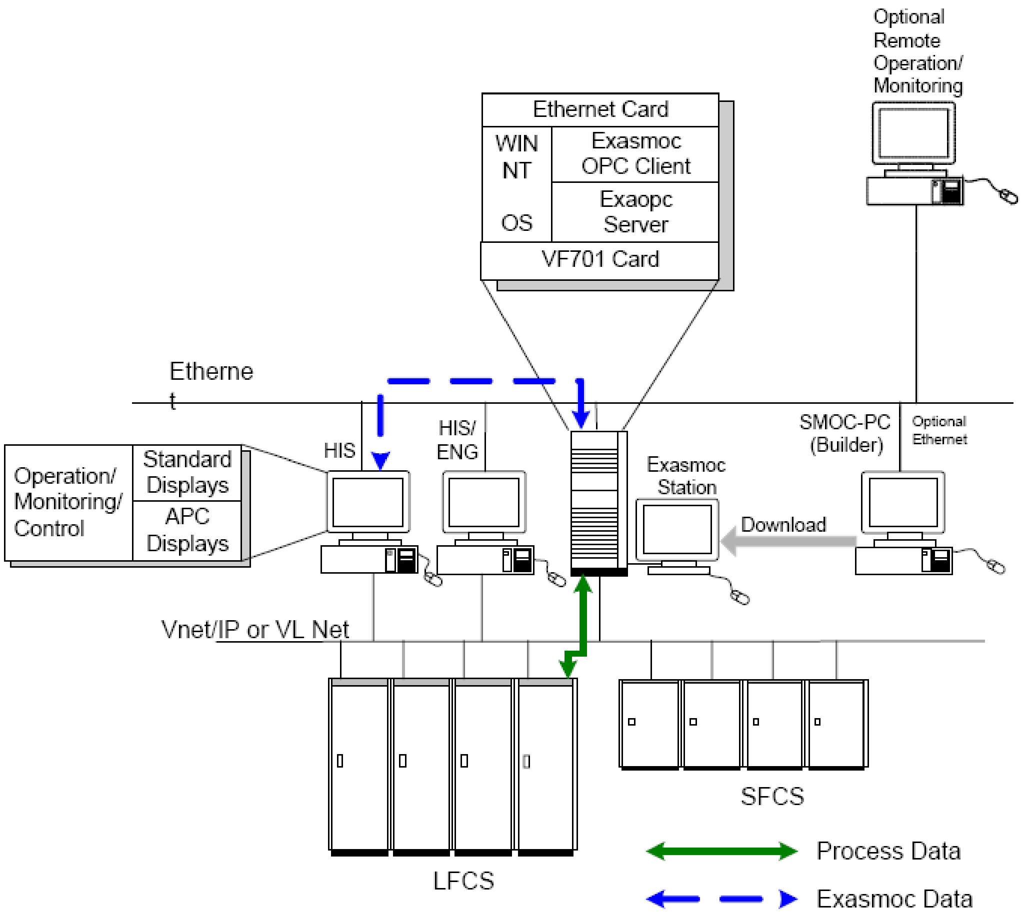


Figure 3.6 (b) System Configuration and Components [36]

Description of the System Configuration components

3.3.1 Human Interface Station (HIS)

The HIS is mainly used for operation and monitoring – it displays process variables, control parameters, alarms, graphics etc. necessary for users to quickly grasp the operating status of the plant.

3.3.2 Field Control Station (FCS)

The FCS mainly controls the plant in BRC and ERC modes besides its many other functions. If the COAST modules are used in the user project then it is intended to run under FCS. A Users system may have Standard FCS (LFCS) and/or Compact FCS (SFCS) depending on project demand.

3.3.3 Engineering PC (ENG)

This is the PC with engineering function used to perform CENTUM CS 3000/1000-system generation and maintenance management. It can be the same type of general purpose PC as the HIS.

3.3.4 SMOC-PC Builder

This is software running on Windows 95 or higher OS. The main purpose of this Software is to build/engineer AIDA and/or SMOC model; configure Exasmoc online controller and DCS definition interface.

3.3.5 Exasmoc station

This is a Windows NT based computer where actual Exasmoc online controller Software will be running.

VF701 Card provides Hardware interface between computer and V/VL net. Ethernet card is also provided for Hardware interface between computer and Ethernet.

3.3.6 Exaopc

Exaopc is a server, offering an OPC (OLE for Process Control) Foundation standard interface between CENTUM CS 3000/1000 DCS and application Software such as Exasmoc online controller. Exasmoc is a client; it reads/writes process related data on FCS through Exaopc server.

3.3.7 Remote monitoring and operation

This package will help process control engineer to remotely access Exasmoc controller using Windows NT computer and Visual Basic (VB) based windows.

3.3.8 Vnet/IP

Vnet/IP is a 100 Mbps real time control bus, which links stations such as HIS, FCS, HIS/ENG, Exasmoc and Exaopc. V net is used on CENTUM CS 3000 DCS. This can be single or dual redundant bus.

3.3.9 VL net

VL net is a 10 Mbps real time control bus which links stations such as HIS, FCS, HIS/ENG, Exasmoc station and Exaopc station. VL net is used on CENTUM CS 1000 DCS. This can be single or dual redundant bus.

3.3.10 Ethernet

HIS, HIS/ENG, Exasmoc station, Exaopc station, and optional remote monitoring station (for Exasmoc) can be connected on Ethernet. Ethernet in CENTUM CS 3000 and 1000 DCS has following functions –

- HIS trend data files to PC's
- Equalizing data in two HIS'
- Exasmoc related data to and from Exasmoc operator windows on HIS.
- Exasmoc related data to and from Exasmoc VB Windows on remote monitoring station.

3.4 Multi variable Optimizing controller (MVOC) Design

Multi-variable optimizing controller allows for improved stability of plant control and significant reductions in the operation costs compared with traditional PID control. However whether or not the introduction of MVOC is successful depends on the identification of an accurate process model and the selection of appropriate control, manipulation and disturbance variables. In order to establish the success of the MVOC implementation & guarantee the potential benefits of the project, the existing plant operation needs to be studied with respect to the economic drives of the units that will contribute towards the improvement in operating levels of the unit thereby giving benefits both tangible and intangible. An inappropriate selection of controlled, manipulated or disturbance variables will result in unstable control, even if the model fits the process very well. Non- correlated process variables should be selected as controlled variables, and independent process variables should be selected as manipulated variable or disturbance variables.

The Engineering steps used in the designing MOPC are described below [37]:

1. Deciding coverage of MVOC Base Case Study & Benefit Analysis

The scope of coverage of MVOC is decided. If coverage is too wide, model identification become difficult. Control loops with shorter response time should be controlled by PID controller not MVOC, as MVOC cannot adequately control a fast control loop. Parts that have strong non-linearity should not be included in the scope of MVOC, since ordinary MVOC cannot handle the non-linear process properly.

Potential areas from where benefits shall be accrued are identified and all the applicable historic plant data (laboratory data, production rates and measurement of all constraining operational parameters) for calculating the benefit estimation is collected.

2. PID Tuning Review & Loop Pre-Testing

The scope of these activities is to check all the applicable DCS level regulatory controls, to make sure they are configured properly and tuned adequately for the application of the Advanced Process Control. Normally MVOC's output is the setpoint to a flow controller or temperature controller. If the regulatory controller is not properly tuned, the control performance of MVOC is not effective.

The Loop Pre-Tests involves moving of each of the potential manipulated variable, to check the valve response, monitor the regulatory control system response, configuration and tuning. This allows discovering any basic regulatory level control inadequacies and provides information on the settling time of the process and the move sizes required during plant step response tests. Based on the results from this testing, a Pre-Test Report is issued which specifies the comprehensive list of the Instrumentation (if any) to be fixed.

This phase also includes collection of Data – both Lab & Process required for the development of Inferential Quality Estimators. Typically about 100 to 200 data points (lab values) with corresponding process data is required for each inferential quality estimator development.

3. Provisional selection of CV, MV and DV

CV, MV, and DV are provisionally selected on the basis of the current operation and experience of the operator.

4. Commissioning of Inferential Property Estimators

After the completion of the Pre-testing activity, all the inferential property estimators are commissioned and any fine tuning, if necessary is carried out. The quality estimator which predicts the plant property shall be in line for the DCS operator acceptability and consistent lab updates are be performed by vendor, hereon for achieving maximum benefits.

5. Plant Step Test

The plant test is a very important phase in the implementation of a multivariable controller. Conducting an extensive, high quality plant test ensures that an accurate dynamic model of the plant is obtained. A well-designed controller with a reliable model ensures maximum reliability and the achievement of maximum economic benefits.

The Plant testing involves the application of a sequence of small independent steps to the plant *Manipulated Variable* and *disturbance variable* Set point. Step each MV and DV from 10 to 15 times, while holding all MVs that affect it, at constant value (Minimum: 2 moves @ TTSS, 2 @ 1/3TTSS, 2 @ 2/3 TTSS, 2 @ 4/3 TTSS) to obtain an accurate process model. Make sure steady state is reached between at least 3 steps.

Avoid correlated and compensating moves otherwise individual response cannot be distinguished. MV sizes should be large enough to cause a noticeable move in the affected CVs, but not so large that cause severe upsets in the process. Thump rule is to have a step size 3 to 4 times the normal noise range. Testing during process upsets or transient process conditions (start-up, shutdown, grade changes, feed changes, etc) should be avoided.

6. Model Identification

The most important, time consuming and costly part in the implementation of Multivariable Optimization controller is Model Identification [38]. The response test data is analyzed using identification software to develop the models required for the multivariable model predictive controller. CVs, MVs and DVs are finally decided based on the results of the step response. If some relationship between CV and MV or DV is not identified, the provisional selection of CV, MV or DV is removed from MOC.

Three types of models can be specified:

- The *action model* relating the controlled variables to the manipulated variable moves.
- The *measured disturbance model* relating the controlled variables to changes in disturbance variables.
- The *unmeasured disturbance model* to predict the effect of unmeasured disturbance has on the controlled variables.

The output of this stage is a model file that relates the dynamic relationships of each controlled variable to the manipulated variables and the disturbance variables.

7. Controller Simulation and Tuning

The next stage is to build the multivariable optimizing controller using the model developed in the Model Identification stage. In addition to the process model, other tuning parameters such as the relative priority of the controlled and constrained variables and the relative priority and speed of each manipulated variable are specified.

The output is a controller configuration file that is read by the simulation software that allows the user to "tune" the multivariable optimizing controller parameters. The user can specify a number of scenarios to ascertain the controller performance. These scenarios include set point changes, plant model mismatch and measured/unmeasured disturbances. The multivariable optimizing controller can be continuously fine tuned to meet the operation objectives.

The output of this stage is a tuned controller configuration file that can be read by the multivariable on-line software

8. Operator Interface Development

Interface software to establish the connectivity between multivariable optimizing controller and the DCS will be developed and tested. Also, DCS engineering required for developing Operator interface to Advanced Process Control System will be done during this phase of the project. All the other necessary DCS engineering activities like the ones described below shall also be done as a part of the Operator Interface Development.

Graphics Screen to enable the plant operator to operate the APC system from the DCS consoles, Safety logics for switching off & on the APC system, moving into the default mode of DCS operator control when plant upsets happen beyond the set constraints of the multivariable controller, as well as switching of control from APC to DCS system in case of failure of supervisory system are developed.

9. Test Run

First, MVOC is connected to DCS while MVOC is still in prediction or standby mode which means MVOC is running but does not write MVOC output to DCS. The values of MVOC output and MVOC prediction are checked to see whether or not they are appropriate. If the predictions and outputs of the controller are found appropriate Run or Control mode is set for MVOC, which writes MVOC output to DCS. The MVOC's parameters are finally tuned to obtain the desired control performance.

10. Commissioning

Once the dynamic model has been verified, the controllers will be commissioned. It is required that the control mode be set for a continuous amount of time for MVOC at least once a week. MVOC reduce the CV's standard deviation by half, compared with regulatory control. If this reduction is not achieved, it is assumed that there is a considerable mismatch between the process model and actual process. If necessary additional step response testing and model identification is done.

3.5 Step Response

To obtain an accurate process model the following points are important while doing step response test:

1. MVs and DVs should be changed one by one for the step response test. If more than two MVs or DVs are changed at the same time, each response cannot be distinguished.
2. The step response should have enough magnitude to sufficiently excite the process. At least, change implemented to the CV by the test signal should be greater than that implemented by unmeasured disturbances at a steady state. If the test signal is too small, the process model will not be identified. On the other hand, if the test signal is too big, if might cause quality deterioration. Moreover, process model might be incorrect under the influence by process non-linearity.
3. A different width for step signal is recommended. To identify the correct process gain it is important to have a step signal width that is longer than the TSS (Time to Steady State) and to identify the correct process dead time and time constant it is important to have a step signal width that is shorter than the TSS.

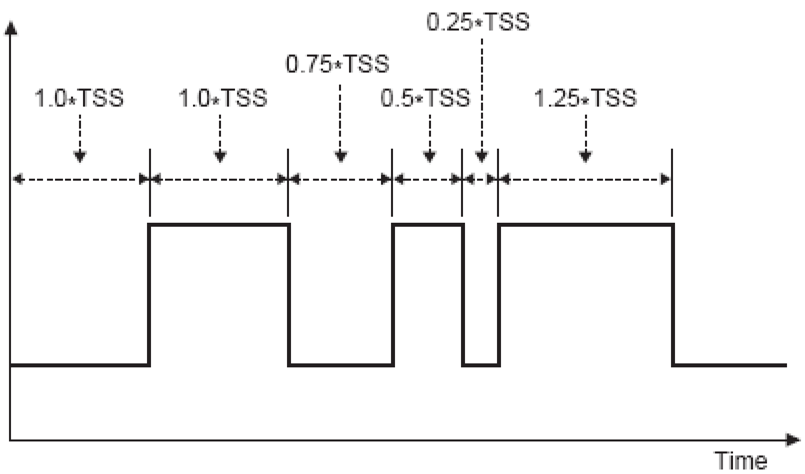


Figure 2.7 Recommended Test Signal [37]

4. The regulatory control loop that indirectly controls CV should be open. If the control loop is closed, there is the possibility that model be strongly affected by the process conditions.

5. Generally it is difficult to identify a model for DV. This is because in most of the processes DV cannot be change at our discretion for identification. To identify the process model long-term normal operation data is used. The DV probably changed many times during this period. The process model is identified from the correlation between DV and CV. The required term for identification from the data is normally 1 or 2 months.

3.6 Quality Estimator

Maximum production at stipulated quality is the byword of any hydrocarbon or chemical processing plant. Measuring production is an easy task – volumetric flow meters, mass flow meters, tank dips and so on. Quality measurement and control is always hampered by delayed information on quality. Sometimes, results are late in coming, asking for costly reprocessing; sometimes it calls for altering plant conditions to make up for what has already been produced so that, overall, the product meets quality specifications. The time delay and discontinuity of signals are inherent to most measurement systems such as say, an on-line analyzer or lab results.

A Quality Estimator seeks to address this problem by bridging the time gap. It delivers, just like a flow meter or temperature element, instantaneous real-time inferential measurement of quality. It, thereby, closes the control loop. A measure of quality is available at increased frequencies, offering the operator real-time information on quality who can use it to alter his plant variables.

3.6.1 Working of Quality Estimator

An inferred measurement is a calculated variable. It infers from selected, related simple measurements (temperature, pressure, flow,...), the current value of a critical product property.

Many quality properties are related to certain easily measurable properties like flow, temperature, pressure, etc. These relations are established as models and the value of quality is inferred. Since, real time values of flow, temperature, pressure are available, accurately, the models established, deliver the quality property, real-time.

Using the more easily measured process variables like temperature, pressure, flow, etc., the quality estimator is able to estimate/predict values of critical or difficult to measure on-line properties like cut point, pour point, flash point etc. This estimator provides information to controller enabling it to directly control a variable of interest.

The value predicted by an estimator is used to close a quality control loop. A property of interest is affected by a number of operating variables, some of which may be related among them. Since analyzers have time lag, it is the estimated value predicted by quality estimators, continuously, that are used to control process variables. Therefore, one should be careful about selecting the type of quality estimator. It is to be understood that the reliability of estimator values is of utmost importance.

The reliability is brought about by raw data conditioning, modeling tools, validity tools and model update tools. The following should be considered before a selecting a Quality Estimator [36]:

- Ease of modeling – A single quality can be influenced by a number of parameters. The relationship between the input and output variables can be linear or non-linear. The input variables selected could be collinear. The list of complexities can be very long. Versatility of modeling tool to handle diverse complex circumstances while simultaneously being easy to navigate will differentiate the leader in the pack of inferential quality estimators.
- Flexibility of modeling tool so as to be used for varying plant situations. No single set of operating parameter or circumstance can describe in full the gamut of situations a plant will really have. Therefore, the model should handle these dynamic situations without as frequent a necessity to go back to the drawing board.
- Extent of mathematical knowledge necessary to develop models.
- Model validation tools – this will help in fine-tuning models before it is downloaded for sensing and control, on-line.
- Model update mechanism – this renders the estimator more effective. The model should be capable of judging between the lab result and its own prediction. This is an important aspect. When an estimator is used to close a control loop, this feature

will help stabilize the process rather than drive it farther away from desired set points.

- Ability to handle uncertain and varying delay of quality reference measurement.
- Ability to handle process fluctuations without driving process wild. The estimator should learn to understand the trend of a process and update its prediction capability instead of "simply" following the process.
- The peripherals that are required to run the package.
- How easily it can be integrated with existing control systems.
- User interface.

3.6.2 Benefits of Quality Estimator

There are several tangible and intangible benefits to be accrued from the use of Robust Quality Estimator

- Consistent on-spec. products. When real-time quality estimations are used for control, excursions from quality targets are minimized. Result – more consistent on specification Product.
- Reduced quality give-away. Oscillations in quality with high standard deviations are "normal" if feedback on quality is associated with huge time delays. The one way to narrow this quality distribution curve is to control parameters associated with quality on a real time basis. This will narrow down the possibility of producing better-than-spec. products. This can be achieved by using QE for delay free, real time predictions for closed loop control.
- Less re-work and consequently less energy usage. This is an outcome of above two benefits of QE. When quality is consistent, obviously there is less need for rework.
- Increased throughput from existing plant. With QE in place, it is possible to smoothen the plant operation. A steady, smooth plant operation automatically translates into increased throughputs.
- Higher APC up-times. When APC is used in conjunction with an on-line analyzer or lab data, uptime of APC and its performance is only as good as the analyzer's health and frequency of measurement. QE with its real-time prediction of quality, smoothens control action and enhances overall plant functioning.

- Improved customer satisfaction. With the product on-specification always, it is possible to deliver product upon customer's demand without violating his specifications leading to greater customer satisfaction.
- Possible to meet product specifications in face of varying plant conditions. The property of "**ROBUSTNESS**" enables QE to learn and adapt to changing conditions without frequent necessity to remodel.
- Real-time quality control. With a robust, reliable quality measurement available real-time, all process variables related to maintaining quality on-target are manipulated on a continuous basis to achieve this aim. With an on-line analyzer or lab data, having time delays quality inevitably swings.
- Possible to diagnose abnormal operations.

3.7 Handling of Unmeasured Disturbances

[37] This feature covers a wide range of situations encountered in a process plant and imparts the MultiVariable Controller versatility and adaptability. While designing a controller and simulating it off-line, the controller works in an ideal environment, free from disturbances, fluctuations, uncertainties and process eccentricities. These hit the controller on the face and cause it to run haywire once it is implemented.

The best efforts of a control engineer to simulate these conditions and tune a controller, off-line, are not good enough to equip the controller to countenance real-life situations.

To get over this situation, the value of a Process Output Variable (POV) measured in the plant is used as feedback by the controller. This measurement is subject to variations or noise. These variations could be due to:

- Simple instrument fluctuations, those less pronounced and marginally influential input parameters whose effects have not been modeled.
- Mismatch between action model, used by the controller and actual process behavior. These effects are incorporated as a simple gain block between the disturbance and POV of interest.
- There are cases where value or directional movement of one process parameter will be indicative of value or directional movement of another.

For example, column top temperature to top quality. Generally, the parameter of interest in this case will be top quality and the parameter used to control this would be top reflux. So logically an action model will be developed indicating relation between top reflux and top quality. In addition to this, a model between top temperature and top quality can be developed, as an 'intermediate variable' (a variable declared between top reflux and top quality).

The model between top temperature and top reflux will again be automatically, incorporated in the unmeasured disturbance model. The effect of this on control action is that, the controller will act to move reflux when it sees a movement in temperature not caused by reflux change. (A practical example of such a situation could be a rainstorm that will bring down column top temperature without the influence of reflux). Column top temperature is neither a controlled variable nor a manipulated variable. Yet, the controller uses it as a watchdog to keep quality on target.

There are numerous occasions in a plant when control action of low-level PID controller is not in synchronization with multivariable optimizing controllers (MVOC) of APC.

It is also possible to incorporate into the action mode, the destabilizing effects of certain process parameters that are neither manipulated nor controlled variables.

The output of an unmeasured disturbance model is an 'Observer Matrix'. When the observer matrix is put through a Kalman Filter, the controller is told to take action only for those fluctuations in the plant that need attention and Random Fluctuations are rejected.

3.8 Error Update Mechanism

When data is gathered from plant, it has in-built noise in it, both process and measurement noise. This is inevitable. Predictions made by using a model developed from such data have a strong likelihood to be erratic. Ideally, a model when used on-line should be intelligent to sense the source of error as due to measurement noise or model inadequacy and accordingly weight measurement or prediction for each step of model updation before it goes over to next step of prediction. It is this quality which has to be invested in the estimator that will make it "robust".

In case of a quality estimator, this problem is further compounded. The feedback that an estimator will receive is not real time information. It is the result of a sample drawn in the past. So, in addition to being capable of handling uncertainty in model, the quality estimator should also handle uncertainty in time delays. It has to go back to past data, past prediction, past plant condition and in fact other statistical criteria before it can update a model.

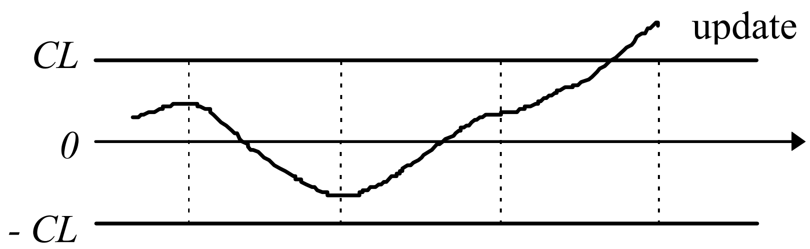
This feature will make a quality estimator "ROBUST".

The property of robustness enables the model to adapt to variations in input variables. This important characteristic allows higher uptime without the necessity to frequently remodel for changed conditions.

There are various criteria available for updating which can be set by the engineer. The QE has to decide on "when" and "how" an update should be carried out. Few model updation criteria are discussed below [36]:

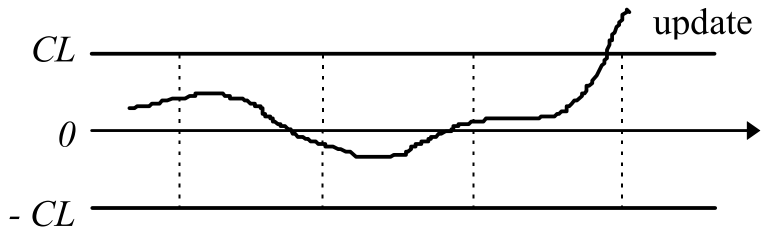
3.8.1 Standard:

The model is updated if the absolute prediction error is larger than some specified threshold CL.



3.8.2 Cusum:

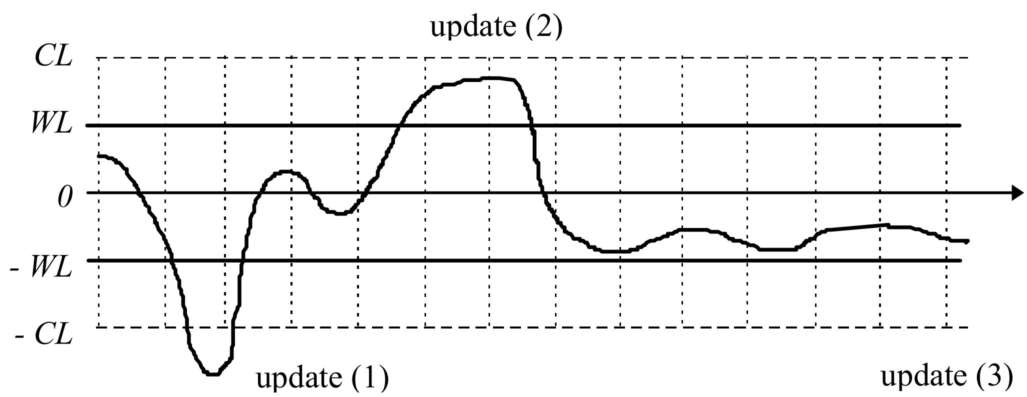
The model is updated if the integrated (over time) prediction error is larger than some specified threshold CL.



3.8.3 Control /Warning Limit:

It has three sub-rules for the model update namely,

- If the absolute prediction error is larger than CL (threshold set by the user), or
- With the average prediction error value if the prediction error is, for 2 subsequent times, of the same sign and larger than a specified threshold WL (smaller than CL) in absolute value, or
- The average prediction error value if the prediction error is, for 7 subsequent times, of the same sign and smaller than WL in absolute value.



Chapter 4
Diesel Hydrotreating

Hydrotreating or catalytic hydrogen treating removes objectionable materials from petroleum fractions by selectively reacting these materials with hydrogen in a reactor at relatively high temperatures at moderate pressures. These objectionable materials include, but are not solely limited to, sulfur, nitrogen, olefins, and aromatics.

The common objectives and applications of hydrotreating are:

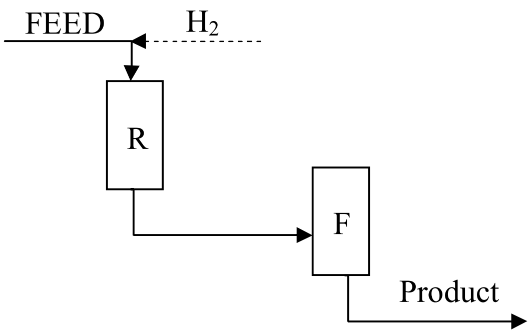
- Kerosene and diesel—to remove sulfur and to saturate olefins and some of the aromatics, resulting in improved properties of the streams (kerosene smoke point, diesel cetane number or diesel index) as well as storage stability.
- Naphtha (catalytic reformer feed pretreatment)—to remove sulfur, nitrogen, and metals that otherwise would poison downstream noble metal reforming catalysts.
- Lube oil—to improve the viscosity index, color, and stability as well as storage stability.
- FCC feed—to improve FCC yields, reduce catalyst usage and stack emissions.
- Resides—to provide low sulfur fuel oils to effect conversion and/or pretreatment for further conversion downstream.

The Diesel Hydro Treating (DHDT) unit of Indian Oil Corporation Limited (IOCL), Panipat refinery is designed to hydrotreat diesel cuts blends containing Straight Run Light Gas Oil (SRLGO), Straight Run Heavy Gas Oil (SRHGO), straight run Kerosene (SRK), straight run Vacuum Diesel (SRVD), Total Cycle Oil (TCO), Light Cooker Gas Oil (LCGO), Cooker Heavy Naphtha (CHN) & Cooker Light Naphtha (CLN) to produce a hydrotreated diesel stream characterized by a cetane number improvement of 10 points over unit feed cetane (and not less than 53.5) and by a low sulfur content (30 ppm wt) while meeting the diesel product stability specification of 1.6mg/100ml.

The unit capacity is 3,500,000 TPA with an on stream factor of 8000 hours per year. The unit design allows a minimum continuous operating cycle of 2 years meeting all product specifications at the design feed processing rate. The unit turndown rate is 50% of the design capacity while making on-specification products.

4.1 Flow schemes

Although the 'hydrotreating process' has several different applications (e.g. desulfurization, olefin saturation, denitrogenation, etc) and is used for a variety of petroleum fractions from naphtha all the way to atmospheric residue, practically all units have the same flow scheme.



R= Reactor, F= Fractionator

Figure 4.1 Schematic Flow Diagram of a Hydrotreater

It consists of a higher-pressure reactor section and a lower pressure fractionation section. This is shown very schematically in Figure 4.1 and is briefly described in the coming sections.

Figure 4.2 shows the overall block flow diagram of DHDT. The DHDT plant can be divided into following sub-sections:

i. Feed reaction and High Pressure (HP) Separation section.
ii. Medium Pressure (MP) separation/ Stripper section.
iii. Stabilizer Section.
iv. Low Pressure (LP)/ Amine Absorber and Off Gas Compression Section.

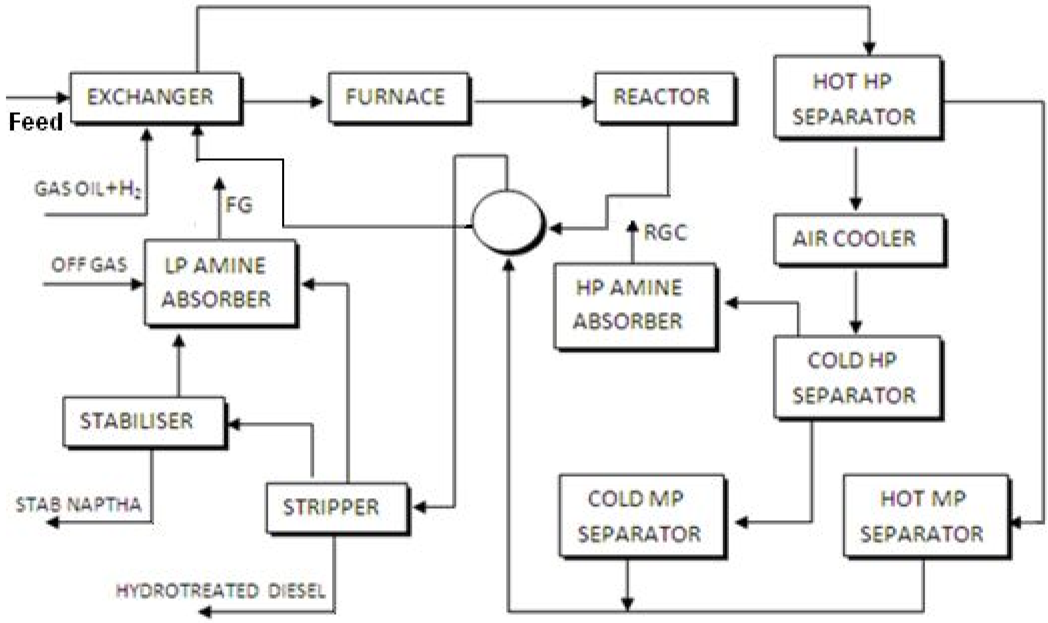


Figure 4.2 Block Flow Diagram

4.1.1 Feed Reaction/ HP Separation Section

A hot blend of straight run material (SRK, SRLGO, SRHGO and SEVD), a hot blend of Cracked Diesel material (CHN and LCGO), a hot TCO stream as well as a cold blend of straight run material (SRK, SRLGO, SRHGO and SRVD) arrive in the unit. The cold blend of straight run material represents about 20% of the unit total feed. The blending of these diesel streams is filtered through the feed filter and is sent to the feed surge drum.

The feed is pumped under flow control to the two parallel reaction section train, via the feed pump. Each reaction section train is made of reactor feed/effluent exchanger, stripper feed preheater, reactor heater and two reactors, and can process 50% of the total feed.

The Hydrogen make-up gas coming from the battery limits is routed to the three-stage compressor machine for compression. The compressed gas from the make-up compressor is sent to the discharge of the recycle compressor to join the recycle gas, to be used as cold quench and recycle gas for each reaction section train. The Process Flow diagram (PFD) of Feed Reaction section is shown in Figure 4.3

The pumped feed is mixed with make-up/recycle hydrogen stream, and is preheated in the reactor feed/effluent exchangers. The hydrogen stream is under flow control for each reaction section train and ensures an adequate hydrogen partial pressure as well as adequate H_2 over HydroCarbon (HC) ratio at the entry of the two reaction section trains. The reactor feed is then brought up to the required temperature in the reactor heater, fired primarily with fuel gas. The reactor inlet temperature is controlled by acting on the fuel oil/ fuel gas burners.

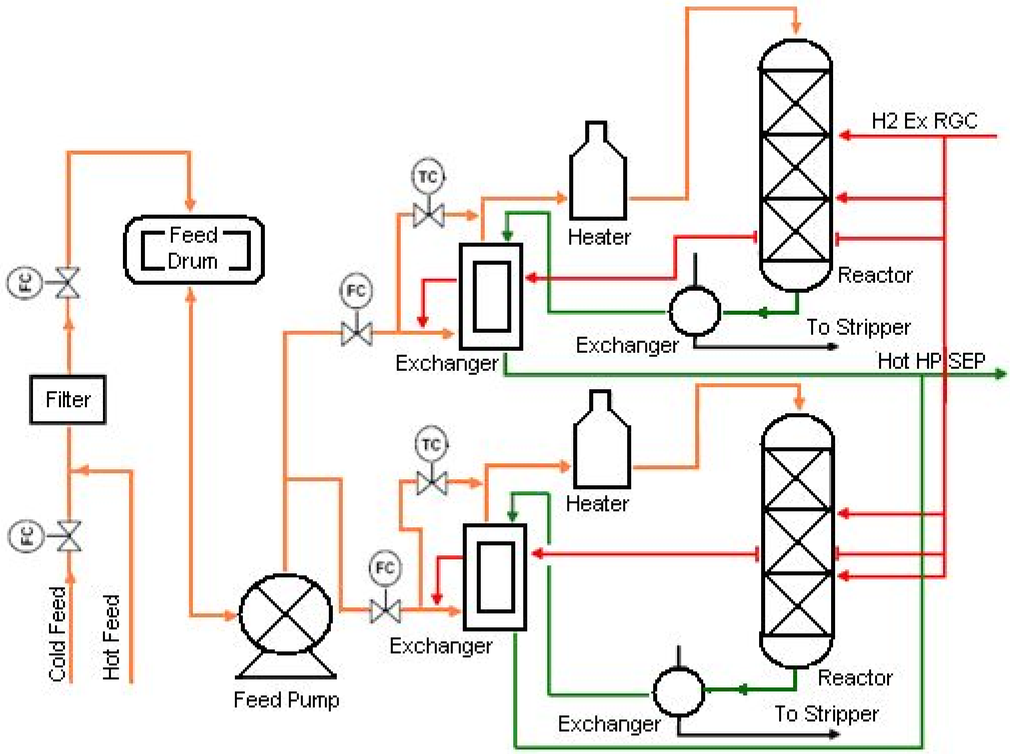


Figure 4.3 Feed – Reaction Schematic Flow Diagram

The fluid is routed to the reactor, which operates down flow and includes three beds in order to limit the temperature increase inside the reactor. Cold quenches are injected at the inter-bed section under flow control reset by catalyst bed inlet temperature.

The reactor effluent is used to exchange heat with the stripper feed in the stripper feed preheater under temperature control of the stripper feed. The effluent outlet of this exchanger is then used to preheat the reactor feed. The cooled effluent of each train are mixed together and collected in the hot HP (High Pressure) Separator.

The vapor phase from the Hot HP separator is cooled and partly condensed by the reactor effluent air cooler. The main part of the liquid phase of the hot HP separator is routed to the hot MP (medium pressure) separator.

The air cooler effluent is collected in the cold HP separator where three phases are separated gas, hydrocarbon liquid and sour water. The sour water containing ammonium salts is partially recycled to the wash water drum and the remaining part is sent to the sour water-stripping unit. The hydrocarbon is sent to the cold MP separator under level control of cold HP separator.

The gas phase of cold HP separator is partly sent to the HP amine absorber where H_2S is removed. The other part bypasses the absorber and is directly routed to the recycle compressor KO drum. This bypass allow for control of H2S concentration in the recycle gas, which should be maintained within the range of 0.1 to 1.0 mol. Percent.

Pressure control in the reaction section is achieved at the recycle compressor Knock Out Drum (KOD) by action on the make-up compressor spillback.

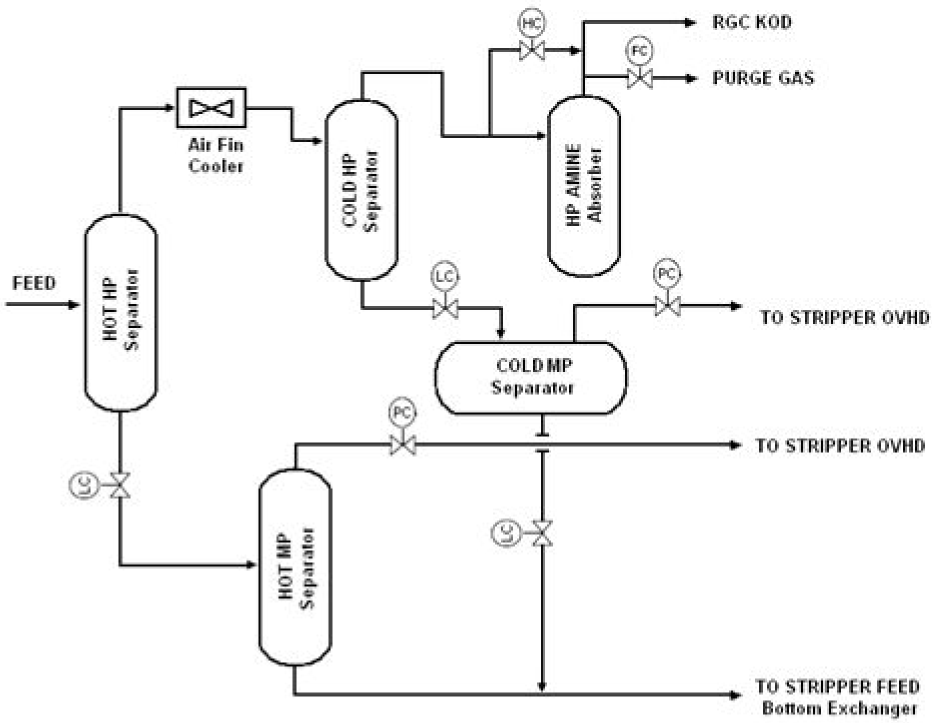


Figure 4.4 Separation Section Schematic flow Diagram

4.1.2 MP separation / Stripper Section

The vapor phases from hot MP separator and cold MP separator is sent to the stripper overhead line under pressure control. The sour water entrained by the HC liquid from the cold HP separator is withdrawn at the boot of the cold MP separator under interface level control, and routed to the sour water stripping unit. The hydrocarbon liquid from the cold MP separator liquid and the hot MP separator liquid is joined and routed to the stripper section. The required stripper inlet temperature is obtained by heat exchanger in between stripper feed streams and the reactor effluent in the stripper feed preheaters.

Medium pressure superheated stream is injected under flow control at the bottom of the stripper in order to obtain a Hydrotreated Diesel with the correct flash point and free of H_2S.

Light ends and H_2S gather at the top of the stripper and are mixed with the vapor from the cold and the hot MP separator. These vapors are condensed first in the stripper air condenser and then in the stripper trim condenser.

The liquid hydrocarbon, water, and vapor phase are separated in the stripper reflux drum. Water is removed from boot under interface level control. The liquid hydrocarbon is pumped partly as reflux and partly as stabilizer feed after preheating. The vapor phase flows to the LP amine absorber section.

The stripper bottom product is pumped by the Hydrotreated Diesel pump and exchange heat against the stripper feed. The Hydrotreated Diesel stream is then cooled down by generating LP steam in the steam generator. The dry Hydrotreated Diesel product is finally sent under stripper bottom level control to battery limit.

4.1.3 Stabilizer Section

The function of this column is to remove H_2S present in the stripper overhead liquid and to adjust the butane content in order to minimize the RVP specifications of the stabilized naphtha product. The stabilizer overhead are mixed with the condensates recovered in the off gas compression section and are partially condensed in the stabilizer air cooler.

The liquid hydrocarbon, water and vapor phase are separated in the stabilizer reflux drum. The stabilizer reflux pump refluxes the total liquid hydrocarbon. The vapor phase flows to the LP amine absorber section under column pressure control.

The stabilizer bottom product is cooled in the stabilizer feed/bottom exchanger then in the stabilized naphtha water cooler before finally routed to storage under cascade level-flow control.

4.1.4 LP Amine Absorber/ OFF gas compression Section

Lean amine (40 wt % MDEA solution) from the amine regeneration unit is routed under level control to the lean amine surge drum and is then pumped by the booster pump partially to the lean amine heater. As lean amine is used in two different absorbers (HP amine absorber and LP amine absorber), an individual differential temperature control is provided for each lean amine stream.

The sour vapor from the stripper is combined with the sour vapor from the stabilizer, off gas from HCU, OHCU, and HGU/CDU/VDU; and flow to the LP amine absorber KO drum. The lean amine is fed at the top of the absorber under flow control. Antifoaming is injected in the lean amine stream at the inlet of the column.

The rich amine from the HP amine absorber is flashed in the LP amine absorber bottom in order to reduce the quantity of dissolved hydrocarbons carried in the rich amine stream to the amine regeneration unit. Under level control the rich amine is withdrawn from the bottom and routed to the amine regeneration unit. The treated off gas at top of the column is sent to the off gas compressor KOD and routed to the Fuel gas Header.

4.2 Chemical Reactions

The chemical reactions involved in the hydrotreating process are of two types:

a) The **desirable reactions:** i.e. the reactions which concur to the purpose of the process. In DHDT following are the Desirable Reactions:

   - Elimination of sulfur.
   - Elimination of nitrogen and oxygen.
   - Elimination of metals.
   - Saturation of olefins and diolefins.

b) The **undesirable reactions:** these are the reactions which result in a loss of valuable components of the feed or a decrease of catalyst activity.

4.2.1 Desirable Reactions

4.2.1.1 Desulfurization reactions

Sulfur removal occurs via the conversion to H2S of the organic sulfur compounds present in the feedstock. This conversion is sometimes referred to as desulfurization or hydro-desulfurization (HDS). Sulfur is found throughout the boiling range of petroleum fractions in the form of many hundreds of different organic sulfur compounds which, in the naphtha to atmospheric residue range, can all be classified as belonging to one of the following six sulfur types: mercaptans, sulfides, di-sulfides, thiophenes, benzo-thiophenes, and di-benzo-thiophenes.

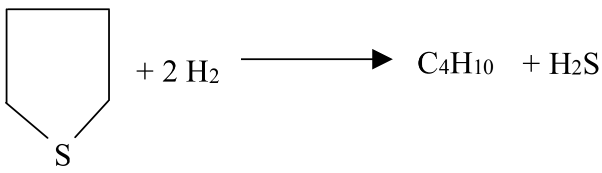
- Mercaptans, sulfides and disulfides react easily leading to the corresponding saturated or aromatic compounds.
- Sulfur combined into cycles of aromatic structure, like thiophene, is more difficult to eliminate.
- These reactions are exothermic; they produce hydrogen sulfide and consume hydrogen.

Examples

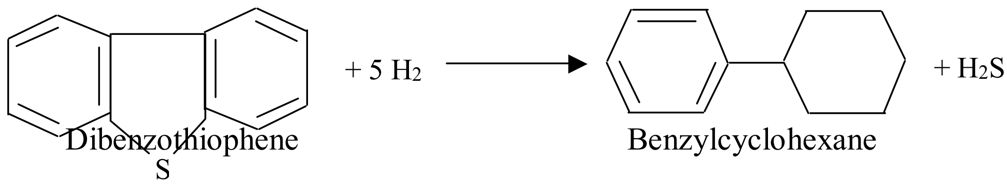
- Mercaptans

  $R - SH + H_2 \rightarrow R - H + H_2S$
- Sulfides

$R\text{-}S\text{-}R + 2\,H_2 \rightarrow 2\,R\text{-}H + H_2S$

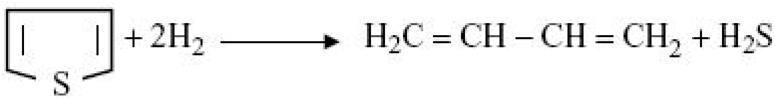


- Thiophene



4.2.1.1.1 Desulfurizatoin mechanism

a) Sulfur removal



b) Olefin saturation

$$H_2C = CH\text{-}CH = CH_2 + 2H_2 \rightarrow H_3C\text{-}CH_2\text{-}CH_2\text{-}CH_3$$

The ranking of the six sulfur types ranked on the basis of ease of removal: Easiest to remove → Hardest to remove

Mercaptans → Sulfides → Disulfides → Thiophenes → Benzo-thiophenes → Dibenzo-thiophenes

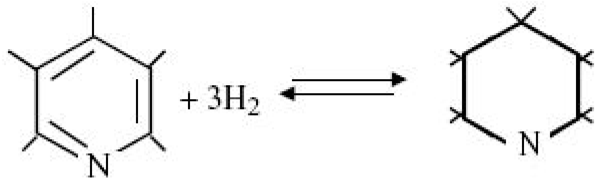
4.2.1.2 Denitrification reactions

Nitrogen is mostly found in the heaviest end of petroleum fractions in five- and six membered aromatic ring structures. Both the molecular complexity and quantity of nitrogen containing molecules increases with increasing boiling range, making them more difficult to remove. The denitrogenation reaction proceeds through a different path from that of desulfurization. While in desulfurization the sulfur is removed first and the olefin created as an intermediate is saturated, in denitrogenation, the aromatic is saturated first and then the nitrogen is removed.

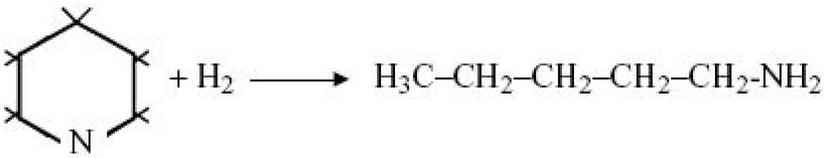
- The rate is lower than for the desulfurization reactions.
- These reactions lead to ammonia formation.
- These reactions are also exothermic.

4.2.1.2.1 Denitrogenation mechanism

a) Aromatic hydrogenation



b) Hydrogenolysis



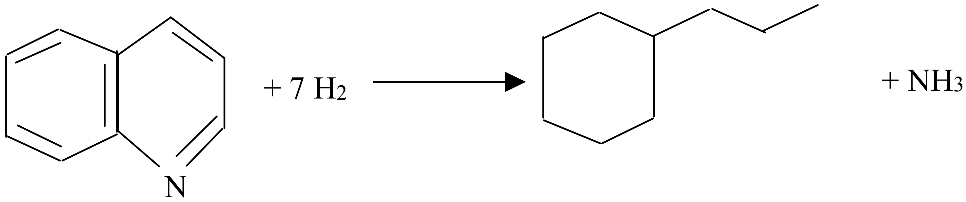
c) Denitrogenation

H3C-CH2-CH2-CH2-CH2-NH2 + H2 → H3C-CH2-CH2-CH2-CH3 + NH3

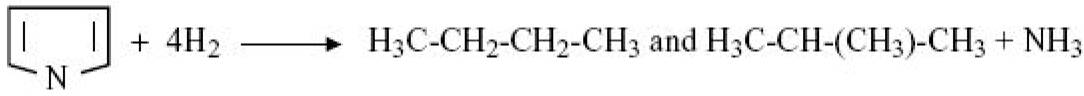
Some typical examples of denitrogenation reactions are shown below.

a) Amine

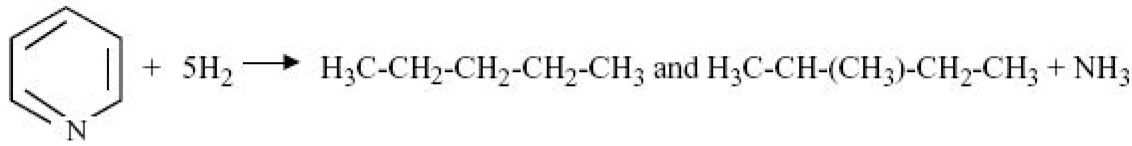
H3C-CH2-CH2-CH2-NH2 + H2 → H3C-CH2-CH2-CH3 + NH3



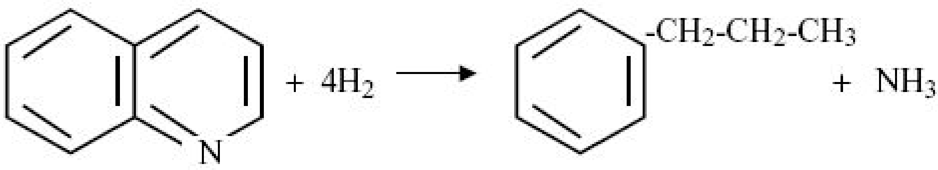
b) Pyrrole



c) Pyridine



d) Quinoline

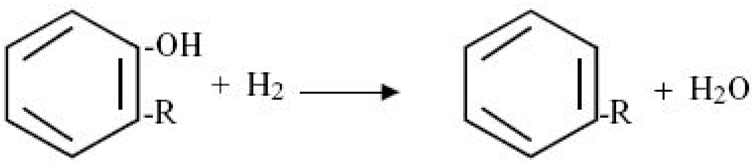


Nitrogen is more difficult to remove and consumes more hydrogen than sulfur removal because the reaction mechanism involves aromatic ring saturation prior to nitrogen removal. In desulfurization, the sulfur is less often associated with aromatic rings and when it is, the sulfur can be removed without ring saturation. Hydrogenation of associated aromatic ring structures is very dependent on hydrogen partial pressure and is the rate limiting reaction step in nitrogen removal. Nitrogen removal is therefore dependent on H2 partial pressure.

4.2.1.2 Hydrogenation of oxygenated compounds

Most petroleum crudes contain low levels of oxygen. The oxygen-containing compounds are converted, by hydrogenation, to the corresponding hydrocarbon and water. The lower molecular weight compounds are easily hydrogenated, however, the higher molecular weight compounds—e.g. furans—can be difficult to remove.

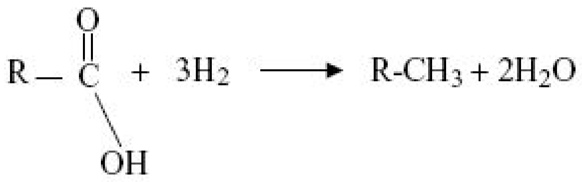
a) Phenols



b) Oxygenates

$(CH_3)_3\text{-C-O-}CH_3 + 2H_2 \rightarrow (CH_3)_3\text{-CH} + H_2O + CH_4$

c) Naphthenic Acids



4.2.1.3 Hydrogenation of olefinic compounds

Olefins are not found in petroleum, but are formed when processed in thermal or catalytic units. In general, fractions containing olefins are unstable and thus must be protected from contact with oxygen prior to hydrotreating to prevent the formation of polymer gums. That is especially true for feedstocks derived from thermal cracking operations

- These reactions are highly exothermic. Olefins and diolefins are converted to saturated compounds.
- The hydrogenation rate of olefins and diolefins is faster than the hydrodesulfurization rate.

Examples

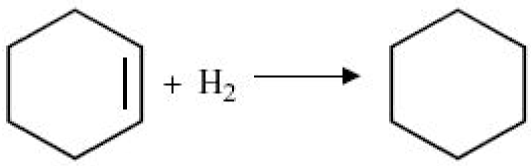
a) Olefins

$R - CH = CH_2 + H_2 \rightarrow R - CH_2 - CH_3$

b) Hexene

$C_6H_{12} + H_2 \rightarrow C_6H_{14}$

c) Cyclohexene



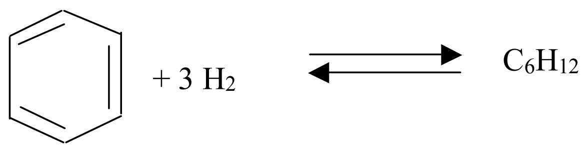
4.2.1.4 Hydrogenation of aromatic compounds

Saturation of aromatics is desirable for improvement of the properties of petroleum products e.g. smoke point, diesel index, etc. The aromatics found in the naphtha to gas oil boiling range are present as one, two, and three ring aromatics—often referred to as mono, di, and tri aromatics.

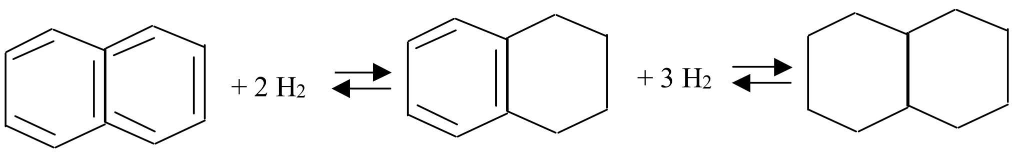
- The hydrogenation of aromatics has thermodynamic limitations. These reactions are exothermic and the number of molecules decreases. So they are favored by low temperature and high pressure.
- For a given pressure, when the temperature increases the hydrogenation rate increases first, to reach a maximum, and then decreases as the temperature continues to increase.
- For a given temperature, the hydrogenation rate increases rapidly with the pressure.

Examples:

a) Benzene

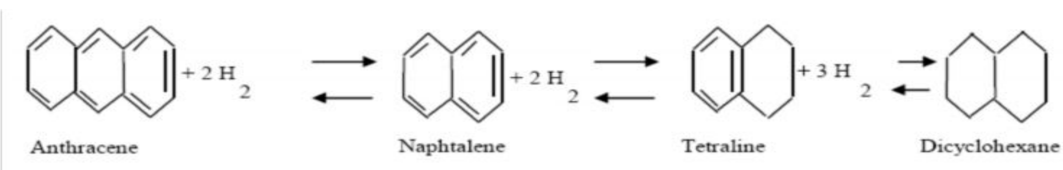


b) Naphthalene



Naphthalene Tetraline Dicyclohexane

c) Tri Aromatic saturation:



4.2.1.6 Demetalization

The organometal compounds (containing As, Pb, Cu, Ni, Va...) are cracked and the metals are trapped on the catalyst.

4.2.2 Undesirable reactions

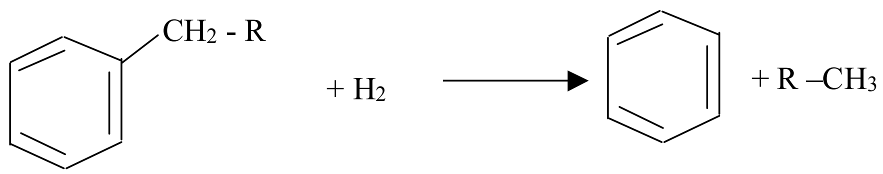
The maximum product yield is achieved by limiting the undesirable reactions.

4.2.2.1 Hydrocracking

It is an undesirable reaction which has to be minimized, because it consumes hydrogen, reduces the product yield and the hydrogen purity of the recycle gas.
It is limited by the selection of catalysts with low hydrocracking capacity and working at low temperature.
Hydrocracking increases with the temperature (for kinetical reasons).

Example:

- $R\text{-}CH_2\text{-}CH_2\text{-}R'+H_2 \rightarrow R\text{-}CH_3 + R'\text{-}CH_3$



4.2.2.2 Coking

Under the design operating conditions, heavy molecules are adsorbed on the acidic sites of the catalyst, may be condensed and progressively polymerize on the catalyst and form coke. The coke deposit is the main cause of catalyst activity reduction.

4.3 Process Variables

The unit is designed to process different feedstocks and to obtain the corresponding products in quality and quantity, during the run. To achieve these performances, different operating parameters have to be considered.

The process variables are:

- Temperature
- Liquid hourly space velocity
- Hydrogen partial pressure
- Hydrogen/hydrocarbons ratio
- Feed quality and Rate

The effect on the unit performance by each of independent variable is discussed below

4.3.1 Temperatures (WABT: Weight Average Bed Temperature)

For a given catalyst, a given feed composition and a given LHSV a minimum temperature exists, suitable for obtaining the expected results. This temperature is the one to be adjusted at the inlet to the reactor beds. In case of a new or regenerated catalyst this temperature is called “Start Of Run”. With the other parameters constant, it will be necessary to progressively increase the inlet temperature during a run to balance the catalyst deactivation.

Hydrotreating reactions are exothermic. The temperature rise in the reactor is dependent on the relative amount of sulfur and unsaturated compounds in the feedstock.

However, the furnace outlet temperature (or reactor inlet temperature) is not necessarily the correct approach to study the effect of reaction temperature on the catalyst. For this purpose another representative of temperature measurement, the **Weight Average Bed Temperature (WABT)** is considered.

In case of multiple beds and/or reactors, the WABT is defined as follows:

$$\text{WABT} = \frac{(\text{wt of catalyst } R_1) \times \text{WAT}_1 + (\text{wt of catalyst } R_2) \times \text{WAT}_2 + \ldots + (\text{wt of catalyst } R_i) \times \text{WAT}_i}{\text{Total wt of catalyst}}$$

WAT_1,…, WAT_i	Are the Weight Average Temperatures of catalyst bed of reactors R_1, …, R_i (arithmetic average of all the bed thermocouples including inlet and outlet).
(wt of catalyst R_1, …, R_i)	Are the weight of catalyst in reactors R_1, …, R_i.

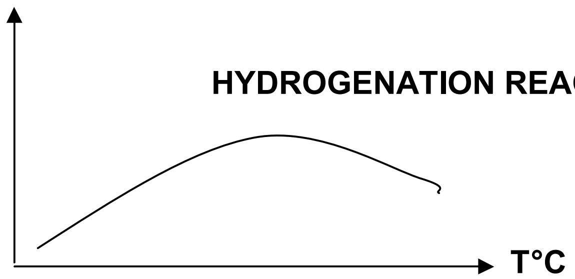
4.3.1.1 Impact of WABT on reaction:

Hydrotreating reactions are favored by temperature increase. However, this increase of temperature increases the hydrocracking reaction and coke deposit on the catalyst as well. The chosen range of temperature is a compromise between long catalyst life, an optimal quantity of catalyst and a hydrotreatment as complete as possible.

An increase of temperature (i.e. WABT) has the following effects, assuming the space velocity (i.e. the feed rate) and feed characteristics stay unchanged:

- Increase catalyst activity (desulfurization, denitrogenation, hydrocracking…).
- Decrease the recycle gas purity.
- Increase the coke deposit.

A temperature increase favors all the hydrogenation reactions: (of both olefins and aromatics) up to maximum, as shown here under:



For feedstock with olefins, the reactor inlet temperature is adjusted at the value required for the initiation of the olefins hydrogenation. This value is a function of the design feed.

At constant WABT, the aging of the catalyst would result in a slight but steady loss of activity. A slight increase of temperature (WABT) through the life of the catalyst makes up for this activity loss.

4.3.2 Liquid Hourly Space Velocity (LHSV)

The space velocity is the amount of liquid feed, expressed in volume that is processed in one hour, divided by the amount of catalyst, expressed in volume. Volume of feed and catalyst must be expressed with the same unit.

$$\text{Liquid Hourly Space Velocity: LHSV} = \frac{\text{Volume of feed at 15°C (per hour)}}{\text{Volume of catalyst}}$$

The reverse of the liquid hourly space velocity i.e. $(LHSV)^{-1}$ is linked with the residence time of the feed in the reactor. The space velocity then affects directly the kinetics of the hydrotreating reactions.

Reactor process conditions, while affecting hydrotreating reaction rates and degree of completion, also affect catalyst life and activity by controlling the rate of coke laydown on the catalyst.

Reduction of reactor pressure or recycle gas rate below design values may result in premature catalyst deactivation. A combination of high temperature and inadequate hydrogen partial pressure is detrimental to catalyst activity.

It is important that the level of coke laydown be controlled by good operation to secure prolonged catalyst activity. Continuous operation under adverse conditions should be avoided.

When the catalyst activity is down, it will not be possible to obtain the degree of reaction at the end of run temperature, or the pressure drop through the reactors becomes too high to get the desired recycle gas rate.

As the quantity of catalyst is constant, the only way to modify the LHSV is by varying the feed capacity which will change the space velocity and the reactor inlet temperature must be changed to maintain the same severity.
Both High and Lower LHSVs are undesirable, because

- Higher LHSV will lead to higher WABTs, faster coking which in turn will lead to reduced cycle length.
- Lower LHSV will lead to lower pressure drops which will lead to liquid maldistribution.

4.3.3 Hydrogen Partial Pressure

An increase in hydrogen partial pressure (ppH_2) favors the hydrogenation reactions and reduces polymerization reactions and coke deposit thus favours catalyst life and may result in better catalyst activity. Reduction in operating pressure below the design level will have a negative effect on the activity of catalyst and will accelerate catalyst deactivation due to coke formation.

The ppH2 mainly results from four operating parameters:

- The hydrogen make-up flow rate / the purge flow rate (these two being intimately linked).
- The hydrogen recycle gas purity.
- The hydrogen recycle flow rate.
- Operating pressure.

Reduction in hydrogen partial pressure in recycle gas than design will result in inadequate availability of hydrogen at reaction sides and will adversely affect the desirable reactions.

Higher hydrogen partial pressure in recycle gas is not of much consequence except for the case where the catalyst is exposed to pure hydrogen at high temperature where leaching of catalyst will take place.

4.3.4 Hydrogen Recycle Ratio

The H_2/HC ratio, at the fist reactor inlet, is the ratio of pure hydrogen in the recycle gas (make-up excluded) in Sm^3/h to the fresh feed flowrate (m^3/h at 15°C).

$$\frac{H_2}{HC} = \frac{\text{Pure hydrogen (sm}^3\text{ / hour) in recycle}}{\text{Fresh feed flow rate (m}^3\text{ / hour) at 15°C}}$$

The amount of hydrogen supplied in the reaction includes the hydrogen that will be consumed by chemical reaction and an excess of hydrogen necessary to obtain sufficient hydrogen partial pressure.

Hydrogen is consumed in the reactions occurring in the hydrotreating reactors. A greater degree of completion of these reactions is achieved with higher hydrogen recycle rates.

Maintaining proper hydrogen recycle gas purity and recycle gas to feed ratios is essential for suppressing the formation of heavy condensed hydrocarbons which would subsequently deposit as coke on the catalyst.

There is a close relationship between the hydrogen recycle ratio and the hydrogen partial pressure.

At a given feed flowrate and composition hydrogenation depends on the quantity of recycle hydrogen through the reactor. A high value of this ratio has a favorable influence on the hydrogenation (higher hydrogen partial pressure) and so on the cycle length.

This ratio is maintained relatively higher to the design value due to following reasons:

- Excess hydrogen ensures that the reactions are carried to the completion.
- Absorbs some of the heat of reaction thus minimizing the catalyst bed temperature.
- Minimizes furnace & feed exchangers tubewall temperatures by increased flow.

4.3.5 Feed Quality and Rate

An increase in feed rate will require higher reactor temperature to achieve the desired desulphurization, as well as higher recycle gas to maintain constant ration of H_2 to HC. Reduced feed rate will lead to bad flow distribution through the catalyst, such that higher temperature will be required to obtain good product quality. In order to minimize effect of variations in feed rate, reduce reactor temperature before reducing feed rate & conversely increase feed rate before increasing temperature.

Heavier feed will increase coke deposition due to more precursors & increase pressure drop due to increased quantities of metals.

Lighter feed of the same boiling range is an indication of higher unsaturates. This type of feed will result in increased H_2 consumption and higher temperature rise across catalytic beds. It also contains material that easily condenses to form coke in reactors and other equipments.

4.4 Action of process variables on reactions

The action of process variables on the chemical reactions involved in the hydrodesulphurization process are:

a) Hydrogenation of aromatics

As these reactions are strongly exothermic, they have thermodynamic limitations.
For a given pressure, when the operating temperature increases, the thermodynamic equilibrium is displaced towards the aromatic, meaning that the hydrogenation is limited.

For a given temperature, the theoretical maximum hydrogenation rate increases rapidly with the operating pressure.

b) Hydrogenation of olefins and diolefins

With increasing in operating pressure, the hydrogenation of olefins and diolefins increases faster than the hydrodesulfurization rate.

c) Cracking

This is an undesirable reaction which is to be minimized, because it consumes hydrogen, reduces the product yield and reduces the hydrogen purity of the recycle gas. It is limited by the selection of catalysts with low cracking capacity and operating at low temperature. Cracking increases with the operating temperature.

d) Hydrogenation of nitrogen compounds

These reactions have common features with the hydrogenation of aromatics:

- Hydrogenation of aromatic cycles
- Hydrogenation of C-N bond

e) Coking

Coking is limited by operating at the lower temperature possible, with a sufficient hydrogen partial pressure and adequate liquid hourly space velocity.

4.5 Summary table

The effects of variables on the process reactions are summarized in Table 4.1

Table 4.1 Action of Variables on Process Reactions

VARIABLE/ REACTIONS	HYDROGEN PARTIAL PRESSURE	OPERATING TEMPERATURE	LIQUID HOURLY SPACE VELOCITY
DESULFURIZATION	↗	↗	↘
HYDROGENATION OF OLEFINS AND AROMATICS	↗	↗→↘	↘
CRACKING	↘	↗	↘
COKING	↘	↗	↘
DENITRIFICATION	↗	↗	↘

Chapter 5

Proposed Control Algorithm and Results

The objective of APC is to maximize the Plant throughput and optimize the Fuel oil viscosity subject to quality and other limiting constraints. To achieve this, the APC controller manipulates the independent process variables (temperatures, pressures, flows, etc.) to push the unit to the optimum set of operating limits without compromising unit safety and reliability.

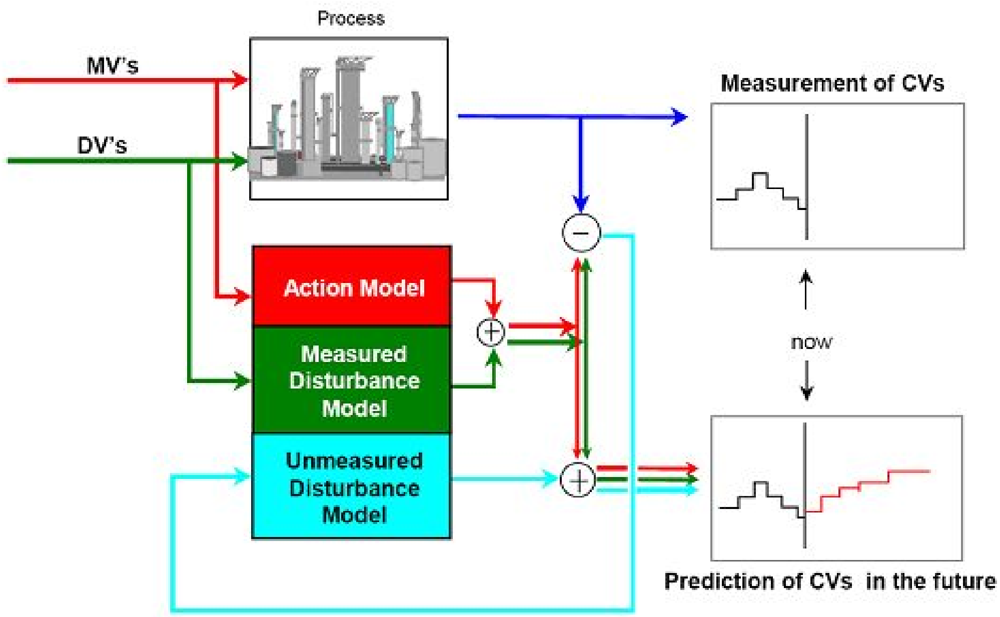


Figure 5.1 Input and output variables around a chemical process

The Multivariable Optimizing Controller implementation stabilizes the process operations, provides tighter control to operating targets and makes it possible to operate closer to key constraints. Using model predictive control, the Multivariable Optimizing Controller reduces the variability of the process. This reduction in process variability permits operating the unit closer to constraints. As a result, unit profitability is improved. A linear program optimizer and a predictive dynamic control algorithm coordinate the movement of the manipulated variables. The predictive control algorithm uses dynamic models relating the controlled variables to the manipulated variables using the models generated during step testing of the unit and subsequent model identification and analysis.

5.1. DHDT Multivariable Optimizing Controller

The objective of the controller is to provide control of Diesel quality, minimization of power loss by recovering more power and maximization of throughput while operating within all constraints

From the process control perspective the plant can be divided into these independent sections

a) DHDT Reactor

b) Diesel Stripper Column

c) Miscellaneous sections

5.1.1. The Objectives APC Reactor Controller are:

a) Controlling Reactor Temperatures.

b) Controlling Reactor Outlet temperature deviations.

5.1.2. The Objectives APC Stripper Controller are:

a) Minimize Diesel Flash Point.

b) Controlling Stripping Steam Ratio.

5.1.3. The Objectives APC Controller for Miscellaneous section are:

a) Maximize Power recovery.

b) Maximize DHDT plant throughput.

5.2. DHDT Reactor Controller

5.2.1. Present DCS Strategy

Presently the Reactor temperatures are controlled using the Reactor inlet temperature and hydrogen quenches. The quenches are operated looking at the bed temperature. WABT is also monitored to have optimum and uniform temperature across the bed.

5.2.2. Proposed APC Strategy:

1. Having reactor inlet temperature and reactor quenches as MV, the bed temperature will be kept under control.
2. Maximum temperature of individual bed will be kept under control using the quenches.
3. DCU feed ratio and feed flows will be taken as a disturbance variable. They will be used as feed forward input for predicting the bed temperature.
4. WABT will be controlled so as to get the optimum and uniform bed temperature.

The controller structure is depicted in the table

Variables	Present Strategy	Proposed Strategy
Controlled Variables	a) Individual Bed Max Temperature b) Individual WABT	a) Individual Bed Max Temperature b) Individual WABT
Manipulated Variables	a) Reactor Inlet Temperature b) Hydrogen Quenches	a) Reactor Inlet Temperature b) Hydrogen Quenches
Disturbance Variables		a) Feed Flow b) DCU Feed Ratio

Feed flow is selected as a disturbance variable as it has a direct effect on the reactor temperature and system pressure. The variation in Feed flow is mainly due to feed coming from DCU and also the unsaturate in the feed from DCU is more. With increase in DCU feed, the temperature across the bed will shoot up and subsequently will increase the hydrogen requirement. As the consumption increases, the system pressure drops. Therefore to have a better control on the system pressure the Feed flow particularly DCU feed is to be monitored closely to give a feed forward action to pressure control as well as reactor temperature control.

5.3.Diesel Stripper Controller

5.3.1 Present DCS Strategy:

Stripper top temperature and stripping is manipulated in the stripper to ensure the lighter stripping, proper flash point and required diesel 5% distillation point.

5.3.2 Proposed APC Strategy:

1. Feed flow will be treated as disturbance so as to give the feed forward effect to the controller.
2. The stripping steam and the top temperature will be manipulated to have a better control on the column temperature profile.
3. Column Pressure Compensated Temperature (PCT) will also be monitored to ensure proper composition at the TOP & Bottom.
4. Diesel 5% will be predicted by Quality Estimator and will be controlled accordingly.
5. Main function of the controller will be maximization of diesel recovery by minimizing Diesel 5% and flashpoint.
6. Proper stripping steam ratio will also be controlled by manipulating the stripping steam so that the effective lighter stripping takes place.

The controller structure is depicted below in the table

Variables	Present Strategy	Proposed Strategy
Controlled Variables	a) Stripper Bottom Temperature b) Diesel Flash Point	a) Stripper Column top PCT b) Stripper Bottom Temperature c) Diesel 5% distillation point predicted by Quality Estimator d) Diesel Flash Point predicted by Quality Estimator e) Stripping steam ratio.
Manipulated	a) Stripper Feed Temperature	a) Stripper Feed Temperature

Variables	b) Stripper Top Temperature c) Stripping Steam to Stripper	b) Stripper Top Temperature c) Stripping Steam to Stripper
Disturbance Variables		a) Feed Flow b) Stripper Feed Flow

The composition of the hydrocarbons on top can normally be inferred from the temperature and pressure on top, which is being done in the present strategy but when the column pressure changes, controlling the temperature alone does not directly control the composition, since it is also affected by pressure. Stripper top PCT thus provides the correction to avoid composition drift due to changing column pressure. Also in the present strategy the Quality measurement i.e. Lab analysis of product is done only twice or thrice in 24 Hours. This discontinuity in quality measurement sometimes ask for costly reprocessing or calls for altering plant conditions to make up for what has already been produced so that, overall, the product meets quality specifications. In proposed strategy Quality Estimators are used to bridge the time gap between quality measurements by instantaneous real-time inferential measurement of quality. The value predicted by an estimator is used to close a quality control loop.

5.4 APC Controller Working

The APC controller working is based on multivariable model predictive control philosophy. Since reactions are pretty fast and the column behavior is slow, the controller has to predict the process behavior for future few hours about 2-3 hours. The APC control strategy is:

1. APC fetches the current data from the DCS
2. Based on all the MV and DV changes in the past, the controller predicts the future changes in the CVs for the next about 6 hours.
3. The current CV values obtained from DCS are compared with the current CV prediction. Any deviations from the predictions are considered to be due to the unmeasured disturbances. The future CV trends are compensated for unmeasured disturbances. However, as the behavior of the unmeasured disturbances is not

known in the future the prediction corrections due to unmeasured disturbances are very small. It is assumed that there will not be any unmeasured disturbances in future.

4. Based on all the high-low MV and CV constraints and MV move sizes specified by the DCS-operator and the tuning parameters in controller, APC calculates a series of MV moves for about 2-3 hours in future so as to honor all the constraints specified. If APC is in optimization mode, then at each control interval multivariable optimizing controller also plans to optimize the process in its future plan.
5. The first move in the ‘move plan’ calculated by the multivariable optimizing controller is downloaded as MV values
6. The procedure is repeated at every control interval.

5.5 Results

Multi-Variable Control allows for improved stability of plant control and significant reductions in operation costs compared with traditional control approach. However, the key to the success of MVC depends on the selection of appropriate Control Variables, Manipulation Variables and Disturbance Variables and on the identification of an accurate process model. As for the selection of CVs, MVs and DVs, each CV should not have a correlation to each other and MVs and DVs should be independent variables. The model gain matrix between CVs and MVs & DVs resulted from the step response of the plant is shown in Table 5.1a,b,c. On the horizontal axis are the CVs while the vertical axis contains the MVs and DVs.

Table 5.1a shows the gain between CVs and MVs & DVs of the Diesel Stripper Controller selected during the controller design. Table 5.1a also shows that none of the selected MV or DV is independent variable.

Table 5.1a Model Gain Matrix for Diesel Stripper Controller

DESCRIPTION	DIESEL FLASH POINT	STRIPPER TOP TEMP PCT	STR BTM	STRIPPING STEAM RATIO	STRIPPER REFLUX RATIO
R-01 BED 1 O/L QUENCH	0.0	0.0	0.0	0.0	0.0
R-01 BED 2 O/L QUENCH	0.0	0.0	0.0	0.0	0.0
R-02 BED 1 O/L	0.0	0.0	0.0	0.0	0.0

QUENCH					
R-02 BED 2 O/L QUENCH	0.0	0.0	0.0	0.0	0.0
R-01 RIT	0.0	0.0	0.0	0.0	0.0
R-02 RIT	0.0	0.0	0.0	0.0	0.0
MUG 3RD STG KICK BACK	0.0	0.0	0.0	0.0	0.0
DHDT THRUPUT	0.0	0.0	0.0	0.0	0.0
DCU FEED RATIO	0.0	0.0	0.0	0.0	0.0
STR FEED EX E-003	0.005433	0.023621	0.40285	0.0	0.0
STR FEED EX E-004	0.005433	0.023621	0.40285	0.0	0.0
STR STM TO STR	0.000901	0.0	-0.000631	0.002534	
STR TOP TEMP	0.443647	1.021	0.05128	0.0	-0.00161
STRIPPER FEED	0.426979	0.01485	0.02971	-0.04216	-0.003531

Table 5.1b and 5.1c shows the gain between CVs of Reactor 1 & Reactor 2 and MVs and DVs of the Multivariable Optimizing Controller respectively. As shown in the Tables the selection of variables made during the Reactor Controller design step was right as the Reactor 1 Controlled variables are only related with the Reactor 1 Quenches (R-01 BED 1 O/L QNCH and R-02 BED 1 O/L QNCH), Reactor 1 Inlet Temperature (R-01 RIT) and DCU feed ratio shown in Table 5.1b.

Table 5.1b Model Gain Matrix for Reactor 1 Controller

DESCRIPTION	R1 BED 1 ROT	R-1 BED 2 ROT	R-1 BED3 ROT	R 1 WABT	R 1 BED2 TEMP Deviation
R-01 BED 1 O/L QNCH	0.0	-0.515842	-0.48227	-0.360327	-0.257921
R-01 BED 2 O/L QNCH	0.0	0.0	-0.535548	-0.176731	0.0
R-02 BED 1 O/L QNCH	0.0	0.0	0.0	0.0	0.0
R-02 BED 2 O/L QNCH	0.0	0.0	0.0	0.0	0.0
R-01 RIT	1.892387	3.083998	1.407	1.988775	0.595805
R-02 RIT	0.0	0.0	0.0	0.0	0.0
MUG 3RD STG KICK BACK	0.0	0.0	0.0	0.0	0.0
DHDT THRUPUT	0.0	0.0	0.0	0.0	0.0
DCU FEED RATIO	72.153152	63.378284	49.449421	53.301876	-4.387434
STR FEED EX E-003	0.0	0.0	0.0	0.0	0.0
STR FEED EX E-004	0.0	0.0	0.0	0.0	0.0

STR STM TO STR	0.0	0.0	0.0	0.0	0.0
STR TOP TEMP	0.0	0.0	0.0	0.0	0.0
STRIPPER FEED	0.0	0.0	0.0	0.0	0.0

Table 5.1c shows the gain between CVs of Reactor 2 and MVs and DVs of the Multivariable Optimizing Controller. Table 5.1c also shows the effect of DCU Feed on System Pressure. The negative gain shows that with increase in DCU feed system pressure decreases.

Table 5.1c Model Gain Matrix for Reactor 2 Controller and System Pressure

Descriptions	R2 BED 1 ROT	R2 BED 2 ROT	R2 BED 3 ROT	R2 WABT	R2 BED2 TEMP DEVIATION	SYSTEM PRESSURE
R-01 BED1 O/L QNCH	0.0	0.0	0.0	0.0	0.0	0.0
R-01 BED2 O/L QNCH	0.0	0.0	0.0	0.0	0.0	0.0
R-02 BED1 O/L QNCH	0.0	-0.21319	-0.209555	-0.234242	-0.106595	0.0
R-02 BED2 O/L QNCH	0.0	0.0	-0.399436	-0.263628	0.0	0.0
R-01 RIT	0.0	0.0	0.0	0.0	0.0	0.0
R-02 RIT	1.618644	1.582848	1.788781	2.297538	-0.017898	0.0
MUG 3RD STG KICK BACK	0.0	0.0	0.0	0.0	0.0	-0.672239
DHDT THRUPUT	0.0	0.0	0.0	0.0	0.0	0.0
DCU FEED RATIO	64.689064	55.537888	57.860088	79.351974	-4.575588	-15.6
STR FEED EX E-003	0.0	0.0	0.0	0.0	0.0	0.0
STR FEED EX E-004	0.0	0.0	0.0	0.0	0.0	0.0
STR STM TO STR	0.0	0.0	0.0	0.0	0.0	0.0
STR TOP	0.0	0.0	0.0	0.0	0.0	0.0
STRIPPER FEED	0.0	0.0	0.0	0.0	0.0	0.0

A comparison of process data collected before and after commissioning of Multivariable Optimizing Controller based on the CVs, MVs and DVs shown in the above Model Gain Matrix indicates a reduction in standard deviation for all quality variables. This data is provided in the table below.

Table 5.2 Lab Data for Diesel 5%, IBP and ΔT without and with Multivariable Optimizing Controller (MOC)

WITHOUT MOC			
JANUARY			
DATE	5%	IBP	ΔT (5%-IBP)
01.01.2008	186.000	157.0	29.0
02.01.2008	181.000	150.0	31.0
03.01.2008	176.000	153.0	23.0
04.01.2008	189.000	162.0	27.0
05.01.2008	180.000	148.0	32.0
06.01.2008	178.000	146.0	32.0
07.01.2008	174.000	147.0	27.0
08.01.2008	175.000	148.0	27.0
09.01.2008	170.000	143.0	27.0
10.01.2008	171.000	145.0	26.0
Average	178.000	149.9	28.1
S/D	6.146		
Range	165.708		
	190.292		

WITH MOC	
JULY	
DATE	5%
21.07.2008	178.00
22.07.2008	178.00
23.07.2008	175.00
24.07.2008	177.00
25.07.2008	179.00
26.07.2008	170.00
27.07.2008	172.00
28.07.2008	172.00
29.07.2008	172.00
30.07.2007	182.00
Average	175.50
S/D	3.89
Range	167.72
	183.28

5.6 Benefit Analysis

5.6.1 Areas to consider for Benefit Evaluation

1. Diesel Maximization by controlling Diesel Flash point.

5.6.2 Cost Data to be Considered

1. $Cost_{GAS}$ = 20298.35 RS/MT
2. $Cost_{Naphtha}$ = 29144.70 RS/MT
3. $Cost_{DIESEL}$ = 32720.60 RS/MT
4. Feed Incentive (CI) 232.71 RS/ MT
5. Unit On stream Hours: 8000 hrs.
6. Online factor = .95
7. Dollar Conversion rate = DR = Rs 45, shall remain firm for evaluation purposes

5.7 PROCEDURE FOR CALCULATION

1. Calculation of standard deviation:

As a first step, for calculating the Standard Deviation of the parameter(s), data collected during major process upsets shall be discarded. Then, the Standard

Deviation shall be calculated using the formula given in Microsoft Excel. Once the Standard Deviation has been calculated, the parameter values, which differ form, the average value by (± 2*Standard Deviation) shall be considered out-liers and shall be excluded from the data. Then a new Standard Deviation shall be calculated which can be designated as S or Sc as the case may be.

The amount that the process variable can be pushed towards constraints by use of Advance Process Control (MVOC) can be found by using the statistical formula, namely "the Same Limit Rule" [39].

$\Delta x = k^* (S-Sc)$

Where,

Δx = Distance/ gap the process variable can be moved towards constraint.

S = Std. Dev. of process variable without MOC in line

Sc = Std. Dev. of process variable with MOC in line

K = Factor depends on the frequency of violation of process variable

If the violations are allowed 20% of the time then k = 0.8

If the violations are allowed 10% of the time then k = 1.3

If the violations are allowed 5% of the time then k = 1.65

If the violations are allowed 2.3% of the time then k = 2.0

Allowing frequency of violation of most constraints within 5 % of the time the value k= 1.65 is considered for calculations

Therefore, $\Delta x = 1.65^* (S-Sc)$ (5.1)

Table 5.3 Shows the Lab Data for Diesel 5% and Calculated Standard Deviation, Average and Range

WITHOUT MOC		WITH MOC	
JANUARY		JULY	
DATE	5%	DATE	5%
01.01.2008	186.000	21.07.2008	178.00

02.01.2008	181.000	22.07.2008	178.00
03.01.2008	176.000	23.07.2008	175.00
04.01.2008	189.000	24.07.2008	177.00
05.01.2008	180.000	25.07.2008	179.00
06.01.2008	178.000	26.07.2008	170.00
07.01.2008	174.000	27.07.2008	172.00
08.01.2008	175.000	28.07.2008	172.00
09.01.2008	170.000	29.07.2008	172.00
10.01.2008	171.000	30.07.2007	182.00
Average	178.000	Average	175.50
S/D	6.146	S/D	3.8944
Range	165.708	Range	167.72
	190.292		183.28

Table 5.3 shows the Lab Data for Diesel 5% before the implementation MOC (data of January) and after the implementation of MOC (data for the month of July). The Average and Standard Deviation for the data is calculated as per the above procedure. As all the data values lie within the Range (average ± 2*Standard Deviation), no data point is considered as out-liers.

Hence,

$S = 6.146$ (5.2)

$S_c = 3.89$ (5.3)

Where,

S = Standard Deviation of Diesel 5% without MOC in line

S_c= Standard Deviation of Diesel 5% with MOC in line

2. Increase in Diesel 5% point = $\Delta x = (S-S_c)*1.65$ (5.4)

Where,

S - Standard deviation of Diesel 5% point without MOC in line

S_c- Standard deviation of Diesel 5% point with MOC in line

Putting the value in above Equation 4, from 2 and 3

$\Delta x = (6.146-3.8944)*1.65$

$\Delta x = 3.715$ (5.5)

3. Slope of average lab values of 5% point & IBP of Diesel, = M_{Diesel}

= ($\Delta T/\Delta\%V$)

Where,

ΔT= Temperature difference between the IBP and 5% of the Diesel without MOC in line.

$\Delta\%V$= % Change in Volume from IBP to 5%.

The Lab values of ΔT for the month of January (i.e. without MOC) are given in Table 6.2 with the average value of 28.1 ^{o}C.

As % Change in Volume from IBP to 5% is 5, therefore M_{Diesel} is:

M_{Diesel} = 28.1/5 = 5.62 (5.6)

4. %

Increase in Diesel production = $\Delta v = \Delta x$/ MDiesel (5.7)

Putting the values of Δx and M_{Diesel} from 5 and 6 respectively in the above equation 7

ΔV = 3.715/5.62 = 0. 661032028 (5.8)

5. Th

e Average Diesel flow rate without MOC in line = F = 311125.9029 Kg/hr. (5.9)

6. Benefits due to Diesel maximization

= ΔV/100*F*[CDiesel– CNaphtha]* Online Factor Rs /Hr (5.10)

Putting the values of F and ΔV from 8 and 9 in above Equation 10, the benefit is:

= . 661032028*311.125* [32720.6-29144.7]*.95/100

= 6986.62837 Rs/Hr = 155.2584 $/Hr (5.11)

7. Averag

e thru'put without MVPC in line = F_m= 341.125 MT/hr. (5.12)

8. Averag

e Diesel density without MVPC in line = d= .8438 kg/m^3 (5.13)

9. Number of Barrels consumed per year = F_b = (Fm/0.1589*d), bbl/Hr (5.14)

Putting the values of F_m and d from 12 and 13 respectively in 14 the F_b is

F_b = 341.125/ (0.1589*.8438) = 2544.193 bbl/Hr (5.15)

10. Benefits in cents/ barrel = 155.2584*100/2544.193 = 6.10 Cents/Barrels

5.8 Calculations Summary

1. Diesel maximization by controlling Diesel Flash Point

Δ X	= 3.715	C_{Diesel}	= Rs 32720.6
M_{diesel}	= 5.62	$C_{Naphtha}$	= Rs 29144.7
Δ V	= 0.661032028	On Stream	= 8000 Hrs
Average diesel flowrate F = 311125.9029 kg/hr		Online Factor	= 0.95

2. Benefit From Diesel max = 55893026.96 Rs/Annum = 1242067.266 $/Annum

3. Benefits in Cents /Barrel

Average Feed thru'put without MOC = 341125.0573 Kg/Hr

Average Feed Density without MOC = .8438 kg/m^3

Barrels per Hr = 2544.193 bbl/hr

Benefit Per Hr = 15525.84 cents/hr

4. Benefit in Cents / Barrel= 15525.84/ 2544.193 = 6.10 cents/ barrel

Chapter 6
Conclusion

In this thesis, the Design and Implementation of Multivariable Control System on Diesel Hydrotreater Process of IOCL Panipat Refinery is considered. Different control strategies were examined on each process and implementation results showed that the new control schemes results in smoother operation of plant, reducing impacts of process disturbances and providing consistent operation at optimal constraints. A comparison of process data collected before and after commissioning of Multivariable Optimizing Controller indicates a reduction in standard deviation from 6.146 for conventional control to 3.894 for the new implemented control strategy for Diesel Quality (5% Temperature). While operating within all constraints Multivariable Optimizing Controller provide a control on Diesel quality, minimization of power loss by recovering more power and maximization of throughput and thereby achieving an economic benefit of more than 6 cents per Barrel from the smoother operation of the plant.

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