DESIGN OF ADVANCED PROCESS CONTROL SYSTEM FOR DELAYED COKER UNIT

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ABSTRACT

DESIGN OF ADVANCED PROCESS CONTROL SYSTEM FOR DELAYED COKER UNIT

It is essential for refineries to optimize the upgrading vacuum residue (VR) processes due to reducing of conventional light crude oil resources and increasing of fuel global demands. Delayed coking is a thermal cracking process used in refineries to upgrade and convert vacuum residuum into liquid and gas product streams including Light Coker Gas Oil (LCGO), Heavy Coker Gas Oil (HCGO), Sour Liquefied Petroleum Gas (LPG), Sour Coker Product Gas, Stabilized Naphtha and Petroleum Coke as a solid concentrated carbon material. Delayed coking is a semi-batch process where one or more pairs of coke drums are used for the thermal cracking and coking process. Simultaneously in each pair of coke drums, the feed stream is switched between two drums and one drum is online for the coking process while the other drum is offline undergoing decoking. The switching of the coke drums severely destabilizes the operation of the main fractionator and downstream process units. Applying advanced control concepts minimizes the disturbances and improves product quality and unit stability. Delayed coking is one of the most difficult refinery units to operate and control due to disturbances. Industrial chemical processes must operate at maximum efficiency and one of the ways to save energy and still obtain high quality product by using Advanced Process Control (APC) systems. The objective of thesis is to design an advanced process control system for main fractionator column of the delayed coker unit using Honeywell RMPCT. The aim of the APC is to decrease standard deviation of LCGO Final Boiling Point (FBP) quality in main fractionator column during steady state operation. The methods used in this thesis are the determination of the controller matrix and the application of pre-step and main tests to obtain process models for the advanced process control. According to obtained results, standard deviation for the LCGO FBP quality results are compared before and after APC implementation. It is shown that when the APC is turned on, the standard deviation of the LCGO product FBP quality is decreased by 3 ℃.

ÖZET

GECİKTİRMELİ KOKLAŞMA ÜNİTESİ İÇİN İLERİ PROSES KONTROL SİSTEMİ TASARIMI

Rafinerilerin, geleneksel hafif ham petrol kaynaklarının azalması ve global yakıt talebinin artması nedeniyle, vakum distilasyon kolonu dip ürünü olan vakum kalıntısı (VR) işlemlerini optimize etmeleri gereklidir. Gecikmeli koklaşma ünitesi, rafinerilerde vakum kalıntısını değerli ürün olan, Hafif Koklaşma Gaz Yağı (LCGO), Ağır Koklaşma Gaz Yağı (HCGO), Sıvılaştırılmış Petrol Gazı (LPG), Kok Ürün Gazı, Stabilize Nafta gibi sıvı ve gaz ürün akışlarına dönüştürmektedir, ilave olarak da katı yoğun karbon malzemesi olan petrol kok ürününe dönüştürmektedir. Gecikmeli koklaştırma, termal parçalama ve koklaştırma işlemi için bir veya daha fazla kok tamburunun kullanıldığı yarı-sürekli bir işlemdir. Eş zamanlı olarak her bir kok tamburu çiftinde, besleme akışı iki tambur arasında değiştirilir ve bir tambur koklaştırma işlemi için çevrim içi iken diğer tambur çevrimdışı olup kok giderme işlemine tabi tutulur. Kok dramlarının değiştirilmesi, ana fraksiyon kolonunun işleyişinde ve aşağı akım proses ünitelerinde bozulma etkisi yaparak, ünite proseslerini ciddi şekilde etkilemektedir. İleri proses kontrol kavramlarının uygulanması, bu tür bozulmaları en aza indirir ve ürün kalitesini ve ünite stabilizasyonunu artırır. Gecikmeli koklaşma ünitesi, bozulmalardan dolayı işletilmesi ve kontrol edilmesi en zor olan rafineri ünitelerinden biridir. Endüstriyel kimyasal işlemler en yüksek verimlilikte çalışmalıdır ve enerji tasarrufu yapmanın ve yüksek kaliteli ürünler elde etmenin yollarından biri İleri Proses Kontrol (APC) methodlarını kullanmaktır. Tez çalışmasının amacı, Honeywell RMPCT kullanarak gecikmeli koklaşma ünitesinin ana fraksiyon kolonunda ileri proses kontrol sistemi tasarlamaktır. APC'nin amacı, stabil operasyon sırasında ana fraksiyonlandırma kolonunda LCGO Son Kaynama Noktası kalitesinin standart sapmasını azaltmaktır. Bu tezde kullanılan yöntemler, ileri süreç kontrolüne yönelik süreç modellerinin elde edilmesi için kontrolör matrisinin belirlenmesi ve ön adım ve ana testlerin uygulanmasıdır. Elde edilen sonuçlara göre LCGO FBP kalite sonuçlarının standart sapması APC uygulamasından önce ve sonra karşılaştırılmıştır. APC devrede olduğunda LCGO ürününün FBP kalitesinin standart sapmasının 3 °C azaldığı gösterilmiştir.

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LIST OF ABBREVIATIONS

VR	Vacuum Residue
LCGO	Light Coker Gasoil
HCGO	Heavy Coker Gasoil
LPG	Liqufied Petroluem Gas
APC	Advanced Process Control
RMPCT	Robust Multivariable Predictive Control Technology
FCC	Fluid Catalytic Cracking
MF	Main Fractionator
PID Controller	Proportional, Integral, Derivative Controller
K_C	Controller Gain
T_I	Integral Time
T_D	Derivative Time
MPC	Model Predictive Control
MV	Manipulated Variable
CV	Control Variable
DV	Disturbance Variable
ARC	Advance Regulatory Control
DCS	Distributed Control System
VCM	Volatile Combustible Matter
DCU	Delayed Coker Unit
MIMO	Multi Input Multi Output
FOPTD	First Order Plus Time Delay
p	Prediction Horizon
m	Control Horizon
Δt	Control Interval
Γu	Weight on Manipulated Variables
$\Gamma \Delta u$	Rate Weight on Manipulated Variables
Γy	Weight on Control Variables
RR	Reflux Ratio
DMC	Dynamic Control Matrix
PCTP	Process Control Technology Package
L	Reflux Flowrate
B	Bottom Product Flowrate
F	Feed Flowrate
X_D	Concentration of Light Components in Distillate
X_B	Concentration of Light Components in Bottom Product
X_F	Concentration of Light Components in Feed
SMOCPro	Shell Multivariable Optimizing Controller
PBRS	Pseudo Binary Random Sequence
FIR	Finite Impulse Response
ARX	AutoRegressive with eXternal input Model
ARMAX	Auto-Regressive Moving Average with external input Model
OE	Output Error Model
PEM	Prediction Error Method
FBP	Final Boiling Point

CHAPTER 1

INTRODUCTION

1.1. General Perspective on Refineries

Crude oil encompasses valuable liquid fuels, solvents, lubricants, and various other products once it undergoes the refining process. These refined crude oil constituents are utilized as both gas and liquid fuels, and they can also function as lubricants for machinery. As a pivotal energy source, the fuels derived from crude oil play a significant role, accounting for roughly one-third to one-half of the worldwide energy supply. Refinery units fractionate crude oil to generate valuable products. The main objective of crude oil distillation units is to separate the diverse hydrocarbon components present in crude oil based on their unique boiling points via a distillation process. These units are tailor-made to handle varying types and densities of crude oil and produce LPG, Naphtha, Kerosene, and Diesel intermediates as their output. Vacuum distillation units serve a dual purpose: they provide feedstock for conversion units while also producing Fuel Oil or Asphalt. The FCC (Fluid Catalytic Cracking) unit plays a vital role in breaking down the Heavy Vacuum Gas Oil obtained from the vacuum distillation columns. It transforms this material into gasoline and LPG, which are more valuable and versatile. This cracking process involves the conversion of heavy hydrocarbons into lighter and more valuable hydrocarbons. To further enhance the value of the products, a hydrocracker unit is employed. This unit operates within a hydrogen-rich environment, at high pressure and temperature, to efficiently break down the medium product derived from Heavy Vacuum Gas Oil obtained during vacuum distillation. The outcome is the production of even more valuable products, including LPG, naphtha, diesel, and kerosene. The objective is to extract pure elemental sulfur by making use of hydrogen sulfide, which is produced during the removal of sulfur compounds from petroleum products. Initially in a liquid form, sulfur is cooled and solidified before undergoing crushing processes to produce solid powdered sulfur. These units have a critical role in the transformation of environmentally harmful byproducts, generated during the purification of petroleum products, into environmentally friendly products that have demand in the market (Speight, 2016) . After refining processes variety of products produced, and Figure 1.1 shows a schematic overview of the refinery.

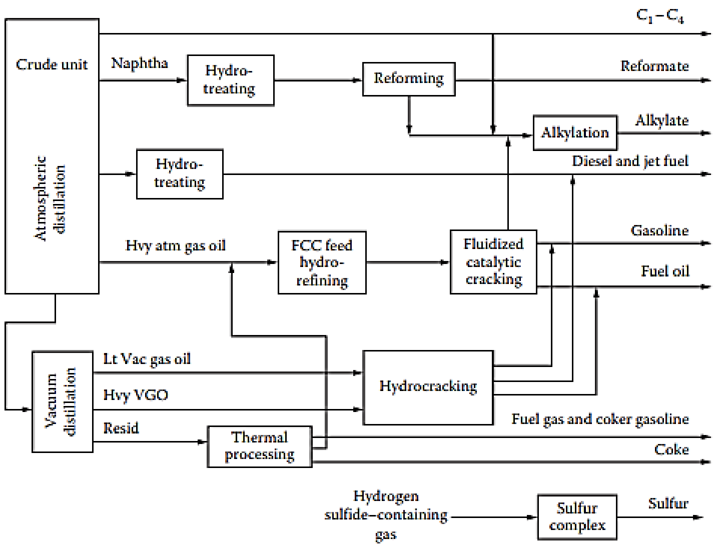

Figure 1.1. Schematic overview of refinery (Speight, 2016)

Boiling fractions of Crude oil is shown in Table 1.1.

Table 1.1. Boiling Fractions of Crude Oil (Speight, 2016)

Fraction	Boiling Range[a]	
	°C	°F
Light Naphtha	-1-150	30-300
Gasoline	-1-180	30-355
Heavy Naphtha	150-205	300-400
Kerosene	205-260	400-500
Light Gas Oil	260-315	400-600
Heavy Gas Oil	315-425	600-800

(cont. on the next page)

Table 1.1. (cont.)

Fraction	Boiling Range[a]	
	°C	°F
Lubricating Oil	>400	>750
Vacuum Gas Oil	425-600	800-1100
Residuum	>510	>950
a: for convience, boiling ranges are converted to the nearest 5°.		

Indeed, gas and gasoline fractions are regarded as more valuable and are lower-boiling products compared to the higher-boiling fractions. Naphtha is sourced from the lighter and middle distillates. The higher-boiling products obtained from crude oil encompass lubricating oils, gas oil, and residuum.

1.2. Refinery Technologies

1.2.1. Atmospheric Distillation

Atmospheric distillation is the process of segregating crude oil into its constituent components by exploiting the varying boiling points of different petroleum products. This separation procedure takes place within distillation towers, operating under specific pressure and temperature conditions. Substances that have low boiling points are referred to as top products, while those with high boiling points are known as bottom products. Petroleum is indeed a complex mixture, and atmospheric distillation involves not only the separation of top and bottom products but also various intermediate products. This process serves as the crucial initial step in the separation of petroleum products. Additionally, it is common for the capacity of a refinery to be determined by the capacity of its atmospheric distillation column because this process establishes the groundwork for subsequent refining procedures. In an atmospheric distillation unit, the initial feed is heated in a furnace to reach the necessary feed temperature. During this process, a portion of the feed is converted into vapor, while the remaining liquid portion collects at the base of the distillation column. The vaporized material then rises up the tower and undergoes fractionation, leading to the separation of gas oils, kerosene, and naphtha (Speight, 2016). Figure 1.2 shows the atmospheric distillation scheme.

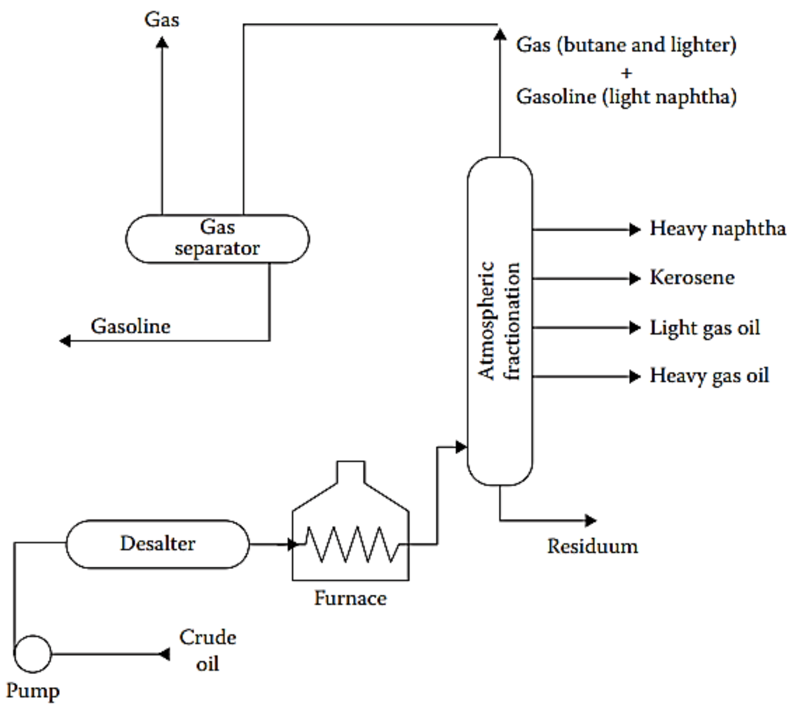

Figure 1.2. Atmospheric Distillation Scheme (Speight, 2016)

1.2.2. Vacuum Distillation

In a vacuum distillation unit, the process takes place under reduced pressure conditions. The typical operating range for vacuum distillation is between 50-100 mm of mercury, whereas atmospheric pressure is around 760 mm of mercury. Vacuum distillation feed consists of components with high boiling points and fewer volatile substances. These high-boiling products require elevated temperatures to undergo decomposition reactions under normal atmospheric conditions. The fractions obtained through vacuum distillation include heavy gas oil, lubricating oil, and residuum. These fractions have various uses, such as in asphalt production, and they can serve as feedstock for the delayed coker unit in refineries.

1.2.3.Thermal Processes

Thermal processes are utilized to transform heavier petroleum products into lighter oils. The resulting liquid products from these thermal processes often contain elevated levels of olefins, aromatics, and sulfur. To improve the properties of these products, hydrogen treatment is essential. Coking is a procedure that entails the removal of carbon, yielding lighter components while leaving behind heavier residues. These lighter components typically have low sulfur content, as most of the sulfur remains in the form of coke. In the thermal cracking of hydrocarbons, the mechanism involves free radical reactions that initiate in the initial step. Because of this reaction mechanism, as the reactions progress, heavier fractions and coke are generated towards the latter stages of the process (Fahim et al., 2010). Figure 1.3 shows the thermal cracking reaction mechanism.

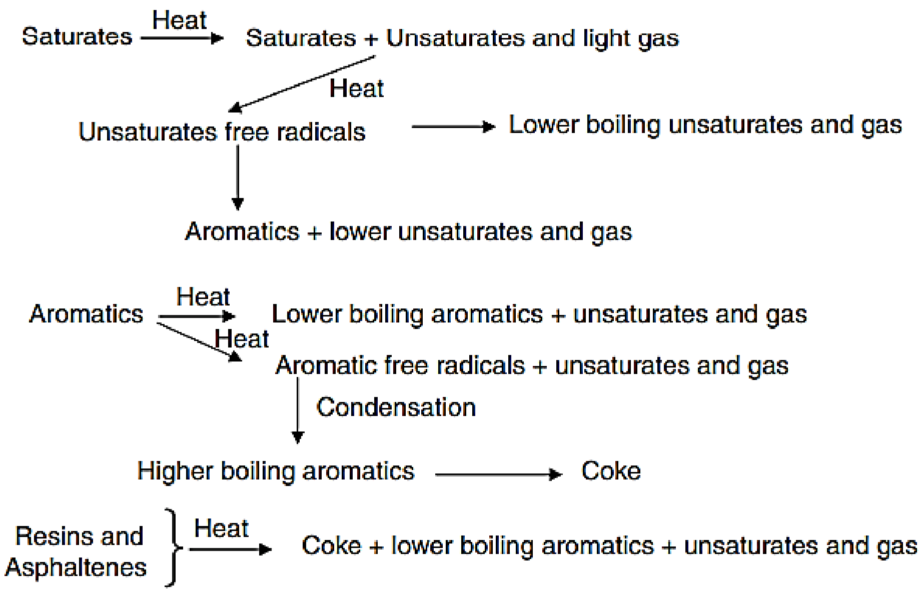

Figure 1.3. Thermal cracking mechanism (Fahim et al., 2010)

There are three types of thermal processes, including mild cracking, which applies gentle heat to break down the residue enough to reduce its viscosity and also produce some lighter products; The second process is delayed coking, in which moderate thermal cracking converts the residue to a lighter state. The third process for producing products and coke involves severe thermal cracking, in which part of the coke is burned and used to heat the feedstock in a cracking reactor, as in liquid coking.

1.2.3.1.Visbreaking

Visbreaking is a thermal process used to generate light products under either vacuum or atmospheric pressure. The goal is to produce a cracked material with a reduced viscosity, typically in the range of 75-85%. This cracked material can be utilized as light products or fuel oil. The feedstock for visbreaking is typically vacuum residue, which is the heaviest fraction obtained from the vacuum distillation process. It comprises heavy hydrocarbons, asphaltene, and resins. The primary reaction in visbreaking involves the thermal cracking of these heavy hydrocarbons and the conversion of high-viscosity materials into lighter and more valuable products.

1.2.3.2. Delayed Coking

Delayed coking is a thermal cracking process where the necessary heat for coking reactions is supplied by a furnace. The thermal cracking reactions commence in specialized drums, and coking occurs within these drums. This process operates in cycles, typically with 24 hours dedicated to coking and 24 hours for decoking. Efficiency is achieved by minimizing the residence time in the furnace, often by introducing steam into the furnace tubes. During the process, coke is formed and remains within the drums, while hydrocarbon products are recovered and directed to other processing units. However, it is important to note that the products obtained from delayed coking are often unstable and contain unsaturated compounds. To enhance their stability and remove impurities, these coker products usually undergo hydrotreating, which is a subsequent treatment process. The feed for the coker unit can consist of vacuum residue and atmospheric residue, both of which contain components like asphaltenes, resins, aromatics, sulfur, and metals. The products produced from the delayed coker unit primarily include olefins as cracked products. Notably, the delayed coker unit is the sole unit in refineries responsible for producing coke. The C3-C4 content of the delayed coker products is typically sent to the LPG (liquefied petroleum gas) plant, while the aromatic naphtha is directed into the gasoline pool. The light coker gas oil product undergoes hydrotreatment and is then channeled into the diesel pool. The heavy coker gas oil product is routed to the hydrocracker unit for further processing. Figure 1.4 illustrates the position of the delayed coker unit within the refinery's unit configuration.

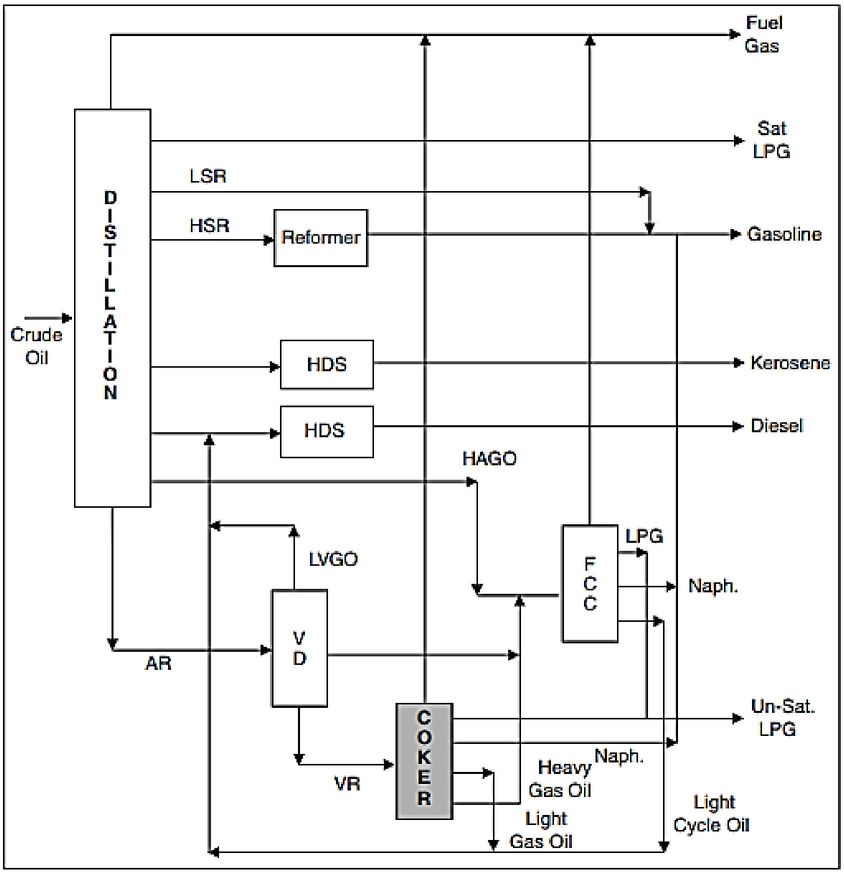

Figure 1.4. Delayed Coker Unit in Refinery Units (Fahim et al., 2010)

1.3.Process Control in Refineries

In refineries, numerous parameters, including operating pressure, temperature, and chemical concentrations, play a crucial role in the effectiveness of various processes. These parameters need to be carefully monitored and controlled to ensure the continuous and safe operation of refinery processes. Operational constraints, such as safety and environmental regulations, must be taken into account when setting and maintaining these parameters within acceptable limits. Control systems are an integral part of refinery operations and consist of instrumentation and control equipment. These include measuring devices to monitor process variables, control valves to regulate the flow of fluids, controllers to manage the operation of equipment, computers for data analysis and process control, as well as plant operators and designers who oversee and optimize the processes. The primary purpose of these control systems is to ensure process safety, reliability, and efficiency by keeping operations within allowable limits and responding to deviations or disturbances in real-time. This helps prevent accidents, maintain product quality, and maximize the overall performance of the refinery. Control systems prevents the disturbances, provides stability of the processes and optimization of the processes requirements (Lahiri, 2017). In refineries, PID (proportional–integral–derivative) regulatory controllers indeed play a crucial role in maintaining process stability and responding to disturbances in a wide range of industrial applications, including refineries. Their ability to provide proportional, integral, and derivative control actions makes them versatile tools for achieving desired process conditions and improving control system performance. The PID controller operates based on three primary control actions. By combining these three control actions, a PID controller can effectively regulate processes, maintain stability, and mitigate disturbances, making it a valuable tool in the control and automation of refinery operations. PID controllers include three control modes: proportional (P), Integral (I) and Derivative (D) controls (Smuts, 2011).

1.3.1. PID Control

1.3.1.1. Proportional Control

The P component responds to the current error between the desired set-point and the actual process variable. It applies a control output that is proportional to the error, which helps reduce deviations from the set point. If error is large, it requires larger control action to correct errors. The controller gain (K_c) show that how much proportional action is required to correct error (Smuts, 2011).

$$Proportional\ action = K_c * E \qquad \text{Eqn 1.}$$

where, K_C is the controller gain, E is the error between process value and set point.

1.3.1.2. Integral Control

The I component considers the accumulated past errors over time. It acts to eliminate any sustained or steady-state error by continuously adjusting the control output. The equation for integral control action is as below;

$$Integral\ action = \frac{K_c}{T_I} * \int E\, dt \qquad \text{Eqn 2.}$$

where, K_C is the controller gain, T_I is the integral time, E is the error between process value and set point (Smuts, 2011).

1.3.1.3. Derivative Control

The D component anticipates future error by evaluating the rate of change of the error. It helps dampen rapid changes and reduces overshooting of the setpoint (Smuts, 2011).

$$Derivative\ action = K_c * T_D * \frac{dE}{dt} \qquad \text{Eqn 3.}$$

where, K_C is the controller gain, T_D is the derivative time, E is the error between process value and set point.

1.3.2. Advanced Process Control

PID controllers cannot optimize complex processes, which have multivariable structures. Optimizing complex processes often requires more advanced control strategies and techniques, such as Advanced Process Control (APC). These methods take into account the relationships and interactions between multiple process variables and use mathematical models and optimization algorithms to achieve the best possible process performance. Advanced Process Control is a control system including, feedforward control, multivariable control system and inferential control system. MPC (Model Predictive Control) is an Advanced Process Control system and a software package for multivariable control system (Nicolae et al., 2019) . MPC predicts the process behavior considering the past behavior of the process dynamics.

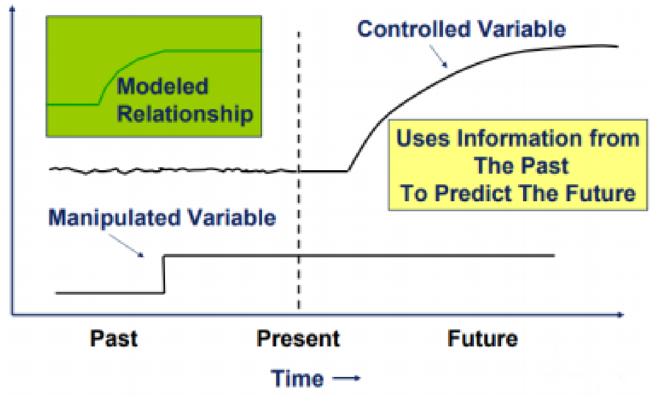

Figure 1.5. MPC Technique (Nicolae et al., 2019)

MPC (Model Predictive Control) is a powerful control strategy that takes into account a range of process constraints such as such as pressure limit, furnace maximum temperature limit, compressor amper limit, column flooding limit, product purity limit and feed supply limit and economic objectives to optimize the operation of a plant or refinery. It operates by continuously predicting the future behavior of the process based on mathematical models and historical data, and then calculates the optimal control actions to keep the process within desired limits while maximizing economic performance. Control operators and production engineers try to operate the plant at the center of the acceptable operating region. Figure 1.6 shows the operator comfort zone and optimum operating point of the process. According to the red point, MPC goal is to keep the process operating within this "economically optimum zone," which is the region where the process is both economically efficient and compliant with all constraints (Lahiri, 2017).

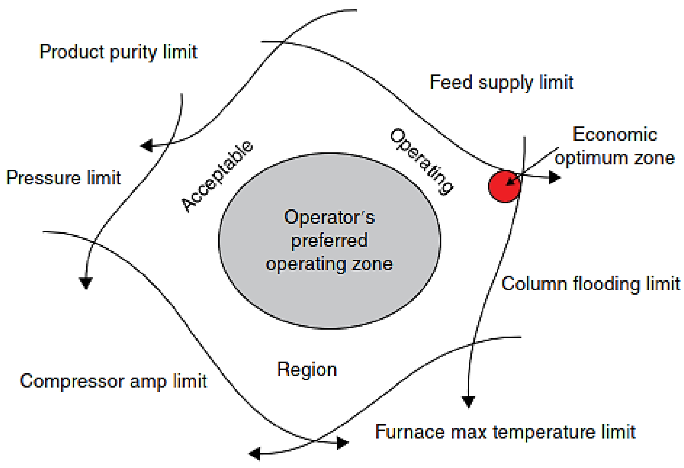

Figure 1.6. Optimum Operating Point versus Operator Comfort Zone (Lahiri, 2017)

1.3.3. Variables Used in MPC

1.3.3.1. Manipulated Variables (MV)

Manipulated variables are the inputs that can be changed by the control system to influence the process and maintain the CVs within their desired ranges. In the context of refinery or industrial processes, manipulated variables can include parameters like reflux flow, feed temperature, feed flow rate, compressor speed, overhead pressure, and many others (Lahiri, 2017).

1.3.3.2. Controlled Variables (CV)

Controlled variables are the process conditions or parameters that are actively controlled to maintain the desired state or performance of a system. Control variables can be the process conditions such as temperature, pressure, delta pressure, product quality inferential calculations, valve positions and measured analyzer values (Lahiri, 2017).

1.3.3.3. Disturbance Variables (DV)

Disturbance variables are factors that can influence the control variables (CVs) in a process but are typically outside the direct control of the Model Predictive Control (MPC) system. Disturbance variables can be feed temperature, feed composition and ambient temperature (Lahiri, 2017).

1.3.4. Benefits of MPC

MPC provides feedforward control by taking into account the influence of disturbance variables like feed temperature and composition and MPC can proactively adjust manipulated variables to maintain desired control variable values and stabilize the process. Additionally, MPC closes controlled variables through operational constraints. Figure 1.7 shows the MPC stabilization effect and after MPC is implemented, process variables are closed the operating limits (Lahiri, 2017).

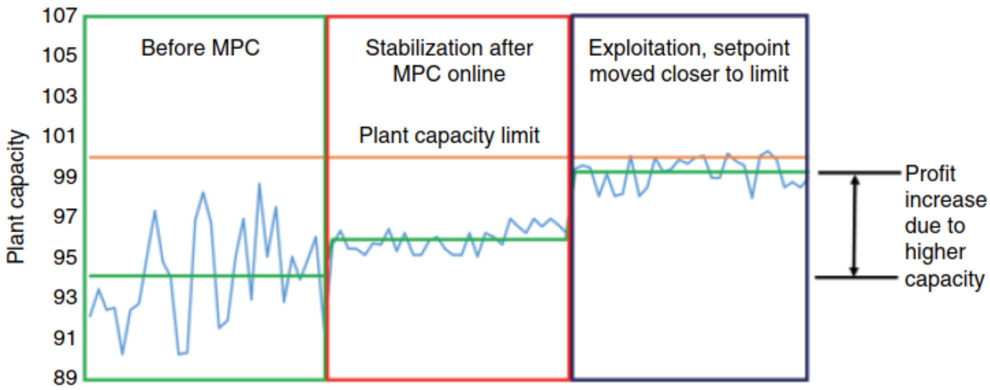

Figure 1.7. MPC Stabilization Effect (Lahiri, 2017)

Before MPC is implemented, Operators typically focus on controlling basic process parameters such as temperature, pressure, and level. The primary objective is to maintain these parameters within safe and acceptable ranges while ensuring stable operation. The control actions are often reactive, responding to deviations from set-points or disturbances. After MPC is implemented, MPC takes a predictive and proactive approach, continuously optimizing manipulated variables to achieve these performance and constraint objectives. By shifting the focus to performance parameters and using MPC's predictive capabilities, better process conditions can be obtained. This results in improved overall process efficiency, product quality, and adherence to operational constraints, ultimately contributing to increased profitability and reduced operational risks in industries such as refining. As shown in Figure 1.7, process stabilization is obtained and this cause less product quality variations and decreased the downstream unit variability.

1.3.5. Position of MPC in Control Hierarchy

MPC position in the control hierarchy is given in Figure 1.8.

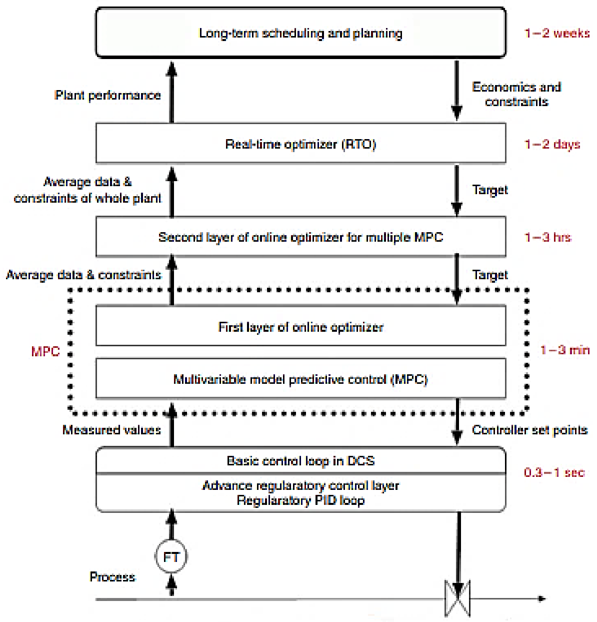

Figure 1.8. Hierarchy of plant-wide control framework (Lahiri, 2017)

1.3.5.1. PID Control Layer

The bottom part of the control hierarchy is regulatory PID Control Layer, which consists of the instruments (transmitters, valves) of the plant single sensing element and single final control element. Simple conventional temperature, pressure, flow control loops along with cascade control, and ratio controls are example of PID Controllers. Base level control provides disturbance rejection, and operational stability (Lahiri, 2017).

1.3.5.2. Advance Regulatory Control (ARC) Layer

The second layer above the regulatory PID control layer is called the advanced regulatory control. It helps optimize the process further, ensure product quality, and maintain stability by considering multiple inputs and outputs and using more advanced control techniques. Pressure-compensated temperature, pressure, temperature, and density-compensated flow or mass flow, simple feedforward control based on auxiliary measurements, and override or adaptive gain controls are example of MISO systems. Control frequency of advanced regulatory PID control layer is in between 0,3- 1 second (Lahiri, 2017).

1.3.5.3. Multivariable Model-Based Control

MPC is characterized by its ability to simultaneously consider and control multiple controlled variables (CVs) while adjusting multiple manipulated variables (MVs). In a MIMO system, the control actions are based on the interactions and relationships between various CVs and MVs, allowing a comprehensive and coordinated approach to control. MPC relies on dynamic mathematical models of the process to predict the future paths of control variables. These models take into account the historical behavior of the process and the interactions between variables to make predictions. In control hierarchy, multivariable model predictive is above a regulatory control implemented in DCS and takes measured data values from DCS and give set point to the regulatory control. Control frequency of MPC is in between 1-3 minutes (Lahiri, 2017).

1.3.5.4. Economic Optimization Layer

Optimization part is figured above the multivariable control layer. Optimization layer includes three layers as following;

1.3.5.5. First Layer of Optimization

MPC plays a crucial role in optimizing the operation of the process. It focuses on taking control variables (CVs) within specified limits while considering various constraints and objectives. MPC achieves this by predicting the future behavior of the process using dynamic mathematical models and then calculating optimal manipulated variable (MV) adjustments to maintain the CVs within desired ranges.

1.3.5.6. Second Layer of Optimization

Second layer of optimization is figured above the first layer of optimization. The aim is to increase the profit of the plant based on the maximization or minimization of the objective function shown in below equation 4.

$$minimize\ obj = \sum_i p_i CV_i + \sum_i q_i^2((CV_i - CV_{0i})^2) + \sum_j p_j\, MV_{ij} + \sum_j q_j^2 \left(\left(MV_j - MV_{0j} \right)^2 \right) \quad \text{Eqn 4.}$$

In the provided equations: "p_i" represents the linear coefficients associated with the Controlled Variables (CVs), "p_j" represents the linear coefficients associated with the

Manipulated Variables (MVs)," q_i" represents the quadratic coefficients associated with the CVs, "q_j" represents the quadratic coefficients associated with the MVs," CV_{0i}" stands for the desired resting values of the CVs," MV_{0j}" stands for the desired resting values of the MVs. Maximizing the objective function rather than minimizing can be achieved by multiplying each term in the objective function by -1. The controller's goal is to minimize or maximize the negative of this objective function while ensuring that all controlled variables (CVs) remain within specified limits or at their set points, and all manipulated variables (MVs) stay within their control limits.

1.3.5.7. Third Layer of Optimization

This level of optimization focuses on maximizing the overall profitability of the plant by making strategic decisions based on real-time information considering the market demand and raw material availability.

1.4. Applications and Benefits of MPC in Industry

In industry, MPC has indeed come a long way since its inception in the 1970s. Its applications have expanded beyond chemical plants and oil refineries to include diverse fields such as robotics, space exploration, and biochemical plants. Over the years, MPC technology has undergone structural modifications, and now it is a widely applied technology in chemical companies, petrochemical companies and refineries. Table 1.2. shows the obtained benefits by MPC in petrochemical industry.

Table 1.2. Typical Benefits of MPC Implementation in Petrochemical Industry (Lahiri, 2017)

Petrochemicals	**Benefit (per year)**
Ethylene	2-4% Increase in production
VCM	3-5% Increase in capacity(1-4% yield improvement
Aromatics	3.4-5.3 M US$
Chemicals	
Ammonia	2-4% Increase in capacity
Polyolefins	2-5% Increase in production
Oil & Gas	
Upstream Production	-
Industrial Utilities	-
Cogeneration/Power Systems	2-5% Decrease in operating costs
Pulping	-
Bleaching	10-20% Reduction in Chemical Usage
TMP (Thermos Mechanical Pulping)	$1M-$2M

Table 1.3. shows the benefits that can be obtained by MPC in refinery units.

Table 1.3. Typical Benefits of MPC implementation in Refinery (Lahiri, 2017)

Refining	**Benefit (per year)**
Crude Distillation	2.7-7 M US$
Coking	2.2-4.8 M US$
Hydrocracking	3.3-7.6 M US$
Catalytic Cracking	2.4-5.4 M US$
Reforming	1.8-4.7 M US$
Alkylation	1.1-2.8 M US$
Isomerization	0.3-1.8 M US$

The usage of MPC application is increased and except from petrochemical and refinery industry, MPC is increasingly utilized in polymer, oil and gas, pulp and paper, power/steam generation and chemicals industries.

1.5. Dynamic Control Strategy of MPC

MPC is implemented to the Distributed Control System (DCS) systems as a higher-level control strategy. DCS connecting to various sensors and transmitters that monitor key process variables such as flow, temperature, pressure, and level. Dynamic control strategy begins with plant DCS system. Inferential control, as part of the dynamic control strategy, takes this input data from the DCS and utilizes it to predict future steady-state values for controlled variables (CVs). These predictions are essential for making informed decisions and optimizing the control actions within the system. A steady-state optimization module takes predicted Controlled Variable (CV) values as input. These predictions are often generated by inferential models or other methods based on real-time data. The module's goal is to find steady-state optimum targets for both CVs and Manipulated Variables (MVs). To determine dynamic strategy, obtained MV and CV targets are fed to dynamic control module to calculate MV movement value. Dynamic control modules are responsible for determining how to adjust MVs in response to changes in the process to maintain CVs at or near their targets. To formulate this dynamic control strategy, the module requires additional inputs, including MV and CV limits (constraints) and tuning constants. Figure 1.9 shows the dynamic strategy of MPC.

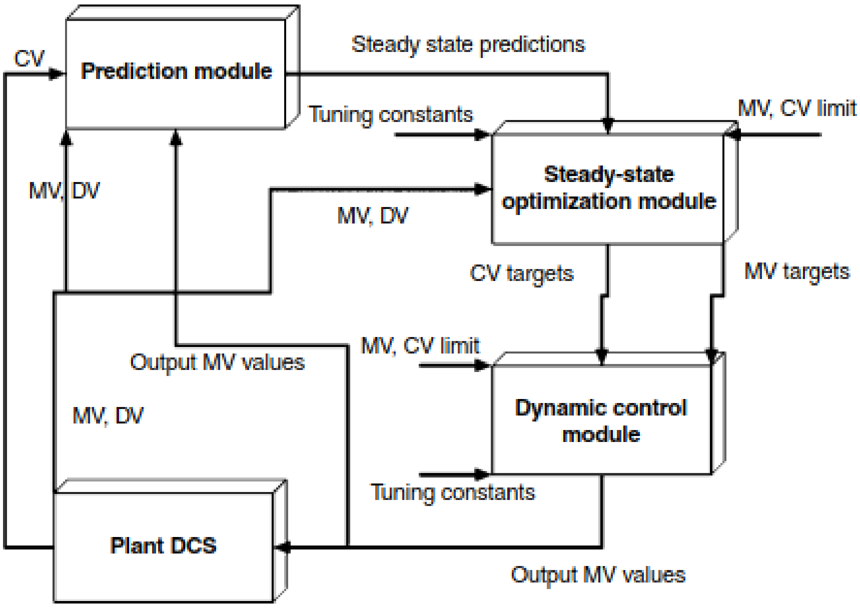

Figure 1.9. Dynamic Control Strategy of MPC (Lahiri, 2017)

1.6. Soft Sensors (Inferential)

Soft sensors are used to calculate controlled variables (CVs) within the process. These CVs are important for MPC because they represent key process parameters that need to be controlled to achieve specific objectives, such as product quality or process efficiency. In refining and petrochemical processes, product impurities, qualities (e.g., Initial Boiling Point, Final Boiling Point), and other attributes are critical for ensuring product consistency and meeting regulatory standards. Soft sensors help infer these quality attributes based on available data and measurements. Quality inferential, which are essentially soft sensor outputs, are used as CVs in MPC models. This is important because maintaining product quality within specified limits is a primary objective in many refining and petrochemical processes. In refineries, for most of the critical qualities, analyzers are used to measure product properties and soft sensors are use as backup when there is a calibration issue in analyzer (Lahiri, 2017).

1.7. Functional Design of MPC Controllers

Functional design shows the MPC control strategy including MV, CV, DV of the models, the key process variables and parameters that will be included in the MPC model. This involves selecting the Manipulated Variables (MVs), Controlled Variables (CVs), and Disturbance Variables (DVs) that are most relevant to achieving the desired process objectives. In MPC, an objective function is determined to quantify the process's performance goals. This function may include economic objectives, such as maximizing production rates or minimizing energy consumption, as well as constraints on CVs and MVs.

1.7.1. Identify Process Constraints

Process constrains should be specified when a MPC is being designed. A MPC increases the throughput considering process limitations, safety limitations, equipment limitations, raw material and utility limitations and product limitations.

1.7.2. Variable Selection

In this part of the functional design, MV, CV and DV of the process are determined. Manipulated variables are changed to control CVs. Controlled variables are the process conditions to be controlled. When the desired CV is not measurable such as yield, selectivity etc., there should be calculation and inferential to identify the CVs. Disturbance variables are measured disturbances in the process that affect the CVs but it is not changed by MPC control.

1.7.3. Preliminary Process Test and Step Test

1.7.3.1. Pre-Step Test

The primary purpose of pre-stepping is to prepare the control system for the main step test. By making controlled movements in MVs and DVs before the main test, the control team can observe how these adjustments affect the controlled variables (CVs). This process helps in assessing the control system's response and identifying any issues or improvements needed. Step size should be large enough to induce a noticeable change in the relevant CVs, allowing the control team to observe the system's response clearly. Before starting the step test, tuning of the controllers should be available and performance of the inferential should be good. Before pre-step test is started, expected control matrix including all MVs and CVs and their gain direction (negative or positive) is created and follow to ensure the CV responses are correct. Figure 1.10 shows the example of control matrix including MVs, CVs and DVs and their expected response.

	CV1	CV2	CV3	CV4	CV5	CV6
MV1	✓	✓	✓	✗	✗	✗
MV2	✓	✓	✓	✓	?	?
MV3	✓	?	?	✓	✓	✓
DV1	✗	✓	✗	✗	✓	?

Figure 1.10. Expectational Control Matrix (Lahiri, 2017)

Objective of the pre-step test is to determine the settling time of the system. The pre-step test provides an opportunity to observe and analyze any disturbances or variations in the process that occur before the main step test. After pre-step test is applied, main step test is completed and dynamic models between MVs and CVs determined. Figure 1.11 shows that basic concept of step test and CV response due to change of MV.

Obtaining good MPC models, responses should be clear, and the direction of response should be correct.

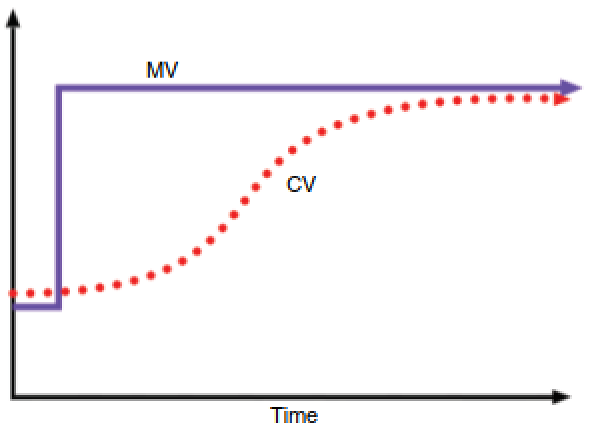

Figure 1.11. Basic Concept of Step Test (Lahiri, 2017)

1.8. Delayed Coker Unit Process Description

Delayed Coker Unit processes atmospheric and vacuum residue as unit charge, which is the bottom product of atmospheric and vacuum distillation columns coming from the crude oil unit in refinery. The process includes a furnace, two coke drums, fractionator and stripping section. Vacuum residue enters the bottom of the flash zone in the distillation column or just below the gas oil tray. Fractions lighter than heavy gas oil are flashed off and the remaining oil are fed to the coking furnace. Steam is injected in the furnace to prevent premature coking. The feed to the coker drums is heated above 496 °C. The liquid–vapor mixture leaving the furnace passes to one of the coking drum. Coke is deposited in this drum for 24 h period while the other drum is being decoked and cleaned. Hot vapors from the coke drum are quenched by the liquid feed, thus preventing any significant amount of coke formation in the fractionator and simultaneously condensing a portion of the heavy ends which are then recycled. Vapors from the top of the coke drum are returned to the bottom of the fractionator. These vapors consist of steam and the products of the thermal cracking reaction (gas, naphtha and gas oils). The vapors flow up through the quench trays of the fractionator. Figure 1.12 shows the scheme of delayed coker unit.

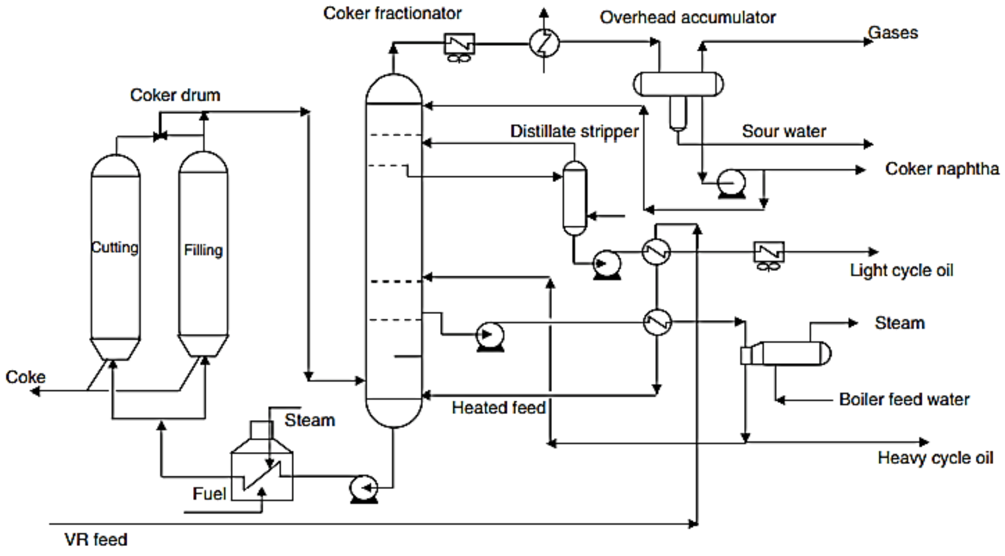

Figure 1.12. Delayed Coker Unit (Speight, 2016)

Vacuum residue is received at the unit battery limits and preheated by a series of exchangers: the HCGO Product / Feed Exchanger and the HCGO Pump around / Feed Exchanger. Recycle from the Coker Fractionator shed section combines with the fresh feed in the bottom of the tower. The combined fresh feed and recycle flows to the heater charge pumps, which are equipped with the coke crushing impellers. The liquid is pumped under flow control through each pass of the Coker Heaters, where it is rapidly heated to the desired temperature for coke formation in the Coke Drums. Delayed Coking is a thermal process in which a residuum material is rapidly heated in a furnace and then thermally cracked in coke drums under proper conditions of temperature and pressure. Products from the Delayed Coker are Sour Coker Product Gas, Sour LPG (C3s and C4s), Full Range Stabilized Coker Naphtha, Light Coker Gas Oil (LCGO), Heavy Coker Gas Oil (HCGO), and Coke (Fuel Grade). Delayed Coking is an endothermic reaction with the furnace supplying the necessary heat of reaction.

1.8.1. Delayed Coker Unit Process Variables

The yields and quality of the products are directly related to three process variables as temperature, pressure, throughput ratio (TPR). Throughput ratio is defined as the ratio of total liquid feed to the coker heater to total fresh feed entering from the battery limits. In general, an increase in coking temperature decreases coke production, decreases coke volatile combustible matter (VCM), increases liquid hydrocarbon yield, and increases the propensity to produce shot coke. The effect of increasing pressure and throughput ratio is to increase gas and coke make and to decrease liquid hydrocarbon yield. At constant pressure and throughput ratio, the coke yield decreases with increasing temperature. More of the charge is flashed off at the higher temperature and hence, is not converted to coke and gas. Since the reaction is endothermic, the furnace must supply the heat of reaction. Based on the physical properties of the charge, the temperature drop from the heater outlet to the top of the coke drum may vary. In actual practice, the furnace outlet temperature and the drum outlet temperature may vary only between relatively narrow limits. At too low temperature the reaction does not proceed far enough, and a soft coke or pitch with a high volatile combustible matter (VCM) is produced. At too high a temperature, the coke is too hard and is difficult to remove from the drum with hydraulic cutting equipment. Also, at higher temperatures the possibility of coking in the heater tubes and transfer line is increased. At constant temperature and throughput ratio, increasing the pressure increases the liquid trapped in the drum (by suppressing vaporization); thereby increasing coke and gas make. The gas oil end point is also reduced, as is the yield of liquid hydrocarbons. Increasing the throughput ratio at constant temperature and pressure also, increases coke and gas make at the expense of liquid hydrocarbon yield. The throughput ratio is used primarily to control the end point of the Heavy Coker Gas Oil (HCGO). Figure 1.13 shows each heater effluent flows into one of a pair of coke drums where, under the proper time-temperature-pressure conditions, the trapped liquid is converted to coke and hydrocarbon vapors. A control valve system directs the feed to enter one of the drums, where the reactions take place and coke is deposited on the drum walls, and the products flow back to the main fractionator column. In this case, the drum is in the filling mode. At the same time, the other drum is cut off from the rest of the system while the coke is being removed. The drum in this case is in the cutting mode. When a drum is filled with coke, the heater effluent is directed through one of the coker switch valves into the other drum of each pair. Each heater is dedicated for a pair of Coke Drums.

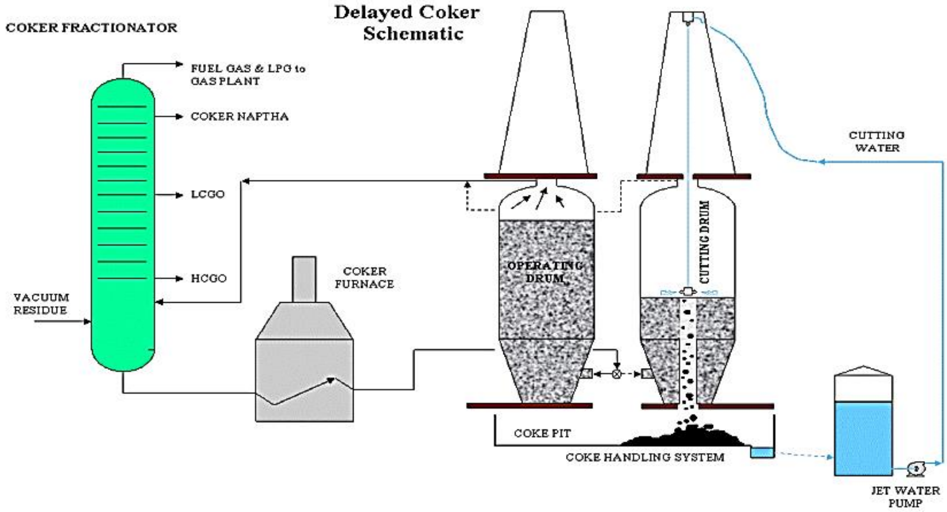

Figure 1.13. Delayed Coker Unit-Coke Drums (Kedia et al., 2019)

The flow to each coke drum is maintained for twenty-four hours. The filled drum is decoked in twenty-four hours. Thus, each drum goes through a 48-hour cycle. While one drum is in coking service other drum is in various stages of decoking.

Decoking operation occur in following 8 steps;

1. Steam out to Fractionator,
2. Steam out to Blowdown,
3. Quenching and Filling,
4. Water draining and Unheading,
5. Decoking Operation (Coke cutting),
6. Reheading and Testing,
7. Preheating,
8. Drum Switch

- In steam out to fractionator step, The coke-filled drum is steamed out to the Coker Fractionator Column. This operation permits recovery of light material entrained in the coke.
- In Steam out to Blowdown step, Quench steam is routed through the coke drum to the Coker Blowdown Tower.
- In quenching and filling step, water for cooling the coke drum is furnished by the quench water pump. Quenching proceeds until the coke drum overhead is cooled.
- In water draining and unheading step, after the coke drum is vented to atmosphere through the coke drum, water draining is provided after drain valve is opened.
- In decoking operation step, after the top and bottom heads have been opened, the coke cutting pump and hydraulic cutting tool are commissioned, and the decoking operation begins.
- In reheading and testing step, after decoking, the top and bottom heads are closed. The drum is first purged and then pressure tested with steam.
- In preheating step, after pressure testing the coke drum, the empty drum is preheated by vapors from the other coke drum, which is in the final stage of the coking operation.
- In drum switch step, the preheated coke drum is returned to coking service, and the decoking cycle is repeated for the other drum in the pair.

1.9. Disturbance Effects of Decoking Steps

Drum switch and preheating steps of decoking operation cause disturbance to the operation in the fractionation column. When the drum is switched, the hot charge coming out of the heater is converted from the coke filled drum to the empty drum. In the meantime, since the temperature of the empty drum is not at a sufficient temperature for the cracking process to start, the temperature profile of the column decreases abruptly as the amount and temperature of the hydrocarbon vapor sent from the top of the drum to the fractionation column decreases. The temperature reaches its maximum value within 3-4 hours after the drum switch. In the preheating process, approximately 5-6 hours before the drum switch starts, the hot top vapors from the coking drum is used to heat the empty drum instead of being sent to the fractionation column and result with decreasing temperature profile of fractionator column. In the study, which is aimed to investigate handling of the delayed coker disturbances with APC. In his study, four disturbance events are indicated (Jaguste, 2016). In the first event, approximately six hours before switching coking drums, the hot vapors from the active coking drum are sent to an empty drum for vapor preheating. This causes sudden temperature decreases in the main fractionator column and creates a disturbance in the distillation process. Temperature changes can affect the separation efficiency and the distribution of hydrocarbon fractions in the column. This step is done to improve the efficiency of the coking process and reduce energy consumption. In the second event, after the preheating step, the empty drum is warmed up. This warming process likely involves heating the drum to prepare it for receiving hot vapors from the coking process. In this step about one-third of the hot vapors generated in the coking drum are directed to the bottom of the empty drum. The third event involves changing the active coking drum to allow for continuous coking operations. During the drum switch, the effluent from the furnace, which contains hot hydrocarbon feedstock, is directed to the empty drum. The empty drum's temperature is not sufficient for the cracking reactions that need to occur and both the heat and vapor mass that should be generated during cracking are reduced. In the fourth event, after drum switch occur and temperature of the empty drum is increases by the cracking reactions and the temperature profile of the main fractionator increases since, vapor flow to the main fractionator increase. The effects of four events about disturbances are illustrated in Figure 1.14. According to Figure 1.15, 1AB/BA and 1CD/DC represent the first event, which corresponds to the preheating step. During this event, the temperature profile of the main fractionator decreases, resulting in a decrease in the HCGO draw temperature in the column. On the other hand, 2AB/BA and 2CD/DC represent the second event, which occurs between the drum switch and preheating steps. During this event, one-third of the hot vapor from the coking drum is directed to the bottom of the empty drum, causing an increase in the temperature profile of the HCGO draw temperature. 3AB/BA and 3CD/DC represents the third event that is drum switch step, there is a sudden temperature reducing effect since, both the heat and vapor mass sent to the main fractionator is reducing. 4AB/BA and 4CD/DC represents the fourth event, which occur after the drum switch step, temperature of the empty drum is increases gradually by the cracking reactions. Therefore, HCGO draw temperature profile increases since, heat and mass sent to the main fractionator increases.

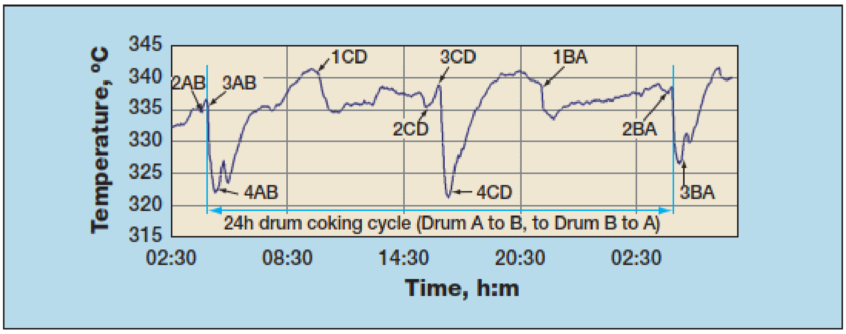

Figure 1.14. HCGO Draw temperature profile in drum switch event in 24 hours (Jaguste, 2016)

Due to drum switch and preheating operations, temperature profile of the main fractionator column is affected by the vapor load changing to the main fractionator column. The disturbance effect by the drum switch and preheating steps is shown in Figure 1.15 and it shows that HCGO draw temperature trend when the drum switch occurs in 24 hours between AB drum pairs and CD drum pairs. HCGO draw temperature profile is changing due to the logically inferred drum switch and (vapor heating) preheating pulses. When drum switch and preheating occur, this causes a major disturbance effect and the temperature profile of the column decreases and resulting in decreasing HCGO draw temperature.

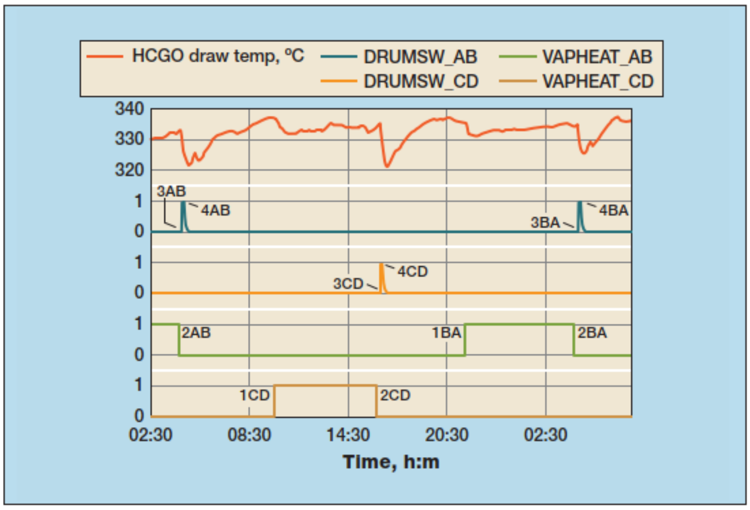

Figure 1.15. HCGO Draw Temperature - Drum switch/Preheating Pulses (Jaguste,2016)

The operation of the main fractionator plays a critical role in determining the product yields and qualities. When the drum switch and preheating steps occur within the unit, significant disturbances are introduced into the main fractionator column. These disturbance effects can be mitigated by carefully balancing heat and mass flows. Inside the main fractionator column, there are internal reflux flows, such as the HCGO wash oil flow and HCGO pump around flow. These circulating refluxes can be adjusted quickly before the drum switch and preheating steps begin. In the Delayed Coker Unit, operators take various actions when the drum switch and preheating steps occur to prevent any reduction in product quality and the generation of off-spec products. This proactive approach helps maintain the integrity of the product and ensures that it meets the required specifications. Handling disturbances caused by drum switch and preheating steps can be effectively managed through an APC (Advanced Process Control) system that incorporates multivariable predictive control (MPC) and product quality inferential techniques. The design of the APC system relies on dynamic models obtained from step tests. In the Delayed Coker Unit (DCU), operations are not continuously in a steady state due to the drum switch occurring every 12 hours. The operation remains stable for approximately 3-4 hours each day. To achieve the optimal design for the DCU APC and to mitigate disturbances caused by the drum switch and preheating steps, it is essential to incorporate these disturbances as inputs during the modeling phase of the APC system. Figure 1.16 displays a step test trend for the HCGO circulating reflux, and it provides both plant data and model predictions for the response of HCGO draw temperature. During the step test, the effects of drum switch and preheating disturbances are reflected in the results, allowing for a more comprehensive understanding of their impact on the process. This information is valuable for designing an effective APC system that can proactively manage these disturbances and ensure stable and high-quality operation.

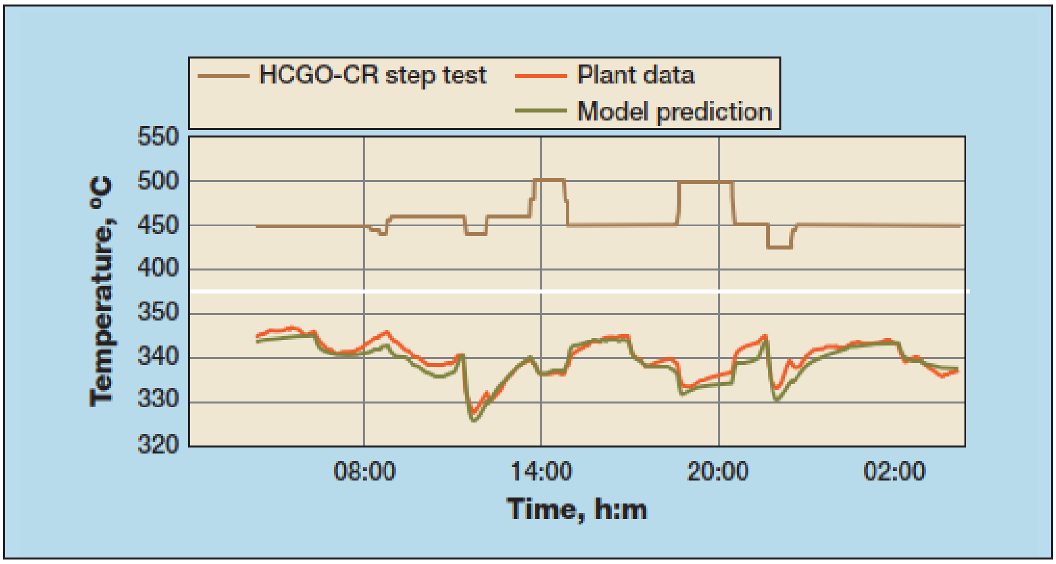

Figure 1.16. HCGO-CR Circulating Reflux Step- test (Jaguste, 2016)

During drum switch and preheating steps, to prevent product quality give aways and off spec production, control priorities can be changed. In drum switch and preheating steps, both heat and mass sent to the main fractionator column reduces. To provide heat balance, when drum switch and preheating steps start HCGO circulating reflux should be reduced to prevent heat removal by HCGO circulating reflux. However, after the drum switch step vapor flow to the main fractionator increases gradually and HCGO circulating reflux flow should be increased to control temperature by changing control priority. Figure 1.17 shows that HCGO circulating reflux (HCGO-CR) actions with APC when the drum switch and preheating steps occur. To provide disturbance rejection, HCGO circulating flow is reduced aggressively when the drum switch occurs.

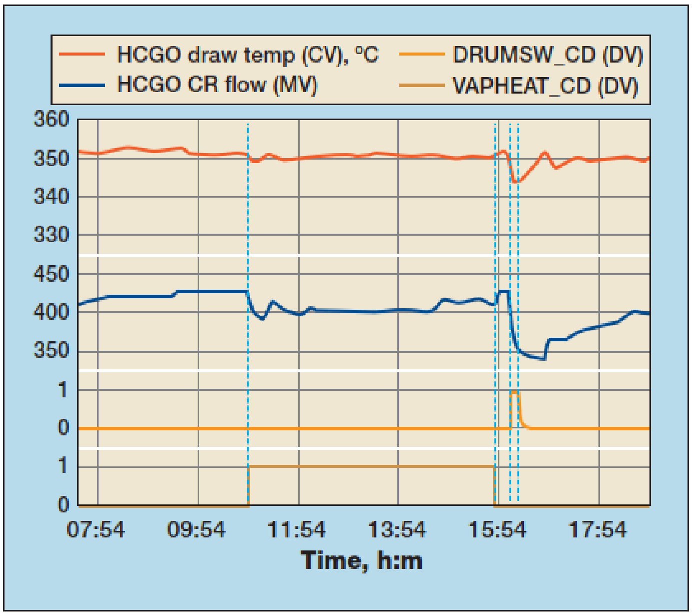

Figure 1.17. Control of HCGO draw temperature by feed-forward actions (Jaguste,2016)

In this study, the inferred drum switch pulses are used for predictive feed-forward control and when the drum switch occurs HCGO circulating flow is decreased aggressively to provide the stabilization of the HCGO draw temperature. Figure 1.18 shows that HCGO draw temperature profile control with APC. Due to Figure 1.18, by the quick manipulation of the HCGO circulating flow, HCGO draw temperature is increased.

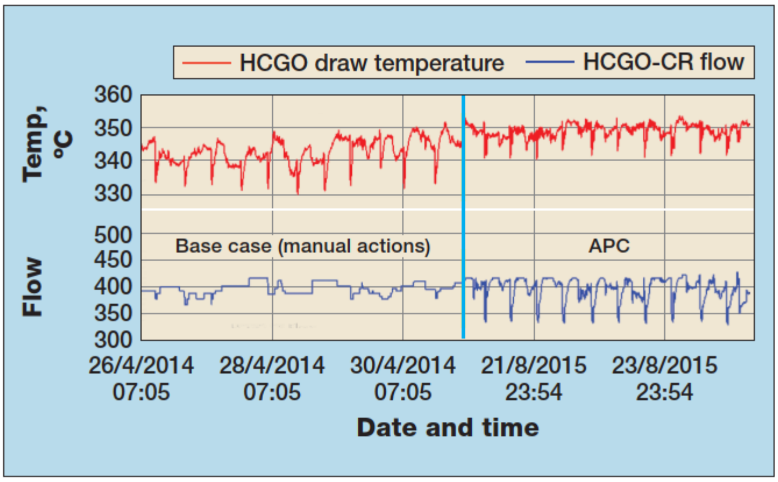

Figure 1.18. HCGO Draw Temperature Control with APC (Jaguste, 2016)

When the drum switch occur before APC is implemented, LCGO product was condensed and this cause reducing effect on the LCGO tray level in the main fractionator column. To prevent the loss of tray level, LCGO draw flow is manipulated by APC. Since drum switch and preheating pulses are used as inputs, tray level stabilization is provided by feed forward control with APC. Figure 1.19 shows that after APC is implemented , quick manipulation of the LCGO draw flow caused LCGO tray level stabilization.

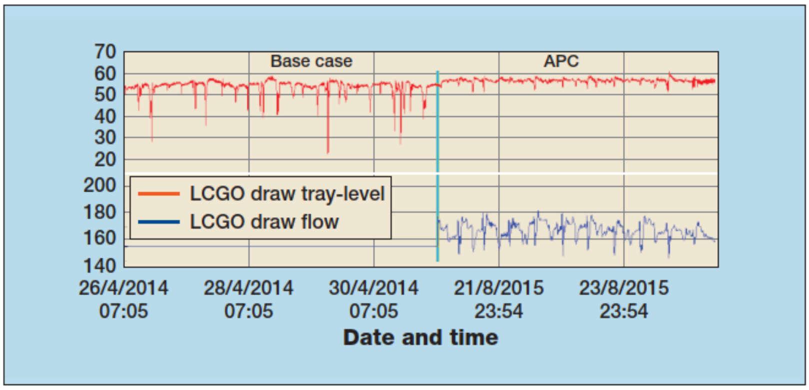

Figure 1.19. LCGO Tray Level Control with APC (Jaguste, 2016)

1.10. The aim of this thesis

The aim of this thesis is to design an advanced process control system for the delayed coker unit in SOCAR STAR Refinery, Izmir. In the delayed coker unit main fractionator column, there are disturbance effects in the column because of the drum switch and preheating steps. Therefore, standard deviation of the valuable LCGO product FBP quality is high even in the steady state operation. In this thesis study, it is aimed to decrease the standard deviation of the valuable product LCGO FBP Quality between LCGO FBP planning order and laboratory results in the steady state operation with the constrained MPC controller.

CHAPTER 2

LITERATURE SURVEY

In the literature, there is a limited number of studies about the DCU APC applications. However, there are several APC studies about other refinery and petrochemical units, as discussed below. In this chapter of the thesis study, different APC applications are represented from the literature for refinery units in industry. The implementation of Advanced Process Control (APC) leads to a decrease in standard deviation of the control variables, enabling the process variable to move closer to its specified target with optimal control effort. Consequently, APC maximizes the yield of the more valuable product. This is achieved by incorporating plant and process economics considerations while staying within the specified limits, ultimately optimizing the overall production process. In the study which includes a method for estimating the reduction in the standard deviation of control variables for the Delayed Coker Unit's main fractionator column as a case study to investigate and quantify the effects of proposed method on the control variables within the system (Kedia et al., 2019). Methods of their study includes following steps; data-collection and analysis (pre-APC data/ base-case identification), process modelling, disturbance characterization/ modelling, controller design and Simulation parts. In the data collection and analysis section, the researchers collected data from DCS history system including pre-advanced process control (APC) data and performed an initial assessment of the base case to identify the existing control system's characteristics. Process modeling section represents the dynamics response of the Delayed Coker Unit's main fractionator column. These models likely helped them understand how the process responds to different inputs and disturbances. MATLAB System Identification Toolbox is used and process is modelled as multiple-input multiple-output (MIMO) model with each input and output as first order plus time delay (FOPTD) model. Disturbance Characterization/Modeling of their study involved characterizing and modeling disturbances that affect the system. This step likely aimed to understand how external factors affects the main fractionator column and its control variables.

In the controller design section, the researchers designed controllers, likely Advanced Process Controllers (APCs), to optimize the performance of the main fractionator column. This step involved creating control strategies and tuning parameters. The study is simulated to evaluate the performance of the designed controllers within the context of the main fractionator column, providing a platform to assess how the APCs affected control variables and reduced standard deviations. Disturbances are characterized using ramp like signal shown in Figure 2.1 This approach is particularly suitable for addressing dynamic systems where signals transition or shift in a step-like manner at discrete time intervals.

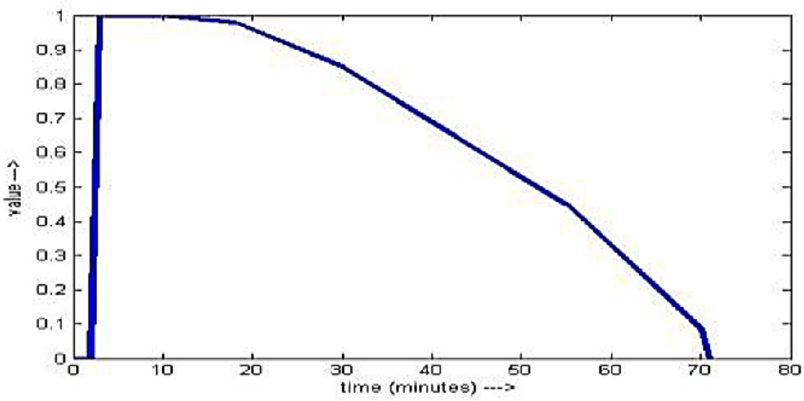

Figure 2.1. Ramp like Variation (Kedia et al., 2019)

MATLAB, MPC Toolbox is used to design the controllers. In the MPC toolbox, MV's, CV's & DV's variables are determined, and sampling period is selected. Tuning parameters of the controllers are MPC prediction horizon (p), control horizon (m), control interval (Δt), weight on MV's (Γu), rate weight on MV's ($\Gamma \Delta u$), weight on CV's (Γy). Prediction horizon (p) defines how far into the future the controller looks when making control decisions and it is set due to the maximum settling time of the process. Additionally, control horizon is selected as 1/4th or 1/5th of the prediction horizon and It represents how many steps into the future the controller plans control actions. It is often chosen based on the desired control aggressiveness. In their study, LCGO and HCGO draw temperature values are controlled as control variables by disturbance characterization. In the study ramp like signal is used to characterized disturbances using real plant data and characterized disturbance data (Kedia et al., 2019).

Figure 2.2 and 2.3 show that ramp like signals for actual and characterized disturbances including drum switch and preheating steps respectively, for AB and CD drum pairs. Obtained results are very similar to each other compared to the actual and the characterized signals.

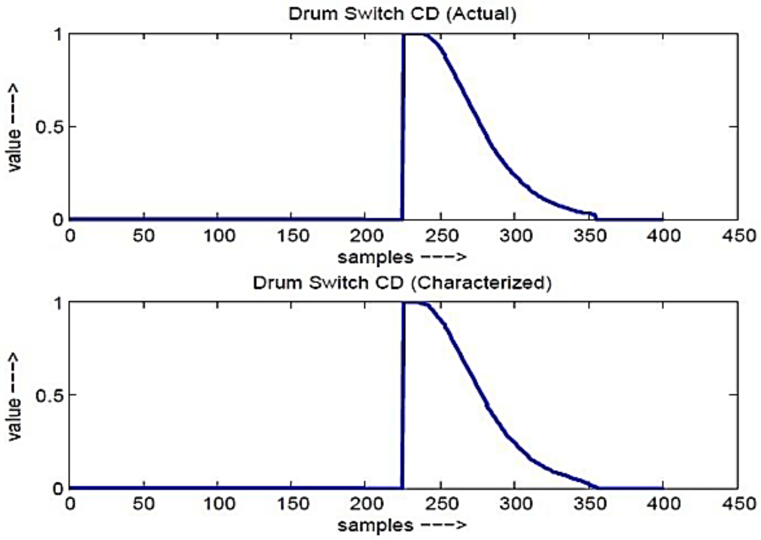

Figure 2.2. Drum Switch Events as a Ramp like Signal (Kedia et al., 2019)

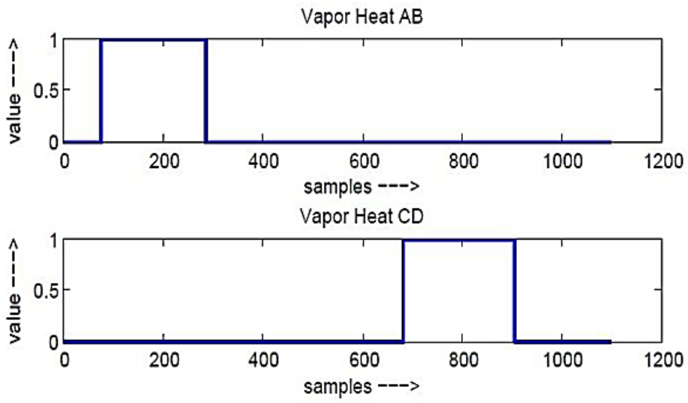

Figure 2.3. Preheating Characterization by Ramp Like Signal (Kedia et al., 2019)

In this study, Main fractionator top temperature is characterized as a function of ramp like, mean & standard deviation. Due to Figure 2.4, the researchers have likely observed that when a preheating step is concluded, the top temperature of the main fractionator exhibits a decreasing trend since; the temperature of the preheated drum is not sufficiently high to sustain the cracking reactions required for the desired processes.

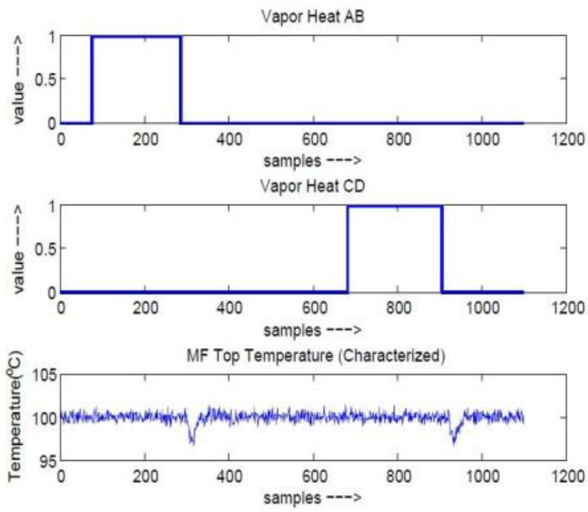

Figure 2.4. Characterized Main fractionator (MF) top temperature (Kedia et al., 2019)

In this study as controlled variable (CV), LCGO and HCGO draw temperatures are determined. By implementing feedforward control, the researchers aim to stabilize the LCGO and HCGO draw temperatures, ensuring that these critical process variables remain within the desired operating range and that the product quality meets the required specifications. This approach helps enhance the overall control performance and product consistency in the studied process. Before APC is implemented, standard deviation of the LCGO and HCGO draw temperatures are shown in Table 2.1.

Table 2.1. Standard Deviation of Control Variables Before APC (Kedia et al., 2019)

Standard Deviation Pre-APC	
CV1- LCGO Draw Temperature	1.7343
CV2- HCGO Draw Temperature	2.2839

After APC is implemented, the standard deviation of the LCGO and HCGO draw temperatures are reduced by disturbance characterization and shown in Table 2.2.

Table 2.2. Standard Deviation of Control Variables After APC (Kedia et al., 2019)

Standard Deviation Post-APC			
	Actual Plant Data	Disturbance Characterization	% Error
CV1	1.261	1.17	7.24
CV2	1.438	1.36	5.44

In another study, it is studied an industrial application of model predictive control for Crude Distillation unit of TÜPRAŞ refinery, Izmit (Kemaloğlu et al., 2009).The primary objective of the MPC controller was to regulate the heating of crude oil through a series of process flows, furnace heating, and a distillation column equipped with product strippers. Figure 2.5 shows the process drawing of atmospheric crude distillation column. The crude oil is initially heated using hot streams within the unit before and after the desalting operation. This preheating is crucial for optimizing the distillation process. There are two parallel furnaces in operation, which heat the crude oil to temperatures typically ranging between 320-350 ºC. These furnaces play a pivotal role in elevating the temperature of the incoming crude oil. The heated crude oil from the furnaces is directed into the distillation column. Inside the column, the crude oil is separated into various products based on their boiling points. The main products are kerosene, light diesel, and heavy diesel, each extracted at different heights in the column. At the top of the distillation column, there is a mixture of LPG (liquefied petroleum gas), light straight run naphtha, and heavy straight-run products. This mixture is then directed to a naphtha splitter column, where LPG and light naphtha are separated from heavy naphtha. The liquid product from the naphtha splitter upstream is further processed in the debutanizer column. In this column, the liquid product is separated into light naphtha and LPG, two valuable products. The bottom product residue is fed to vacuum distillation column. This column operates at reduced pressures, allowing for the separation of additional products from the residue.

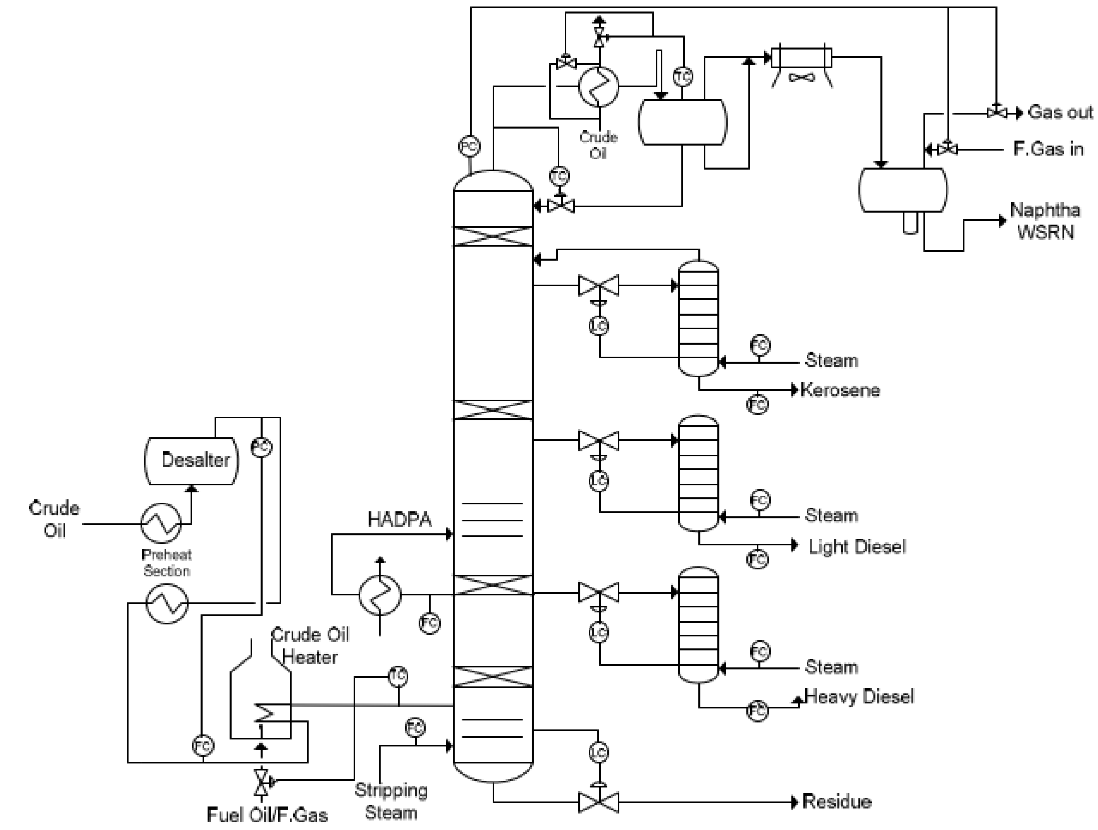

Figure 2.5. Characterized Main fractionator (MF) top temperature (Kemaloğlu et al., 2009)

In the design of the controllers, Shell Multivariable Optimizing Controller, SMOCPro is used to implement predictive controller in TUPRAS Izmit Refinery Crude Unit[8]. In the controller design section of the APC totally, 28 manipulated variables are determined, preheat section includes 17 MV and crude distillation column section includes 11 MV including feed flow controllers, furnace coil flow controllers and distillation column pressure, temperature and flow controllers. There are 3 disturbance variables as amount of total feed and inlet flow rates to two furnaces are selected. There are 15 controlled variables from the crude distillation part and four controlled variables are in preheat section of the unit. Control variables are quality inferential which are created by statistical regression of empirical data heavy naphtha, light diesel and heavy diesel 95% distillation points and kerosene flash point qualities , unit constrains and economic variables. Empirical data were obtained by applying test to the manipulated variables. According to the change in manipulated variables, column dynamics were changed and settled, and laboratory results were obtained and quality inferential were modelled using RQE Pro, a software in the Process Control Technology Package (PCTP) of Shell Global Solutions International BV. After the inferential was created, to design APC, response tests were started. During the response tests, it is important to get clear responses in the control variables test data. For each of the 28 manipulated variables, tests were carried out separately in sequence, groups of six to eight steps were made in each. The sequence was repeated afterwards, obtaining a test data of sixteen to twenty moves for each variable. In the dynamic modelling part, the step test data were analyzed and mathematically fit to obtain predictive process model using Shell Multivariable Optimizing Controller, SMOCPro is used to implement predictive controller. Similar to what is used in most advanced process control algorithms; SMOC algorithm also follows a reference trajectory by the future outputs on the prediction horizon and penalizes the control effort on the control horizon. General objective function of the controller can be written as;

$$min = \sum_{i=1}^{P} |\hat{y}(n+i) - r(n+i)|^2 \, w_1 + \sum_{j=1}^{C} |\Delta u(n+i-1)|^2 \, w_2 \qquad \text{Eqn 5.}$$

'u' represents inputs, 'y' is used to define outputs and the superscript ^ represents the predicted values. Δu is the input variation and r is the reference trajectory of the outputs. In this optimization problem, the first term is used to minimize the error resulting from the difference between predicted outputs and reference trajectory during prediction horizon, P. The second term is the difference of control actions taken at each time step during control horizon, C. Weighting matrices $w_1$and w_2 are positive definite matrices, with different magnitudes for all MV's and CV's.

Economic Variables

Determining the APC object is important to provide benefit from the project. That's why the economic function was defined as follows:

- Minimizing column top temperature, column pressure and stripping steam ratio to the feed.
- Maximizing heavy diesel pump around duty, product draws to stripper level constraints and furnace heater duties.
- Maximizing the amount of heavy diesel by letting heavier cuts into heavy diesel and leaning to high limit.
- Maximizing the amount of kerosene by letting heavy naphtha into kerosene and approaching to low limit.

According to the APC commissioning results, The Naphtha yield decreased and kerosene yield for a five weeks period of pre-commissioning and four weeks period of post-commissioning of the controller with the almost same crude density.

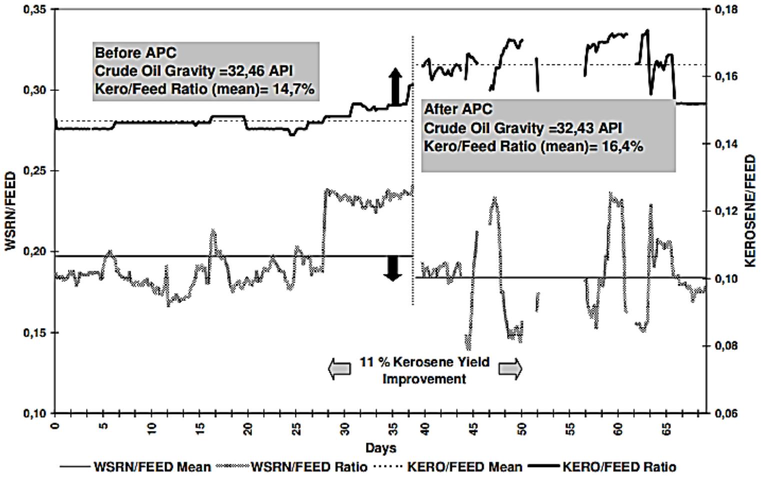

Figure 2.6. Change in the naphtha yield before and after commissioning (Kemaloğlu et al., 2009)

Kerosene flash point is decreased by increasing naphtha yield in the kerosene. Figure 2.7 shows the kerosene flash point decreasing after APC applied.

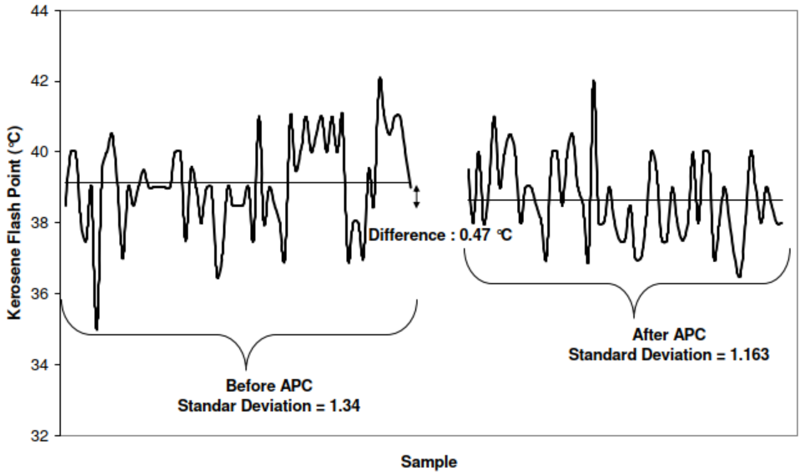

Figure 2.7. Change in kerosene flash point before and after commissioning (Kemaloğlu et al., 2009)

In another study, MPC model of the butane-butylene distillation column was studied, and Figure 2.8 shows the block diagram including L (reflux flowrate), B (bottom product flowrate), F (feed flowrate), x_F(concentration of light components in feed),x_D (concentration of light components in distillate), x_B (concentration of light components in bottom product). Flowrates L and B are the manipulated variables, while variables F and x_F are the disturbances.

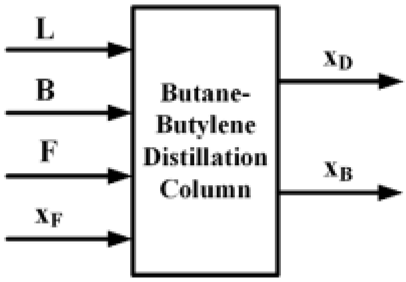

Figure 2.8. Block diagram of butane-butylene distillation column (Nicolae et al., 2019)

In Petrobrazi refinery, by using MATLAB the four inputs were modified and the transfer functions for each input and output variable of the process were identified and are presented in Table 2.3.

Table 2.3. The transfer functions for each input – output (Nicolae et al., 2019)

	X_D	X_B
L	$\frac{0.246}{400s^2+40s+1}e^{-10s}$	$-\frac{0.529}{1190s^2+99s+1}e^{-15s}$
B	$\frac{0.13}{440s^2+51s+1}e^{-10s}$	$\frac{1.3578}{89s+1}e^{-10s}$
F	$-\frac{0.446}{418s^2+49s+1}e^{-14s}$	$-\frac{0.6728}{1853s^2+126s+1}e^{-13s}$
X_F	$\frac{0.296}{494s^2+51s+1}e^{-13s}$	$\frac{2.4896}{2272s^2+103s+1}e^{-15s}$

Figure 2.9 shows the MPC control system for the butane-butylene distillation column. In the MPC design L and B are the manipulated variables and outputs are x_D, and x_B.

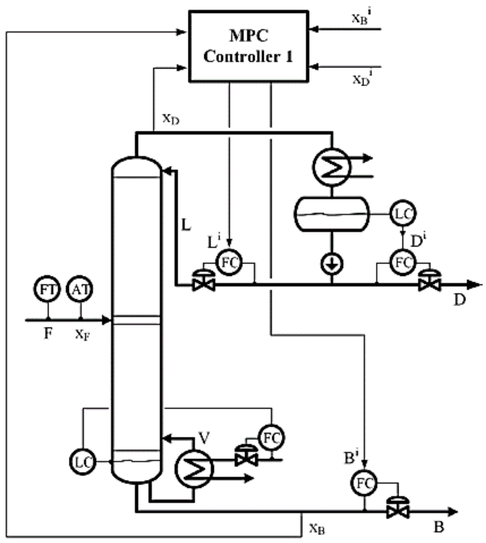

Figure 2.9. MPC control system for butane-butylene distillation column (Nicolae et al., 2019)

According to the control system MPC model 1, set points of the manipulated variables were changed separately and the response of the control variables were obtained. Figure 2.10 shows the x_D and x_B step change graph. The tuning parameters for the MPC controller are: sample time=0.4; prediction horizon=170; control horizon=2.

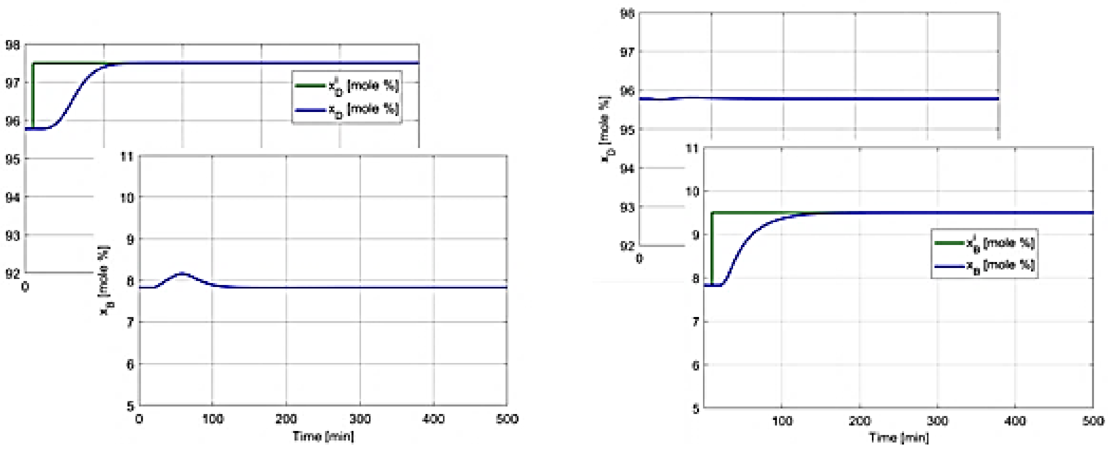

Figure 2.10. Step change in x_D and x_B (Nicolae et al., 2019)

According to the step change in x_D and x_B, obtaining response for B and L shown in Figure 2.11.

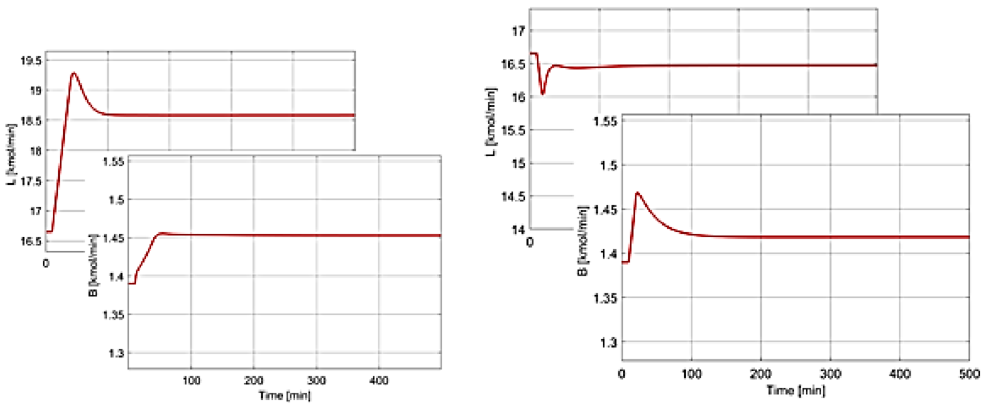

Figure 2.11. Time evolution of L and B for the x_D and x_B set-point change (Nicolae et al., 2019)

From Figure 2.11 it can be observed that the MPC controller brings the controlled variables (x_D and x_B) at the set-point values, without overshoot or oscillations, with a transient time smaller than the one of the process. In addition, the process interactions are successfully handled, the influences on the crossed channels (L-x_B and B-x_D) being very small.

Disturbance Effect on Controlled Variables

Figure 2.12 shows the disturbance F effect on the control variables x_D and x_B.

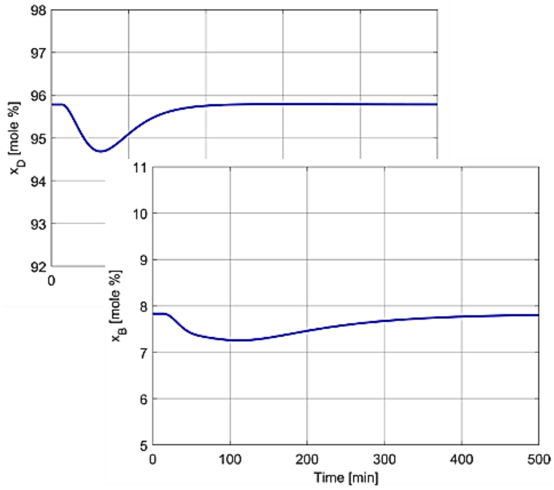

Figure 2.12. Time evolution of x_D and x_B as step change of disturbance F (Nicolae et al., 2019)

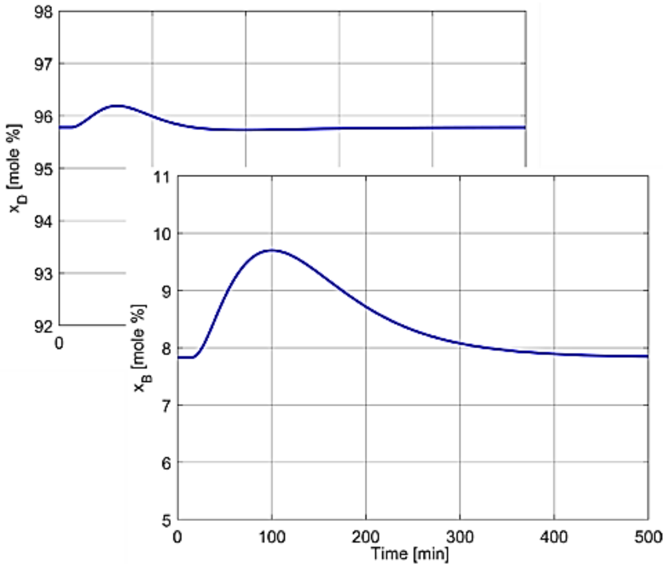

Figure 2.13. Time evolution of x_D and x_B as step change of disturbance x_F (Nicolae et al., 2019)

In order to improve the system's response to disturbances changes a new MPC controller is designed based on a process model, which uses the transfer functions on all process channels, including disturbances – outputs channels. The block diagram of the control system is presented in Figure 2.14. In this structure, the two disturbances (F and x_F) are measured.

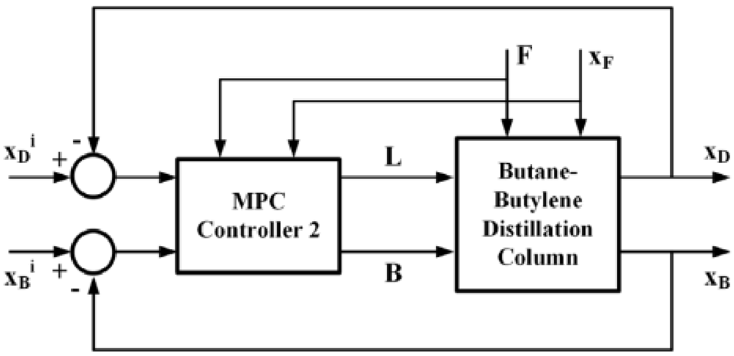

Figure 2.14. Block diagram of the MPC Controller 2-based control system (Nicolae et al., 2019)

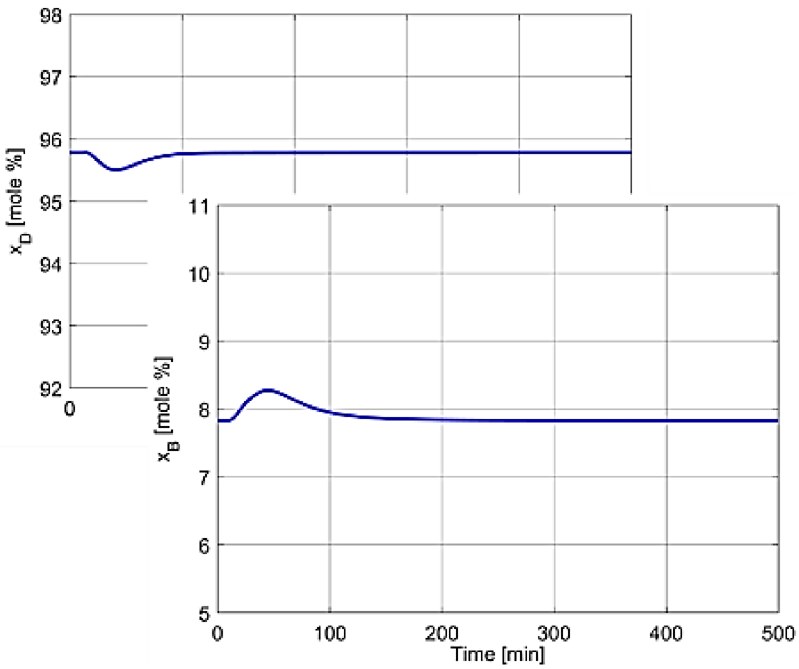

Figure 2.15. Time evolution of x_D and x_B as step change of disturbance F (Nicolae et al., 2019)

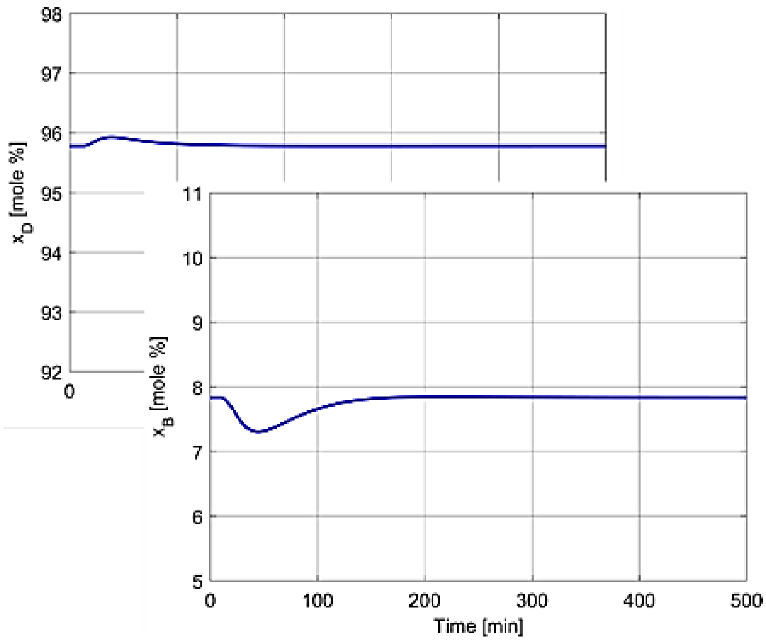

Figure 2.16. Time evolution of x_D and x_B as step change of disturbance x_F (Nicolae et al., 2019)

As it can be observed from Figures 2.15-2.16, the MPC Controller-2 compensates the effect of the disturbances on the outputs with much better results than in the case when the MPC Controller-1 which does not include a model of the process on the disturbances on outputs. In another study which is Optimizing Diesel Production Using Advanced Process Control and Dynamic Simulation, an application that shows the advantages of combining APC strategies and Dynamic simulation for optimizing a Diesel blending system in a large Brazilian refinery (Garcia et al., 2014). Figure 2.17 shows the Diesel Blending system in Brazilian Refinery.

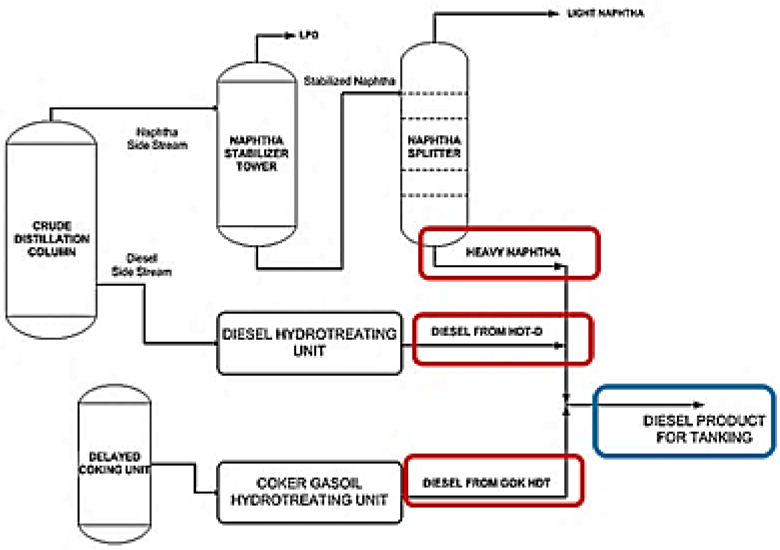

Figure 2.17. The Diesel Blending System (Garcia et al., 2014)

The feed of the naphtha splitter column comes from the Stabilizer Column of the Crude Distillation Unit. Figure 2.18 shows the naphtha splitter column.

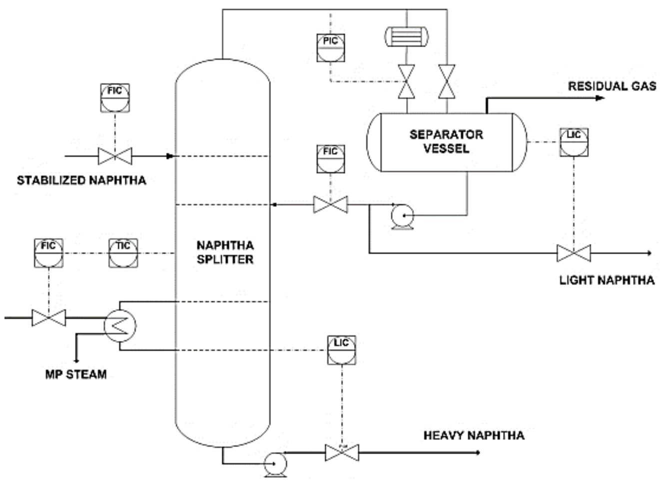

Figure 2.18. Naphtha Splitter (Garcia et al., 2014)

The control of the sensitive plate temperature in the Splitter column is achieved by regulating the heat exchange between medium-pressure steam and the column's side reflux. This control mechanism ensures that the temperature at the sensitive plate remains within the desired range, contributing to the overall efficiency and performance of the column. In this process, the top reflux of the Splitter column is primarily composed of the Light Naphtha obtained from the top separator vessel. Any excess Light Naphtha that is not required for the process is exported as Petrochemical Naphtha, which may have different economic values and applications. On the other hand, the column's bottom flow consists of Heavy Naphtha. The Heavy Naphtha stream is added to the Diesel blending system. This decision is based on the economic considerations related to the value of the products. Diesel typically has a higher economic value when compared to Naphtha. Therefore, the economic yields are optimized by directing a portion of the Heavy Naphtha stream to the Diesel blending system. APC is designed by DMC (Dynamic Matrix Control) algorithm and matrix is shown in Table 2.4 (Garcia et al., 2014). The Splitter’s APC manipulates the economic related variables including the processed feed, the medium pressure steam consumption and the reflux flow. The CVs represent the operational constraints, i.e., the PID controller’s output signals and the inferential variables: The Heavy Naphtha’s flash point, the Heavy Naphtha / T5% ratio (RQT5) and the reflux ratio (RR), which are used to evaluate the column’s split quality. T5% refers to the distillation temperature in which 5% of the total volume of Naphtha is recovered from the gaseous state and it is directly related to the Naphtha’s initial boiling point.

Table 2.4. MV-CV Matrix for Naphtha Splitter (Garcia et al., 2014)

	MV		
CV	Splitter’s Feed	Steam Flow	Reflux Flow
TIC Process Variable		↑	↓
Bottom LIC Control Signal	↑	↓	↑
PIC Control Signal		↑	
Naphta’s Flash Point	↓	↑	↓
RQT5	↑	↓	↑
RR	↓		↑

Figure 2.19 shows the increase of the daily-average Heavy Naphtha flow and the six-month average line before after the APC commissioning. Before the APC project, the

Splitter’s temperature was controlled to a fixed set-point, which represented a hard constraint for the operational optimization. The more flexible APC’s band control strategy, in counterpart to the regulatory target control, adds up one more degree of freedom, which is used to maximize the processed feed.

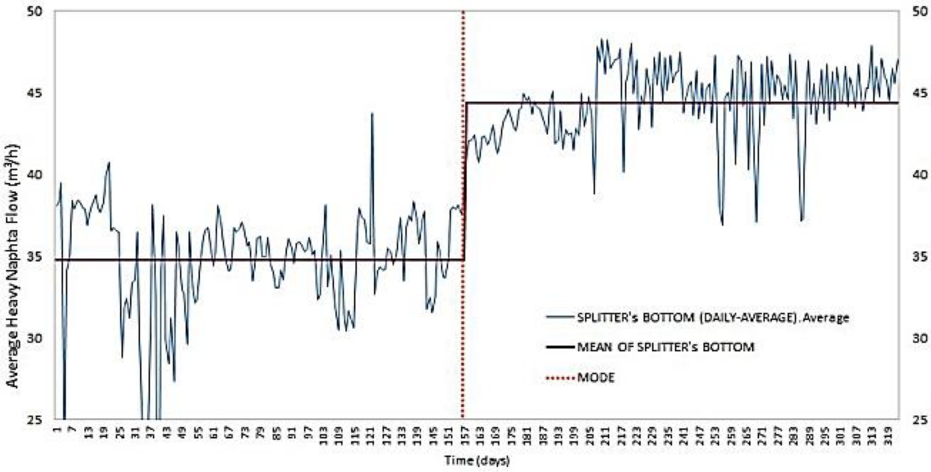

Figure 2.19. Heavy Naphtha flow before and after APC (Garcia et al., 2014)

2.1. Summary of Literature Search

According to the literature search, there are not many works available about the APC studies in DCU unit main fractionator column. However, there are APC studies about the different refinery units. As shown in the represented literature studies, process models and controller designs are done using MATLAB MPC toolbox, Shell Multivariable Optimizing Controller (SMOCPro) and DMC (Dynamic Matrix Control) algorithm. APC applications provide following benefits; product quality stabilization, process optimization implying higher throughput, improved product yields, energy conservation, improved operations reliability, and reduced operator actions.

CHAPTER 3

MATERIALS AND METHODS

APC case is studied in main fractionator column of Delayed Coker Unit (DCU) at SOCAR Izmir Refinery. In this study, the Honeywell RMPCT controls the LCGO final boiling point quality. To determine APC control for controlling LCGO FBP quality, the following methods were applied.

3.1. Determination of APC control Matrix for product quality

In this step, advanced process control strategy is determined. In manual operation, operators are changing LCGO product drawing flow to control the FBP product quality. Therefore, APC will manipulate the LCGO product drawing flow to control LCGO FBP quality.

3.2. Conduct the Pre-Step Test and Main Test

Pre-step test is important to provide time to steady state for control variable. (LCGO FBP quality) and data for initial model identification. During the test, it is required to have for each MV 8-15 step changes (Qin et al.,2003). MV steps are changed one by one while the other MV values keep constant. Figure 3.1 shows the step test procedure. After the MV step changes are applied, time to steady state is determined for CV.

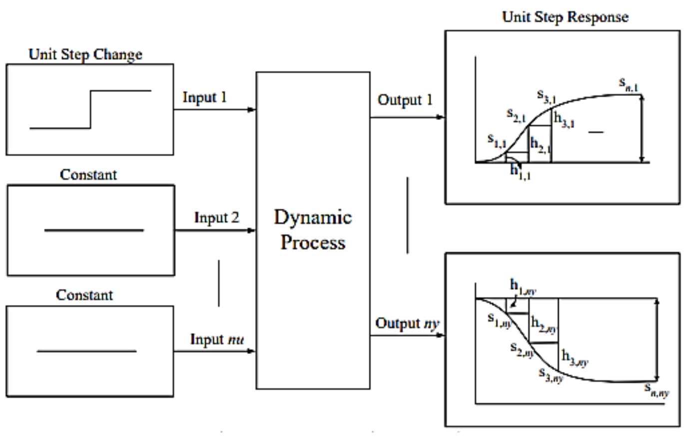

Figure 3.1. Step Test Procedure (Mariéthoz et al., 2012)

Additionally, to determine process response for CV, PBRS (Pseudo Binary Random Sequence) type step test is applied. In this test method, MV's steps are changed simultaneously, and CV response are obtained. Below Figure 3.2 shows, the PBRS type step change for the dynamic test.

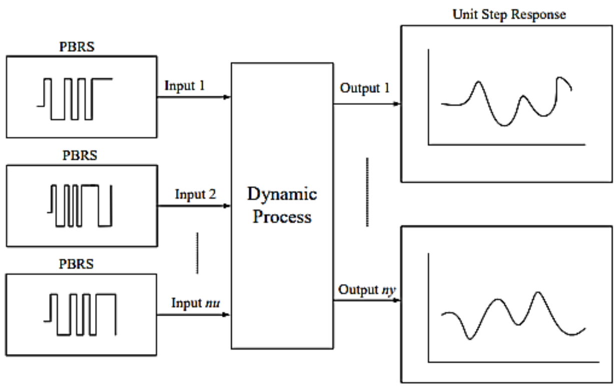

Figure 3.2. PBRS type step test (Mariéthoz et al., 2012)

3.3. Identification of Process Models

System identification is an approach that empowers people to generate mathematical representations of a dynamic system by utilizing collected data. Achieving this is done by refining the parameters within a given model until its output aligns with the observed or measured output. Model sets or model structures comprise a variety of models defined by adjustable parameters. The task of parameter estimation entails discovering the most suitable values for these parameters. The core challenge in system identification lies in not only selecting an appropriate model structure but also acquiring precise numerical values for its parameters. Parametric identification methods are methodologies used to estimate parameters within predetermined model structures. In essence, they involve a numerical search process to pinpoint the numerical values of these parameters that yield the closest match between the model's simulated or predicted output and the measured data. Non-parametric identification methods are procedures designed to estimate the behavior of a model without the requirement of a predefined parametric model set. Common non-parametric techniques encompass correlation analysis, used to gauge a system's impulse response, and spectral analysis, employed to assess a system's frequency response. In traditional Model Predictive Control (MPC) identification, the initial step involves the use of a Multi-Input Multi-Output (MIMO) Finite Impulse Response (FIR) model to estimate system parameters. This estimation is typically performed using the least-squares method. However, it is common for this approach to yield models with step responses that exhibit non-smooth behavior. To address this issue and improve the model's performance, model reduction or smoothing techniques are applied. These techniques are employed to transform the initial model into one that produces smoother step responses, enhancing its suitability for control and prediction tasks. Numerous common models and methods are frequently encountered for system identification.

3.3.1. ARX (Autoregressive with external input) Model

Also referred to as the least-squares model, the ARX model incorporates autoregressive and exogenous input terms to describe a system's behavior. It is a widely used choice for modeling dynamic systems. Parametric models have two purpose, model order reduction and the removal of variance present in models obtained from raw data. When working with standard low-order ARX (AutoRegressive with eXternal input) models, because of the biased estimates ARX models often provide inadequate results. However, the prefiltered form utilized in the APC identifier addresses this issue by automatically emphasizing the fit at low frequencies. As a result, it yields high-quality models that accurately capture system dynamics and minimize estimation bias. General ARX model structure is given in below equation where the prime symbol (') represents a prefiltered value. Additionally, 'n' and ’d’ refer to the order and delay of the sub process, respectively.

$$P(z)y'(t) = B(z)u'(t-d) + e(t) \quad \text{Eqn 6.}$$

ARX Model Transfer Function is given as below equation[3];

$$T(z) = \frac{(b_1 z^{-1} + b_2 z^{-2} + \cdots + b_n z^{-n})z^{-d}}{1 + p_1 z^{-1} + \cdots + p_n z^{-n}} \quad \text{Eqn 7.}$$

3.3.2. OE (Output Error) Model

The OE model centers on capturing the output behavior of a system in response to input signals. Its objective is to minimize the error between the model's predicted output and the actual measurements (Lahiri, 2017).

General OE Model is given in below equation;

$$w_t + f_1 w_{t-1} + f_2 w_{t-2} + \cdots + f_n w_{t-n} \quad \text{Eqn 8.}$$

$$= b_1 u_{t-1-d} + b_2 u_{t-2-d} + \cdots + b_n u_{t-n-d}$$

$$y_t = w_t + e_t$$

$$y(t) = \frac{B(z)}{F(z)} u(t-d) + e(t) \quad \text{Eqn 9.}$$

According to the equation, it is shown that in the regression matrix does not include the output variable 'y'. Obtained transfer function equation is shown in below equation.

$$T(z) = \frac{(b_1 z^{-1} + b_2 z^{-2} + \cdots + b_n z^{-n}) z^{-d}}{1 + f_1 z^{-1} + \cdots + f_n z^{-n}} \quad \text{Eqn 10.}$$

Although the output error model has the advantageous as quality of being unbiased even without prefiltering, it comes with the requirement that the estimation parameters must appear in the regression matrix. Consequently, this leads to a nonlinear estimation problem. This nonlinearity implies that solving for the output error model demands more computational effort compared to solving for the ARX model. The increased complexity in estimation makes the output error solution computationally more demanding.

3.3.3. ARMAX Model

Expanding upon the ARX model, the ARMAX (Auto-Regressive Moving Average with external input) model introduces a moving average component. It considers past output values in addition to input and output error terms.

3.3.4. State Space Models

State-space models are widely used representations of dynamical models. They describe a linear difference relationship between inputs and outputs, similar to the ARX (Autoregressive with external input) model. However, state-space models are organized in a way that simplifies the expressions, typically using only one delay in the equations. This rearrangement makes state-space models a concise and often more intuitive way to represent the dynamics of a system. State Space expression is given in below equation where x (t) is the vector of state variables and the model order is the dimension of vector.

$$x(t+1) = Ax(t) + Bu(t) + Ke(t) \quad \text{Eqn 11.}$$

$$y(t) = Cx(t) + Du(t) + e(t)$$

3.3.5. Box-Jenkins Model

This modeling methodology, known as the Box-Jenkins approach, involves a systematic procedure for identifying, estimating, and validating time series models. It typically incorporates autoregressive (AR), moving average (MA), and differencing components, rendering it suitable for modeling complex time series data. These models and methods offer a diverse array of tools for modeling and comprehending the behavior of dynamic systems. The selection of a specific model or method hinges on the unique characteristics of the system being studied and the objectives of the identification process. In literature, it is common to categorize ARX, OE, ARMAX, and Box-Jenkins models as parametric models. These models are considered parametric because they have specific mathematical structures with adjustable parameters, and their form is defined based on certain assumptions about the underlying system dynamics. Conversely, the FIR model is typically referred to as a nonparametric model. This classification is because the FIR model does not assume a specific mathematical structure with adjustable parameters to describe the system. Instead, it represents the system's response solely as a weighted linear combination of past input values, making it more flexible and less constrained by predefined model structures. In both FIR (Finite Impulse Response) and ARX (AutoRegressive with external input) models, the error term is linear in the model parameters. This linear relationship between the error and parameters is a significant advantage because it allows for the use of linear least-squares methods in parameter estimation. Linear least-squares methods are numerically straightforward and reliable, making them practical for estimating the model parameters. This property contributes to the popularity of FIR models in industrial identification. The simplicity and reliability of linear least-squares methods make the estimation process more accessible and well suited for practical applications, where robustness and ease of implementation are often crucial considerations. Indeed, different MPC (Model Predictive Control) vendors approach the model-building procedure with their unique styles and techniques. Each MPC technology provided by different vendors may come with its own set of identification techniques and choices of models available in their software as shown in Table 8. These distinctions can significantly affect how engineers and users perform system identification and control. For instance, as you mentioned, DMC Plus offers two types of modeling choices FIR

(Finite Impulse Response) and subspace identification providing users with options to select the modeling approach that best suits their specific needs and system characteristics. The diversity in identification techniques and model choices among MPC vendors reflects the adaptability and customization potential of these systems. Users can choose the vendor and software that aligns most effectively with their control objectives and the particular dynamics of the processes they are managing. This variety allows tailored solutions to address a wide range of industrial and control system requirements. It is evident that RMPCT uses both FIR (Finite Impulse Response) and prediction error method (PEM)-based modeling approaches as part of its system identification capabilities. This means that users of RMPCT have the flexibility to choose between these two modeling techniques when identifying and characterizing the dynamics of the system they wish to control. As mentioned earlier, different vendors and software providers in the field of Model Predictive Control (MPC) offer various identification techniques and models in their software packages. The choice of identification method often depends on the specific requirements and characteristics of the system being controlled and the preferences of the users or engineers working with the software. In this study, Honeywell Profit Suit Engineering Studio, Finite Impulse Response (FIR) model RMPCT (Robust Multivariable Predictive Control Technology) algorithm is used for process output predictions. FIR model algorithm can be used in robust predictive control. In industrial APC applications, mostly FIR algorithm is used since, error is linear in the parameters and linear least square method can be used for parameter predictions (Zhu et al., 2004) . RMPCT is the industrial model predictive control technology produced by Honeywell and has following properties; Graphical interface , economic and quadratic programming objective function, identification technologies considering prediction error methods (Qin et al., 2003).

Table 3.1. Companies and products included in Linear MPC technology (Qin et al., 2003)

Company	Product Name	Description
Adersa	HIECON	Hierarchical constrains control
	PFC	Predictive functional control

(cont. on the next page)

Table 3.1. (cont.)

Aspen Tech	DMC-plus	Dynamic matrix control package
	DMC-plus model	Identification package
Honeywell	RMPCT	Robust model predictive control technology
Shell Global Solutions	SMOC-II[a]	Shell multivariable optimizing control
Invensys	Connoisseur	Control and identification package

In RMPCT, there is a funnel control in order to keep the CV values within the control limits. It gives advantage to control CV values within a certain range. Funnel control is shown in Figure 3.3. In the Figure 3.3, it is shown that, until the CV value is within the hard limits to solve the control problem there is a high MV movement. After the CV value is kept in the control limits, there is minimum MV movement.

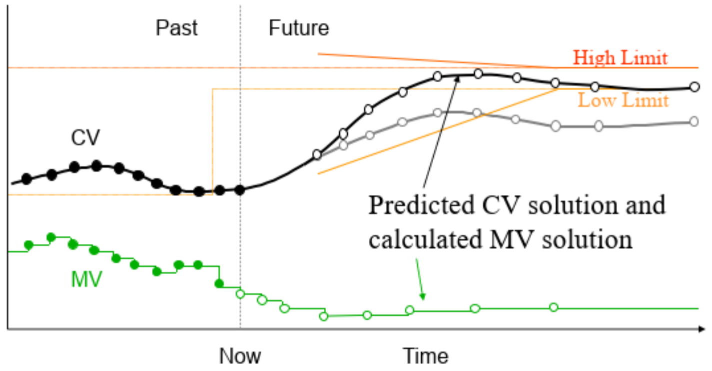

Figure 3.3. RMPCT Funnel Control Strategy (Lahiri, 2017)

Below Figure 3.4 shows the funnel, reference trajectory, control zone and set point of the CV. When the CV value is in the outside of the control horizon, MV set point will change by RMCT to keep the CV value within the control zone (Qin et al., 2003). Shaded areas show violations.

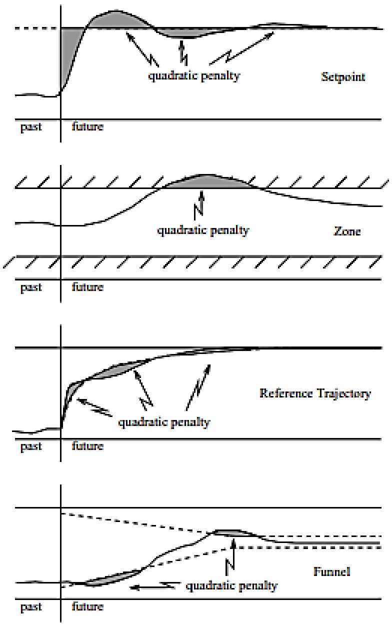

Figure 3.4. Options for specifying future CV behavior (Qin et al., 2003)

The slop of the funnel shows the ratio between the desired time to keep the CV within the control zone to open-loop response time called as performance ratio. Performance ratio is the one of the tuning parameters for RMPCT, lower performance ratio means faster control to keep the CV value in the range. In the RMPCT model, a prediction horizon shows future value of the CV. When the prediction horizon is long, it is better to observe the MV moves effects. Figure 3.5 shows the Prediction horizon for RMPCT.

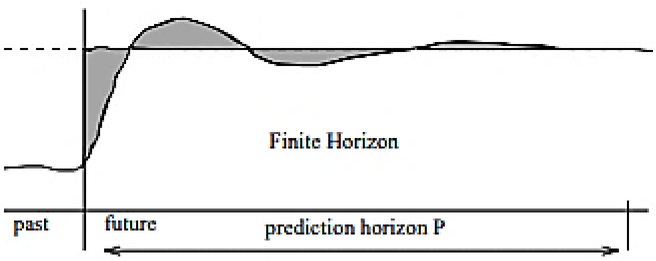

Figure 3.5. Prediction horizon (Qin et al., 2003)

3.3.6 FIR Model (Finite Impulse Response)

This model characterizes a system by expressing it as a linear combination of its input signals with a finite number of past input values. It is distinguished by its finite impulse response, indicating that it doesn't rely on feedback (Lahiri, 2017). When properly formulated and applied, the FIR (Finite Impulse Response) approach can indeed be an exceptionally effective estimator in system identification. The FIR model, with its simplicity and flexibility, is often used as a foundation for various identification and control techniques. One notable example is the APC (Advanced Process Control) identifier, which leverages the FIR model as its fundamental structure. The FIR model, which characterizes a system as a linear combination of past input values, has advantages in capturing short-term dynamics and transient behaviors. Its effectiveness can be further enhanced through appropriate model formulation and parameter estimation techniques. This adaptability and effectiveness make the FIR approach a valuable tool in system identification and control, particularly when dealing with processes that exhibit rapid changes or short-term dynamics. In the below expression which is the positional form of the FIR (Finite Impulse Response) model impose inherent limitations on the structure of the model. Each sub-model element, denoted as (i, j), is free to accommodate as many coefficients as needed to effectively capture and replicate the observed response of the system.

$$
\begin{aligned}
(p_0{}^{i,1}u_t{}^1 + p_1{}^{i,1}u_{t-1}^1 + p_2{}^{i,1}u_{t-2}^1 + \cdots + (p_{n1}{}^{i,1}u_{t-n1}^1) + (p_0{}^{i,2}u_t{}^2 + p_1{}^{i,2}u_{t-1}^2 \\
+ p_2{}^{i,2}u_{t-2}^2 + \cdots + (p_{n2}{}^{i,2}u_{t-n2}^2) + \cdots + (p_0{}^{i,m}u_t{}^m + p_1{}^{i,m}u_{t-1}^m \\
+ p_2{}^{i,m}u_{t-2}^m + \cdots + (p_{nm}{}^{i,m}u_{t-nm}^m)
\end{aligned}
$$

Eqn 12.

Where, p is the value of the impulse response and the coefficient of the FIR filter, y is the output signal and x is the input signal in the equation. This inherent adaptability is a valuable feature of the FIR model. It allows engineers and analysts to fine-tune the model's complexity to match the specific characteristics and dynamics of the system they are working with. By adjusting the number of coefficients within each sub-model, they can achieve an optimal balance between model accuracy and computational efficiency, ensuring that the model accurately represents the behavior of the observed system.

3.4. Model Validation

In traditional Model Predictive Control (MPC) identification, the validation and selection of models are typically carried out based on a combination of process knowledge, the tuning of model gains, and the comparison of simulated Controlled Variables (CVs) with their actual measurements. This process involves the following steps, process knowledge; domain experts provide insights into the expected behavior of the system and guide the identification process. This knowledge helps in defining the initial model structure and selecting appropriate parameters. Gain tuning, adjustments to model gains, such as proportional, integral, and derivative terms (PID tuning), are performed to ensure that the model's response closely matches the desired control objectives. This step is crucial for achieving effective control. Model fits, the identified model is simulated, and the simulated CVs are compared with the measured CVs from the real system. Good model fits are indicative of a well-identified model that accurately represents the system's dynamics. Validation, the identified model's performance is rigorously validated using various techniques. This validation process ensures that the model not only fits the data but also generalizes well to different operating conditions and remains robust in the face of disturbances. By combining process knowledge, gain tuning, and careful evaluation of model fits and validation results, traditional MPC identification aims to develop models that reliably represent the system and enable effective control. In the context of model validation, several assessments are conducted on full-order models, considering various metrics and statistical measures. Confidence Limits, these are used to assess the level of confidence in the model's predictions. Confidence limits provide a range within which the actual system behavior is expected to fall, given the model's uncertainty. Noise Bounds, noise bounds help determine the level of noise or uncertainty present in the measured data and its impact on the model's accuracy. Null Hypothesis Tests are employed to evaluate whether the model's predictions statistically match the observed data. They assess the hypothesis that there is no significant difference between the model's output and the actual measurements. Step Response Sensitivities, this metric examines how sensitive the model's step response is to small perturbations or changes in the model parameters. It helps in understanding the model's stability and robustness. Based on the results of these assessments, full-order models are automatically ranked, typically on a scale from 1 to 5, with 1 indicating excellent agreement with the observed data and 5 implying that the model is essentially useless for its intended purpose. These model rankings can be employed to automatically determine whether corresponding reduced-order models should be nullified or not. This feature, often user-selectable, helps in making informed decisions about model reduction and selection, ensuring that only the most reliable models are used for control and prediction purposes.

3.5. Offline Simulation and Tuning

After the final models are selected and implemented, it is required to test dynamic response offline simulations, we collaborate with the operations department to define varying upper and lower limits for Manipulated Variables (MV) and Controlled Variables (CV). Additionally, we configure different tuning parameters for the controller to optimize its real-time performance between the MV and CV with offline simulation in Honeywell RMPCT. Offline simulation requires following steps including setting up the simulator in Honeywell RMPCT and determination of simulation case study. Figure 3.6 shows the advanced tuning parameters for MV, CV parameters and optimization.

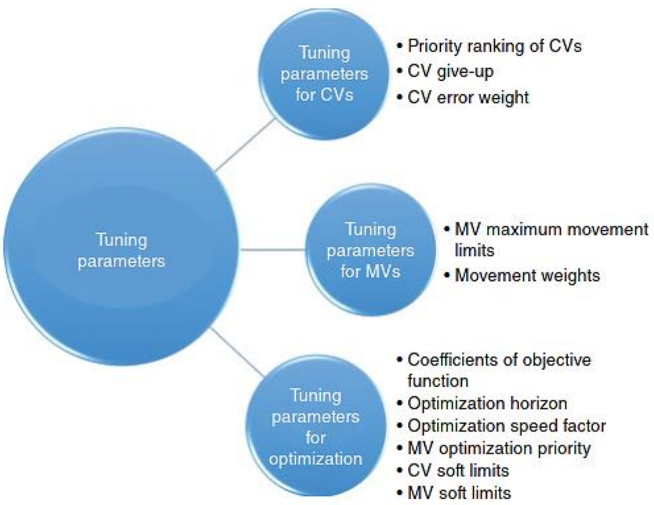

Figure 3.6. Advanced Process Control Tuning Parameters (Lahiri, 2017)

CHAPTER 4

RESULTS AND DISCUSSION

In this thesis, APC is studied in the main fractionator column of the Delayed Coker Unit (DCU) at Star Refinery. This chapter includes applied methodology and obtained results to design APC in fractionator column. LCGO Final Boiling Point and LCGO T95 quality is controlled by APC by using commercial Honeywell RMPCT application.

4.1. Determination of APC Control Matrix for Product Quality

Before creating an MPC (Model Predictive Control) application for a specific process, it is crucial for the control engineer to acquire a thorough comprehension of the process. This includes understanding its relevant limitations, how it generates profits, and identifying opportunities for increasing profitability. In this stage, Manipulated Variables (MVs), Controlled Variables (CVs), and Disturbance Variables (DVs) are determined. Additionally, constraints and limitations of the plant is evaluated and MPC opportunities are determined to increase profitability. The success of the MPC controller is significantly influenced by how well these functional designs are developed. In the main fractionator column of the DCU unit, since drum switch and preheating steps are done in every 10-12 hours, it effects the LCGO product qualities because of the disturbance effect. In Figure 4.1, HCGO tray temperature trend including 2 days data is shown to see disturbance effect of drum switch and preheating steps on the column temperature profile. In Figure 4.1, yellow points represent the points that preheating occurs and orange points represents the points that drum switch step is occurred. Additionally, sections marked as transparent represents the steady state operation areas. According to the control strategy, APC will be studied in the steady state areas of the operation to stabilize the LCGO quality. Because of the disturbance effect of the drum switch and preheating steps, it is hard to control LCGO product qualities with the APC.

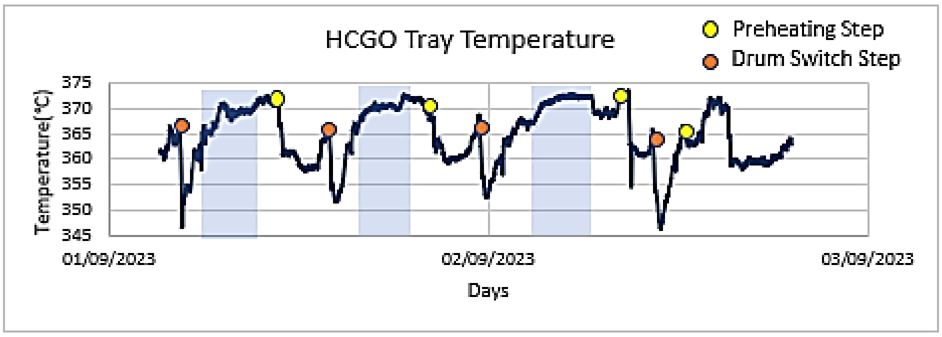

Figure 4.1. Change of the HCGO tray temperature as a function of time

According to the base layer control of the column, LCGO product T95 and FBP is controlled by changing set point of the LCGO draw flow controller by operators. Therefore, APC will manipulate the set point of the LCGO draw flow controller to control the LCGO T95 and LCGO FBP qualities as control variables. In terms of the profit scope, since LCGO is added to the diesel pool, APC aim is to maximize LCGO T95 and LCGO FBP control variables by increasing LCGO draw flow to increase the diesel production. Addionally, APC is aimed to decrease standart deviation between laboratory result and planning order for LCGO product qualities. Table 4.1 shows the control matrix for LCGO quality control with APC and expectational response of the MV change on the CV values.

Table 4.1. Control Matrix for LCGO Quality Control

	LCGO T95 Soft Sensor	LCGO FBP Soft Sensor
	CV1 (°C)	CV2 (°C)
LCGO Draw Flow (Sm3/h)	Positive response	Positive response
MV1		

4.2. Applied Step-Test

Since the control matrix is determined for LCGO product quality, step test is applied to determine the time to steady state representing settling time of the MV change response for CV. In Figure 4.2, 4 days step test trend is shown.

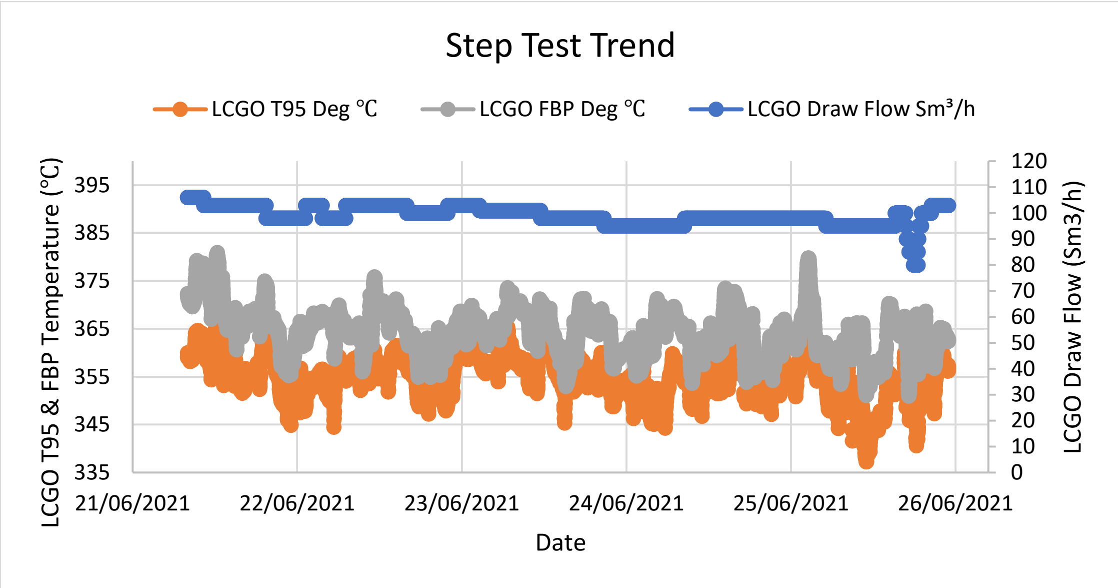

Figure 4.2. Step Test Trends for 4 days

4.3. Model Identification

After the step test is completed, 4 days test data is imported from the Honeywell RMPCT program and model identification was done with FIR algorithm in Honeywell RMPCT. Model identification is conducted by utilizing the process data gathered during the plant step test. Essentially, this involves the establishment of a relationship between Manipulated Variables (MV) and Controlled Variables (CV) for each specific pair.

Linear model identification

The model parameter estimation approaches in the MPC products are mainly based on minimizing the following least-squares criterion (Lahiri, 2017),

$$J = \sum_{k=1}^{L}(y_k - y_k^m)^2 \qquad \text{Eqn 13.}$$

In the case of a Finite Impulse Response (FIR) model, the estimated settling time serves as the model order. According to the Honeywell RMPCT results, FIR analysis response results are obtained for different trial settings including settling time estimation as below Figure 4.3,

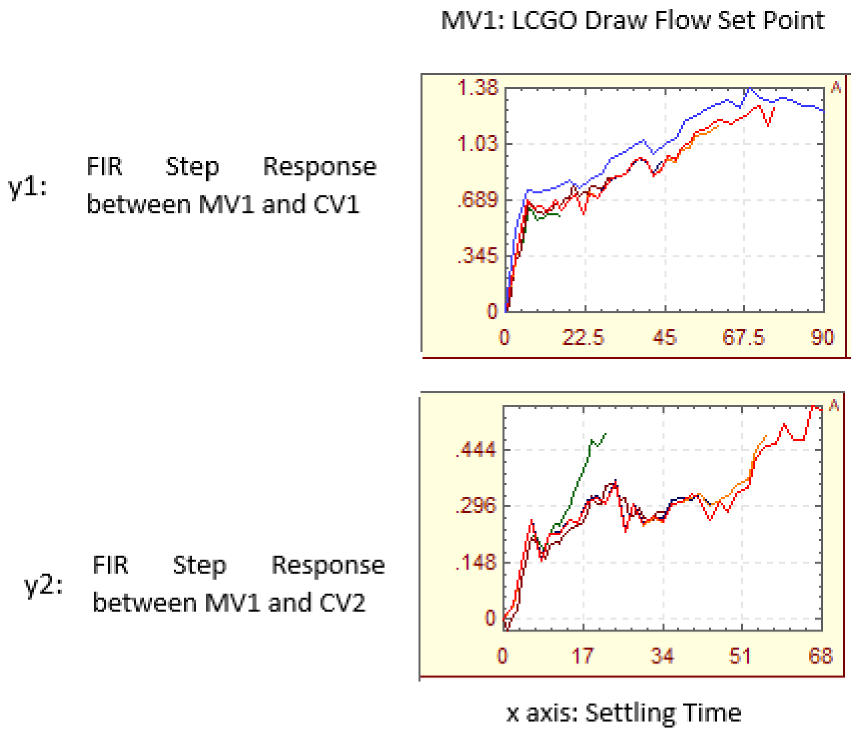

Figure 4.3. Honeywell RMPCT FIR Analysis for different trial settings

After the FIR analysis, step responses generated using FIR coefficients can exhibit significant variability or high variance. To decrease the model variance parametric fit is applied. The main objective of fitting a parametric model is primarily to decrease model variance. In addition to this, parametric models offer the advantage of having the minimum number of model parameters necessary to accurately represent the system's dynamic behavior. FIR step response parametric fit methods are Laplace Transform and

ARX. ARX Parametric Fit often produce biased estimates, but when using the prefiltered form in the APC (Advanced Process Control) identifier, it automatically gives more weight to the low-frequency fit, resulting in higher-quality models. Based on the ARX method, obtaining transfer function of the model is obtained in the below form; where, n is order of the model and d is the delay time of the process.

$$T(z) = \frac{(b_1 z^{-1} + b_2 z^{-2} + \cdots + b_n z^{-n}) z^{-d}}{1 + p_1 z^{-1} + \cdots + p_n z^{-n}} \qquad \text{Eqn 14.}$$

According to Laplace Domain Parametric Model method, transfer function can be obtained in the Laplace domain and obtaining transfer function is in the below form;

$$T(s) = \frac{k(\tau s + 1) e^{-ds}}{s(\tau_1 s + 1)(\tau_2 s + 1)} \qquad \text{Eqn 15.}$$

Both ARX and Laplace Domain Parametric model method is applied in Honeywell RMPCT. Figure 4.4 and Figure 4.5 shows the obtaining Laplace domain parametric model transfer function results between LCGO Draw Flow- LCGO T95 and LCGO Draw Flow-LCGO FBP, respectively. According to the results, first order model without dead time is obtained for both LCGO T95 and FBP model with LCGO draw flow change.

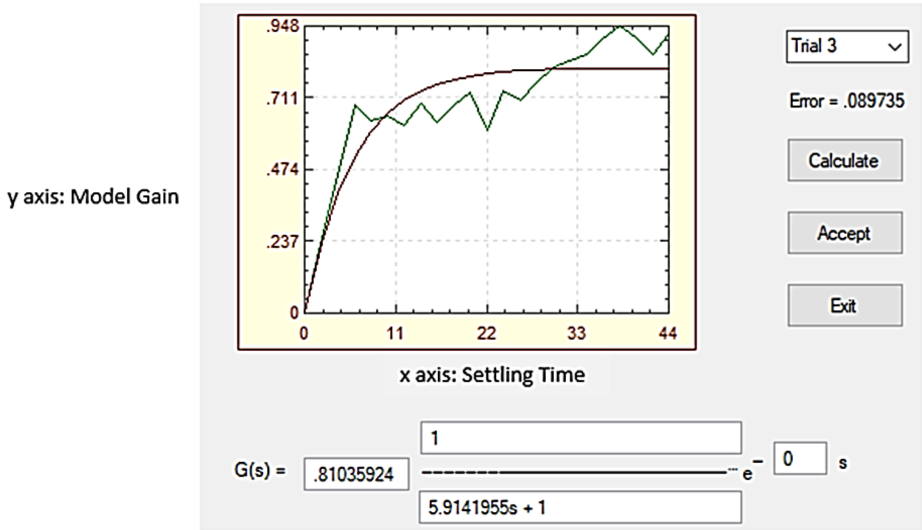

Figure 4.4. Model Transfer Function for LCGO Draw Flow- LCGO T95

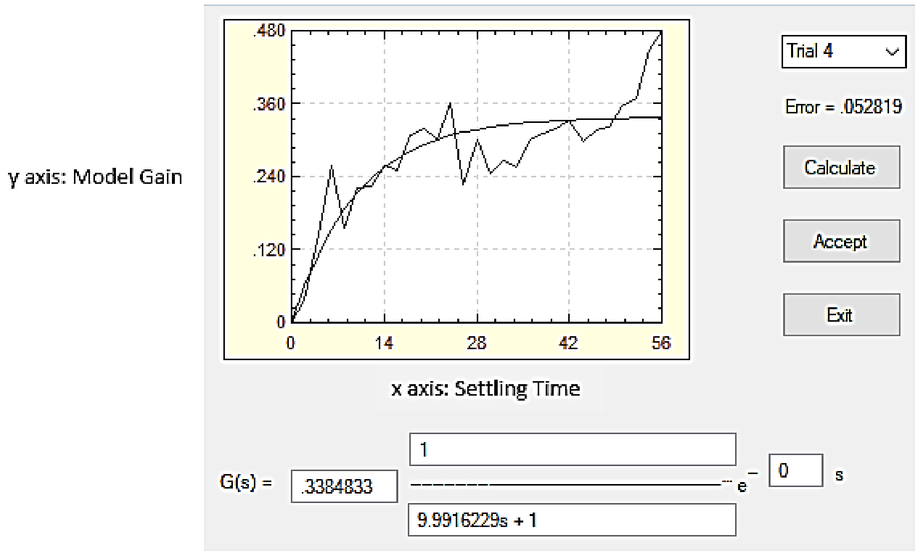

Figure 4.5. Model Transfer Function for LCGO Draw Flow- LCGO FBP

4.4. Model Validation

In the traditional process of MPC identification, model validation and selection are typically conducted by drawing upon process knowledge. This involves a particular emphasis on factors such as gains and an evaluation of the extent to which simulated Controlled Variables (CVs) align with their actual measured values. According to the obtaining models, model validation results are shown in Figure 4.6. Model validation results for LCGO T95 and LCGO FBP is rank 2 and 3 respectively, which represents the models are useful for control. Additionally, based on the process knowledge since, obtained process gains and settling time is logical; models are selected as final model.

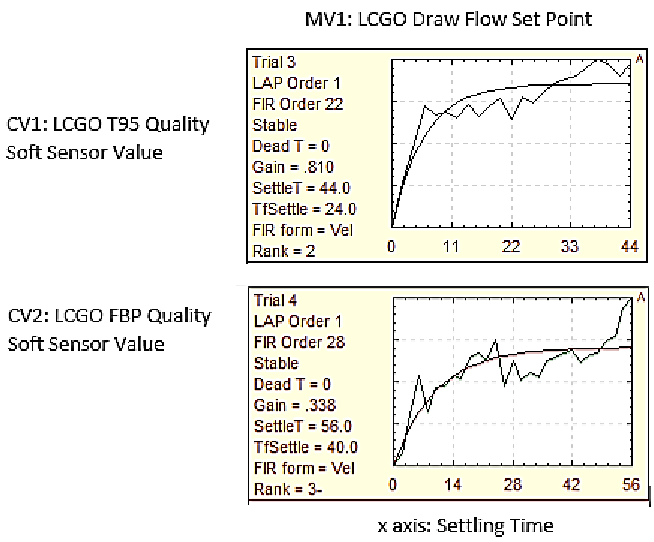

Figure 4.6. Honeywell RMPCT Model Validation Results

4.5. Offline Controller Simulation and Tuning

After the final models are selected and MPC is implemented, it is important to test model quality. Prior to implementing the controller in an actual process plant, it is crucial to understand its performance in a real-time scenario while in offline mode. Offline controller simulation entails running the controller on a separate offline computer to observe the dynamic responses between Manipulated Variables (MV) and Controlled Variables (CV) of the process. In the offline simulation, some cases are studied to analysis APC model performance.

4.5.1. MV tuning Parameter- MV weight

Manipulated Variable (MV) movement weights serve the purpose of either encouraging or discouraging controller actions on specific variables. When the objective is to minimize the movement of a particular MV, or to prevent it from moving unless necessary, a movement weight is applied. This movement weight essentially penalizes the MV's movement and influences the controller's decision regarding alternative MV adjustments. In Honeywell RMPCT, effect of MV weight is simulated when the LCGO T95 and LCGO FBP values are below the low limit values. After the change of MV weight value from 1 to 0.2, that shown with 2nd hairline in Figure 4.7, MV change movement is increased and slop of the MV change is increased because greater values for the movement weight reduce the inclination to utilize a specific manipulated variable (MV) when there are an adequate number of degrees of freedom within the control system.

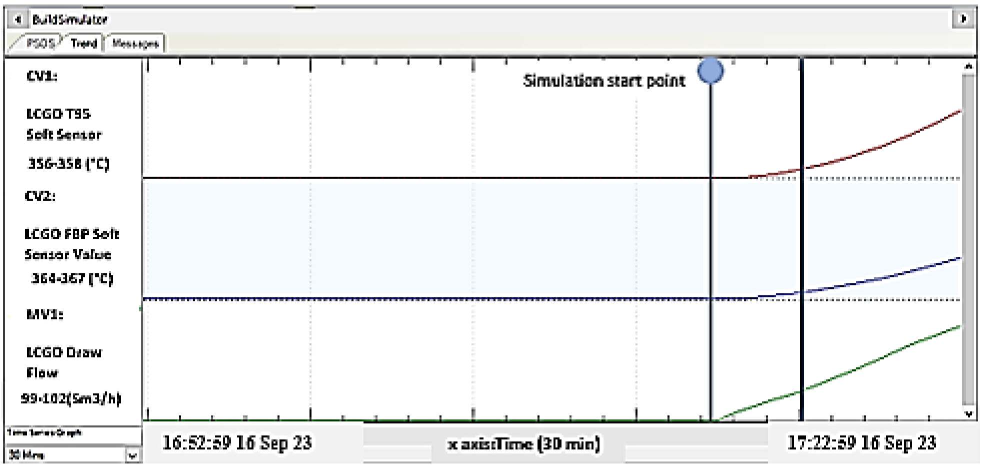

Figure 4.7. MV weight tuning parameter effect on MV Control

4.5.2. CV Tuning Parameter-EU Give up

Controlled Variable (CV) give-up values are determined based on the priority of adhering to CV constraints. When the give-up value is smaller, it indicates a higher importance placed on keeping that particular CV within its constraints. Consequently, the controller will make more effort to minimize the error associated with that CV. Give-up values are relative to each other, meaning they establish a hierarchy of importance among the CVs, guiding the controller's actions to prioritize the most critical CVs when minimizing errors and optimizing control. In Honeywell RMPCT, CV EU give up parameter is simulated. To investigate the effect of CV EU Give up, for CV1 LCGO T95 Soft Sensor low and high hard limits, narrow limits are given, for CV2 LCGO FBP Soft Sensor value low and high hard limits, large limits are given as shown in Figure 4.8.

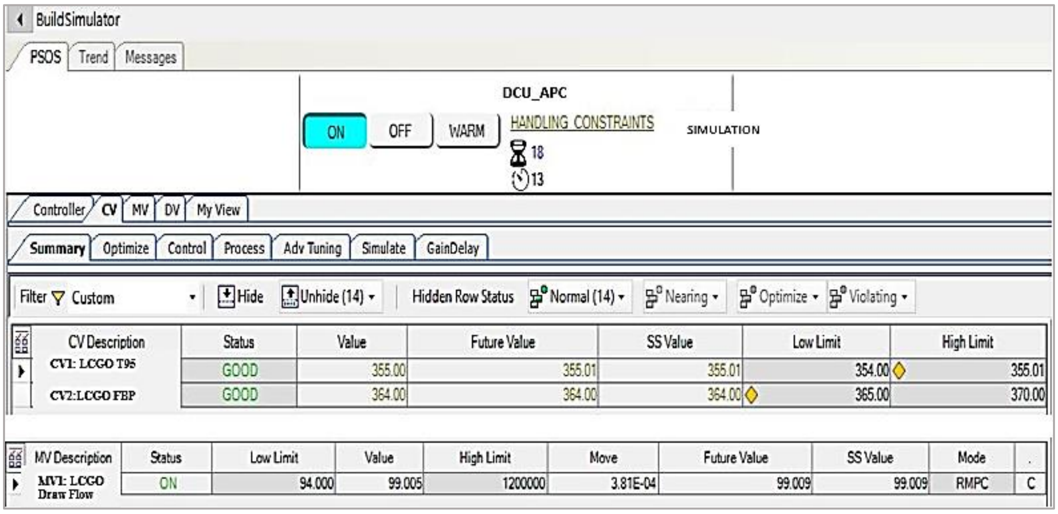

Figure 4.8. Honeywell RMPCT Interface- Simulation for CV EU Give Up

Additionally, CV low and high EU give up values for LCGO T95 and LCGO FBP CV's, are given 0 and 1 ,respectively. Since, the LCGO T95 current value is close to high limit value and high EU give up value is given as zero, although LCGO FBP current value is out of the limits, MV movement is very less. In Figure 4.9 MV 1 (LCGO Draw Flow) value is increased from 99 Sm^3/h to 99.005 Sm^3/h since, the LCGO T95 value is reached to the high limit value as 355.01°C.

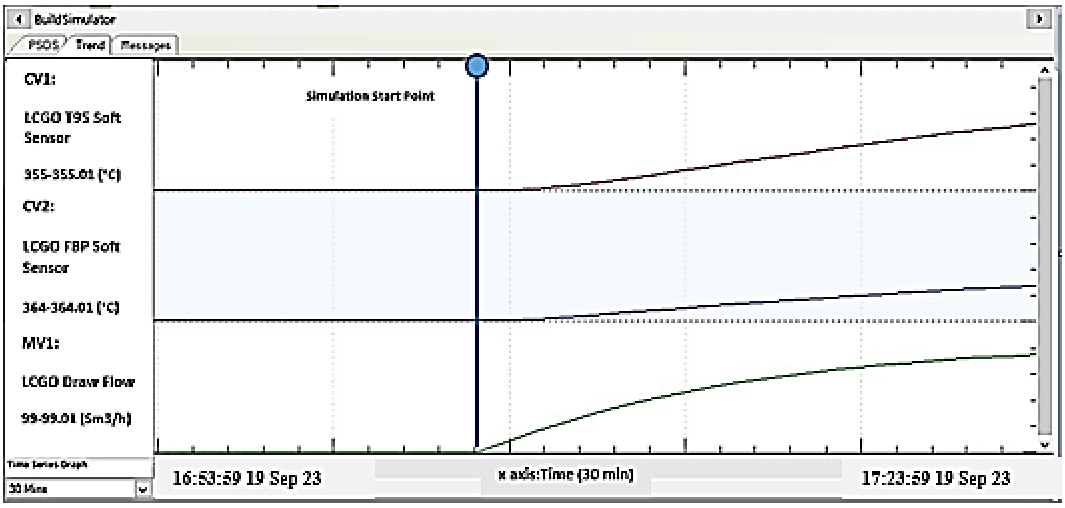

Figure 4.9. CV EU giveup tuning parameter effect on CV Control

4.5.3. Optimization Parameter-Linear Objective Function

In MPC applications, keeping all variables within their limits cannot use all the degrees of freedom in controller. Even when there are more Controlled Variables (CVs) than Manipulated Variables (MVs), there can still be surplus degrees of freedom, particularly if certain CVs have variable ranges instead of fixed set points, which is a common situation. Control engineers can make use of these extra degrees of freedom by formulating an objective function that guides the controller in optimizing specific aspects of the process in addition to its primary control tasks. Control objective function is shown as below equation;

$$\sum_i p_i C\,V_i + \sum_i qi^2 (CV_i - CV_{0i})^2 + \sum_j p_j M\,V_{ij} + \sum_i qj^2 (MV_j - MV_{0j})^2 \qquad \text{Eqn 16.}$$

p_i and p_j represent linear objective function for CV and MV, respectively. q_i and q_j parameters represent quadratic objective function for CV and MV, respectively. To transform the objective function into a maximization problem instead of a minimization problem, you can multiply each term by -1. This is because minimizing the negative of something is equivalent to maximizing it. Therefore, the controller's objective is to minimize the negated objective function (maximize the original objective function) while ensuring that all Controlled Variables (CVs) remain within specified limits or at their set points, and all Manipulated Variables (MVs) stay within their designated limits.

4.5.4. Optimization Parameter-Optimization Horizon

The optimization horizon defines the timeframe within which the controller is required to bring the objective function to its optimal value. Importantly, this horizon is established independently of the error correction horizons associated with the Controlled Variables (CVs).

4.5.5. Optimization Parameter-Optimization Speed Factor

Optimization speed factor default value is 1 which, shows optimization horizon approximately six times the CV overall response time. If optimization speed factor is set to zero, it effectively disables the optimizer, rendering the objective function ineffective. In this state, both the CV and MV objective coefficients no longer influence the process's direction, meaning that the controller will not actively optimize the process according to the defined objectives. To investigate the linear objective function and optimizer speed factor tuning parameter effect on objective function, simulation is done. Figure 4.10 shows the Honeywell RMPCT interface for optimization simulation. Linear objective function values are given as -1 since, objective is to maximize CV1 and CV2.

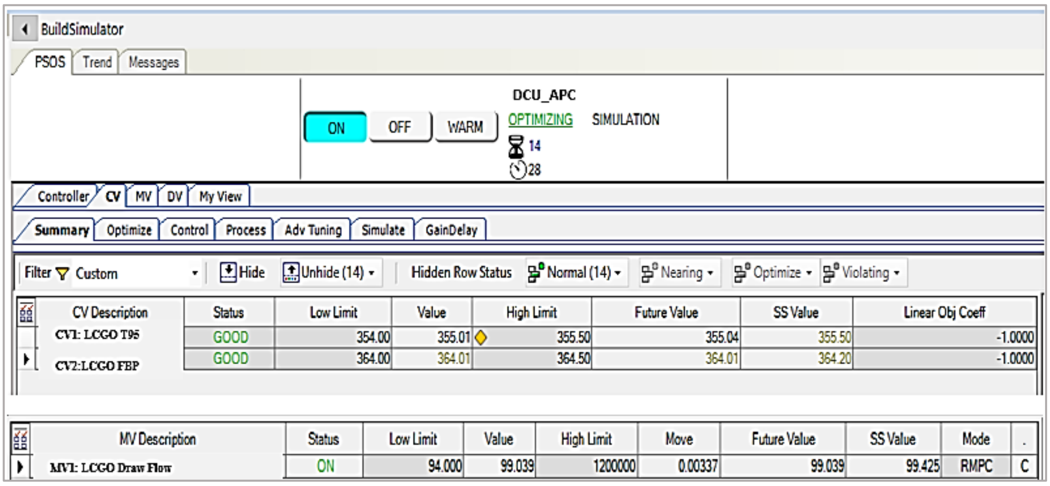

Figure 4.10. Honeywell RMPCT Interface-Simulation for Optimization

At the beginning of the simulation, in the first region Optimization speed factor is given as 0.1, and after that in the second region it is increased to 1. Obtained simulation trend is shown in Figure 4.11. When optimization speed factor is increased, MV movement is increased in order to maximize CV1 and CV2 variables.

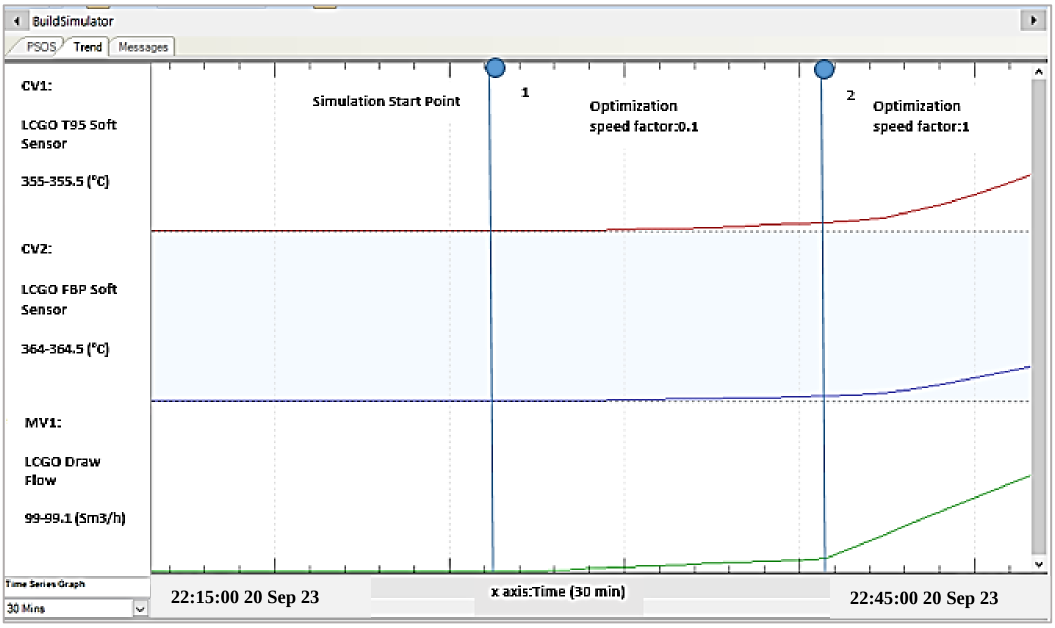

Figure 4.11. Optimization Speed Factor and Linear Objective Function

4.5.6. Stabilizing Effect of MPC

In most cases, variations in process parameters can be characterized by their average (mean) value and standard deviation (a measure of variability). In Model Predictive Control (MPC), it is common practice to aim at reducing the standard deviation by approximately 50 percent. This reduction allows operators to adjust the average value closer to its predefined limit by shifting the set point, all while maintaining a relatively constant or even reduced risk of temporary violations of process constraints. In other words, MPC helps improve process stability by minimizing variability, enabling more precise control around set point values. The restrictions encompass quality requirements, restrictions on equipment design, and limitations on valve positions, safety boundaries, and restrictions enforced by interlock systems. The most cost-effective operation of the process occurs when it operates very close to these constraints and is only occasionally exceeded. The acceptable frequency of exceeding these limits is determined based on experiences, the consequences of exceeding them, and the significance of the parameter in question and its impact on economic factors. The stabilizing effect of MPC (Model Predictive Control) enables a shift in the average operating point closer to the operational limit. In this assumption, the operating point is adjusted in a manner that maintains the same frequency of violations as observed before the implementation of MPC, which is considered a satisfactory level of process operation. The economic impact of this shift toward the operational limit is then calculated to determine the benefits derived from the implementation of MPC. Based on experience, MPC (Model Predictive Control) generally results in a reduction in the standard deviation, typically ranging from 40 to 70 percent. However, the extent of this reduction depends on various factors, including the specific process being controlled and the effectiveness of the implementation team, the accuracy of the control model, and other relevant factors. Assuming that the frequency of violations remains the same both before and after MPC implementation, mathematical description of the benefit is shown as below equation;

$$\text{Shift in average operating point} = \beta(\sigma_{\text{before}} - \sigma_{\text{after}}) = \beta x \sigma_{\text{before}} x a \qquad \text{Eqn 17.}$$

where, σbefore is the standard deviation of the process variable before MPC implementation, σafter is the standard deviation of the process variable after MPC implementation, α is the fractional reduction in standard deviation due to MPC. In thesis study, LCGO FBP laboratory results are recorded and analysis for before and after APC implementation. Only the sections for which the product quality maximization target was given by the planning team were taken from the laboratory results. Standard deviation analysis was performed for data covering the period of 2020-2022 using Delayed Coker Unit data in SOCAR. Obtained results are shown in below Table 4.2.

Table 4.2. LCGO FBP Laboratory Standard Deviation Results

APC On/Off	Laboratory Results-Standard Deviation	Average Δ1 (Instruction –Lab)*	Average Δ2 (Instruction-Lab)**
OFF	10.0	8.0	6.2
ON	7.0	7.0	4

Average Δ1 (Planning Order –Lab)* : Average deviation of laboratory values below the maximum instruction from the maximum instruction.

Average Δ2 (Planning Order –Lab)** : Average deviation of laboratory values above the maximum instruction from the maximum instruction

Improvement in LCGO FBP laboratory results standard deviation values are shown in Figure 4.12 when the APC is On and Off. The commissioning of APC in September 2021 has clearly resulted in stabilization in the LCGO FBP samples. The standard deviation has decreased, and values that were previously above and below the set instructions have been brought closer to the instructions, leading to a narrowing.

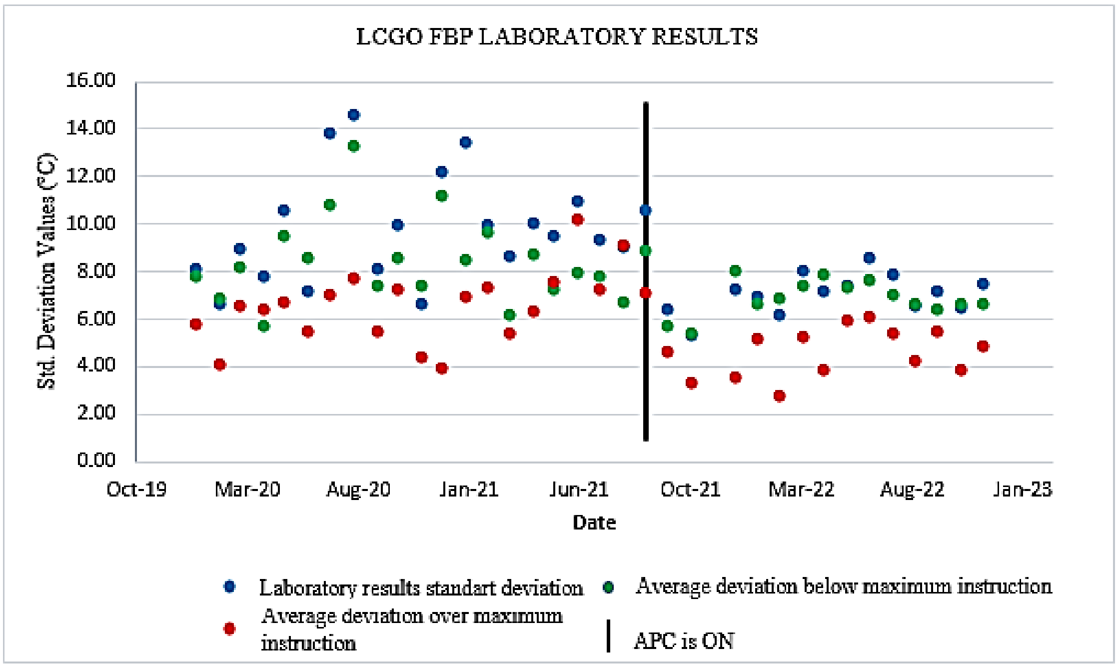

Figure 4.12. LCGO FBP Standard Deviation Improvement with APC

According to the obtained result, standard deviation of the LCGO FBP quality is decreased which is similar to one of the literature study shown in Chapter 2.

4.6. Closed Loop Control with SIMO MPC in MATLAB

In the thesis study, the MPC controller is also designed with MATLAB MPC Toolbox and Simulink (see in APPENDIX A). Plant model is design as single input and multi output model (SIMO).The plant is modelled as first order model without dead time with input and outputs. Since the plant is continuous time model, the controller automatically converted to discrete time state space model for prediction using sample time (ts). A state-space model describes a system by employing a set of first-order differential or difference equations. These equations incorporate inputs, outputs, and state variables to represent the system's dynamics. State-space models are a versatile and widely used framework in control theory and system analysis for characterizing the behavior of dynamic systems. According to simulation results in matlab, obtained discrete time state space function for 1 second sample time is as following equation assuming there is no disturbance added to measured output;

$$plant =$$

$$A = \begin{bmatrix} 0.8247 & 0 \\ 0 & 0.9047 \end{bmatrix}, B = \begin{bmatrix} 0.7367 \\ 0.3235 \end{bmatrix}, C = \begin{bmatrix} 0.1927 & 0 \\ 0 & 0.1001 \end{bmatrix}, D = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

MPC controller sample time is taken as 1 second. Prediction horizon is generally selected based on the maximum settling time and control horizon is selected as $1/4^{th}$ or $1/5^{th}$ of the prediction horizon. Additionally, controller is used default weight value for MV as 0 and MV rate as 0.1, for CV1 weight which is for LCGO T95 is taken as 1 and LCGO FBP it is taken as 0 . APC hard limits are also given for both MV and CV variables. According to closed loop simulation for obtained MPC controller, MV-CV response trend is shown in Figure 4.13.

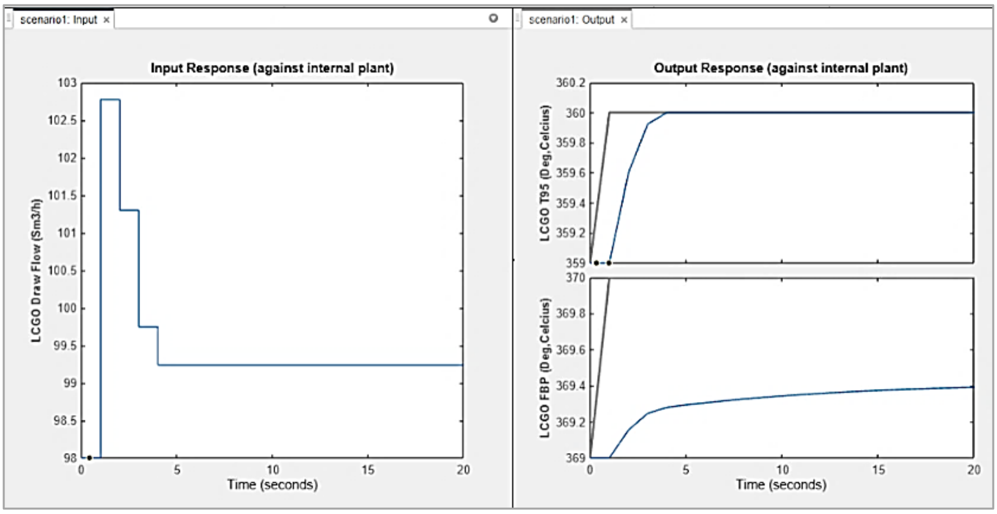

Figure 4.13. Matlab MPC Toolbox MV-CV Closed Loop Response Trend

Figure 4.13 shows that, since the LCGO T95 quality is reach its high hard limit in a few seconds, LCGO Draw flow is decreasing in order not to exceed LCGO T95 reference value. In the MPC tuning part, control horizon and prediction horizon parameters are changed in order to observe the effect on input and output response. Figure 4.14 shows the input and output response trend when the MPC controller sample time is taken as 1 second, prediction horizon and control horizon is taken as 60 steps and 3 moves, respectively.

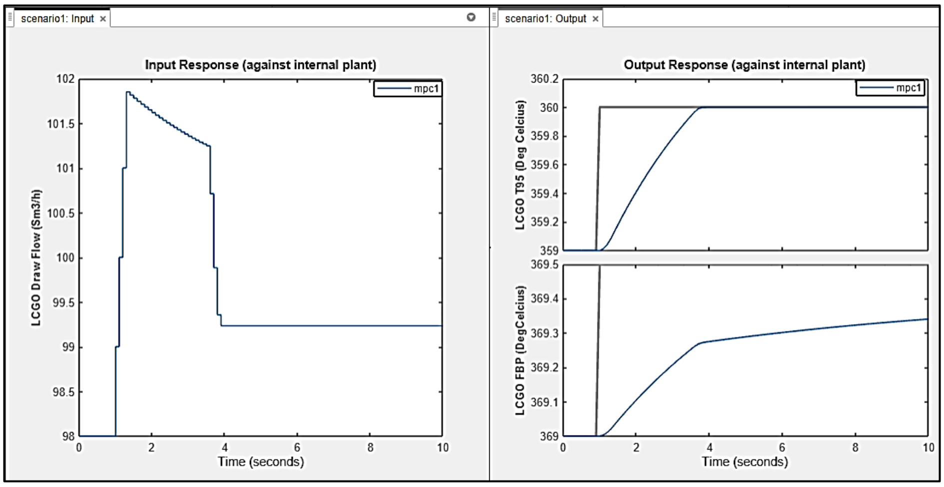

Figure 4.14. MV-CV Response Trend for Control Horizon:3, Prediction Horizon:60

Figure 4.15 shows the input and output response trend when the MPC controller sample time is taken as 1 second, prediction horizon and control horizon is taken as 60 steps and 12 moves, respectively.

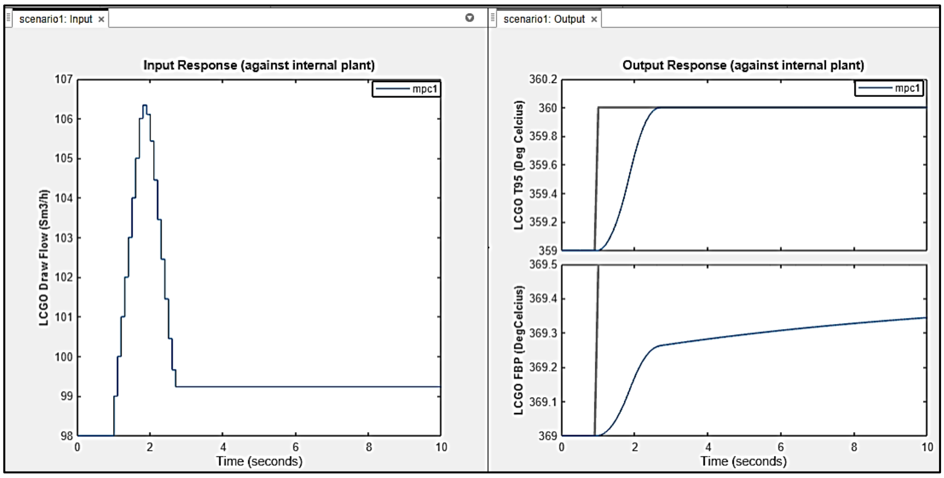

Figure 4.15. MV-CV Response Trend for Control Horizon:12, Prediction Horizon:60

In the Figures 4.14 and 4.15, it is shown that, when the control horizon parameter is increased from 3 to 12 with the same prediction horizon value as 60, the number of MV movements increased and faster response is obtained for the outputs. Figure 4.16 shows the input and output response trend when the MPC controller sample time is taken as 1 second, prediction horizon and control horizon is taken as 30 steps and 2 moves, respectively.

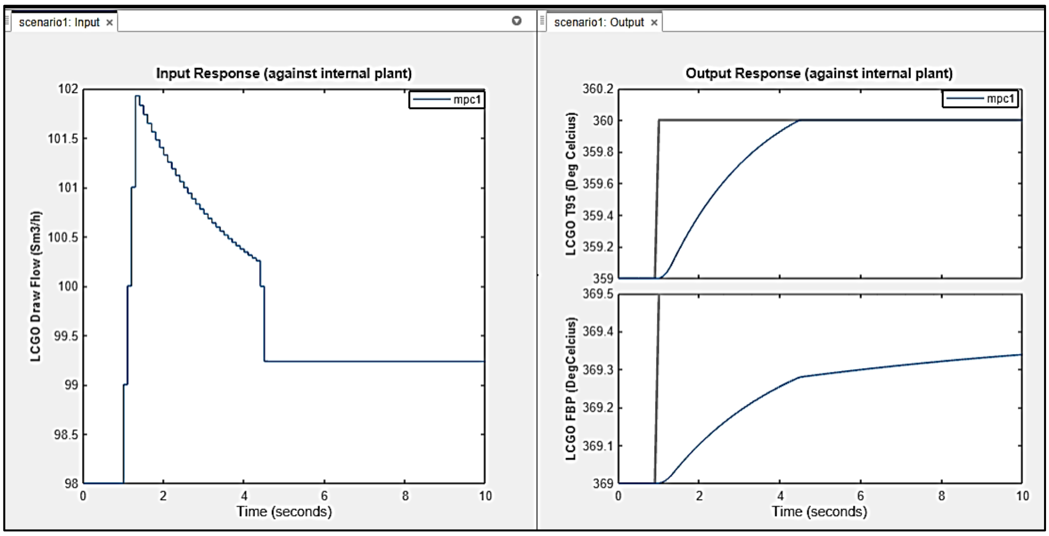

Figure 4.16. MV-CV Response Trend for Control Horizon:2, Prediction Horizon:30

Figure 4.17 shows the input and output response trend when the MPC controller sample time is taken as 1 second, prediction horizon and control horizon is taken as 60 steps and 2 moves, respectively.

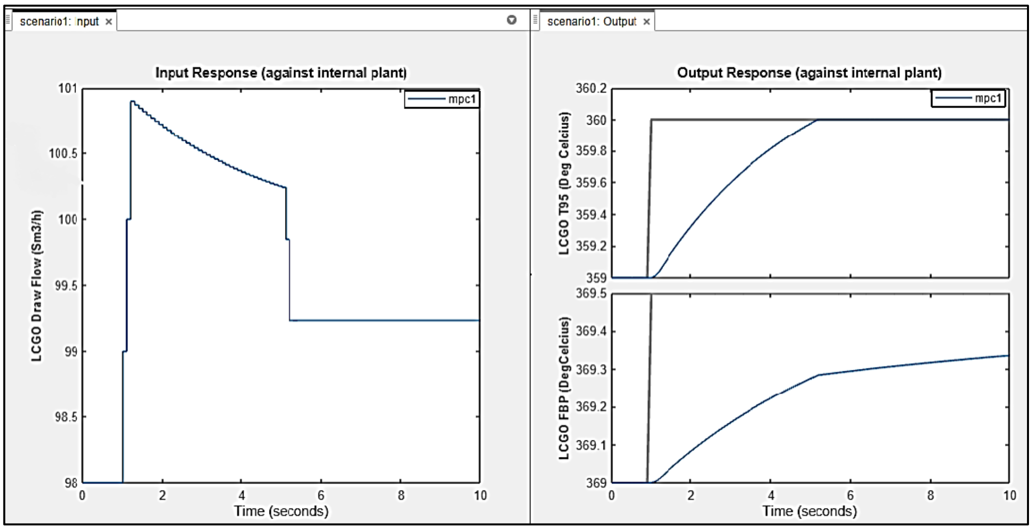

Figure 4.17. MV-CV Response Trend for Control Horizon:2, Prediction Horizon:60

Prediction horizon refers to the number of future time intervals over which the controller predicts the system's behavior while optimizing its manipulated variables (MVs) at each control interval. Therefore, longer prediction horizon causes slower dynamics between MV and CV. In the Figures 4.16 and 4.17, it is shown that when the prediction horizon value is increased from 30 to 60 with the same control horizon value as 2, slower CV response is obtained. Prediction horizon should be long enough to increase ability for future prediction. According to the tuning part of the MPC controller, control horizon and prediction horizon is selected as 12 and 60 respectively, since faster response is obtained. For the state space models, it is important to assess controllability and observability of the derived models. If the state-space model is not observable or controllable, implementing Model Predictive Control (MPC) in the system becomes challenging or infeasible. The system is controllable if the below matrix has rank value which is equal to number of states in the state space model.

$$\text{Controllability} = [B\ AB\ A^2B\ \dots\ A^{1-n}B] = \begin{bmatrix} 0.7367 & 0.6076 \\ 0.3235 & 0.2927 \end{bmatrix} = Rank\ 2$$

The system is observable if the states are known from output of the model and the rank is equal to the number of states. Observability of the derived model is calculated using below equation;

$$\text{Observability} = [C\ CA\ A^2C\ \ldots\ A^{1-n}C] = \begin{bmatrix} 0.1917 & 0 \\ 0 & 0.1001 \\ 0.1589 & 0 \\ 0 & 0.0906 \end{bmatrix} = Rank\ 2$$

According to the observability and controllability of the derived model, rank values are equal to the number of state in the space model and model can be implement. Rank values that obtained by using matlab about the model controllability and observability is similar to model validation results that obtained by using Honeywell RMPCT.

4.7. Summary of the Results

In this thesis, an APC system is designed to control one of the most valuable products of the Delayed Coker Unit which is LCGO FBP quality. To design the APC system, the following methods are applied including functional design to determine control matrix, step test planning and application, process model identification and validation using FIR algorithm in Honeywell RMPCT, offline APC simulation and tuning. In the modelling section of the thesis, 4 days step test data is used and the points when the drum switch and preheating steps are occurred as disturbance effect, are removed as outlier. According to the obtained data, model identification is done using FIR algorithm and first order models are obtained for LCGO T95 and LCGO FBP qualities without dead time. Model validation is done and the gain of the model is investigated. Advanced tuning parameters are studied using offline simulation of the APC controller. Matlab MPC toolbox and Simulink is used to create MPC controller and model is created with the state space model identification. Additionally, control horizon and prediction horizon tuning parameters are changed in the model to determine the better MV and CV response. Standard deviation of the LCGO FBP quality laboratory results are compared for before APC and after APC regions. According to obtained results, when the APC is on standard deviation of the LCGO FBP quality results are decreased 3°C.

CHAPTER 5

CONCLUSION

In this thesis, a real refinery case is studied to design an advanced process control system in the Delayed Coker Unit of Star Refinery in Izmir. The objective of the APC is to provide the stabilization of the valuable product qualities, closing the controlled variables through the economically optimum zone. In this thesis, the main objective is to decrease the LCGO FBP quality standard deviation in steady state operation after the disturbance effects . Functional design is done to provide control matrix and step test is applied for LCGO FBP quality in main fractionator column. According to obtained step test data, Honeywell RMPCT application is used to obtain the model between MV and CV variables. Model identification is applied using FIR algorithm based on characterizes a system as a linear combination of past input values. Obtained models are implemented in the main fractionator column of the Delayed Coker unit. Additionally, Matlab MPC toolbox and Simulink is used to create MPC controller and model is created with the state space model identification. Control horizon and prediction horizon tuning parameters are changed in the model to determine the better MV and CV response. According to obtained results, standard deviation for the LCGO FBP quality results are compared before and after APC implementation. It is shown that when the APC is turned on, the standard deviation of the LCGO product FBP quality is decreased by 3 °C. Additionally, operator actions to the LCGO product draw flow controller set point is decreased since, the set-point of the LCGO draw flow controller is controlled by the APC considering both LCGO T95 and LCGO FBP quality soft sensor values.

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APPENDIX A

MPC Controller Design in Matlab Simulink

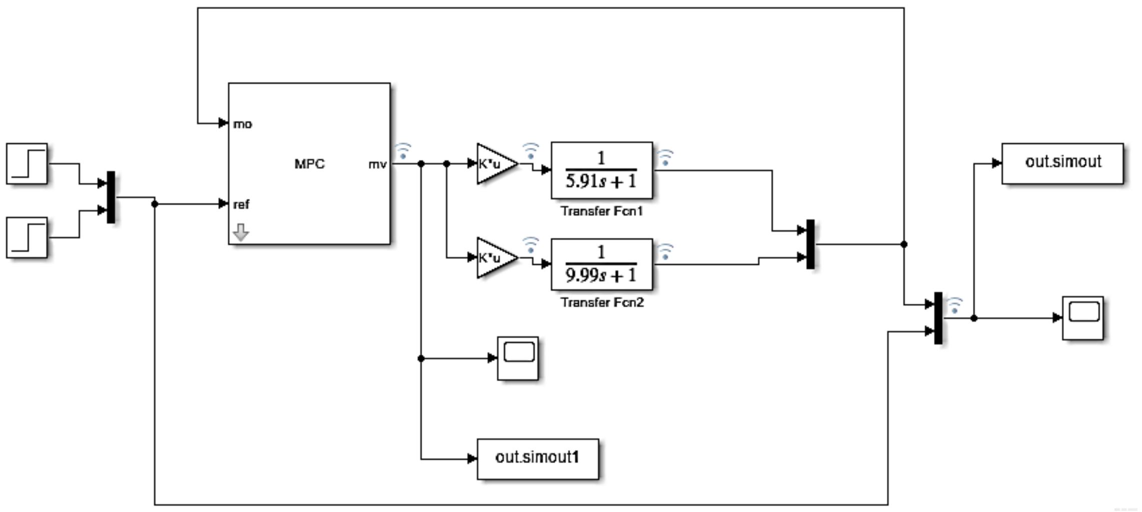

Figure A.1. MPC Controller Design in Matlab Simulink

Matlab Code- Command Window

s = tf('s')

h11 = 0.81*(1/(5.91*s+1));

h21 = 0.34*(1/(9.99*s+1));

s =

  s

Continuous-time transfer function.

>> H = [h11; h21]

H =

  From input to output.

```
         0.81
   1:  ----------
       5.91 s + 1
         0.34
   2:  ----------
       9.99 s + 1
Continuous-time transfer function.
>> plantTF = tf([h11; h21])
plantTF =
  From input to output...
         0.81
   1:  ----------
       5.91 s + 1


         0.34
   2:  ----------
       9.99 s + 1
Continuous-time transfer function.
>> Ts = 1;               %sample time
mpcobj = mpc(plantTF,Ts,10,3);   %% create MPC controller object with sample time
```

%% specify weights

```
mpc1.Weights.MV = 0;
mpc1.Weights.MVRate = 0.1;
mpc1.Weights.OV = [1 0];
mpc1.Weights.ECR = 100000;
```

-->The "Weights.ManipulatedVariables" property is empty. Assuming default 0.00000.

-->The "Weights.ManipulatedVariablesRate" property is empty. Assuming default 0.10000.

-->The "Weights.OutputVariables" property is empty. Assuming default 1.00000.

for output(s) y1 and zero weight for output(s) y2

%% specify prediction horizon

```
mpc1.PredictionHorizon = 10;
```

%% specify control horizon

```
mpc1.ControlHorizon = 3;
```

%% specify nominal values for inputs and outputs
mpc1.Model.Nominal.U = 98;
mpc1.Model.Nominal.Y = [359;369];
%% specify constraints for MV and MV Rate
mpc1.MV(1).Min = 98;
mpc1.MV(1).Max = 120;
mpc1.MV(1).RateMin = -2;
mpc1.MV(1).RateMax = 2;
%% specify constraints for OV
mpc1.OV(1).Min = 350;
mpc1.OV(1).Max = 360;
mpc1.OV(2).Min = 360;
mpc1.OV(2).Max = 370;

>> mpcobj.MV = struct('Min',0,'Max',30,'RateMin',-10,'RateMax',10);

Tstop = 30;   % simulation time

Nf = round(Tstop/Ts);   % number of simulation steps

r=[ones(Nf,1);ones(Nf,1)];

sim(mpcobj,Nf,[r,r]);   %simulation

-->Converting the "Model.Plant" property to state-space.

-->Converting model to discrete time.

-->Assuming output disturbance added to measured output channel #1 is integrated white noise.

-->Assuming output disturbance added to measured output channel #2 is integrated white noise.

-->The "Model.Noise" property is empty. Assuming white noise on each measured output.

%Controllability Analysis of the MPC controller

A = [0.8247,0;0,0.9047];

B = [0.7367;0.3235];

C = [0.1927,0;0,0.1001];

D = [0;0];

sys = ss(A,B,C,D);

>> Co = ctrb(sys);

>> Co = ctrb(sys)

Co =

    0.7367   0.6076

```
    0.3235    0.2927
>> rank(Co)
ans =
  2
```

%observability analysis for MPC model

```
A = [0.8247,0;0,0.9047];
B = [0.7367;0.3235];
C = [0.1927,0;0,0.1001];
D = [0;0];
>> sys = ss(A,B,C,D);
>> Ob = obsv(sys)
Ob =
    0.1927         0
         0    0.1001
    0.1589         0
         0    0.0906
>> rank(Ob)
ans =  2
```