MPC for Upstream Oil & Gas Fields

a practical view

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Dedicated to my Parents and Family

ABSTRACT

This work aims to improve corporate functional departments' confidence in adopting modern control approaches in new scenarios and thus presents control structure solutions based on model predictive control (MPC) for two control problems facing existing upstream oil and gas production plants. These are the disturbance growth in the series connected process and the control system dependency on operators. The suggested control solution integrates MPC as a master controller for the existing classical control of each subsystem, with a focus on those with high interaction phenomena. The proposed approach simply and inexpensively encompass MPC features such as predictions, optimizations, coordination and constraint handling as well as PID features like simplicity and ease of troubleshoot. In addition, the proposed control concept utilises the process safeguarding information and enhances the plant-wide optimal performance. The suggested control solution supports the role of control room operators, which is shown to reduce the growth in the impact of process disturbances. Compared with some alternative control structures (centralised MPC, decentralised MPC, distributed MPC (DMPC), and hierarchical DMPC) this proposal is simple, inexpensive to implement, and critically, builds on the local team operational experience and maintenance skills.

Three process models were developed that representing the common gas treatment processes in upstream oil and gas plants, gas sweetening, gas dehydration and hydrocarbon dewopointing. The models were utilised to examine different control structures and proposals. These models are not only of benefit to studies on upstream oil and gas processes, but also to Large Scale Systems (LSS) in general. The models were used to analyse the disturbance impacts on a series connected processes, therefore to

provide answers about how process malfunctions and different disturbances affect the processing operations.

The proposed control system is designed on a cascade strategy and thus provides a flexible system control almost like a decentralised structure in dealing with disturbances and unit failures, and at the same time improves the closed loop performance and the plant-wide optimal operation. The control system contain MPC's that are designed to regulate the critical loops only while the rest of the uncritical loops will continue to function in a decentralised fashion under PID control algorithm. This minimises any design and set up costs, reduces demand on the communication network and simplifies any associated real time optimisations. The improved local control reduced the need for control room operator interactions with their associated weaknesses. The proposed control structure communicate with the process safeguarding system to enable prompt response to disturbances caused by unit failures, and shares critical information with adjacent MPC's, which indeed works as a feed-forward, to reduce the impact of process disturbances and enhance optimality. The control system design is simple, inexpensive to implement and significantly reduces the frequency of plant shut downs and saves on operating costs by properly controlling the disturbance growth in the process.

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STATEMENT OF ORIGINALITY

Unless otherwise stated in the text, the work described in this thesis was carried out solely by the candidate. None of this work has already been accepted for any degree, nor is it concurrently submitted in candidature for any degree.

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ADCHEM	Advanced Control of Chemical Processes
CARIMA	Controlled Auto Regressive Integrated Moving Average
CO2	Carbon Dioxide
COS	Carbonyl Sulphide
DCS	Destributed Control System
DMC	Dynamic Matrix Control
DMPC	Distributed Model Predictive Control
d.o.f.	Degree of freedom
DPIC	Differential Pressure Indicator Control
DYCOPS-CAB	Dynamics and Control of Process Systems Including Biosystems
E&P	Exploration and Production
FCV	Flow Control Valve
FF	Feed Forward
FIC	Flow Indicator Control
GDU	Gas Dehydration Unit
GHV	Gross Heating Value
GOR	Gas to Oil Ratio
GPC	Generalised Predictive Control
GSU	Gas Swetning Unit
H2S	Hydrogen Sulphide
HCDP	HydroCarbon DewPointing
HMI	Human Machine Interface

IDCOM	Identification and Command
IGV	Inlet Guide Vanes
IM	Independent Model
LCV	Level Control Valve
LIC	Level Indicator Contro
LMFD	Left Matrix Fraction Description
LQE	Linear Quadratic Estimation
LQG	Linear Quadratic Gaussian controller
LQR	Linear Quadratic Regulator
LSS	Large Scale System
MAC	Model Algorithm Control
MFD	Matrix Fraction Description
MIMO	Multiple Inputs Multiple Outputs
MMSCMD	Million Metric Standard Cubic Meter per Day
MPC	Model Predictive Control
MPHC	Model Predictive Heuristic Control
PCV	Pressure Control Valve
PDO	Petroleum Development of Oman
PIC	Pressure Indicator Control
PID	Proportional Integral Derivative
ppm	Parts Per Million
QDMC	Quadratic Dynamic Matrix Control
QIC	Quality Indicator Control
QP	Quadratic Programing
RHC	receding horizon control
SISO	Single Input, Single Output
SMOC	Shell Multivariable Optimising Control
TCV	Temperature Control Valve
TIC	Temperature Indicator Control

TABLE OF NOTATIONS

A, B, C	State space matrices
$\mathbf{D}_n$	Feed forward term
d	Process disturbance
e_1	First element of a vector
H, P, Q	Prediction matrices
I	Identity matrix
$[i]$	The process being controlled
J	Cost function
$\mathbf{L}$	Scaling factor matrix
n_u, n_y	Input and output prediction horizons
$\mathbf{r}$	Process set point
$\mathbf{u}$	Process Inputs
$\mathbf{x}$	Process state
$\mathbf{x}_k$	Value of $\mathbf{x}$ at sample k
$\underset{\to k}{\mathbf{x}}$	Vector of future values of $\mathbf{x}$
$\underset{\leftarrow k}{\mathbf{x}}$	Vector of past values of $\mathbf{x}$
$\mathbf{y}$	Process Outputs
$\underline{\mathbf{y}}$, $\overline{\mathbf{y}}$	Upper and Lower output constraints
z^{-1}	Unit delay operator
Δ	Difference operator $(1 - z^{-1})$
$\Delta\mathbf{u}$	Incremental input $(u_k - u_{k-1})$

Chapter 1

INTRODUCTION

Control system application has continued to improve since the discovery of the first commercial oil well in the mid-nineteenth century [33]. The growth in demand for upstream hydrocarbon gathering and production plants stimulated the need for changes from manual control systems to fully automated ones. Oil and gas industry is customarily divided into three major components: upstream (also known as the exploration and production E&P), midstream and downstream. The upstream operations consist of oil and gas reservoir exploration, drilling of appraisal and operation wells, and gathering & initial processing of the recovered oil and gas. The midstream operations include crude transportations, storage and wholesale marketing. While the downstream commonly refers to oil refineries, petrochemical industries, and petroleum products distribution and retail operations. Due to process safety reasons related to crude transportation, upstream sector may involve primary processing of crude oil and natural gas, normally considered as midstream operations, in the gathering fields. For example, crude oil stabilisation process and natural gas processing plants which dehydrate and purify the gas from acidic components and removes heavier hydrocarbons. Accordingly, these processes will be considered as upstream operations in this thesis.

Today, the majority of the upstream production plants still mainly utilise classical Proportional-Integral-Derivative (PID) control laws to regulate process variables. Indeed, these are largely sufficient for oil and gas production plants and will certainly continue to play an important role in the process industries. PID control is robust and transparent but its main weakness is in being Single Input Single Output (SISO), thus giving a decentralised process control system. The risk here arises from the lack of co-ordination between controllers because each controller has to cope alone in meeting objectives (except in cases where a cascade approach is applied).

On the other side of the petroleum industry, PID control architectures were clearly an obstacle to optimal operation of refinery processes. The majority of the control loops in refineries and power generation plants are Multi Input Multi Output (MIMO) control loops where each controller output not only regulates a particular process variable but also affects other process variables within the system. Poorly tuned interacting controllers severely limit the best achievable closed loop performance and thus incur extra operational costs [14]. Despite the vast array of tuning tools, such as those presented in [67, 64], tuning MIMO PID controllers is still difficult and may not give good solutions [38].

Based on this rationale, Model based Predictive Control (MPC) was developed as a systematic multi-variable control scheme for refineries and power plants. MPC has become a standard approach and its popularity in the chemical process industries has increased steadily due to its ability to deal with process constraints, multi-variable and complex dynamics systems. MPC relies on an explicit mathematical model of the process to predict the future response of the plant and the definition of a cost function (measure of performance). MPC computes the sequence of optimal future control actions (inputs) over a specified future time horizon in order to optimise the expected performance of the system. Only the first optimum input is sent to the plant while the rest of the sequence is discarded. Then, process measurements are fed back to the controller to update the optimiser in order to calculate the next control input; and the control horizon is displaced one step towards the future at each time instant. These control procedures are then repeated at each subsequent time interval [13].

The globally rising demand for fossil fuel leads to overconsumption of valuable resources alongside a deficiency in the discovery of new reservoirs. Therefore, there is a necessity to optimise the production operation of the current assets. Unfortunately, the control difficulties of the upstream oil and gas fields have not received the same research attention as the downstream processes. The two major control issues affecting the current upstream production plants are:

(1) *The control system dependency on operators*. Thwaites (2008) [72] found that in general, 75% of industrial physical locations are under process control worldwide and the performance of more than 60% of the controlled loops are below expectations. Li et al. (2011) [45] questioned why the prevalent applications of process control methodologies has not ensured continual enhancement of plant performance worldwide. They concluded that the reason was in ignoring the critical role of the control room operator in the design of the modern process control systems. McKee (1999) [49] conducted a study on the status of process control in mineral process. The reviewer examined different factors affecting efficacious control systems. One of the highlighted important factors to achieve successful control system was the need for skilled operational team to maintain and operate the process. The review clearly stated that the performance of the control room operator sometimes imposes a constraint on the overall control system performance. Li et al. (2010) [44] observed and studied the process control behaviour of twenty operators in two industrial processes. One of the survey conclusions was that, the intention of control optimisation such as managing a stable and efficient production flow was not evident in operator control behaviours. Conversely, the control room operators preferred to let the control system run independently rather than intervene. They tended to respond only when things were going wrong (e.g. unit trip), hence most often their actions were too late. Such control behaviour is expected to reduce process production and clearly extends process shutdown periods. In order to improve the process control system performance, McKee (1999) pointed out two thoughts regarding the role of control room operators. Either to agree that the operators are critical to the successful operation of a control system and hence must be selected and trained accordingly. Alternatively, accept operator limitations in understanding the process and the control

system in depth, and consequently strives to develop control system that require minimal operator intervention. [49].

(2) *The disturbance growth in the series connected process*. Feed disturbance and equipment failure are the two common causes of major process disturbances in upstream production plants [4, 3]. Such disturbances have the potential to cause significant deviation of the process and potentially cause violation of operation constraints. In series connected systems where one process output is the feed to the successor process, the effect of disturbances can be magnified due to system gain. If an extraordinary or more than one antagonistic condition develops at the same time, the control room operator may not be able to react satisfactorily and the consequences are a larger risk of a major disturbance event.

The intention of this research is to target these control issues and to provide an inexpensive feasible control concept based on MPC for the benefit of existing upstream oil and gas plants. As per the authors' knowledge, no specific study has been reported so far to tackle these control issues and to provide a friendly inexpensive upgrade based on MPC to the **existing** upstream oil and gas plant (brownfield) and its classical control system. This thesis brings attention to the control challenges facing upstream oil and gas production plants, especially for existing plant, and discusses different solutions to handle the challenges. The prime focus is on developing a control system with improved disturbance rejection techniques by cheaply integrating MPC in the process PID control system.

1.1 Motivation

Upstream oil and gas companies who are seeking to reduce operation costs and to increase profitability need to upgrade their plant control systems on a regular basis, in a way that guarantees the product specifications are met subject to energy costs, environmental constraints, and safety demands. There is always a constant push towards a higher product quality and continuous good operation safety records with lower operation cost initiated by the escalating product quality specifications that become stricter, tight environmental regulations, and demands for productivity growth. As a consequence, petrochemical industries are, nowadays, confronting a strong competitive environment. Hence, extracting greater value from manufacturing assets becomes a major challenge.

The rapid development of control technology endorses novel theories, different philosophies, extra challenges, and new applications lead to developments of new industrial processes, new controllers, actuators, sensors, and computer systems. Novel control strategies offer a potential to implement more advanced control algorithms but in reality, most industrial engineers prefer to select a robust and transparent process control structure that uses simple controllers. This is one reason why the PID remains industry's most preferred controller. However, this approach can imply limitations on the process efficiency [74]. One such limitation is the possible lack of a systematically achieved performance within the process hierarchy. For example, in the case of reference tracking, PID control might be too short sighted for the tracking performance. An additional limitation is the omission of a facility to accommodate and handle process operational constraints.

All plants have inputs and outputs, which are limited in size due to the presence of safety or physical constraints. Furthermore, an industrial process design might also require a certain level of performance, which can be translated into additional constraints on the controlled system. Depending on the underlying applications, a violation of these constraints might result in system failure, which in turn increases the maintenance and operation costs and also could possibly waste valuable resources and/or become a human hazard. Including these constraints in the controller design will lead to a control action that can prohibit constraint violations.

The current interest in the industry, due to the emergence of advanced control techniques, provides a great opportunity to improve process efficiency and optimality in the presence of constraints. Advanced control literature includes a vast number of methods, which provide important ways to improve production situations. Model based predictive control is one of the most successful solutions for an appropriate operation [62]. MPC requires a detailed enough linear model to maintain the process at a desired steady state. A well identified model helps the MPC to converge to an optimal solution in a short time, which is preferred by most manufacturing applications [24, 25, 5, 62, 21].

Complex processes such as petrochemical and oil and gas plants consist of a number of sub processes to ensure the desired product specifications and quality are met. While Model Based Predictive Controllers have emerged as a powerful paradigm for dynamic real time optimization and offset free control for power plants and refineries [21, 62], most of upstream oil and gas plants are still controlled by the conventional SISO PID controllers. Large scale processes that are controlled by PID controllers are most susceptible to major control upsets during disturbances due to the reactive control theme of the PID algorithm as well as the lack of coordination between subsystem controllers. Feed disturbance and disturbances related to equipment failure or mis-operation can cause escalating control disruption affecting all predecessor and successor sub-processes.

Obviously, to overcome the control issues described above, the control structure of the existing upstream production plants needs to simply and inexpensively encompass MPC features such as predictions, optimizations, coordination and constraint handling as well as PID features like simplicity and ease of troubleshoot. In order to upgrade the control system to perform safe and optimal operations, these aspects need to be considered:

1- **A feasible control concept** which is: simple in structure, easy and inexpensive to implement, satisfies the typical control objectives, addresses process disturbances and considers operational constraints. The new control structure must also inexpensively integrate the team experience and operational knowledge within it. The approach should require as little retrofitting as possible, that is to build on existing infrastructure and expertise as much as possible, as this reduces cost, training requirements and simplifies validation.

2- **Process model** representing upstream oil and gas processes are scarce in the literature. Hence to examine different control structures and proposals, it is necessary to have a suitable benchmark model reflecting the realistic upstream oil and gas operations. Such a model would not only be of benefit to studies on upstream oil and gas processes, but also to Large Scale Systems (LSS) in general.

3- **Analysis of disturbance impacts on series connected processes** helps to provide answers about how process malfunctions and different disturbances affect the processing operations. This valuable knowledge is important to develop control strategies that quickly anticipate and tackle disturbance growth in the series connected processes.

4- **Control system design**. The key long term goal is to design a simple, inexpensive and specific control system that significantly reduces the frequency of plant shut downs and also saves on operating costs by properly controlling the disturbance growth in the process. These improvements are also expected to reduce energy fluctuations in the process and save fuel.

1.2 List of Contributions and Supportive Publications

The following list summarises the contributions provided by this thesis supplemented by the dedicated supportive publications:

1- A feasible control structure based on PID and MPC control algorithms. A proposed control system to solve series connected process disturbance growth; and Control system operator dependency in the existing oil and gas fields. The control concept was presented in the 9^{th} International Symposium on Advanced Control of Chemical Processes ADCHEM 2015; and published by IFAC:

- Al-Naumani, Y.H. and Rossiter, J.A., (2015). Distributed MPC for Upstream Oil & Gas Fields-a practical view. *IFAC-PapersOnLine, 48(8)*, pp.325-330.

2- A new validated model for gas phase train in upstream oil and gas fields. The model presented in the 11^{th} IFAC Symposium on Dynamics and Control of Process Systems Including Biosystems DYCOPS-CAB 2016.

- Al-Naumani, Y.H., Rossiter, J.A. and Bahlawi, S.J., (2016). Gas Phase Train in Upstream Oil & Gas Fields: PART-I Model Development. *IFAC-Papers OnLine, 49(7)*, pp.875-881.

3- A study of disturbance impact on the gas train in the upstream oil and gas fields. The study presented in the 11^{th} UKACC International Conference on Control 2016.

- Al-Naumani, Y.H. and Rossiter, J.A., (2016). Gas phase train in upstream oil & gas fields: Part-II disturbances impact study. In *Control (CONTROL), 2016 UKACC 11th International Conference on* (pp. 1-6). IEEE

4- Design and implement a control structure solution based on MPC and PID algorithms for the control problems affecting gas phase train in existing oil and gas production plants. The control design paper was submitted, and accepted for presentation, to the 20^{th} World Congress of the International Federation of Automatic Control.

- Al-Naumani, Y.H. and Rossiter, J.A., (2017). Gas Phase Train in Upstream Oil & Gas Fields: PART-III Control System Design. *Submitted to the* 20^{th} *World Congress of the International Federation of Automatic Control*.

5- Design of the feasible control structure based on PID and MPC control algorithms which targets the series connected process disturbance growth and the control system operator dependency in the existing upstream oil & gas plants. *In preparation journal paper*.

1.3 Thesis Overview

The thesis consists of nine chapters and two appendices. Hereinafter, a summary of each chapter:

Chapter 2, presents the literature review of the model predictive control (MPC). The chapter starts with a generic historical introduction about MPC followed by an overview describing the features and main principles of MPC. The chapter thereafter discusses MPC core components and provides a brief description about MPC algorithms evolution. Then, presents the basic concepts of predictions accompanied by the basic MPC algorithms, that provides a common theoretical framework necessary for arguments in this thesis. Finally, the chapter provides description about constraint handling in MPC.

Chapter 3, provides an insight to the upstream oil and gas operations and the associated control challenges. Those challenges form the research problems, which this thesis aims to solve. These are the control system operator dependency and series connected process disturbance growth. The chapter provide detailed discussions about process safety, control and disturbances issues confronting the upstream oil and gas producers.

Chapter 4, presents a feasible control concept for upstream oil and gas fields. The chapter starts by presenting the current control strategies implemented in the industry to enhance plants control systems. Then, the drawbacks of each method are thoroughly explained. Finally, the chapter provides and discusses a feasible control concept to overcome the research problems.

Chapter 5, Provides and verify a model for the gas phase operation in upstream oil and gas plants suitable for system analysis and control design investigations. The process model captures the three main gas conditioning processes found in most upstream oil and gas processing plants: gas sweetening, gas dehydration, and hydrocarbon dew-pointing. The model provide a realistic process representation to test and verify different process control approaches, specifically those which deals with highly interactive control loops. The developed models of the gas treatment train processes were verified and validated against real process responses to the same disturbances taken from PDO Harweel site in Oman.

Chapter 6, focuses on analysing a variety of process disturbances, malfunctions, and load changes on the gas train process operation and verifying the utility of the model for capturing key industrial scenarios. Knowledge about how different disturbances and process malfunctions affects the gas processing operations is certainly valuable for process control engineers.

Chapter 7, demonstrates the design and implementation of the feasible control concept. The chapter examines the integration of small size MPC's with the classical PID control system in handling interactive control loops in three series gas treatment processes. The chapter starts by illustrating the proposed feasible control solution of the gas train followed by a brief description and solution to the MIMO loop interaction challenges. The overall controller design is then presented. The following two sections provides the experimental results of the proposed control structure performance in confronting sudden feed change disturbance and process unit malfunction to analyse control performance and constraint handling. After that, the chapter discusses the achievements on the pre-set thesis objectives. While, the last section provides discussion and conclusions.

Chapter 8, is designated to examine the transferability of the new control system by implementing it in a different interactive processes. The chapter starts by illustrating the process model of the case study and then presents process model analyses. The overall controller methodology is then presented step by step starting from PID controllers design followed by inner loop controllers design and matrix fraction description equation computations; and ended by MPC algorithm design. While, control analysis and simulation plans is presented next. The following two sections provides the experimental results of the proposed control structure performance in confronting sudden feed change disturbance and process unit malfunction to analyse control performance and constraint handling. Finally, discussions and conclusions are presented in the last section.

Chapter 9, presents the overall conclusions and summarises the original contributions of the thesis followed by reconsiderations of future work.

Finally, **Appendices A and B**, hold complementary informations for chapters 7 and 8. MATLAB program file to create a left matrix fraction description (LMFD) equations from a continuous process model is presented in **Appendix A**. While, **Appendix B** presents a MATLAB code to obtain LMFD equations to represent a model with it's relevant SISO PID controllers. **Appendix C** presents the real process responses to a 20% feed step.

Chapter 2

LITERATURE SURVEY

Model Predictive Control (MPC) has attracted significant attention over the past four decades. In 1962, Zadeh and Whalen recognized the connections between the closely related minimum time control problem and Linear Programming [29]. The year after, Propoi [1] proposed the moving horizon approach which is the core of all MPC algorithms.

Nothing was done from then until the rediscovery of MPC by Richalet and co-authors in the mid-seventies. Richalet et al. [63] proposed a technique called Model Predictive Heuristic Control (MPHC), later known as Model Algorithm Control (MAC). This algorithm employs a finite horizon pulse response (linear) model, a quadratic cost function, and input and output constraints. The algorithm software was known as (IDCOM) an acronym for Identification and Command [62].

Shortly thereafter, Cutler and Ramaker [19] introduced the predictive control algorithm called Dynamic Matrix Control (DMC) which has been hugely successful in the petrochemical industry. One main reason for that is the fact that DMC employs a step response model of the process for the predictions. Since then, MPC's attractiveness in the chemical process industries has increased steadily. Accordingly, Shell has applied MPC algorithms to many industrial processes including a fluid catalytic cracking unit [60] and a highly non-linear batch reactor [29]. MPC industrial acceptance was widened significantly during the 1980s to comprise new applications. Mehra et al. [50] reviewed a number of industrial applications including a super-heater, a steam generator, a wind tunnel, a utility boiler connected to a distillation column and a glass furnace. The first generation of MPC technology epitomised by the early DMC and IDCOM algorithms had a massive impact on industrial process control and assisted in defining the industrial MPC standard.

Before the mid-eighties, a Quadratic Dynamic Matrix Control (QDMC) was introduced as a second MPC generation to overcome a constraint handling limitation in the previous methods. Quadratic programming is employed to solve the constrained open loop optimal control problem [28]. During the same period, the use of linear programming was being studied by Gutman [32]. Later on, an extensive theoretical effort was dedicated to scrutinise previous schemes, provide conditions for guaranteeing feasibility and closed-loop stability, and emphasise the relations between MPC and the linear quadratic regulator [48].

The third generation of MPC algorithms differentiate between several levels of constraints (for example soft and hard constraints); provides some recovery mechanism from an infeasible solution; and provides a wider range of process dynamics and controller specifications. The Shell multivariable optimising control (SMOC) algorithm is one example. SMOC utilises state space models; general disturbance models; and state estimation via Kalman filtering [48, 47].

This chapter presents the literature review of the model predictive control. The chapter starts with a generic historical introduction to MPC followed by an overview to MPC, describing the features and main principles of MPC, presented in section 2.1. MPC core components are then discussed in section 2.2, while section 2.3 provides a brief description about MPC algorithms evolution. Then, in section 2.4, the basic concepts of predictions are presented. Whereas, the basic MPC algorithms are presented in section 2.5. Section 2.6 describes the constraint handling and finally, the chapter contents are summarised in section 2.7.

2.1 An Overview to Model Predictive Control

Model based predictive control (MPC) is a famous control theme in the research communities as well as process industries. New MPC control algorithms continued to flow in the literature since 1970s till now focusing on various aspects and aiming to improve MPC performance and reliability. Hundreds of papers and several books have been published presenting new control algorithms that use a mathematical model of the process and past knowledge about the inputs and outputs to predict and optimise the future output moves. MPC algorithms were published in the literature under different names such as receding horizon control (RHC), moving horizon, embedded optimisation, real time optimisation, and model based predictive control. MPC led the industrial control technology and became favourable by control engineers to control complicated systems due to the ease of process constraints inclusions in the controller context [21, 24, 62].

The basic MPC approach determines a sequence of future optimal control actions (inputs) over a future time horizon in order to optimise, based on an internal mathematical model, the performance of the controlled system. Given the current measurements, the algorithm predicts the future behaviour of the real system with respect to changes in the control inputs. The first control input is then sent to the final control element in the plant, while the rest of the sequence is discarded. The same procedure is continually repeated at subsequent control intervals and at each instant the horizon is displaced one step towards the future. The control loop provides a feedback mechanism for the MPC which in turn compensates for the prediction errors, due to structural mismatch between the internal model and the real system, as well as for disturbances.

The essence of the MPC algorithms comes from the ease of including physical and operation constraints in the control framework. MPC control became industrially desirable because of this important feature. The industrial applications gain, by using

MPC, was great and the main achievements can be summarised in three points:

- The possibility to express constraints explicitly in the problem formulation offers a natural way to state a broad class of control problems.
- Often the best performance, which may correspond to the most efficient or profitable operation, is obtained when the system is made to operate near the constraints.
- In the presence of actuator saturation's, a control approach that is aware of the constraints never generates control inputs beyond the saturation values, and this removes the wind-up problem.

In addition, MPC approaches are powerful and robust in comparison with standard PID control. MPC can directly reflect many performance criteria of relevance to the process industries and it can utilise any available process model. Therefore, it is not restricted in terms of the model, objective function and/or constraint functionality [29]. Due to that, MPC becomes the standard approach in the process industries to control systems with complex dynamics such as time delays, and interactive multivariable control systems [21].

The basic principle of MPC is illustrated in Fig. 2.1, where a single input single output system is considered. The figure trends both output and input trajectories with their upper and lower constraints. The output trajectory shows the previous process measurements alongside with the output predictions. Similarly, the input trajectory shows the implied input at and before time instant k as well as the predicted optimised inputs. At each sampling time k, using the current state of the process as the initial state, a finite horizon optimal control problem is solved over a prediction horizon. The output is required to follow a reference point r. The online optimisation problem takes account of system dynamics, constraints, and control objectives. The optimisation yields an optimal control sequence represented as control horizon in Fig.

2.1. Only the control input representing the present time is applied to the process while the rest of the calculated sequence is discarded. At the next time instant, using the concept of the receding horizon, the horizon is shifted forward by one sample and the optimisation is restarted with new state measurements.

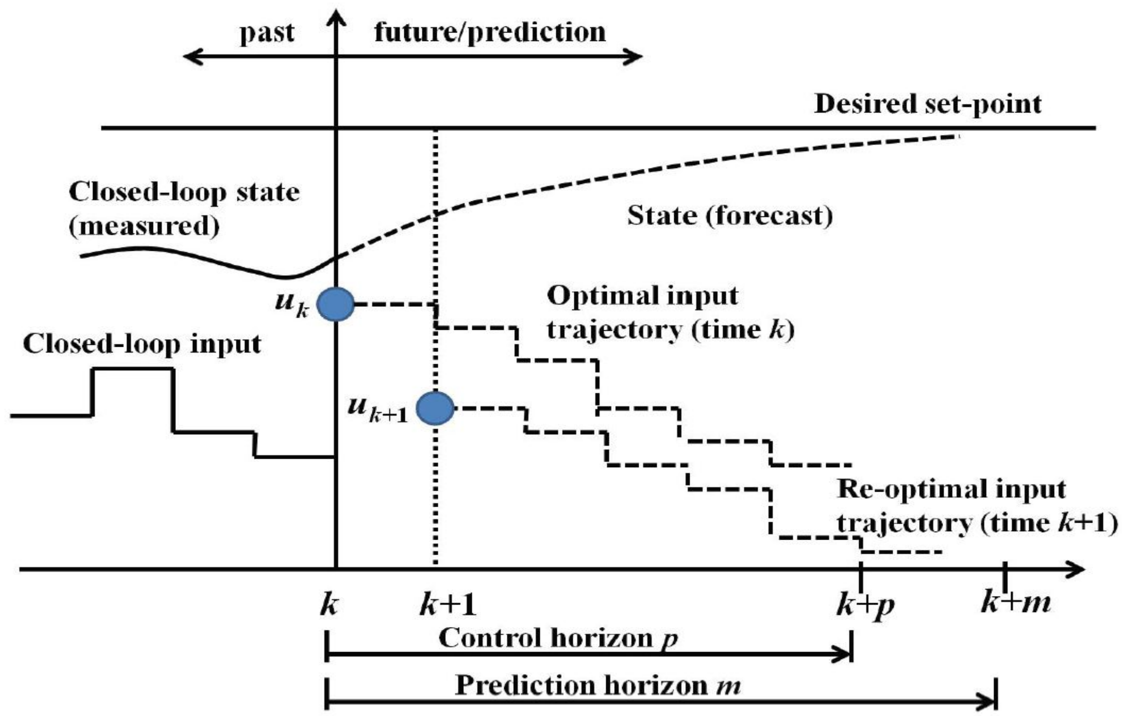


Figure 2.1: Principle of Model Predictive Control [20]

2.2 MPC Core Components

MPC as described above is an anticipation control strategy where it implements control actions which are predicted to lead to the best output over some limited horizon. MPC utilises an internal model of the process to be controlled and constantly updates the decisions when a new observation become available. To do so, a predictive control law depends on the following components:

- **Predictions.** For safe and robust control, the prediction horizon should be long enough beyond the process key dynamics (such as settling time) [65]; otherwise performance may be poor and important events may be unobserved.

- **Receding horizon.** The prediction horizon is always relative to the current position, and thus recedes away at each sample. Hence, the prediction horizon stays the same with time. As illustrated in Fig. 2.2, MPC solves the optimisation problem for the time duration between t (time at current sampling instance) and $t + t_r$ (t_r is the receding horizon time) to find the optimal future control trajectory and uses the first optimum value as input to the process for the current control cycle at time t. Then, the receding time domain shifts to the next time step and the above described process repeated. The continual update of predictions and decision making, to take account of the most recent target and measurement data, introduces feedback.

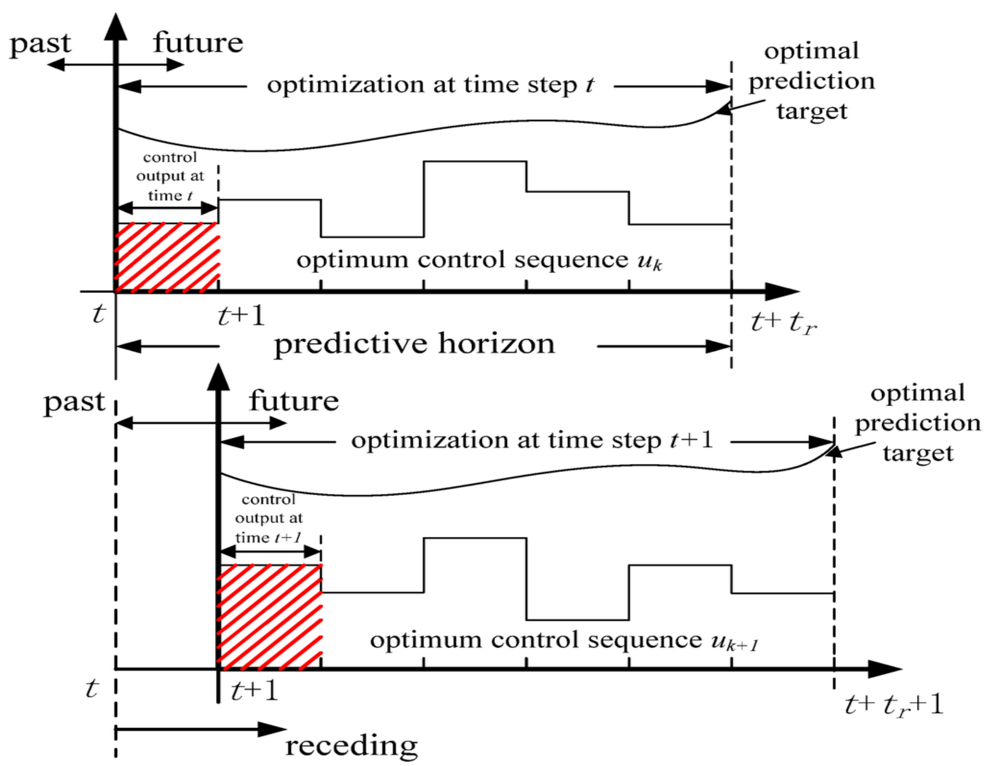


Figure 2.2: MPC Receding Horizon [35]

- **Modelling.** A mathematical model that represents the system behaviour is required in order to automate predictions. However, simple models that give accurate enough predictions and also capture the key dynamic changes during transients are usually preferred [65]. Small modelling errors will be corrected by feedback.

- **Performance index.** The performance index is how to go from a concept to a control strategy. It allows multiple sets of information to be compiled into an overall numeric measure. Quadratic performance indices are commonly used as they give a simple and well-conditioned optimisation with a unique minimum and generally smooth behaviours. Complex performance indices may affect system robustness and ability to deal with uncertainty; henceforth, they are not desirable (unless they are justified).

- **Degrees of freedom.** Describes the complexity of the control input predictions. It states the total number of control changes that are available for the optimiser to drive the process output to the target. Consequently, the number of degrees of freedom (d.o.f.) is linked to prediction accuracy.

- **Constraint handling.** One major advantage of predictive control is that it embeds constraints into the strategy development, meaning the proposed input trajectory is optimal while satisfying constraints and also leading to effective and robust closed loop behaviour.

- **Multivariable systems.** There are many industrial examples of multivariable processes which have numerous inputs and outputs where changing one input often changes all the outputs. Therefore, an effective control law has to consider all inputs and outputs simultaneously. Unlike typical control, MPC framework automatically takes account of process interactions.

2.3 Evolution of MPC Algorithms

The advancement of modern control concepts can be referenced to the work of Kalman et al. in the early 1960s [62].

2.3.1 LQG

Linear Quadratic Gaussian controller (LQG) is the combination of an optimal linear quadratic estimation (LQE) with an optimal linear quadratic regulator (LQR) as sketched in Fig. 2.3 where, w and v are process and measurement noise respectively. LQE, also known as Kalman filter, estimates the current state variables with uncertainties. The estimates are based on observation of previous measurements series. At the time when the next measurement becomes available, these estimates are updated using a weighted average factor. Due to the algorithm recursive nature, it can be implemented as real time control with only the present input measurements; and the earlier calculated state and its uncertainty matrix. LQE estimates, in practice, are more precise than those algorithms based on a single measurement alone.

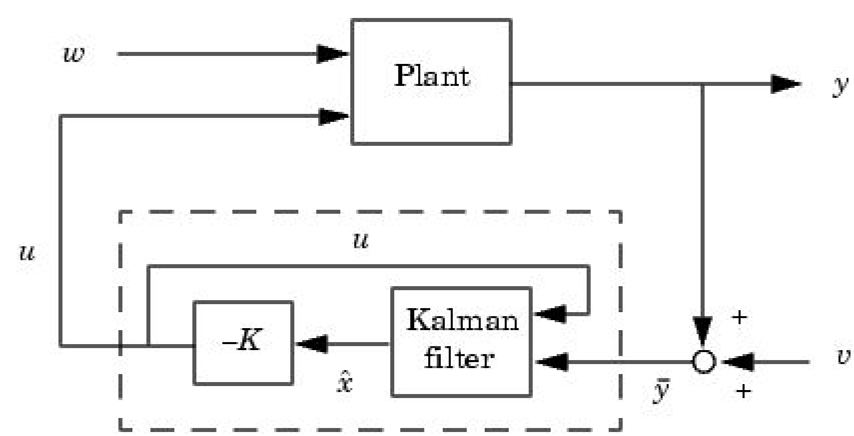


Figure 2.3: Sketch of LQG Regulator [75]

2.3.2 Model Predictive Heuristic Control MPHC / IDCOM

Model Predictive Heuristic Control (MPHC) whose software is called Identification COMmand (IDCOM) appeared in the literature in 1978 by Richalet [63]. MPHC contains an internal process model that performs the predictions. The model is constructed by process identification using impulse test of the relevant multivariable process. The model inputs and outputs are updated in regular bases utilising the actual process operating data.

Control inputs trajectory are computed, utilising the internal model, in a heuristic way by comparing the real process outputs with reference trajectory. Therefore, the best control input vector defines the closed loop behaviour of the process, which in turn minimises the tracking error in adequate time [34].

Richalet et al. [63] describe applications of the MPHC algorithm to a fluid catalytic cracking unit (FCCU) main fractionator column, a power plant steam generator and a poly-vinyl chloride (PVC) plant. All of these examples are constrained multivariable processes. The main fractionator example involved controlling key tray temperatures to stabilize the composition of heavy and light product streams. The controller adjusted product flow-rates to compensate for inlet temperature disturbances and to maintain the level of a key internal tray. The power plant steam generator problem involved controlling the temperature and pressure of steam delivered to the turbine. This application is interesting because the process response time varied inversely with load on the system. This nonlinearity was overcome by executing the controller with a variable sample time. Benefits for the main fractionator application were reported as $150 000/yr, due to increasing the flowrate of the light product stream. Combined energy savings from two columns in the PVC plant were reported as $220 000/yr.

2.3.3 DMC

In the 1979, a new unconstrained multivariable control algorithm called dynamic matrix control (DMC) was introduced by Cutler and Ramaker [62]. One year later, Prett and Gillette [60] presented an industrial application of the new DMC algorithm at a catalytic cracking unit wherein the algorithm was improved to handle nonlinearities and constraints.

The DMC controller aims to ensure the process measured variables track the set-point and reduces offset in the least squares sense. The algorithm also uses a penalty term to penalise large input moves. As a result the computed input moves becomes smaller, hence the process output responds smoothly. As with the IDCOM reference trajectory, DMC offers a degree of robustness to model error. The control horizon and penalisation factors are the main tuning parameters in DMC [62].

A summary of the DMC control algorithm key features are:

- A plant linear step response model.
- A quadratic performance objective over a finite prediction horizon.
- The future plant output behaviour is identified by the demand to follow the reference trajectory as close as possible.
- Optimal inputs are calculated as the solution to a least squares problem.

The DMC linear step response model relates alterations in the process output to the weighted sum of the past input moves.

DMC industrial acceptance was widened significantly during the 1980s to comprise new applications. Mehra et al. [50] reviewed a number of industrial applications including a super-heater, a steam generator, a wind tunnel, a utility boiler connected to a distillation column and a glass furnace. Shell has applied DMC algorithms to many industrial processes including a fluid catalytic cracking unit [60] and a highly non-linear batch reactor [29]. In their paper, Prett and Gillette [60] described an application of DMC technology to FCCU reactor/ regenerator control. Four such applications were already completed and two additional applications were underway at the time the paper was written. Prett and Gillette described additional modifications to the DMC algorithm to prevent violation of absolute input constraints. When a predicted future input came sufficiently close to an absolute constraint, an extra equation was added to the process model that would drive the input back into the feasible region. These were referred to as time variant constraints. Because the decision to add the equation had to be made on-line, the matrix inverse solution had to be recomputed at each control execution. Prett and Gillette developed a matrix tearing solution in which the original matrix inverse could be computed off-line, requiring only the matrix inverse corresponding to active time variant constraints to be computed on-line.

2.3.4 QDMC

QDMC is an upgraded version of Shell's Dynamic Matrix Control (DMC) multivariable algorithm which offers a direct and efficient method for handling process constraints. Numerous online applications have proved its excellent constraint handling properties, transparent tuning, and robustness while demanding minimal online computational load. The algorithm uses a quadratic program to compute future moves on process manipulated variables which in turn keep controlled variables as close as possible to their set points while inhibiting violations of process constraints [18, 28].

A summary of the QDMC control algorithm key features contain:

- A plant linear step response model.
- A quadratic performance objective over a finite prediction horizon.

- Provides a systematic way to implement input and output constraints.
- Future plant output behaviour is identified by the demand to follow the reference trajectory as close as possible
- Optimal inputs are calculated as the solution to a quadratic program.

The QDMC algorithm imposes the MPC problem as a quadratic program (QP) with the solution provided by standard QP codes. Consequently, it provides a systematic way to implement input and output constraints. Thus the QDMC algorithm is considered as a second generation of MPC paradigm [62].

Garcia and Morshedi [28] described an application of QDMC to a pyrolysis furnace. The QDMC controller adjusted fuel gas pressure in three burners in order to control stream temperature at three locations in the furnace. Their test results demonstrated dynamic enforcement of input constraints and decoupling of the temperature dynamics. They reported good results on many applications within Shell on problems as large as 12 X 12 (12 process outputs and 12 process inputs). They stated that above all, the QDMC algorithm had proven particularly profitable in an on-line optimization environment, providing a smooth transition from one constrained operating point to another.

2.3.5 GPC

In 1987 D. W. Clarke [16] developed a prediction algorithm called generalized predictive control (GPC) which turned out later on to be the most popular predictive control algorithm. GPC caters for offsets, since it uses integrated controlled auto regressive moving average (CARIMA) model, feed-forward signals, and multivariable plant without detailed prior knowledge of structural indices. GPC is conceptually equivalent to DMC, but the main differences between GPC and DMC are the plant description model and the dynamic matrix formulation.

A CARIMA model obtains output predictions, by utilising the internal process model, and optimise a sequence of future control inputs to minimise a multistage performance index defined over a prediction horizon. Inclusion of a disturbance model helps to deduce the correct controller structure. Practically, GPC has wider application areas compared with other methods. It adeptly tracks both constant and varying future references. A Proper choice of prediction and control horizons ensures satisfactory performance. Clarke [15] described successful GPC applications in the cement industry, drying towers and in robot arms.

2.3.6 Implicit MPC

Implicit MPC by definition relies on the use of a real-time optimisation solver which is complex in general. It is required to compute the updated optimal control input sequence for each new set of measurements. Until the 90s, MPC was only used for plants with slow dynamics because the optimisation procedure is to be repeated every time step. Although computational speed and optimization algorithms are continuously improving, traditionally such solvers have only been able to handle relatively low control input update rates. Therefore, conventional MPC applications have been limited to situations which, in some sense, justify the cost of such hardware and software and which allow a sufficient time span for solving the overall optimisation problem.

2.3.7 Explicit MPC

In contrast to the implicit nature of standard MPC implementations, explicit MPC solutions provide a more accurate and deep intuitive understanding of the control behaviour and properties, allowing analysis of performance such as safety verifications. That's because the explicit MPC approach is based on optimisation technology called multi-parametric programming which allows the optimal solution of an optimisation problem to be determined as an explicit function of certain varying parameters. Therefore, multi-parametric programming avoids the need to solve a new optimization problem when the parameter changes, since the optimal solution can readily be updated using the pre-computed function.

This allows the online computational effort to be reduced to a series of function evaluations, eliminating the need of a real-time optimization solver. Commonly, explicit MPC formulations provide the explicit optimal solution as a piecewise function of the system state variables. The typical domain of interest is a subset of the state space, which is partitioned in a finite number of regions referred to as a critical regions. For each critical region, a particular state feedback control law yields the optimal value of the control input. All together, these control laws form the piecewise function which represents the explicit optimal MPC solution [10, 30, 9].

2.4 Basic Concepts of Prediction

Prediction is one of the core concepts of MPC. The general predictions format of system future behaviour were logically presented by J. A. Rossiter [65]. The prediction concept in summarised in the following equation:

$$\underset{\rightarrow k}{\mathbf{y}} = H\Delta \underset{\rightarrow k-1}{\mathbf{u}} + P \underset{\leftarrow k-1}{\mathbf{x}} \tag{2.1}$$

where:

* $\underset{\rightarrow k}{\mathbf{y}}$ is a vector of future process outputs; $\Delta \underset{\rightarrow k-1}{\mathbf{u}}$ is a vector of current and future control increments; and $\underset{\leftarrow k-1}{\mathbf{x}}$ is a vector of the past process states.

* H is the Toeplitz matrix $C_{G/\Delta}$ of the system step response, and P is a matrix whose coefficients depend on the model parameters in a straight forward but non-linear manner.

2.4.1 Prediction with state space models

A common discrete state space model is given as:

$$\begin{aligned} \mathbf{x}_{k+1} &= A\mathbf{x}_k + B\mathbf{u}_k \\ \mathbf{y}_k &= C\mathbf{x}_k + d_k \end{aligned} \tag{2.2}$$

where d_k is the disturbance and assuming it is slowly varying, therefore constant. Then rewriting eq (2.2) to:

$$\begin{aligned} \mathbf{x}_{k+1} &= A\mathbf{x}_k + B\mathbf{u}_k \\ \mathbf{y}_{k+1} &= C\mathbf{x}_{k+1} + d_k \end{aligned} \tag{2.3}$$

Implicitly discrete models are one step ahead prediction model, Therefore finding the two step predictions is straight forward:

$$\begin{aligned} \mathbf{x}_{k+2} &= A\mathbf{x}_{k+1} + B\mathbf{u}_{k+1} \\ \mathbf{y}_{k+2} &= C\mathbf{x}_{k+2} + d_k \end{aligned} \tag{2.4}$$

At the second step prediction, the first step predictions is known. Hence substituting eq (2.3) in eq (2.4) to eliminate $\mathbf{x}_{k+1}$ gives:

$$\begin{aligned} \mathbf{x}_{k+2} &= A^2\mathbf{x}_k + AB\mathbf{u}_k + B\mathbf{u}_{k+1} \\ \mathbf{y}_{k+2} &= C\mathbf{x}_{k+2} + d_k \end{aligned} \tag{2.5}$$

Generally this recursion can be continued to give the n-step ahead predictions as:

$$\begin{aligned} \mathbf{x}_{k+n} &= A^n\mathbf{x}_k + A^{n-1}B\mathbf{u}_k + A^{n-2}B\mathbf{u}_{k+1} + ... + B\mathbf{u}_{k+n-1} \\ \mathbf{y}_{k+n} &= C[A^n\mathbf{x}_k + A^{n-1}B\mathbf{u}_k + A^{n-2}B\mathbf{u}_{k+1} + ... + B\mathbf{u}_{k+n-1}] + d_k \end{aligned} \tag{2.6}$$

Thereafter the whole vector of future predictions up to a horizon n_y can be written in the following form:

$$\underbrace{\begin{bmatrix} \mathbf{x}_{k+1} \\ \mathbf{x}_{k+2} \\ \mathbf{x}_{k+3} \\ \vdots \\ \mathbf{x}_{k+n_y} \end{bmatrix}}_{\underset{\to k}{\mathbf{x}}} = \underbrace{\begin{bmatrix} A \\ A^2 \\ A^3 \\ \vdots \\ A^{n_y} \end{bmatrix}}_{P_x} \mathbf{x}_k + \underbrace{\begin{bmatrix} B & 0 & 0 & \dots \\ AB & B & 0 & \dots \\ A^2B & AB & B & \dots \\ \vdots & \vdots & \vdots & \dots \\ A^{N_y-1}B & A^{N_y-2}B & A^{N_y-3}B & \dots \end{bmatrix}}_{H_x} \underbrace{\begin{bmatrix} \mathbf{u}_k \\ \mathbf{u}_{k+1} \\ \mathbf{u}_{k+2} \\ \vdots \\ \mathbf{u}_{k+n_y-1} \end{bmatrix}}_{\underset{\to k}{\mathbf{u}}} \tag{2.7}$$

and

$$\underbrace{\begin{bmatrix} \mathbf{y}_{k+1} \\ \mathbf{y}_{k+2} \\ \mathbf{y}_{k+3} \\ \vdots \\ \mathbf{y}_{k+n_y} \end{bmatrix}}_{\underset{\to k}{\mathbf{y}}} = \underbrace{\begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ \vdots \\ CA^{n_y} \end{bmatrix}}_{P} \mathbf{x}_k + \underbrace{\begin{bmatrix} CB & 0 & 0 & \dots \\ CAB & CB & 0 & \dots \\ CA^2B & CAB & CB & \dots \\ \vdots & \vdots & \vdots & \dots \\ CA^{N_y-1}B & CA^{N_y-2}B & CA^{N_y-3}B & \dots \end{bmatrix}}_{H} \underbrace{\begin{bmatrix} \mathbf{u}_k \\ \mathbf{u}_{k+1} \\ \mathbf{u}_{k+2} \\ \vdots \\ \mathbf{u}_{k+n_y-1} \end{bmatrix}}_{\underset{\to k}{\mathbf{u}}} + \underbrace{\begin{bmatrix} \mathbf{d}_k \\ \mathbf{d}_k \\ \mathbf{d}_k \\ \vdots \\ \mathbf{d}_k \end{bmatrix}}_{Ld} \tag{2.8}$$

Hence the predictions for model (2.2) can be written in a compact form as follows:

$$\begin{aligned} \underset{\to k}{\mathbf{x}} &= P_x\mathbf{x}_k + H_x \underset{\to k}{\mathbf{u}} \\ \underset{\to k}{\mathbf{y}} &= P\mathbf{x}_k + Ld_k + H \underset{\to k}{\mathbf{u}} \end{aligned} \tag{2.9}$$

which is clearly separated in parts which is known, $P_x\mathbf{x}_k$ and $P\mathbf{x}_k + L\mathbf{d}_k$, and decision variables part, $H \underset{\to k}{\mathbf{u}}$, that is the future inputs which is also the degree of freedom (d.o.f)

2.4.2 Prediction with transfer function model (CARIMA model)

A CARIMA (Controlled Auto-Regressive Integrated Moving Average) model is the most common transfer function used with MPC in the literature [16]. It is favoured because it incorporates a slowly varying disturbance estimates and therefore can give unbiased predictions in the steady state irrespective of some parameter uncertainty. It is given as:

$$a(z)y_k = b(z)u_k + T(z)\tfrac{\zeta_k}{\Delta} \tag{2.10}$$

where ζ is a zero mean random variable. Hence, $\frac{\zeta}{\Delta}$ represents a slowly varying disturbance and $T(z)$ is considered as a design parameter, generally treated as a d.o.f because it has direct effects on loop sensitivity [16, 76].

It is common to write transfer function models in the equivalent difference equation form as follows:

$$y_{k+1} + a_1 y_k + a_2 y_{k-1} + \ldots + a_n y_{k-n+1} = b_1 u_k + b_2 u_{k-1} + \ldots + b_n u_{k-n+1} + d_k \tag{2.11}$$

and then rewrite it into the one step ahead prediction form as given below:

$$y_{k+1} = b_1 u_k + b_2 u_{k-1} + \ldots + b_n u_{k-n+1} + d_k - a_1 y_k - a_2 y_{k-1} - \ldots - a_n y_{k-n+1} \tag{2.12}$$

Where: $a(z) = 1 + a_1 z^{-1} + \ldots + a_n z^{-n}$; $b(z) = b_1 z^{-1} + \ldots + b_n z^{-n}$; and
d_k is the disturbance term $T(z)\frac{\zeta_k}{\Delta}$

For convenience, the above equation can be separated into components which depend on past inputs and outputs (known), and the future input increments (d.o.f.):

$$y_{k+1} = -a_1 y_k - a_2 y_{k-1} - \ldots - a_n y_{k-n+1} + b_1 u_k + b_2 u_{k-1} + \ldots + b_n u_{k-n+1} + d_k \tag{2.13}$$

In practice, the incremental form is used for predictions. That can be formed by multiplying both sides of eq (2.11) by Δ:

$$y_{k+1} + A_1 y_k + A_2 y_{k-1} + \ldots + A_n y_{k-n+1} = b_1 \Delta u_k + b_2 \Delta u_{k-1} + \ldots + b_n \Delta u_{k-n+1} + T(z)\zeta_k \tag{2.14}$$

In the above equation $A = a(z)\Delta$. The disturbance term $T(z)\zeta_k$ normally assumed as a zero mean term, not time varying, hence can be ignored for simplicity.

Then, the one step ahead prediction eq (2.14) can be used recursively to compute the ny-step ahead predictions:

$$
\begin{aligned}
y_{k+1} + A_1 y_k + A_2 y_{k-1} + \ldots + A_{n+1} y_{k-n} &= b_1 \Delta u_k + b_2 \Delta u_{k-1} + \ldots + b_n \Delta u_{k-n+1} \\
y_{k+2} + A_1 y_{k+1} + A_2 y_k + \ldots + A_{n+1} y_{k-n+1} &= b_1 \Delta u_{k+1} + b_2 \Delta u_k + \ldots + b_n \Delta u_{k-n+2} \\
&\vdots \\
y_{k+ny} + A_1 y_{k+ny-1} + \ldots + A_{n+1} y_{k+ny-n+1} &= b_1 \Delta u_{k+1} + b_2 \Delta u_k + \ldots + b_n \Delta u_{k-n+2}
\end{aligned}
\tag{2.15}
$$

Thereafter the whole vector of future predictions up to a horizon n_y can be written in the following form:

$$
\begin{aligned}
&\underbrace{\begin{bmatrix} 1 & 0 & \ldots & 0 \\ A_1 & 1 & \ldots & 0 \\ A_2 & A_1 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}}_{C_A} \underbrace{\begin{bmatrix} \mathbf{y}_{k+1} \\ \mathbf{y}_{k+2} \\ \vdots \\ \mathbf{y}_{k+n_y} \end{bmatrix}}_{\underset{\to k+1}{\mathbf{y}}} + \underbrace{\begin{bmatrix} A_1 & A_2 & \ldots & A_{n+1} \\ A_2 & A_3 & \ldots & 0 \\ A_3 & A_4 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}}_{H_A} \underbrace{\begin{bmatrix} \mathbf{y}_k \\ \mathbf{y}_{k-1} \\ \vdots \\ \mathbf{y}_{k-n} \end{bmatrix}}_{\underset{\leftarrow k}{\mathbf{y}}} = \\
&\underbrace{\begin{bmatrix} b_1 & 0 & \ldots & 0 \\ b_2 & b_1 & \ldots & 0 \\ b_3 & b_2 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}}_{C_b} \underbrace{\begin{bmatrix} \Delta\mathbf{u}_k \\ \Delta\mathbf{u}_{k+1} \\ \vdots \\ \Delta\mathbf{u}_{k+n_y-1} \end{bmatrix}}_{\underset{\to k}{\Delta\mathbf{u}}} + \underbrace{\begin{bmatrix} b_2 & b_3 & \ldots & b_n \\ b_3 & b_4 & \ldots & 0 \\ b_4 & b_5 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}}_{H_b} \underbrace{\begin{bmatrix} \Delta\mathbf{u}_{k-1} \\ \Delta\mathbf{u}_{k-2} \\ \vdots \\ \Delta\mathbf{u}_{k-n+1} \end{bmatrix}}_{\underset{\leftarrow k-1}{\Delta\mathbf{u}}}
\end{aligned}
\tag{2.16}
$$

Eq (2.16) is a compact matrix which represents a set of simultaneous equations where the unknowns are the predicted future outputs. Then the vector of output predictions can be easily separated by multiplying through by C_A inverse:

$$\underset{\to k+1}{\mathbf{y}} = C_A^{-1}[C_b \underset{\to k}{\Delta\mathbf{u}} + H_b \underset{\leftarrow k-1}{\Delta\mathbf{u}} - H_A \underset{\leftarrow k}{\mathbf{y}}] \tag{2.17}$$

Finally, predictions model (2.17) can be represented in a convenient and compact form:

$$\underset{\to k+1}{\mathbf{y}} = H_1 \underset{\to k}{\Delta\mathbf{u}} + P \underset{\leftarrow k-1}{\Delta\mathbf{u}} + Q \underset{\leftarrow k}{\mathbf{y}} \tag{2.18}$$

where $H_1 = C_A^{-1} C_b$; $\quad P = C_A^{-1} H_b$; $\quad$ and $\quad Q = -C_A^{-1} H_A$.

2.5 Model Predictive Control Basic Algorithms

Model Predictive Control has a wide scale adoption in industry due to its almost unique ability to handle hard constraints making it become the industry standard in some important applications. Indeed, the importance of model predictive control derives from being an approach to control design rather than a specific algorithm. Different MPC algorithms evolved during the MPC development history, motivated by the industrial challenges, to achieve the safest and most optimal control. MPC algorithms are a way of thinking; and were presented, in the literature, in so many different ways. Most of the MPC algorithms and equations presented in this section are referred to J. A. Rossiter book [65].

MPC algorithms relay into two core components: prediction model, ex. (2.18), and performance index (cost function). The control law is obtained from a minimisation of a two norm measure of predicted performance. Generally, the performance index consists of a sum of the predicted tracking errors, from the initial horizon n_1 to an output horizon n_y, added with the sum of either: the control increments or the inputs deviation from their steady state values u_{ss} over the control horizon n_u. Here is a typical cost function based on control increments:

$$J = \sum_{i=n_1}^{n_y} \|W_y(\mathbf{r}_{k+i} - \mathbf{y}_{k+i})\|_2^2 + \lambda \sum_{i=0}^{n_u-1} \|W_u(\Delta \mathbf{u}_{k+i})\|_2^2 \tag{2.19}$$

where W_y and W_u are output and input weighting factors. These are positive definite and diagonal matrices used to handle and stabilise interactive control loops in multi-variable systems. In practice, they are often set to I, to reduce the design parameters, unless there are a visible benefits from tuning them. For example a multivariable system with slow and fast interactive loops could benefit from the waiting factors. Usually, W_y and W_u are designed with constant values but they may be designed to vary exponentially with time. For example, consider the following designing equation to obtain an exponential output weighting factor W_y along the prediction horizon:

$$W_y(i) = \alpha^{n_y - i} \tag{2.20}$$

A tighter control trajectory can be achieved from an exponentially decaying weighting factors by setting $\alpha > 1$. Hence, the first errors are more penalised. On the other hand, setting $0 < \alpha < 1$ gives rise to smoother control due to the exponentially rising weighting factors which tends to penalise the closest errors less than the farthest in time.

The parameter n_1 in (2.19) denotes the minimum prediction horizon and it is common to assume that n_1 = 1. However, for processes with dead time, the value of n_1 is preferred to be more than or equal to the dead time. It is also assumed that, there are no control changes beyond the control horizon n_u, therefore:

$$\Delta \mathbf{u}_{k+i} = 0, \qquad i \geq n_u \tag{2.21}$$

For unity weight, the performance index (2.19) can be written in a simple compact form using vectors and matrices as follows:

$$J = \|\underset{\rightarrow}{\mathbf{r}} - \underset{\rightarrow}{\mathbf{y}}\|_2^2 + \lambda \|\Delta \underset{\rightarrow}{\mathbf{u}}\|_2^2 \tag{2.22}$$

where $\underset{\rightarrow}{\mathbf{r}}$ is vector of references; $\underset{\rightarrow}{\mathbf{y}}$ is obtained from a prediction model such as (2.18); right arrow implies predictions vector; and left arrow implies past data.

The cost function (J) enables offset free tracking as it implies that both the error $(\underset{\rightarrow}{\mathbf{r}} - \underset{\rightarrow}{\mathbf{y}})$ = 0; and the control increment is also zero at the minimum performance index ($J = 0$).

The prediction model (2.18) was constructed assuming all the future inputs $(\Delta \underset{\rightarrow k}{\mathbf{u}})$ could be selected. However, In practice a finite future control horizon is used. It is set by selecting a subset of the future inputs (n_u) and assuming that the control input becomes fixed after n_u steps (2.18). Consequently, these vectors comprise the d.o.f. in any optimisation. It is noted, from (2.18), that the square matrix H_1 multiplies upon $\Delta \underset{\rightarrow k}{\mathbf{u}}$. This implies that only the first n_u columns of H_1 matrix are needed to be multiplied on the restricted $\Delta \underset{\rightarrow k}{\mathbf{u}}$. Hereafter the $H_1 \Delta \underset{\rightarrow k}{\mathbf{u}}$ term on the prediction equation

(2.18) will be replaced by $H\underset{\to k}{\Delta\mathbf{u}}$. Hence, the modified prediction equation is:

$$\underset{\to k+1}{\mathbf{y}} = H\underset{\to k}{\Delta\mathbf{u}} + P\underset{\leftarrow k-1}{\Delta\mathbf{u}} + Q\underset{\leftarrow k}{\mathbf{y}} \tag{2.23}$$

2.5.1 *Generalised Predictive Control*

GPC control law is computed by using the cost function (2.22) and predictions (2.23) . Expanding (2.22) gives:

$$J = [\underset{\to k+1}{\mathbf{r}^T} - \underset{\to k+1}{\mathbf{y}^T}]\,[\underset{\to k+1}{\mathbf{r}} - \underset{\to k+1}{\mathbf{y}}] + \lambda\underset{\to k}{\Delta\mathbf{u}^T}\underset{\to k}{\Delta\mathbf{u}} \tag{2.24}$$

Substituting $\underset{\to k}{\mathbf{y}}$ into (2.24) yields:

$$J = [\underset{\to k+1}{\mathbf{r}} - H\underset{\to k}{\Delta\mathbf{u}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}]^T\,[\underset{\to k+1}{\mathbf{r}} - H\underset{\to k}{\Delta\mathbf{u}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] + \lambda\underset{\to k}{\Delta\mathbf{u}^T}\underset{\to k}{\Delta\mathbf{u}} \tag{2.25}$$

Then, the performance index J will be optimised with respect to $\underset{\to k}{\Delta\mathbf{u}}$. Therefore, it will be convenient to split (2.25) into terms which depends on $\underset{\to k}{\Delta\mathbf{u}}$ and terms which does not:

$$\begin{aligned} J = {} & [\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}]^T\,[\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] + [H\underset{\to k}{\Delta\mathbf{u}}]^T\,[H\underset{\to k}{\Delta\mathbf{u}}] \\ & -[2(H\underset{\to k}{\Delta\mathbf{u}})^T]\,[\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] + \lambda\underset{\to k}{\Delta\mathbf{u}^T}\underset{\to k}{\Delta\mathbf{u}} \end{aligned} \tag{2.26}$$

The term $[\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}]^T\,[\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}]$ will not affect the optimum when optimising J with respect to $\underset{\to k}{\Delta\mathbf{u}}$, because it did not depend on $\underset{\to k}{\Delta\mathbf{u}}$, hence can be omitted:

$$\underset{\underset{\to k}{\Delta\mathbf{u}}}{min}\ J = [H\underset{\to k}{\Delta\mathbf{u}}]^T\,[H\underset{\to k}{\Delta\mathbf{u}}] - [2(H\underset{\to k}{\Delta\mathbf{u}})^T]\,[\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] + \lambda\underset{\to k}{\Delta\mathbf{u}^T}\underset{\to k}{\Delta\mathbf{u}} \tag{2.27}$$

Combining common terms gives:

$$\underset{\underset{\to k}{\Delta\mathbf{u}}}{min}\ J = \underset{\to k}{\Delta\mathbf{u}^T}(H^TH + \lambda I)\underset{\to k}{\Delta\mathbf{u}} - [2(H\underset{\to k}{\Delta\mathbf{u}})^T]\,[\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] \tag{2.28}$$

The cost function (2.28) is quadratic, always positive and therefore, has a unique minimum which can be identified by setting the first derivative to zero.

$$\frac{dJ}{d\underset{\to k}{\Delta\mathbf{u}}} = 2(H^TH + \lambda I)\underset{\to k}{\Delta\mathbf{u}} - 2H^T[\underset{\to k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] = 0 \tag{2.29}$$

Therefore,

$$2(H^T H + \lambda I)\underset{\rightarrow k}{\Delta \mathbf{u}} = 2H^T[\underset{\rightarrow k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta \mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] \tag{2.30}$$

Hence, the optimum solution is:

$$\underset{\rightarrow k}{\Delta \mathbf{u}} = (H^T H + \lambda I)^{-1} H^T[\underset{\rightarrow k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta \mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] \tag{2.31}$$

The optimum trajectory of future control increments (2.31) depends linearly on the future reference; and past inputs and outputs.

The optimisation is carried out at every sampling instant, but the GPC control law is defined by the first value of the optimum input trajectory. Therefore, the first element of the $\underset{\rightarrow k}{\Delta \mathbf{u}}$ is implemented:

$$\Delta \mathbf{u}_k = [I, 0, 0, \ldots, 0]\underset{\rightarrow k}{\Delta \mathbf{u}} \tag{2.32}$$

So, the GPC control law is:

$$\underset{\rightarrow k}{\Delta \mathbf{u}} = E_1^T (H^T H + \lambda I)^{-1} H^T[\underset{\rightarrow k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta \mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}}] \tag{2.33}$$

where: $E_1^T = [I, 0, 0, \ldots, 0]$.

The GPC control law (2.33) can be written in a more compact form as follows:

$$\underset{\rightarrow k}{\Delta \mathbf{u}} = P_r \underset{\rightarrow k+1}{\mathbf{r}} - D_k \underset{\leftarrow k-1}{\Delta \mathbf{u}} - N_k \underset{\leftarrow k}{\mathbf{y}} \tag{2.34}$$

where $P_r = E_1^T (H^T H + \lambda I)^{-1} H^T$, $\quad D_k = P_r P$, $\quad$ and $N_k = P_r Q$.

In order to investigate the closed loop stability of the GPC control law, it would be useful to represent it in a transfer function form. The way forward is by expanding the control law (2.34) as follows:

$$\underset{\rightarrow k}{\Delta \mathbf{u}} = [P_{r1}, P_{r2}, \ldots, P_{rn_y}]\underset{\rightarrow k+1}{\mathbf{r}} - [D_{k0}, D_{k1}, \ldots, D_{kb}]\underset{\leftarrow k-1}{\Delta \mathbf{u}} - [N_{k0}, N_{k1}, \ldots, N_{ka}]\underset{\leftarrow k}{\mathbf{y}} \tag{2.35}$$

where the number of terms of: P_{rn_y} is dictated by the prediction horizon , D_{kb} is one less than number of terms in model numerator, and N_{ka} is one more than number of terms in model denominator.

The equivalent difference equation form of (2.35) is:

$$\begin{aligned}\Delta\mathbf{u} = [P_{r1}z + P_{r2}z^2 + \cdots + P_{rn_y}z^{n_y}]\,\mathbf{r} - [D_{k0} + D_{k1}z^{-1} + \cdots + D_{kb}z^{-b}]\,\Delta\mathbf{u} \\ -[N_{k0} + N_{k1}z^{-1} + \cdots + N_{ka}z^{-a}]\,\mathbf{y}\end{aligned} \tag{2.36}$$

Therefore, the control law can be implemented in the following close loop form:

$$\begin{aligned}\underbrace{[1 + D_{k0} + D_{k1}z^{-1} + \cdots + D_{kb}z^{-b}]}_{\tilde{D}_k(z)}\,\Delta\mathbf{u} = \\ \underbrace{[P_{r1}z + P_{r2}z^2 + \cdots + P_{rn_y}z^{n_y}]}_{P_r(z)}\,\mathbf{r} - \underbrace{[N_{k0} + N_{k1}z^{-1} + \cdots + N_{ka}z^{-a}]}_{N_k(z)}\,\mathbf{y}\end{aligned} \tag{2.37}$$

Then, rewriting (2.37) into a conventional compensator form:

$$\mathbf{u} = [\tilde{D}_k(z)\ \Delta]^{-1}\ [P_r(z)\ \mathbf{r} - N_k(z)\ \mathbf{y}] \tag{2.38}$$

which can be represented by a block diagram as follows:

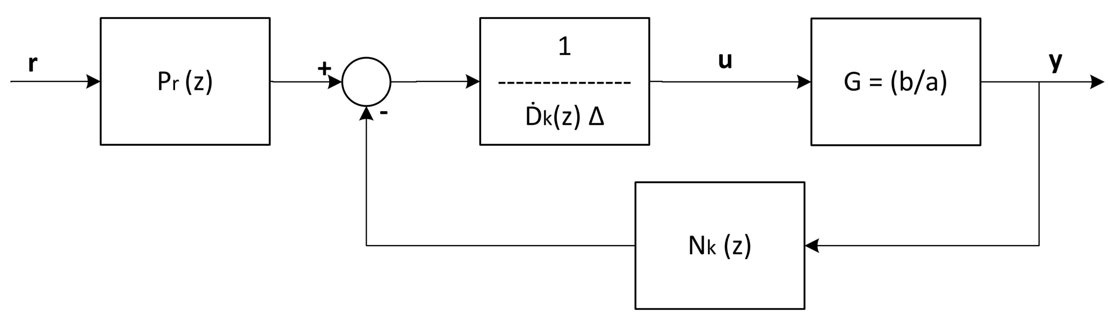


Figure 2.4: GPC block diagram

Hence, the closed loop transfer function of a SISO case is:

$$y = \frac{\frac{G}{\tilde{D}_k\ \Delta}}{1 + \frac{G}{\tilde{D}_k\ \Delta}\ N_k} P_r r\ = \frac{G}{\tilde{D}_k\ \Delta + GN_k} P_r r\ = \frac{b}{\tilde{D}_k\ \Delta\ a + bN_k} P_r r \tag{2.39}$$

So, the closed loop poles can be calculated from the characteristic equation of (2.39): $(\tilde{D}_k\ \Delta\ a + bN_k)$

2.5.2 GPC with State Space model

State space models are preferred over CARIMA for MIMO cases. Unlike CARIMA, state space models are built to represent different vectors with their interactions. The performance index used with CARIMA models was typically based on control increments, whereas it is easier to use input deviation cost with state space model rather than input increments. Where the deviation variables are defined relative to an expected steady state. The deviation variables assumes knowledge of the desired target (r), and a best estimate of the system disturbance.

$$\begin{aligned} \mathbf{r} = \mathbf{y}_{ss} &= C\mathbf{x}_{ss} + d; \\ \mathbf{x}_{ss} &= A\mathbf{x}_{ss} + B\mathbf{u}_{ss} \end{aligned} \tag{2.40}$$

where $\mathbf{y}_{ss}$, $\mathbf{x}_{ss}$, and $\mathbf{u}_{ss}$ are the steady state vectors of output, state, and input respectively.

Deviation variables are defined as the distance of the state and the input from their expected steady state values:

$$\hat{\mathbf{x}}_k = \mathbf{x}_k - \mathbf{x}_{ss}; \quad \hat{\mathbf{u}}_k = \mathbf{u}_k - \mathbf{u}_{ss} \tag{2.41}$$

Thereafter, the system dynamics can be represented with a state space model as follows:

$$\hat{\mathbf{x}}_{k+1} = A\hat{\mathbf{x}}_k + B\hat{\mathbf{u}}_k \tag{2.42}$$

Prediction model (2.9) will be used to build the state space control law in conjunction with the following input deviation cost:

$$J = \textstyle\sum_{k=0}^{n} (\mathbf{e}_{k+1}^2 + \lambda(\mathbf{u}_k - \mathbf{u}_{ss})^2); \quad \mathbf{e}_{k+1} = \mathbf{r}_{k+1} - \mathbf{y}_{k+1} \tag{2.43}$$

The performance index (2.43) can be written as follows:

$$J = \textstyle\sum_{k=0}^{n} [\mathbf{e}_{k+1}^T\, Q\, \mathbf{e}_{k+1} + (\hat{\mathbf{u}}_k)^T\, R\, (\hat{\mathbf{u}}_k)] \tag{2.44}$$

where Q and R are waiting factors.

The predictions, with deviation variables, are given as:

$$\underset{\rightarrow}{\mathbf{e}} = \underset{\rightarrow k+1}{\hat{\mathbf{y}}} = P_x\, \hat{\mathbf{x}}_k + H_x\, \underset{\rightarrow k}{\hat{\mathbf{u}}} \tag{2.45}$$

Substituting predictions model (2.45) into the performance index (2.38) gives:

$$J = [P_x\, \hat{\mathbf{x}}_k + H_x\, \underset{\rightarrow k}{\hat{\mathbf{u}}}]^T\, Q\, [P_x\, \hat{\mathbf{x}}_k + H_x\, \underset{\rightarrow k}{\hat{\mathbf{u}}}] + (\underset{\rightarrow k}{\hat{\mathbf{u}}})^T\, R\, (\underset{\rightarrow k}{\hat{\mathbf{u}}}) \tag{2.46}$$

Thereafter, minimising J with respect to the future control deviations:

$$\underset{\underset{\rightarrow k}{\hat{\mathbf{u}}}}{min}\; J \Rightarrow 2\; [H_x^T Q H_x + R]\, \underset{\rightarrow k}{\hat{\mathbf{u}}} + 2H_x^T Q P_x\, \hat{\mathbf{x}}_k = 0 \tag{2.47}$$

Hence the future control input deviation trajectory is given as:

$$\underset{\rightarrow k}{\hat{\mathbf{u}}} = -[H_x^T Q H_x + R]^{-1}\; H_x^T Q\; P_x\, \hat{\mathbf{x}}_k \tag{2.48}$$

In order to extract the first value from the proposed control trajectory, eq(2.48) will be multiplied by E_1^T

$$\begin{aligned} \underset{\rightarrow k}{\hat{\mathbf{u}}} &= -E_1^T [H_x^T Q H_x + R]^{-1}\; H_x^T Q\; P_x\, \hat{\mathbf{x}}_k; \\ E_1^T &= [I, 0, 0, \ldots, 0] \end{aligned} \tag{2.49}$$

Rewriting the control law (2.49) with actual state and input gives:

$$\mathbf{u}_k - \mathbf{u}_{ss} = -\underbrace{E_1^T [H_x^T Q H_x + R]^{-1}\; H_x^T Q\; P_x}_{K}\, [\mathbf{x}_k - \mathbf{x}_{ss}] \tag{2.50}$$

The derived control law is equivalent to state feedback law ($\mathbf{u}_k - \mathbf{u}_{ss} = -K(\mathbf{x}_k - \mathbf{x}_{ss})$) and moreover, it includes integral action due to the use of steady state estimates.

The input and state steady states, u_{ss} and x_{ss}, can be calculated by the formula (2.40) as follows:

$$\begin{pmatrix} \mathbf{y}_{ss} - d \\ 0 \end{pmatrix} = \begin{pmatrix} C & 0 \\ A - I & B \end{pmatrix} \begin{pmatrix} \mathbf{x}_{ss} \\ \mathbf{u}_{ss} \end{pmatrix} \tag{2.51}$$

The closed loop poles can be determined by substituting (2.50) into (2.42):

$$\begin{aligned} \mathbf{x}_{k+1} - \mathbf{x}_{ss} &= (A - BK)(\mathbf{x}_k - \mathbf{x}_{ss}) \\ \mathbf{y}_k - \mathbf{y}_{ss} &= C(\mathbf{x}_k - \mathbf{x}_{ss}) \end{aligned} \tag{2.52}$$

which reveals a simple close loop dynamics $(A - BK)$.

2.5.3 Independent Model GPC

Independent model (IM) is a method used to address disturbance and parameters uncertainty issues with predictions. These issues implies that the predicted output may not match the real process output especially at steady state situation. An IM can be based on any prediction model such as CARIMA and state space. In order to ensure offset free predictions, IM uses a system model for the predictions and then calculates the offset magnitude (d) by subtracting the model output from the real process one. An IM structure is presented in Fig. 2.5. Clearly, the measured offset (d) captures both the actual system disturbance as well as differences caused by parameters uncertainty.

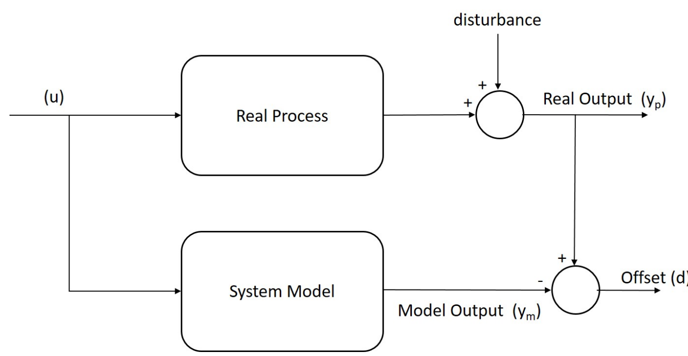


Figure 2.5: Independent Model structure

Therefore, the future predictions for the process output are given by the model predictions plus the offset d:

$$\underset{\rightarrow k+1}{\mathbf{y}} = \underset{\rightarrow m}{\mathbf{y}} + L\mathbf{d}_k \quad ; \qquad \mathbf{d}_k = \mathbf{y}_p(k) - \mathbf{y}_m(k) \tag{2.53}$$

2.5.3.1 IM predictions based on transfer function model

It is obvious that, the IM adds the offset term to the CARIMA predictions model (2.23) to compensate for any bias in the predictions. So the IM prediction equation will be:

$$\underset{\rightarrow k+1}{\mathbf{y}} = H\underset{\rightarrow k}{\Delta\mathbf{u}} + P\underset{\leftarrow k-1}{\Delta\mathbf{u}} + Q\underset{\leftarrow k}{\mathbf{y}_m} + L\mathbf{d}_k \tag{2.54}$$

Substituting the prediction model (2.54) into the cost function (2.24) gives:

$$J = [\underset{\rightarrow k+1}{\mathbf{r}} - H\underset{\rightarrow k}{\Delta\mathbf{u}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}_m} - L\mathbf{d}_k]^T\,[\underset{\rightarrow k+1}{\mathbf{r}} - H\underset{\rightarrow k}{\Delta\mathbf{u}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}_m} - L\mathbf{d}_k]$$
$$+\lambda\underset{\rightarrow k}{\Delta\mathbf{u}^T}\underset{\rightarrow k}{\Delta\mathbf{u}} \tag{2.55}$$

Hence, the optimal inputs can be found by minimising the performance index J with respect to $\underset{\rightarrow k}{\Delta\mathbf{u}}$. Therefore:

$$\underset{\rightarrow k}{\Delta\mathbf{u}} = (H^TH + \lambda I)^{-1}H^T[\underset{\rightarrow k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}_m} - L\mathbf{d}_k] \tag{2.56}$$

The IM control law is defined by the first optimum value, so that:

$$\underset{\rightarrow k}{\Delta\mathbf{u}} = E_1^T(H^TH + \lambda I)^{-1}H^T\,[\underset{\rightarrow k+1}{\mathbf{r}} - P\underset{\leftarrow k-1}{\Delta\mathbf{u}} - Q\underset{\leftarrow k}{\mathbf{y}_m} - L\mathbf{d}_k] \tag{2.57}$$

The control law (2.57) can be written in a compact form as follows:

$$\underset{\rightarrow k}{\Delta\mathbf{u}} = P_r\underset{\rightarrow k+1}{\mathbf{r}} - D_k\underset{\leftarrow k-1}{\Delta\mathbf{u}} - N_k\underset{\leftarrow k}{\mathbf{y}_m} - M_k\mathbf{d}_k \tag{2.58}$$

where $P_r = E_1^T(H^TH + \lambda I)^{-1}H^T, \quad D_k = P_rP, \quad N_k = P_rQ \quad and \quad M_k = P_rL.$

In order to perform close loop sensitivity and performance analysis, the IM GPC control law can be represented by a conventional compensator form by following the same steps from (2.34) to (2.38) in section (2.5.1). Hence, it is straight forward to derive the following compensator form of the IM GPC control law:

$$\mathbf{u} = [\tilde{D}_k(z)\ \Delta]^{-1}\ [P_r(z)\,\mathbf{r} - N_k(z)\,\mathbf{y} - M_k(z)\,\mathbf{d}] \tag{2.59}$$

which can be represented by the block diagram shown in Fig. (2.6):

2.6 Constraints Handling

One key factor for the success of predictive control is the ability to deal with constraints in a systematic manner. In reality, most systems solely exist within a specified domain. Hence, failure to take account of system constraints will result in undesirable

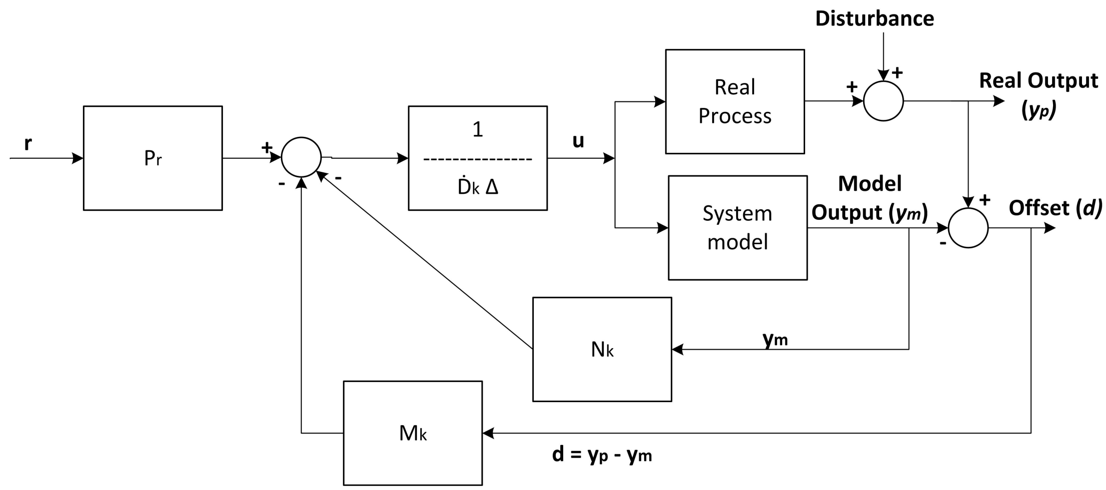


Figure 2.6: IM GPC block diagram

behaviours and can lead to disaster. System bounds could be associated to the physical structure of equipment, safety reasons, or operational considerations. In practice, a plant's most profitable operation point lies close to constraints. Therefore, constraint violations are very likely to occur.

A key weakness of classical linear control strategies, such as PID, is that they take no account of constraints. Whereas, MPC anticipates constraint violations and appropriately corrects the control input signal well in advance. Predictive control is based on the optimisation of predicted performance with respect to predefined d.o.f. within the predictions. So as to ensure that none of the constraints are violated, the optimal predictions need to be compared with the constraints over the prediction horizon in the cost function J. In principle, it is straightforward to include constraints in the optimisation.

Recall that, the GPC was expressed as the minimisation of a two norm cost (2.28) in a form equivalent to a typical quadratic programming optimisation which is expressed as follows:

$$\min_{\mathbf{x}} J = \mathbf{x}^T S \mathbf{x} - \mathbf{x}^T a + c \qquad s.t. \quad M\mathbf{x} \le d \tag{2.60}$$

where $M\mathbf{x} \le d$ are constraints linear inequalities.

Therefore, the next step is to incorporate input and output constraints linear inequalities into the GPC control law.

2.6.1 Input Increment Constraints

Upper and lower limits of the input increments are generally expressed as follows:

$$\underline{\Delta\mathbf{u}} \leq \Delta\mathbf{u}_k \leq \overline{\Delta\mathbf{u}}\ , \quad \forall k \tag{2.61}$$

Given that, within the predictions, the input increments are fixed to zero beyond the control horizon n_u, the input rate constraints can be written as follows:

$$\underbrace{\begin{bmatrix} \underline{\Delta\mathbf{u}} \\ \underline{\Delta\mathbf{u}} \\ \vdots \\ \underline{\Delta\mathbf{u}} \end{bmatrix}}_{\underline{\Delta u}} \leq \underbrace{\begin{bmatrix} \Delta\mathbf{u}_k \\ \Delta\mathbf{u}_{k+1} \\ \vdots \\ \Delta\mathbf{u}_{k+n_u-1} \end{bmatrix}}_{\underset{\rightarrow}{\Delta\mathbf{u}}} \leq \underbrace{\begin{bmatrix} \overline{\Delta\mathbf{u}} \\ \overline{\Delta\mathbf{u}} \\ \vdots \\ \overline{\Delta\mathbf{u}} \end{bmatrix}}_{\overline{\Delta u}} \tag{2.62}$$

Rewriting (2.62) in terms of a single set of linear inequalities gives:

$$\underbrace{\begin{bmatrix} I \\ -I \end{bmatrix}}_{C_{\Delta u}} \underset{\rightarrow}{\Delta\mathbf{u}} \leq \underbrace{\begin{bmatrix} \overline{\Delta u} \\ -\underline{\Delta u} \end{bmatrix}}_{d_{\Delta u}} \tag{2.63}$$

Therefore, the input increment constraints can be represented by the following compact form:

$$C_{\Delta u}\ \underset{\rightarrow}{\Delta\mathbf{u}} \leq d_{\Delta u} \tag{2.64}$$

2.6.2 Input Constraints

Input constraints are generally expressed as follows:

$$\underline{\mathbf{u}} \leq \mathbf{u}_k \leq \overline{\mathbf{u}}\ , \quad \forall k \tag{2.65}$$

Input constraints can be constructed in a similar way as the input rate constraints, with the predictions assumption that the input is constant beyond n_u steps, so that:

$$\mathbf{u}_{k+nu+i} = \mathbf{u}_{k+nu-1} \ , \quad \forall i \geq 0 \tag{2.66}$$

Hence, in a similar manner to the input increment constraints, the input constraints can be expressed by the following compact form:

$$\underbrace{\begin{bmatrix} I \\ -I \end{bmatrix}}_{C_u} \underset{\rightarrow}{\mathbf{u}} \leq \underbrace{\begin{bmatrix} \overline{u} \\ -\underline{u} \end{bmatrix}}_{d_u} \tag{2.67}$$

Furthermore, the input predictions are commonly expressed in relation to the future input increments (d.o.f.) as follows:

$$\mathbf{u}_{k+i} = \mathbf{u}_{k-1} + \Delta\mathbf{u}_k + \Delta\mathbf{u}_{k+1} + \cdots + \Delta\mathbf{u}_{k+i} \tag{2.68}$$

and hence:

$$\underbrace{\begin{bmatrix} \mathbf{u}_k \\ \mathbf{u}_{k+1} \\ \vdots \\ \mathbf{u}_{k+n_u-1} \end{bmatrix}}_{\underset{\rightarrow}{\mathbf{u}}} = \underbrace{\begin{bmatrix} 1 & 0 & \dots & 0 \\ 1 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & \dots & 1 \end{bmatrix}}_{E} \underbrace{\begin{bmatrix} \Delta\mathbf{u}_k \\ \Delta\mathbf{u}_{k+1} \\ \vdots \\ \Delta\mathbf{u}_{k+n_u-1} \end{bmatrix}}_{\Delta\underset{\rightarrow}{\mathbf{u}}} + \underbrace{\begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}}_{L} \mathbf{u}_{k-1} \tag{2.69}$$

So, the input constraints can be expressed in terms of input rate constraints by substituting $\underset{\rightarrow}{\mathbf{u}}$ from (2.69) into (2.67):

$$C_u \ E \ \Delta\underset{\rightarrow}{\mathbf{u}} + C_u \ L \ \mathbf{u}_{k-1} \leq d_u \tag{2.70}$$

2.6.3 Output Constraints

Upper and lower limits of the output are generally expressed as follows:

$$\underline{\mathbf{y}} \leq \mathbf{y}_k \leq \overline{\mathbf{y}} \ , \quad \forall k \tag{2.71}$$

Output constraints can be constructed using an exactly analogous method as both input and input rate constraints. So, the output constraints can be expressed by the following compact form:

$$\underbrace{\begin{bmatrix} I \\ -I \end{bmatrix}}_{C_y} \underset{\rightarrow}{\mathbf{y}} \leq \underbrace{\begin{bmatrix} \overline{y} \\ -\underline{y} \end{bmatrix}}_{d_y} \tag{2.72}$$

In order to represent the output constraints in terms of ($\underset{\rightarrow}{\Delta \mathbf{u}}$), substitute $\underset{\rightarrow}{\mathbf{y}}$ from (2.23) into (2.72) which gives:

$$C_y \; H \underset{\rightarrow k}{\Delta \mathbf{u}} + C_y \; P \underset{\leftarrow k-1}{\Delta \mathbf{u}} + C_y \; Q \underset{\leftarrow k}{\mathbf{y}} \leq d_y \tag{2.73}$$

2.6.4 Constraints compact form

Input rate, input and output constraints were defined in three sets of inequalities (2.64), (2.70) and (2.73) respectively. These constraints were expressed in terms of ($\underset{\rightarrow}{\Delta \mathbf{u}}$) which is the control d.o.f. The way forward is by combining the three sets of inequalities in one compact set as follows:

$$\begin{bmatrix} C_{\Delta u} \\ C_u E \\ C_y H \end{bmatrix} \underset{\rightarrow}{\Delta \mathbf{u}} + \begin{bmatrix} 0 \\ C_u L \\ 0 \end{bmatrix} \mathbf{u}_{k-1} + \begin{bmatrix} 0 \\ 0 \\ C_y P \end{bmatrix} \underset{\leftarrow k-1}{\Delta \mathbf{u}} + \begin{bmatrix} 0 \\ 0 \\ C_y Q \end{bmatrix} \underset{\leftarrow k}{\mathbf{y}} \leq \begin{bmatrix} d_{\Delta u} \\ d_u \\ d_y \end{bmatrix} \tag{2.74}$$

where the top block represent the input rate constraints, the middle block represents the input constraints and the bottom block represent the output constraints.

A more convenient form can be achieved by separating the constraint equations (2.74) into known parts and parts which depends upon the d.o.f:

$$\underbrace{\begin{bmatrix} C_{\Delta u} \\ C_u E \\ C_y H \end{bmatrix}}_{CC} \underset{\rightarrow}{\Delta \mathbf{u}} \leq \underbrace{\begin{bmatrix} d_{\Delta u} \\ d_u \\ d_y \end{bmatrix} - \begin{bmatrix} 0 \\ C_u L \\ 0 \end{bmatrix} \mathbf{u}_{k-1} - \begin{bmatrix} 0 \\ 0 \\ C_y P \end{bmatrix} \underset{\leftarrow k-1}{\Delta \mathbf{u}} - \begin{bmatrix} 0 \\ 0 \\ C_y Q \end{bmatrix} \underset{\leftarrow k}{\mathbf{y}}}_{dd} \tag{2.75}$$

So, the constraint equation can be represented in terms of d.o.f. by the following simple compact form:

$$CC\Delta\underset{\rightarrow}{\mathbf{u}} \leq dd \tag{2.76}$$

where CC is constant and dd is time varying which updated every sample.

2.7 Summary

This chapter provides a general theoretical background of model predictive control. It was designed to deliver a summarised historical evolution of predictive control, a fundamental information about MPC, such as MPC core components, and GPC basic algorithms, which will be the base for the MPC control design afterwards. Formulation of predictions and construction of GPC algorithm were discussed in detail alongside the construction of input rate, input and output constraints. Predictions, constraint handling and ease of including MIMO loops in the control algorithm are the main features of MPC, which are needed to design a feasible control concept for the upstream oil and gas fields.

The next chapter provides an insight to the upstream oil and gas operations and the associated control challenges. Those challenges form the research problems, which this thesis aims to solve. Understanding the control challenges is essential to develop a feasible control concept.

Chapter 3

UPSTREAM OIL AND GAS FIELDS CHALLENGES AND OPPORTUNITIES

At the early stages of oil and gas industry, when the price of oil barrel is around $5 only, commercial producers were solely targeting the so called self-flow reservoirs to extract crude oil and raw gas. The product is gathered and then routed to a production station for primary treatments. Driven by the growth of petrochemical industry since the 1940s, the demands of oil and gas continue to increase and the most difficult reservoirs have now become economically viable. These reserves could be difficult to access, such as deep sea reservoirs, or difficult to process, such as high pressure and sour reservoirs. These source types imply technical challenges and, at the same time, expands the production stations to accommodate complicated processing and treatment units. Consequently, the process control systems have to cope with these challenges in order to operate the process in an optimal and safe manner which in turn results in end-products that satisfies the prerequisite specifications. Therefore, a greater emphasis was put on control algorithms, instrumentation and communication techniques to achieve a satisfactory degree of process control and maintain reliability and safety with lower levels of human intervention.

Nowadays, a significant amount of oil and gas are produced from unconventional resources such as tar sands, shale and deep sour reservoirs. Among these unique challenges appears the high pressure and sour oil and gas production, which would not be viable without the innovation in materials and control technologies. The main hazards incorporated with production of the deep sour hydrocarbons includes high operating pressure (ex. plants operate at 100 *bar*) and a large amount of hydrogen sulphide (H_2S) which is an extremely corrosive, explosive and poisonous gas. H_2S is a highly toxic, colourless and heavier than air, gas produced from the wells as a contaminant in the gas stream. At concentrations of 300 to 500 *ppm* (parts per million) it is considered life threatening and if breathed even for a short period of time, death is likely [61]. The risk of leak and even explosion is very high when processing highly pressurised sour hydrocarbons due to the corrosive nature of H_2S.

Highly pressurised sour hydrocarbons has the potential to badly impact personal safety and to cause severe damage to process equipment's as well as organisation reputation, hence it must be contained at all time. Essentially, production plants encompass enormous lengths of pipes connected by flanges and include valves and other equipment's, which are all connected by bolts. These bolts may become loose with time due to pipework vibrations caused by difference in pressure across flanges and valves during emergency shutdowns and disruptive operations. Consequently, a hazardous containment may leak and cause severe problems. Therefore, these challenges imply constraints on the process control system to efficiently deal with process disturbances.

The chapter provides an insight to the challenges in the upstream oil and gas plants in section 3.1. Then, the research problems are detailed in section 3.2. Finally, section 3.3 summaries the key points of the chapter.

3.1 Insight to upstream production plants

Upstream oil and gas plants are usually distributed over a wide physical area. The plants are typically subdivided into functional units whose number and complexity depend on crude type and plant location. These units are connected in series where the discharge of a unit becomes a feed to the following one in order of treating the raw gas. Each treatment process encompasses many different types of equipment such as pumps, vessels and valves, as well as a significant amount of sensors and controllers. The most common processes in upstream oil and gas plants are illustrated in Fig. 3.1 below. In addition to the main processes, plants also contain utility processes like 'instrument air system' and 'produced water treatment facilities'.

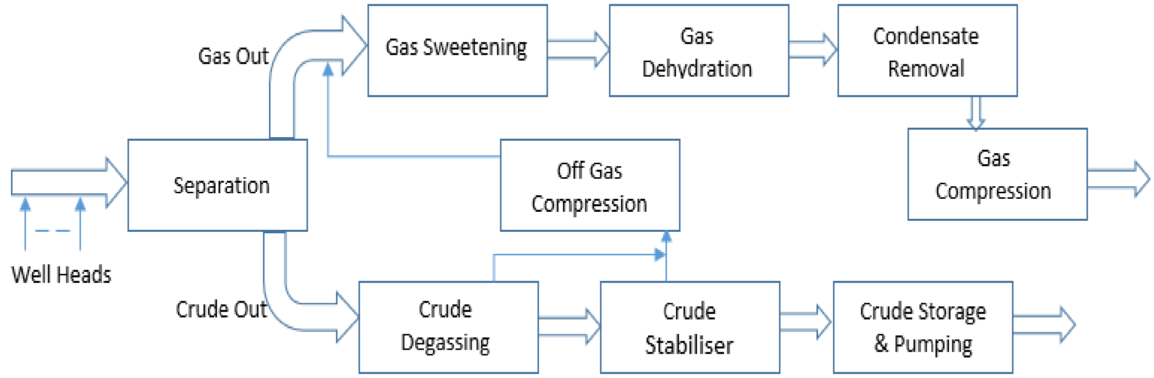


Figure 3.1: Upstream Oil and Gas main Process

The plants are operated by operation teams comprised of field and control room operators. Field operators are the only personal who are authorised to perform physical contacts with process equipments. Their duties for example include: gathering samples; adjusting manual valves; and starting/stopping/resetting field appliances. While the control room operators are tasked to monitor and control the process from a control room via a distributed control system (DCS). Control room operators' main responsibility is to insure safe and optimal process operation. They can trend each variable, evaluate its associated alarm, and change its setpoint.

3.2 Research Problems

There is an obvious importance for upstream oil and gas companies in confronting the control weaknesses in order to cope with an increasing level of process complexity, demanding product specifications, profitability, safety, and environmental sustainability challenges and of course, to ensure they meet production revenue targets. Practically speaking, there are two major control issues which affect the optimal and safe operation of current upstream production plants:

- Control system operator dependency.
- Series connected process disturbance growth.

3.2.1 Control system dependency on operators

For safe and stable operation, plants rely on hundreds of 'Proportional Integral Derivative' (PID) control loops driven by a Distributed Control System (DCS). Since the control structure is too basic to act protectively in advance, companies usually dedicate a number of staff to work as control room operators. Their main task is to monitor the process deviation and amend the controllers' reference values to achieve safe and profitable optimal plant operation. The plant control optimisation and problem solution are totally dependent on the respective operators' efficiency and significantly on their speed of observation when the process deviates from one operation scenario to another. Human operators, the essential part of the total system, have a habit of operating within their comfort zone and their decisions can be exaggerated by the control room environment and the sudden assigned responsibilities and commitments. Previous human control studies in industrial processes illustrate that the quality of human decisions is totally dependent on operator interpretation of the various control room messages and alarms. [12, 46].

3.2.1.1 Related Control issues

Thwaites (2008) [72] found that in general, 75% of industrial physical locations are under process control worldwide and the performance of more than 60% of the controlled loops are below expectations. Li et al. (2011) [45] questioned why the prevalent applications of process control methodologies has not ensured continual enhancement of plant performance worldwide. They concluded that the reason was in ignoring the critical role of the control room operator in the design of the modern process control systems. McKee (1999) [49] conducted a study on the status of process control in mineral process. The reviewer examined different factors affecting efficacious control systems. One of the highlighted important factors to achieve successful control system was the need for skilled operational team to maintain and operate the process. The review clearly stated that the performance of the control room operator sometimes imposes a constraint on the overall control system performance. Li et al. (2010) [44] observed and studied the process control behaviour of twenty operators in two industrial processes. One of the survey conclusions was that, the intention of control optimisation such as managing a stable and efficient production flow was not evident in operator control behaviours. Conversely, the control room operators preferred to let the control system run independently rather than intervene. They tended to respond only when things were going wrong (e.g. unit trip), hence most often their actions were too late. Such control behaviour is expected to reduce process production and clearly extends process shutdown periods.

In order to improve the process control system performance, McKee (1999) pointed out two thoughts regarding the role of control room operators. Either to agree that the operators are critical to the successful operation of a control system and hence must be selected and trained accordingly. Alternatively, accept operator limitations in understanding the process and the control system in depth, and consequently strives to develop control system that require minimal operator intervention. [49].

A new process control development approach called human factors engineering, also known as cognitive ergonomics, had been introduced in the global process control industry in the past decade. The integration of the human element into control system development initiates the releases of several industrial guidelines and standards of HMI (Human machine interface) and alarm design, for example the ISO Standard 11064 (Ergonomic design of control centres). Human factors engineering "aims to achieve an effective integration between humans and technologies by obtaining a better understanding of human cognitive, perceptual and emotional capacities and behaviours and then applying that information to system design" [45].

3.2.1.2 Related Process Safety issues

Bello and Colombari (1980) [8] provide a detailed discussion of the risks caused by the control room operators of process plants. They reviewed a number of industrial disastrous accident surveys conducted prior to 1980, and deduced that human errors were responsible for at least 40% of catastrophic industrial accidents. They relate the main causes of this high figure to the construction of larger plants with higher destructive potential with concentration of many important decisions on one single or few control room operators.

A recent survey study [39] published on 2013 reveals that human and organisational errors are the major cause of equipment failures in the process industries. The survey, which analysed 284 cases involving equipment failures, showed that among 15 common accident contributors, human and organisational accidents head the list of contributing factors causing 20% of failure occasions on average.

Looking to past catastrophic industrial accidents, e.g. Piper Alpha (1988) and Texaco Refinery (1994), human errors were found to be the main factor in almost all reported accidents. The costs in terms of human life and investments are high. Piper Alpha was an offshore oil rig platform located off the east coast of Scotland. The Piper Alpha disaster killed 167 people and completely destroyed the platform in a major explosion and fire. Formal root cause analysis found a number of technical and organisational failures. The investigation outcome identified four human contributions: Inexperience and poor maintenance procedure; poor learning by the organisation; breakdown in communications and the permit-to work system at shift changeover; and safety procedures were not practiced sufficiently [17, 58]. Six years later, another major accident occurred in a Texaco refinery located in the UK. Prior to the incident, the plant was upset by a severe electrical storm which caused various process disturbances. A series of events led to the accident; however, the direct cause of the explosion was a combination of failures in management, equipment and control systems during the plant upset. The preparation of operators and supervisors for dealing with a sustained upset, and therefore stressful, situation was insufficient as per the investigation report conducted by the health and safety executive [41]. The report pointed out that the operational team actions were concentrated on the symptoms of the problem instead of the main causes. That was some managers and supervisors acted as operators rather than performing a strategic and diagnostic role.

Hence, placing efforts on decreasing operator work load may help to reduce human errors and, consequently, save lives and money. Essentially, this thesis brings much needed attention to target these control issues and to provide inexpensive feasible control solutions. In summary, the control structure of the existing upstream production plants needs to simply and cheaply encompass features such as predictions, optimizations, coordination and constraint handling without omitting simplicity and ease of troubleshooting.

3.2.2 Disturbance growth in a series connected process

Feed disturbance and equipment failure are the two common causes of major process disturbances in upstream production plants [3]. Such disturbances have the potential to cause significant deviation of the process and potentially cause violation of operation constraints. In series connected systems where one process output is the feed to the successor process, the effect of disturbances can be magnified due to system gain. If an extraordinary or more than one antagonistic condition develops at the same time, the control room operator may not be able to react satisfactorily and the consequences are a larger risk of a major disturbance event.

To illustrate the impact of the disturbances on series connected Large Scale Systems (LSS), consider the two columns process shown in Fig. 3.2.

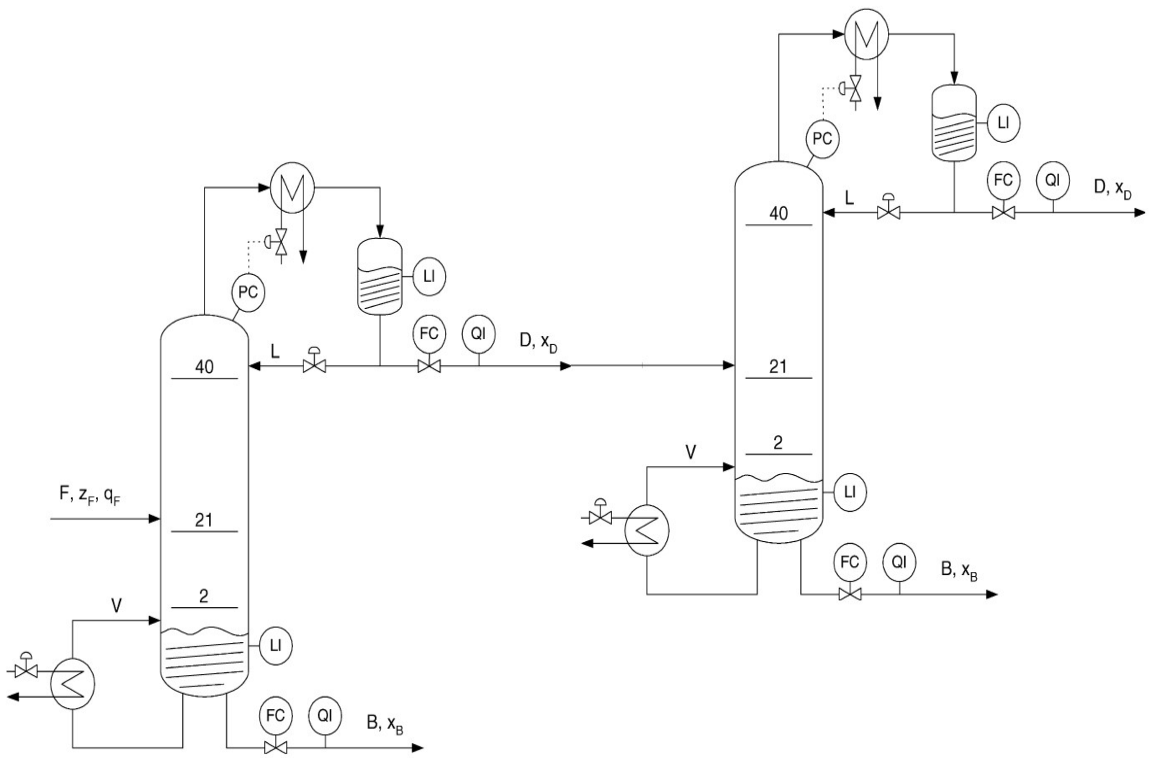


Figure 3.2: Two Columns Process from Muske and Badgwell [52]

Feed (*F*) enters the first column and the overhead distillate flow is connected as inlet feed to the second column with four manipulated variables reflux flow (*L*), vapour flow (*V*) distillate flow (*D*) and bottoms flow (*B*). In this example, the aim is to maintain the overhead composition in both columns at 0.9 *Molfrac* (to aid disturbance comparison). The product stream quality of both columns are continuously measured by in line process analysers (*QI*). Bottom composition (X_B), condensers level, reboiler level, feed composition (Z_F) and feed liquid fraction (q_F) are assumed constant for simplicity.

The process model for this example were presented by Muske and Badgwell [52] as follows:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.799 & -0.00172 & -0.406 & 0.000867 & -0.0457 & -0.0158 \\ 0 & 0 & 0 & 0.645 & 0.444 & 0.535 & 0.159 & 0.139 \\ 0 & 0 & 0 & 0 & 0.12 & 0.00229 & -0.128 & -0.0431 \\ 0 & 0 & 0 & 0 & 0 & 0.0362 & 0.0127 & -0.296 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.00386 & 0.0022 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.000372 \end{bmatrix} \tag{3.1}$$

$$B = \begin{bmatrix} -7.5 & 7.5 & 0 & 7.5 & -7.5 \\ -7.5 & 7.5 & -7.5 & 0 & 0 \\ 0.0713 & -0.0729 & 0 & 0 & 0.734 \\ -0.00697 & -0.0757 & 0 & 0 & 0.179 \\ 0.0131 & -0.0148 & 0 & 0 & 0.00567 \\ -0.035 & 0.0392 & 0 & 0 & 0.00265 \\ 0.00323 & -0.00373 & 0 & 0 & -0.00633 \\ -0.0017 & 0.00201 & 0 & 0 & 0.00435 \end{bmatrix} \tag{3.2}$$

$$C = \begin{bmatrix} 0 & 0 & 1.86 & -0.396 & 0.318 & -0.00136 & 0.00139 & 0.000702 \\ 0 & 0 & 2.28 & 0.354 & -0.0741 & -0.00396 & -0.00102 & -0.000229 \\ 0 & 1 & 0.00102 & -0.000119 & -0.000498 & 0 & -0.000203 & -0.000131 \\ -1 & 0 & -0.00119 & -0.000106 & 0.00046 & 0 & 0.000139 & -0.00017 \end{bmatrix} \tag{3.3}$$

To demonstrate the impact of the feed disturbance on the two columns process, a disturbance of -5 % was introduced in the first column feed rate (F) as illustrated in Fig. 3.3. The resulted disturbance's effects on the overhead composition of both columns are presented in Fig. 3.4 and Fig. 3.5. The results clearly shows that, while the overhead composition of the first column is only affected to a small extent as expected, the impact of the disturbance on the second column product was substantial and indeed caused a violation of the desirable/required operating conditions.

In summary, poor coordination between the controllers for successor processes (here a series connected distillation columns) means that constraints and safeguarding limits are more likely to be violated. However, this issue has received relatively little attention in the literature.

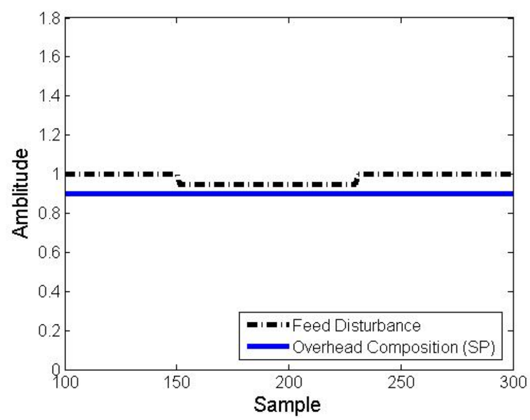


Figure 3.3: References and Disturbances
SP: Reference Setpoint

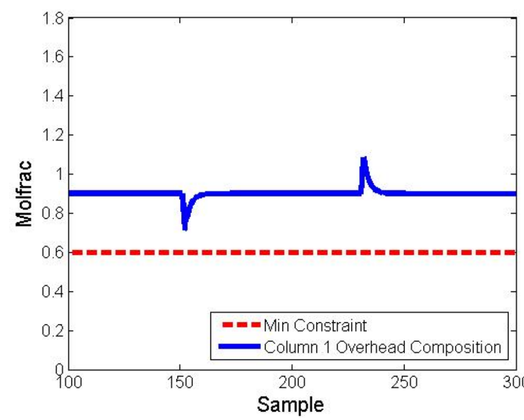


Figure 3.4: First Process Output

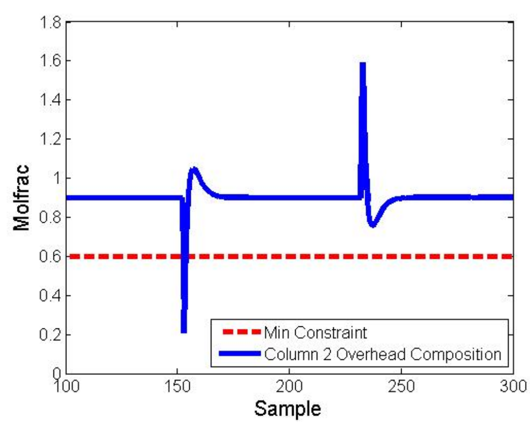


Figure 3.5: Second Process Output

3.3 Summary

The chapter listed two main problems in the current control theme of upstream oil and gas production plants. These control challenges, the control system operator dependency and series connected process disturbance growth, provide a research opportunity to upgrade the conventional process control system. Essentially, oil and gas production plants confront regular increase in complexity with time, while at the same time, the organisations' managements drive towards a reduction in manning. In order to accomplish the above argument, the control system should be able to anticipate the effects of current control inputs on the future plant operation directions. Hence, the process high and low threshold alarms can be set as constraints to the control system which consequently forces the system to weight and judge each control input to satisfy the constraints. The aim is to produce an auto strategy which takes these decisions and therefore is equivalent to an expert control room operator. Accordingly, the control system will safely and optimally operate the plant.

Different control strategies were developed to target similar issues which is discussed in the following chapter. However, while ideal for some applications, these are not acceptable for others such as brownfield upstream oil and gas.

Chapter 4

UPSTREAM OIL AND GAS FIELDS - CONTROL CONCEPT AND FEASIBLE SOLUTION

This chapter presents four control strategies currently implemented in the industry to enhance plants control systems. The advantages and disadvantages of each method are thoroughly explained in section 4.1. Section 4.2 provides and discuss a feasible control concept to overcome the two control challenges in upstream oil and gas production plants: control system operator dependency, and the series connected process disturbance growth. Finally, section 4.3 summaries the key points of the chapter.

4.1 Currently available solutions

There are four main control system structures based on MPC algorithms, widely recognised as practical and high performance, that are successfully implemented in the industry. These are: centralised MPC, decentralised MPC, distributed MPC (DMPC), and hierarchical DMPC. They differ in the implementation structures but all of them apply a receding horizon strategy, systematically accounts for system constraints, and employ a model of the process to obtain the control output as the optimum solution of an associated cost function minimisation. An important question for process operators is to determine which structure best suits their plant requirements and moreover, fulfils current and future commitments? According to Vogel and Down [73] the best overall control structure depends upon typical control objectives, possible process disturbances, all constraints, and robustness obstacles. Practically speaking, the cost of retrofitting and staff education are major factors as well.

4.1.1 Centralised MPC

A control structure is considered to be centralised when the complete plant-wide process is modelled and all control inputs are computed in one controller. In other words all plant-wide interactions are dealt with in a single optimisation problem as illustrated in Fig. 4.1.

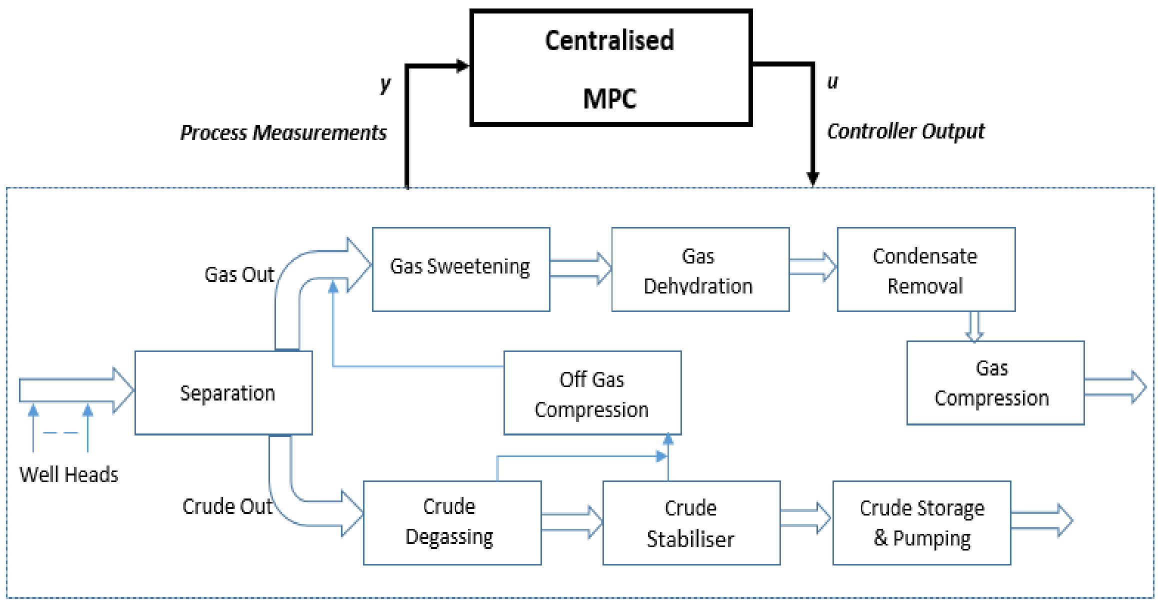


Figure 4.1: Centralised MPC

In the last decade, most DCS vendors have upgraded their systems capability to handle predictive control benefiting from the substantial advances in computational power. Evolution in electronics engineering, specifically the memory and processor microchips, enhances the development of faster optimisation software; higher speed communications; and extra powerful computers. Consequently and with a precisely designed control algorithms for large scale system (LSS), the adoption of a centralised control structure may seem to be a reasonable choice [71, 57].

Centralised strategies are initiated by the aspiration to operate the process in an optimal fashion. Weaknesses of a centralised control structure are mainly related to system complexity, speed of control, and organisational issues. Development of plant-wide interaction model either by mathematical modelling or by utilising system identification methods is a complex task. Major modelling difficulties are due to the addition of unmeasured disturbances and system uncertainties in each subsystem. The developed model should be as representative as possible to the plant, otherwise the MPC controller may fail to stabilise the plant or even to give sensible control strategies. In addition to the complexity issue, the new control loops should execute at a higher sampling rate or at least equivalent to the current classical control. Current DCS in upstream fields executes sampling at sup-second to one second [21]. Notwithstanding the evolution in the computers computational power and microchips processors, a typical DCS is not utilised for superior control performance only but also to do other operational tasks like alarm management, history records, high resolution graphical interface, etc... .

Accordingly, the computational time needed to solve the centralised control problem may be significantly prolonged which in turn hinders the MPC ability to perform real time calculations [14]. Furthermore, Stewart et al. (2010) [71] noticed the organisational objections to the implementation of centralised MPC for LSS plants. Maintenance and troubleshooting of a mega dimension and complex central controller is a tricky practice and will consume a lot of valuable efforts and time. In simple terms, the potential improvements in coordinated behaviour and performance are unlikely to be realised in practice.

4.1.2 Decentralised MPC

A decentralised control structure is the most common control framework implemented in process industry for LSS [66]. In decentralised strategies, the wide-process optimisation problem is divided into sub problems and then solved independently as illustrated in Fig. 4.2. Therefore, each subsystem control is locally centralised by means of one or more non-cooperative controllers depending on the subsystem complexity. Each controller focuses on its own local optimisation problem only and doesn't exchange information with other controllers.

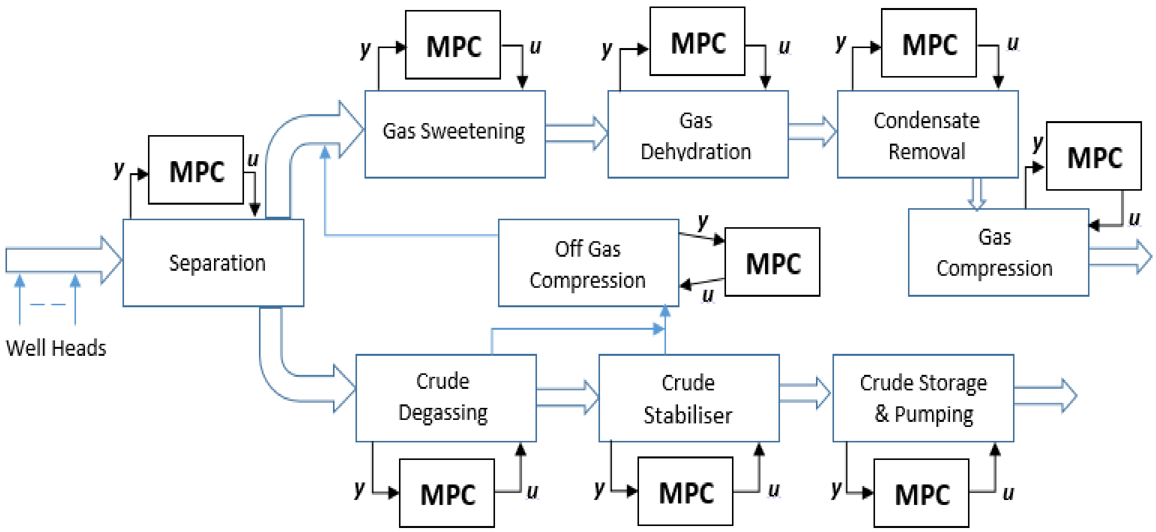


Figure 4.2: Decentralised MPC

Unlike the centralised control structure, a decentralised structure is far easier to design and maintain as well as the real time implementation is not an issue. Nevertheless, since there is no information exchange between subsystem controllers, the decentralised structure can't optimise the plant-wide control problem and thus could result in poorer performance. Decentralised control systems are successful for LSS which have weak interaction between subsystems, for example where these interactions can be considered as disturbances which can be compensated through feedback [14]. A decentralised structure is not recommended for LSS with strong interconnections between the subsystems due to stability concerns and optimum performance achievements.

A key message of this research is to note that many existing oil and gas production plants utilise decentralised control system structure underpinned with PID controllers. Hence the potential for implementing a decentralised control based on MPC is straightforward in principle and companies may achieve a better optimised subsystem operational control, However, the expenditures on training and building up the operational and technical expertise and demonstrating the potential benefits are key obstacles.

4.1.3 Distributed MPC

A distributed MPC (DMPC) control structure (shown in Fig. 4.3) is relatively similar to the decentralised structure except that the local controllers (agents) exchange information and communicate cooperatively among themselves to solve the overall plant-wide control problem [53]. Hence, a distributed MPC control structure reduces the overall achievable performance limitations associated with a decentralised structure. DMPC is structured in such a way that, each controller espouses the interaction between the subsystems with the local control objectives and constraints to optimise the local control problem. Sometimes the controllers are forced to sacrifice their own control objectives in order to achieve the required plant-wide performance. The controllers' communication load and decisions on with whom to communicate, are dependent on the level of interaction between the subsystems and the status of the communication network. Controllers can be constructed to communicate information like their next control move with the neighbouring agents, specific agents or even with all agents in the system.

Although co-operation between agents to solve a global optimisation problem is clearly a sensible proposal, nevertheless co-operation in some cases may lead to a poor local control behaviour and consequently deterioration in the plant-wide control performance. Negenborn and Maestre (2014) [53] surveyed a number of different DMPC approaches and theories which designed to foster co-operation based on process, theoretical, and control architecture commonalities. One of their findings was that out of thirty five DMPC schemes, only one was designed for transfer function models. It is

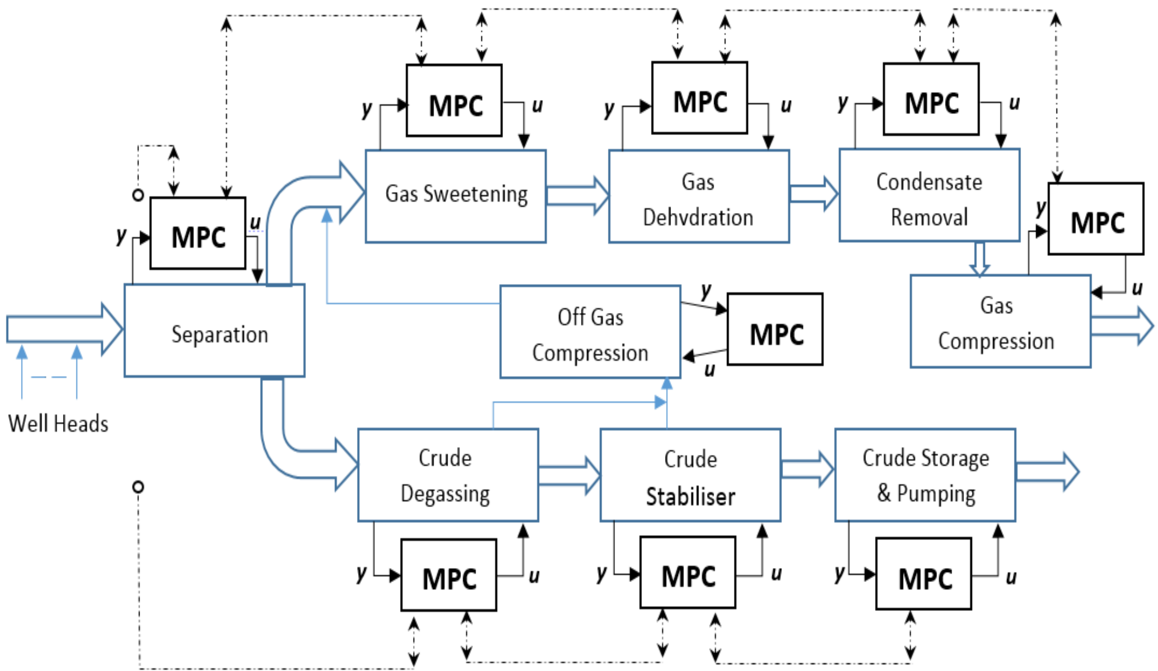


Figure 4.3: Distributed MPC

worth mentioning here that the majority of oil and gas processes are described with transfer function models. Also, the survey suggested the need for researchers to develop flexible DMPC architectures able to modify the control network topology and the communication burden depending on the circumstances.

Practically speaking a DMPC structure is recommended for any new oil and gas plants (greenfield) but it is rather costly to retro-fit on existing plants (brownfield). Moreover, the required operation and maintenance skills might take long time to build among the team which may affect the company's confidence in the efficacy of introducing a new control architecture.

4.1.4 Hierarchical Distributed MPC

A hierarchical DMPC system is structured from two or more control layers which coordinate among themselves to control the process. As presented in Fig. 4.4, the higher layer receives system wide information to perform the real time optimisation and manage the global objective of the process and provide reference signals for the agents in the lower control layer which cooperatively control and regulate the plant control elements. Dividing the overall control system structure into layers helps to ease the control problem and to speed up the control cycles in a Large Scale Systems. The fast system dynamics are being controlled by the faster lower control loops referencing to the latest set-points provided by the higher control layer and without waiting for the real optimisation problem solution.

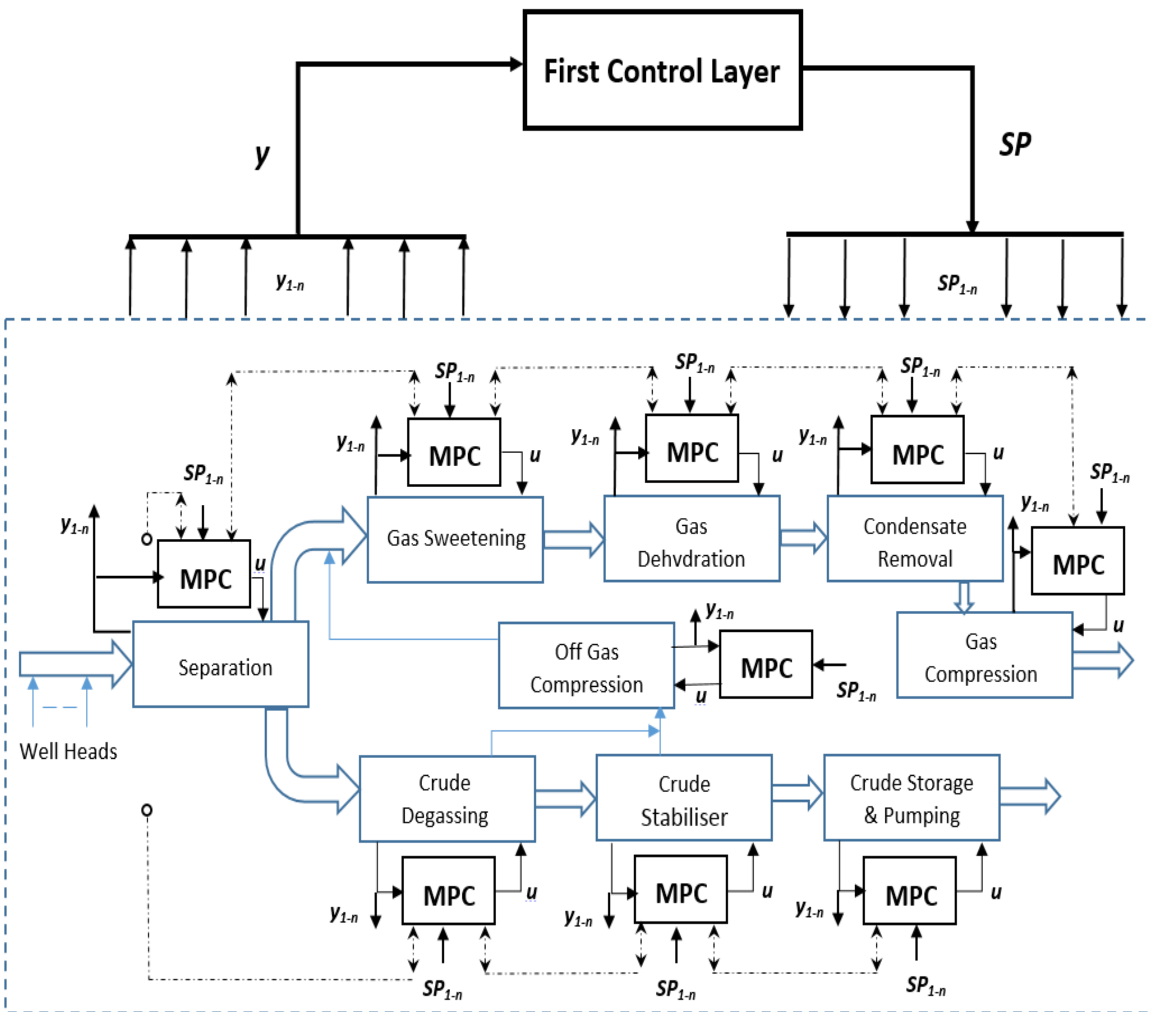


Figure 4.4: Hierarchical DMPC

Due to the complexity of LSS, there exists number of hierarchical control structures in the process industries. Each of these structures are tailored for controlling particular classes of processes. For example Scattolini (2009) [66] reviewed four main hierarchical control architectures: the hierarchical control for coordination where an algorithm at the higher control level coordinates the actions of local regulators placed at the lower control level; the hierarchical control of multi-time scale systems to control systems with slow and fast dynamics; the hierarchical of cascade control structure; and the hierarchical control for plant-wide optimisation.

Even though a plant-wide control strategy will be enhanced by a hierarchical DMPC control structure, the costs of implementing it in brownfield processes to replace existing classical control will be too expensive. Additionally, the new structure is complex and may not be welcomed by the operation team due to the same reasons as for the Distributed MPC control structure discussed earlier.

4.2 A feasible solution for existing oil and gas fields

The previous section had demonstrated that while there are many proposals in the literature, and indeed already being used in practice, these are far more likely to be feasible for a greenfield project but not necessarily for brownfield. The feasibility of retro-fitting a new control structure is influenced by factors like project cost, system simplicity, process safety, running cost, and anticipated gains compared with the existing control system. Critically, from an operational standpoint, the feasible control solution to enhance the current classical control system in the existing oil and gas plants must also inexpensively integrate the **team experience and operational knowledge within it**. Consequently, this section proposes what is considered to be a more pragmatic alternative.

The proposed control system, as being sketched in Fig. 4.5, integrates MPC as a master controller in the existing classical control of each subsystem. The MPC receives system measurements from the process sensors to compute the subsystem optimal control actions and provide local control goals as set-points (SP) for the critical PID controllers only (high interaction control loops). The MPC also receives system unit's status from the process safeguarding system to dynamically update the system constraints. However, a key point is that the MPC shares information like the current performance factor and the next control move with its neighbour controllers to enhance the plant-wide optimal performance. This communication can help with disturbance rejection.

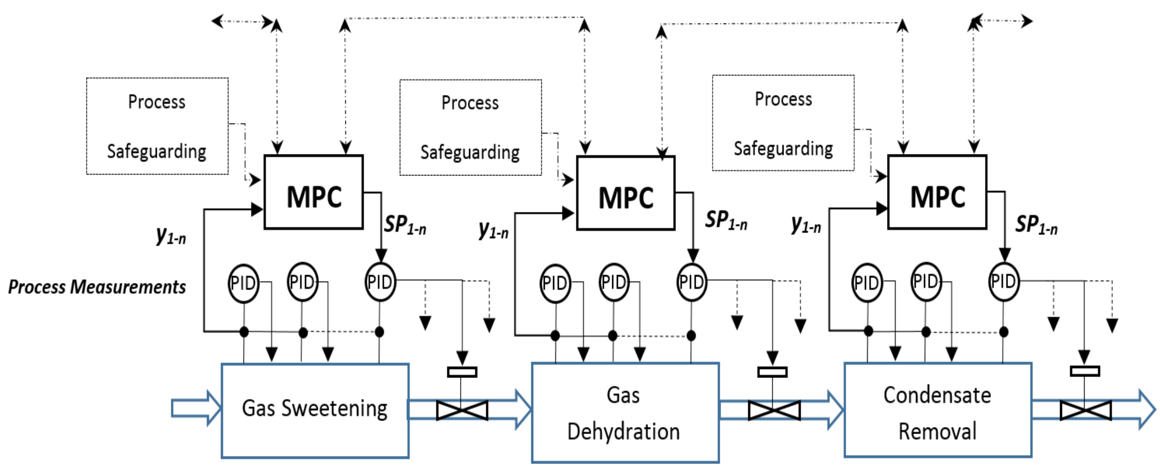


Figure 4.5: Integration of MPC with classical control

The proposed control system is designed on a cascade strategy and thus provides a flexible system control almost like a decentralised structure in dealing with disturbances and unit failures, and at the same time improves the closed loop performance and the plant-wide optimal operation. The MPC is designed to regulate the critical loops only while the rest of the uncritical PID loops will continue to function in a decentralised fashion. This minimises any design and set up costs, reduces demand on the communication network, and simplifies the associated real time optimisations.

The improved local control will reduce the need for control room operator interactions with their associated weaknesses. Moreover, the one way communication from the process safeguarding system enables prompt response to disturbances caused by unit failures while the bidirectional communications with adjacent MPC's in effect enables feed-forward to reduce the impact of process disturbances and enhance optimality.

Fig 4.5 presents control schematic of three main systems of a gas processing train connected in series. Each of these systems constitutes of number of units like pumps, vessels, contactor columns, and automated isolation and control valves. Depending on traditional control approaches only, the system functionality deteriorates notably when one of these units fails leading to system instability and, in the worst case, process shut down. However, the scenario is totally different with the integration of the MPC into the control system. When a unit fails to perform to specification, the relevant MPC will immediately know about it from the safeguarding system before the consequences take effect. Consequently the MPC updates the system constraints and informs the predecessor and successor system controllers about the new limitations to modify the throughput product harmonically. The scenario is more or less similar with feed disturbances. Therefore the proposed control system is expected to reduce process shutdown occasions and to extend the fixing time provided for the maintenance crew.

Compared with the solutions discussed in section 4.1, the proposed control solution is much cheaper and simpler to implement. The MPC system model is quite easy to develop as well as the control algorithms. Nevertheless it almost delivers the same benefits and does not omit the team operational experience and maintenance skills. In addition its performance can be straightforwardly validated in the DCS by altering the cascade mode between auto and manual.

4.3 Summary

A prime contribution of this thesis is to identify a pragmatic approach for control system improvements. An approach, which is attractive to companies and operational team. The approach should require as little retrofitting as possible, that is to build on existing infrastructure and expertise as much as possible as this reduces cost, training requirements and simplifies validation. Moreover, by utilising the existing structures, system testing and performance compared to the classical control can be easily validated by switching the MPC cascade mode in the DCS to manual and comparing the MPC output trends against operator's manual set-points. In addition, the implementation of the new control strategy will take place in the instrument auxiliary room and will not disturb the field arrangements by any means. Consequently, the proposal of this control structure is expected to be straightforward to implement and test.

Nevertheless, one key obstacle were identified as a research challenge in order to progress this theme, to produce stronger evidence, and thus for improving the control of upstream oil and gas plants. This obstacle is **upstream oil and gas process model**. Process models representing upstream oil and gas processes are scarce in the literature. The majority of the process models available in the literature represent single chemical processes. In order to investigate different control structures and proposals it is necessary to have a suitable benchmark model and/or scenario reflecting realistic upstream oil and gas operations. Such a model would also be of benefit to Large Scale System (LSS) and system interactions control research fields.

Chapter 5

MODEL DEVELOPMENT FOR GAS PHASE TRAIN IN UPSTREAM OIL AND GAS FIELDS

This chapter provides a model for the gas phase operation in upstream oil and gas plants suitable for system analysis and control design investigations. The process model captures the three main gas conditioning processes found in most upstream oil and gas processing plants: gas sweetening, gas dehydration, and hydrocarbon dew-pointing. The function of such a model is to provide a realistic process representation to test and verify different process control approaches, specifically those which deal with highly interactive control loops.

Currently there is no benchmark process model available in the literature specifically representing upstream oil and gas processes, despite the necessity to optimise the production operation of the current upstream oil and gas assets [43]. The majority of gas treatment processes are accomplished in the upstream production phase, which implies a continuous need to develop new control approaches to cope with the process complexity alongside the ever increasing demands on product specifications. Moreover, a benchmark process model is also needed to investigate different control structure alternatives and to aid process control engineers in the analysis of how process disturbances can deviate process operation into unstable or unsafe situations [2]. Such a model would not only be of benefit to studies on upstream oil and gas processes, but also to Large Scale Systems (LSS) in general and control research on how to deal with system interactions.

Many of the current upstream oil and gas fields were built in the last century with simple process equipment and hard wired control systems. Thereafter, the processes evolved gradually in response to continuing market demands and operational challenges [27]. Process control systems have also evolved over different stages, beginning from pneumatic control systems through hard-wire control right up to what is called today Distributed Control System (DCS) operated from a user friendly computers and utilising modern communication techniques like 'foundation fieldbus' systems [68]. Modern DCS machines have the ability to host different type of controllers, structures and control algorithms but unfortunately the majority, if not all, of existing oil and gas production plants still rely mainly on Proportional-Integral-Derivative (PID) control laws and often existing control infrastructure to regulate process variables due to their simplicity.

The scarcity of process models in the literature could be due to the fact that many upstream process control objectives are linked to simple process operations such as level control of storage tanks and furnace temperature control and these can be achieved sufficiently well by implementing Single Input Single Output (SISO) control strategies. However, it is often difficult to tune SISO loops effectively to control more complex oil and gas dynamic processes which generally contain a number of interactive control loops [14] such as in the control of crude stabiliser columns, fractionation columns, or compressor surge. Nevertheless, in practice these processes are often controlled using simple control strategies with one consequence being that their performance and stability are sensitive to disturbances and load changes [38].

Looking to the past, Shell Oil's heavy oil fractionater model was one of the earliest models presented in the literature to represent a multivariable interactive control process. The distillation column model introduced by Prett and Morari (1987) [59] has three controlled variables and three manipulated variables which are highly interactive. For decades, this model was the base for many studies of different control approaches and strategies for distillation columns control. A few years later, a famous plant-wide process control problem 'Tennessee Eastman' (TE) was proposed by Downs and Vogel (1993) [22] as a control challenge test problem. It was based on an actual industrial plant and consists of number of linked chemical process units with multi-variable control loops which can be subdivided into four or five interacting subsystems. The TE process characteristics were described by sets of flow sheets and steady-state material balances, rather than transfer function models or model equations.

The main intention of this chapter is to provide the first model representing typical gas train processes in upstream oil and gas plants. This will be an easy, simple to understand, and fit for purpose model based on transfer functions. Disturbance growth in series connected processes [2] is considered a major process control issue affecting the current upstream production plants and the proposed model provides a suitable analysis and design framework for process control designers to investigate such issues.

In addition, the model provides a good opportunity for process control engineers to analyse a variety of process disturbances, malfunctions, and load changes on the process operation and verify their significance. For instance, the model can be used to investigate the potential for a simple or tailored Model Based Predictive Controller (MBPC), built on existing infrastructure, to significantly reduce the frequency of plant shut downs and also to save on operating costs by properly controlling the disturbance growth in the process, hence reducing energy fluctuations and thus saving valuable resources.

The chapter starts with a gas treatment process description in section 5.1. Section 5.2 provides a process models of the gas phase units, while the model validations are presented in section 5.3. Finally, the chapter contents are summarised in section 5.4.

5.1 Process Description

Natural gas processing trains in upstream gas plants contain processes to purify the raw natural gas extracted from underground oil and gas fields and brought up to the surface by production wells. Raw natural gas typically consists primarily of methane. It also contains significant amounts of ethane and varying amounts of heavier hydrocarbon products like natural gas liquids (NGL) (propane, butane, pentane and higher molecular weight hydrocarbons such as crude oil). In addition, the gas contains undesirable impurities, such as liquid or vapour water, carbon dioxide (CO_2), hydrogen sulfide (H_2S), and mercaptans molecules [7, 40]. In line with the strict global regulations, safety procedures, transport requirements and distribution specifications [56] (to reduce levels of sulphur and carbon dioxide inside gaseous hydrocarbons used as fuel), it is necessary to remove sulphur and carbonic dioxide from the gas.

The process model illustrated by Fig. 5.1, consists of three main processes which are commonly found in upstream fields classified as a high gas to oil ratio (GOR). These are: a Gas Sweetening Unit (GSU), a Gas Dehydration Unit (GDU), and a Hydrocarbon Dew Pointing (HCDP). Table 5.1 describes the abbreviations used in Fig. 5.1.

5.1.1 Gas Sweetening Process

Sour gas produced from the oil and gas wells is separated from the crude in the production separators and then routed to the Gas Sweetening Unit (GSU). The GSU extracts undesired acidic gases, specifically hydrogen sulfide (H_2S), and carbon dioxide (CO_2) from the raw natural gas by a counter current gas flow with sulfinol solvent which absorbs acid gas components and other impurities such as mercaptans (RSH) and carbonyl sulphide (COS). The GSU consists of an absorber where the acid gas is removed by a counter current contacting with sulfinol solvent and a regeneration loop where the sulfinol is regenerated via desorption of the acid gas components. The treated gas from the absorber is further washed in the Treated Gas Water Wash Vessel to minimize carryover of solvent to the downstream process. The treated gas subsequently flows to the Dehydration Unit (GDU) and then to the Hydrocarbon Dew Pointing Unit (HCDP) for further treatment to remove moisture, and condensate in order to reach the final product quality specifications.

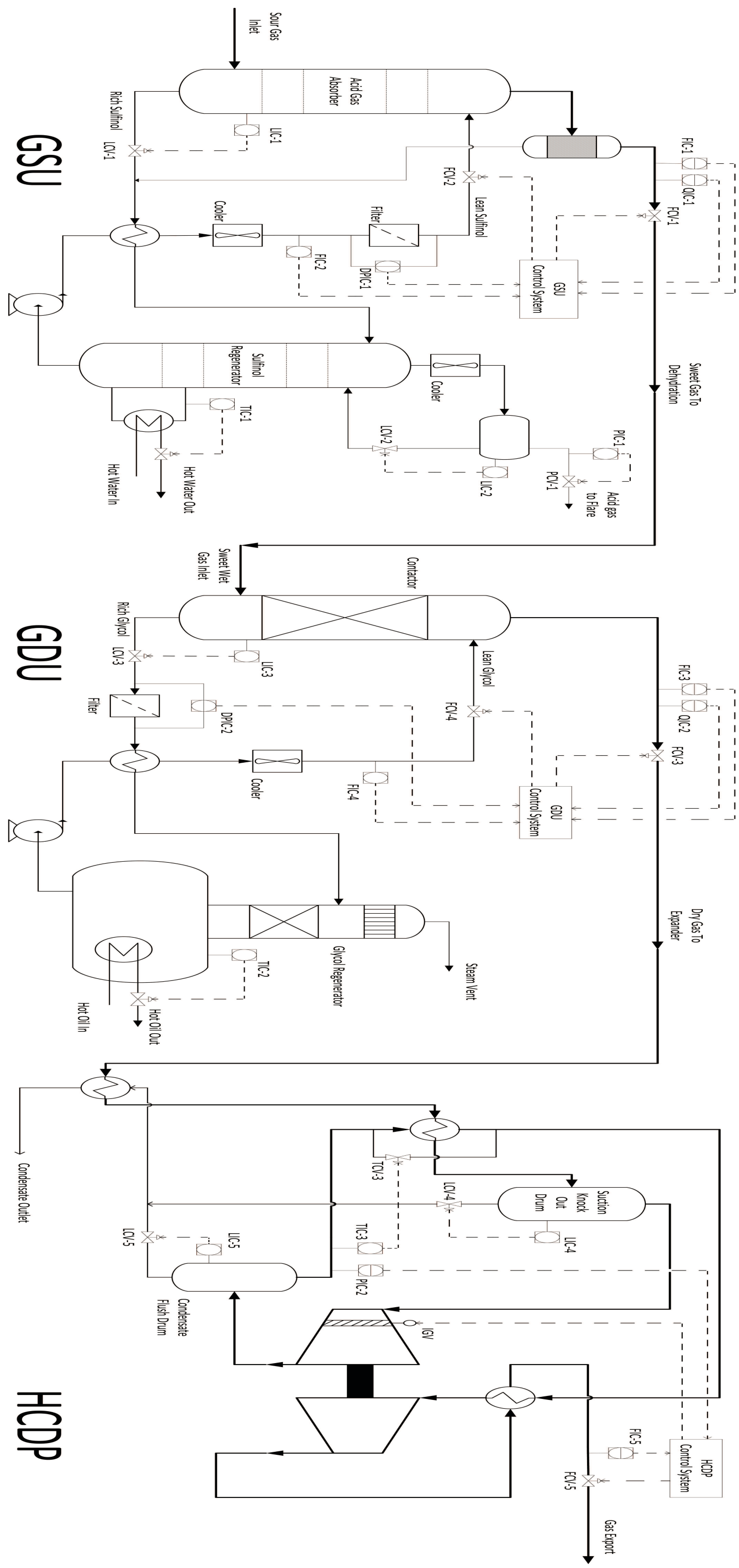


Figure 5.1: Gas Processing Train

Table 5.1: Process figure key

Acronym	**Description**
DPIC	Differential Pressure Indicator Control
FIC	Flow Indicator Control
FCV	Flow Control Valve
GDU	Gas Dehydration Unit
GSU	Gas Sweetening Unit
HCDP	Hydrocarbon Dew Pointing
IGV	Inlet Guide Vanes
LIC	Level Indicator Control
LCV	Level Control Valve
PIC	Pressure Indicator Control
PCV	Pressure Control Valve
QIC	Quality Indicator Control
TIC	Temperature Indicator Control
TCV	Temperature Control Valve

The lean sulfinol flows downward through the GSU absorber contacting the upward flowing natural gas. Sulfinol absorbs acid gas components and other impurities from the natural gas, and leaves the bottom of the absorber as rich sulfinol under level control. Rich sulfinol then flows to the Lean/Rich Heat Exchangers where it is heated by the hot lean sulfinol from the Regenerator column. The pre-heated rich sulfinol is then introduced to the top of the regenerator column, where the sulfinol solvent is regenerated by contacting with the stripping steam and recycled back to the system as lean sulfinol.

5.1.2 Gas Dehydration Process

Water content in the hydrocarbon gas raises problems in the production operation and in the transportation. The water moisture may condense and cause the formation of hydrates, solidify or cause corrosion if the gas contains acidic components [42, 70]. Henceforth, the wet sweet gas stream from the GSU subsequently flows to the Gas Dehydration Unit (GDU). Gas flows upward through the contactor column packing where it is wetted by glycol which has a greater affinity for the water vapour than gas. Afterwards, the dehydrated gas is sent to the Hydrocarbon Dew Pointing unit (HCDP).

After contacting the gas, the water-rich glycol is regenerated in the glycol regeneration package by heating at approximately atmospheric pressure to a temperature high enough to drive off almost all the absorbed water. The regenerated glycol is then cooled and re-circulated back to the contactor.

5.1.3 Hydrocarbon Dew Pointing Process

Dried gas then flows through a further gas conditioning process called the HCDP to remove hydrocarbon liquids from the natural gas in order to achieve a defined export gas specification of Gross Heating Value (GHV), Wobbe Index and hydrocarbon dew point. The process consists in cooling the natural gas under the dew point temperature of the heavy hydrocarbons mainly to condense and remove Propane (C_3H_8) and Butane (C_4H_{10}) from the raw gas, in order to prevent condensation of these volatile components in natural gas pipelines. This is done by expanding the gas from the GDU through a Turbo-Expander or Joule Thompson Valve and removing the condensed heavier hydrocarbon as a liquid stream from the 'cold condensate flash drum'. The gas is then compressed in a re-compressor and flows to gas export metering.

5.2 Process Model

The main aim is to obtain a simple functional relationship between the various process variables that explain the process behaviour of each unit in the gas phase train. Practically speaking, a mathematical model development, even though possible, is tedious to deal with due to the complexity of the underlying process and may result in long and complicated equations. However, an alternative easier modelling approach exists and is expected to yield more useful results. A simple process identification method, also known as empirical process modelling, deals with the process as a black box and the system characteristics are solely identified from the response to a known forcing input, hence a detailed knowledge about the system is not needed [55].

It is worth mentioning the following:

- looking to the gas processing train model presented in Fig. 5.1, the interests are primarily focused on the critical loops only. Those described as high interaction control loops, where SISO control may be suboptimal, and thus assuming most other control loops are sufficiently controlled by single input single output (SISO) PID controllers.

- An extensive communication was made with the sponsored company, Petroleum Development of Oman (PDO), to gain authorisation for process identification and to get access to the fields. Unfortunately, the company refused our demands. Henceforth, since the process identification widely depends on past knowledge of process dynamics, the process models were developed based on historical operational data gathered from PDO Harweel plant located in Sultanate of Oman and buttressed by the writer experience of 15 years in the oil and gas industry. The developed models are then validated, to prove compatibility, by two different verification methods: logical dynamical process description and by comparison with a real industrial process for the same forced input. However, the developed models are not meant to represent specific units, but to denote generic gas train processes and their dynamics and hence, to reflect real process scenarios which they will be compared to.

- The plant processed gas specifications are as follows: 100 *barg* pressure, 45 *°C* gas temperature and a throughput gas flow rate up to 3.0 *MMSCMD* (Million Metric Standard Cubic Meter per day).

The model of the gas phase train is developed using first order transfer functions, where possible, with dead-time. Dead times in the coming mathematical models are indicative only, as the models are generic. Those simple models are sufficient to represent many chemical processes and moreover are favoured in the industry [26]. The benefits of using simple models may not be seen during design and commissioning phases when expert control engineers are present, however, the benefits will be clearly visible during the operation phase when process engineers or plant operators can easily identify a model's gain, delay, and time constant and compare the information with the real process data. Hence, use of such simple models builds confidence amongst the operation team and reduces the risk of large model errors (model-plant mismatch) which may arise due to staff difficulty in understanding and identifying higher order models for a large scale system.

5.2.1 Gas Sweetening Unit (GSU) Dynamical Model

Referring to the GSU in Fig. 5.2, sour gas enters the bottom of the absorber column where the acid gas components are removed in a counter-current contact with the sulfinol flowing downwards from the top. The GSU system has two variables that have to be controlled: the throughput gas flow measured by *FIC-1* and the acid concentration in the gas outlet measured by the process analyser *QIC-1*. The manipulated variables are the absorber gas outlet flow through *FCV-1* and the absorber sulfinol input flow through *FCV-2*. The specification of the acid concentration in the outlet gas is fixed by operational goals and must be kept within 0.5% of its setpoint at steady state. *FIC-*

2 provides lean sulfinol flow measurements to the GSU control system, whereas the differential pressure sensor *DPIC-1* across the sulfinol filter provides measurements of the sulfinol flow disturbances.

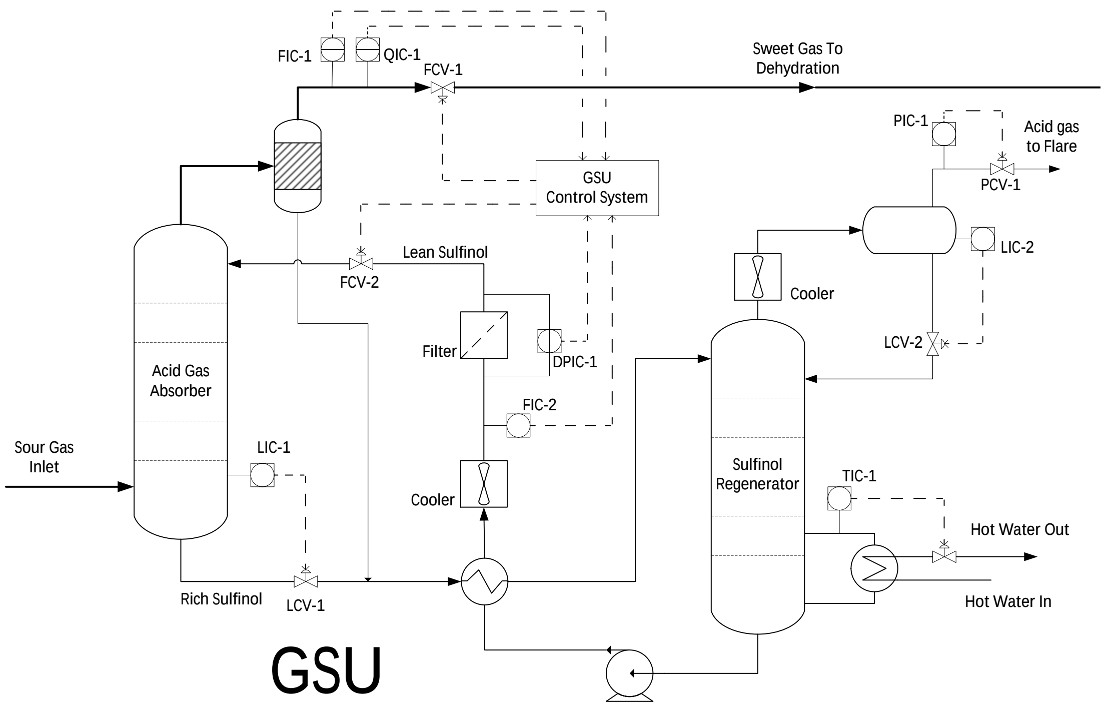


Figure 5.2: Gas Sweetening Unit

The dynamics of the GSU system (inputs *FIC-1*, *QIC-1* and outputs *FCV-1*, *FCV-2* respectively) are approximated by the following model:

$$G_{GSU} = \begin{pmatrix} \frac{-13.5}{18.6s+1}\ e^{-2s} & \frac{16.7}{23.5s+1}\ e^{-6s} \\ \\ \frac{7.3}{9.5s+1}\ e^{-13s} & \frac{20}{15.4s+1}\ e^{-6s} \end{pmatrix} \tag{5.1}$$

The absorber bottom liquid level is maintained by the level controller *LIC-1* which acts on the level control valve *LCV-1*. Level is one of the most common variables in the process industry. The model transfer function of the absorber level control can be represented by:

$$G_{LIC1} = \frac{1.2}{54s+1}\, e^{-12s} \tag{5.2}$$

The rich sulfinol is then routed to a low pressure 'flash vessel', not shown, where most of entrained and absorbed hydrocarbons and some of the sour components like H_2S, CO_2, COS, RSH, and water content are flashed off. Rich sulfinol then flows through the lean/rich heat exchanger, where it will be preheated, towards the top of the sulfinol regeneration column. The absorbed acid gases will be stripped off by the counter-current contacting with a stripping vapour produced by the reboiler beneath the column. The most important controls here are the vapour pressure and temperature. The rich sulfinol is heated in the reboiler and the vapour is returned to the column for stripping the absorbed acid gas components from the solvent. The flow rate of heating media, that is hot water, is controlled through *TIC-1*. The vapour outlet of the regeneration column passes through overhead condenser and is then routed to the overhead separator to capture any volatile hydrocarbon liquids or sulfinol carried over by the gas. Then, the retrieved liquid is recycled back to the regeneration column as a reflux.

5.2.2 Gas Dehydration Unit (GDU) Dynamical Model

The 'gas dehydration unit' is downstream of the sweetening train as shown in Fig. 5.1. The GDU mainly consists of an export gas glycol contactor and dehydration regeneration package. As sketched in Fig. 5.3, the wet gas enters into the bottom section of the contactor column and then flows into the inlet scrubber section of the column where any entrained liquid is removed before the gas is introduced into the dehydration section of the contactor. All the liquids recovered in the bottom of the inlet scrubber are drawn down under level control *LIC-3*. A transfer function model of the level control at the bottom of the contactor is quite similar to the *LIC-1* of the GSU absorber.

Lean glycol enters at the top of the column and is evenly distributed over the whole

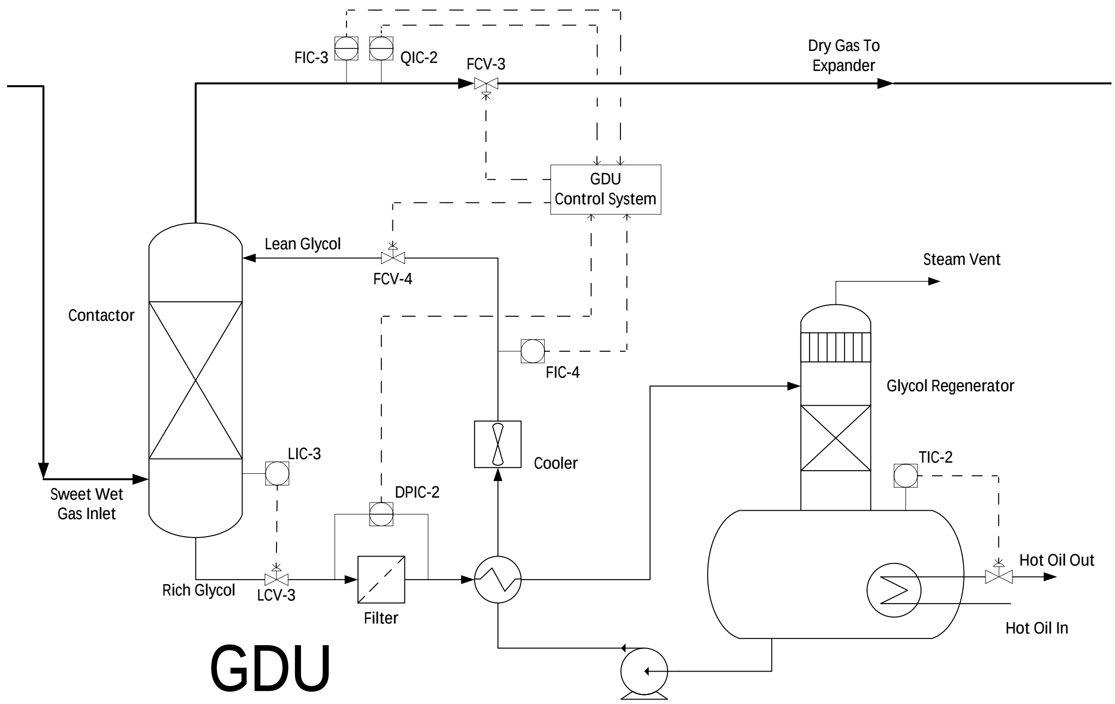


Figure 5.3: Gas Dehydration Unit

section of the column. Dehydration by absorption takes place as the gas flows upwards through, and hence contacting, the wetted surface of the packing. The GDU system has two variables that have to be controlled: the throughput gas flow measured by *FIC-3* and the water load in the gas outlet measured by the process analyser *QIC-2*. Whereas, the manipulated variables are the contactor gas outlet flow through *FCV-3* and the contactor lean glycol input flow through *FCV-4*. The specification of the water content concentration in the outlet gas is fixed by operational goals and must be kept to within 0.5% of its setpoint at steady state. *FIC-4* provides lean glycol flow measurements to the GDU control system, whereas the differential pressure sensor *DPIC-2* across the rich glycol filter provides measurements of the glycol flow disturbances. The dynamics of the GDU system with inputs (*FIC-3*, *QIC-2*) and outputs (*FCV-3*, *FCV-4*) are well defined by the following model:

$$G_{GDU} = \begin{pmatrix} \frac{-8}{15s+1}\ e^{-3s} & \frac{19}{30.3s+1}\ e^{-7s} \\ \\ \frac{6.2}{13.5s+1}\ e^{-13s} & \frac{10}{16.7s+1}\ e^{-7s} \end{pmatrix} \tag{5.3}$$

The rich glycol leaves the contactor towards the 'glycol flash drum' (not shown). The glycol flash drum is a horizontal three phase separator which separates the hydrocarbon liquid phase from the glycol phase and vents any remaining gases. Thereafter, the rich glycol flows through the 'glycol cartridge filters' to remove any solid particles from the rich glycol stream to prevent these solids from fouling the heat transfer surfaces within the glycol regeneration package. Filter chocks are continuously monitored by the differential pressure indicator *DPIC-2* installed across the filter cartridge.

The filtered glycol flows to the 'lean/rich glycol heat exchanger', provided for energy conservation and reduces the total heat input required for the regeneration process. The rich glycol enters the 'glycol regeneration column' and flows down through the packing in a counter-flow stream to the upward water vapours from the reboiler beneath. In the reboiler, the rich glycol is heated to 202 *°C* by a hot oil bundle to remove any volatile materials. The temperature in the glycol reboiler is maintained by the temperature controller *TIC-2* which controls the flow rate of the hot oil. Finally, the regenerated lean glycol flows to the glycol pump which circulates the glycol back into the system.

Control of temperature, like pressure and level, is one of the most common objectives in the process industry. Therefore, the model transfer function of the reboiler temperature control *TIC-2* can be approximated by:

$$G_{TIC2} = \frac{0.5}{45s + s}\ e^{-45s} \tag{5.4}$$

5.2.3 Hydrocarbon Dew-pointing Unit (HCDP) Dynamical Model

The export gas then flows through a further gas conditioning process called 'hydrocarbon dew pointing' (HCDP) to remove hydrocarbon liquids from the natural gas in order to achieve a defined export gas specification of Gross Heating Value (GHV), Wobbe Index and hydrocarbon dew point. The process consists in cooling the natural gas under the dew point temperature of the heavy hydrocarbons, by means of turbo expander, which also maximises the production of the natural gas liquid obtaining LPG (Propane C_3H_8 and Butane C_4H_{10}) from the raw gas.

Turbo expanders are machines used to recover liquids from gas stream and to control dew point of gas prior to transport. Turbo expanders are made of two main parts, carried on the same short and rigid shaft, the turbine and the compressor. Turbo expanders are very efficient as polytropic work is extracted from the gas during expansion. Therefore, turbo expanders generate power that can be used to recompress the expanded gas after being processed. The expansion ratio, and hence the temperature drop, is determined by the dew point specification of the product gas. The expansion ratio and throughput flow can be controlled over a wide range by means of variable inlet guide vanes (IGV).

The feed gas from the GDU, at 45 *°C* and 95 *barg* approximately, is cooled in the first heat exchanger by exchanging heat with the cold condensate return from the condensate flush drum. It is further cooled in the second heat exchanger by exchanging heat with separated gas from the condensate flush drum. The feed gas then flows to the 'suction knock out drum', where the temperature is further reduced to around 2 *°C* by flashing. Thereafter, the gas flows to the 'turbo expander' where it is expanded to 65 *barg* causing the gas to cool to around -15 *°C*. The discharged gas from the turbo expander flows to the 'cold condensate flash drum', in which the condensed hydrocarbon liquid is removed. The treated gas from the 'cold condensate flash drum' is then heated up by exchanging heat with incoming feed gas. Afterwards, the gas is pressurised to around 70 *barg* in the recompressor section and then flows to the export pipeline after cooling via the third heat exchanger.

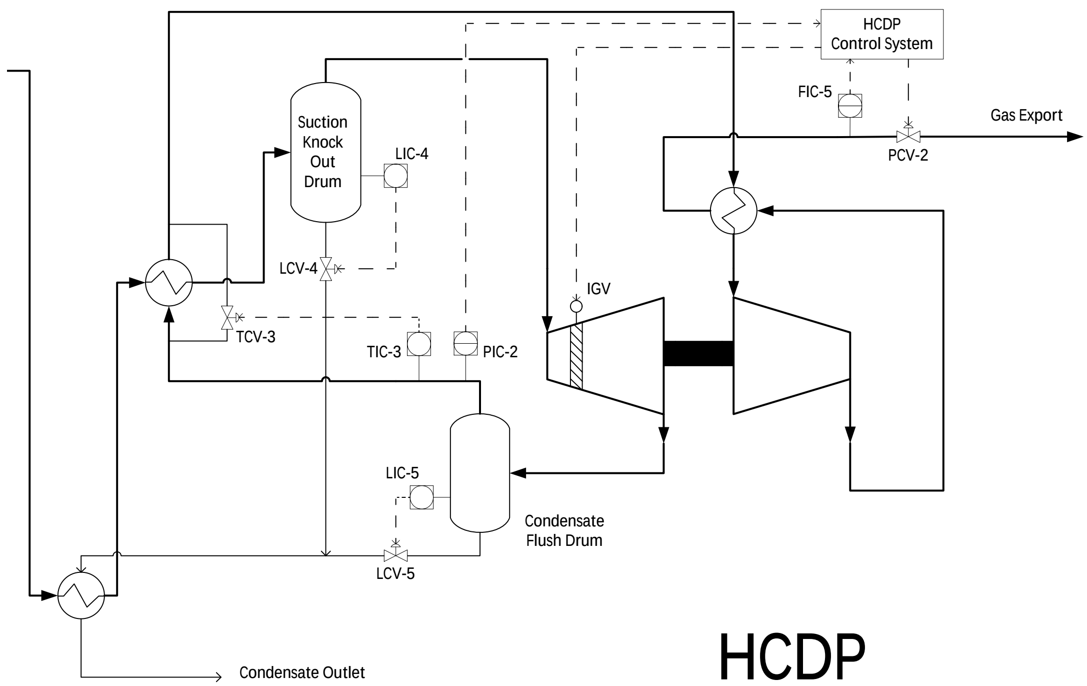


Figure 5.4: Hydrocarbon Dew-pointing Unit

The performance of the HCDP unit is mainly driven by the operating pressure and temperature. The two main controllers for this function are *PIC-2* and *TIC-3* as shown in Fig. 5.4. The temperature control of the turbo expander export gas is achieved by *TIC-3* located at the gas outlet of the condensate flush drum. *TIC-3* throttles the control valve *TCV-3* provided in the cold bypass line of the second heat exchanger to maintain the turbo expander inlet temperature. Achieving this temperature is very important to remove the liquid condensate and attain the export gas specification.

The turbo expander has two variables to be controlled in order to maintain the quality of the product: the unit pressure measured by *PIC-2* which is located at the gas outlet of the condensate flush drum and the load demand on the unit measured by

FIC-5. The manipulated variables are: the recompressor outlet flow measured through *FCV-5* and the expander inlet flow through *IGV* (Inlet Guide Vanes). The dynamics of the turbo expander can be described by the following model (inputs *PIC-2*, *FIC-5* and outputs *FCV-5*, *IGV* respectively):

$$G_{HCDP} = \begin{pmatrix} \frac{0.2\ e^{-s}}{2s^2+4s+1} & \frac{1}{2s+1} \\ \\ \frac{0.3\ e^{-0.5s}}{0.4s^2+s+1} & \frac{-0.3\ e^{-1.3s}}{0.1s^2+3s+1} \end{pmatrix} \tag{5.5}$$

5.3 Model Validation

Model validation and verification is an important step in the model building sequence. The ultimate goals of creating a model representing the gas phase train in upstream oil and gas fields are to aid decision making and to provide engineering solutions to operational problems. The obtained models need to accurately reflect real process scenarios which they will be compared to. Nevertheless, the developed models G_{GSU}, G_{GDU} and G_{HCDP} represent general processes and dynamics and not specific units. Therefore, the models can be validated by graphical comparisons and descriptions of model outputs with data from industrial processes [36].

In brownfield plants, the multivariable interactive control loops are controlled by mean of SISO loops and control room operators. Hence, in order to easily represent this control system, a decentralised non-cooperative multivariable generalised predictive controller (GPC) will be used to verify the models.

5.3.1 Model Validation by Dynamical Process Description

Firstly, the obtained process models of the GSU, GDU and HCDP will be validated by the logical dynamic process descriptions in response to a known process disturbance.

5.3.1.1 Gas Sweetening Unit (GSU) Model Validation for Disturbances in Sulfinol

To evaluate the GSU model behaviour more broadly, a disturbance of 25% sulfinol filter chock has been introduced to the system at sample time 200. Filter chock is expected to limit sulfinol flow to the absorber and hence the gas flow through the absorber will kick off due to the reduction on the opposing flow. In response, the acidic gas is predicted to increase sharply driven by the sudden rise in the gas volumetric flow rate and the reduction of the solvent flow rate.

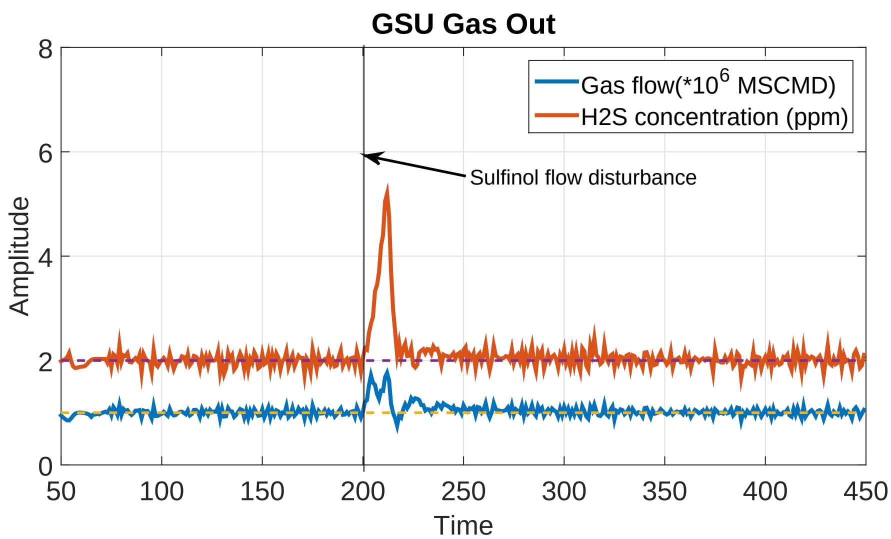


Figure 5.5: GSU gas outlet responses for a solvent filter chock

The GSU model, trended in Fig. 5.5, responds to the solvent filter choke as expected of a real gas sweetening process. The inclusions of the white noise in the measurement parameters are to represent the measurement noise commonly found in real applications.

5.3.1.2 Gas Dehydration Unit (GDU) Model Validation for Disturbances in Glycol

In order to evaluate the model response of the GDU model, a disturbance of 25% glycol filter chock has been introduced to the system at sample time 200. Filter chock is expected to limit glycol flow to the glycol regeneration package and causes disturbances to the regenerated glycol quality. Lean glycol flow to the contactor column is expected to be affected after a while which causes a small fluctuation in the gas flow rate. GDU control fluctuations are predicted to take a longer time to settle because the disturbance affects both operations in the system: the glycol regeneration package and the export gas dehydration.

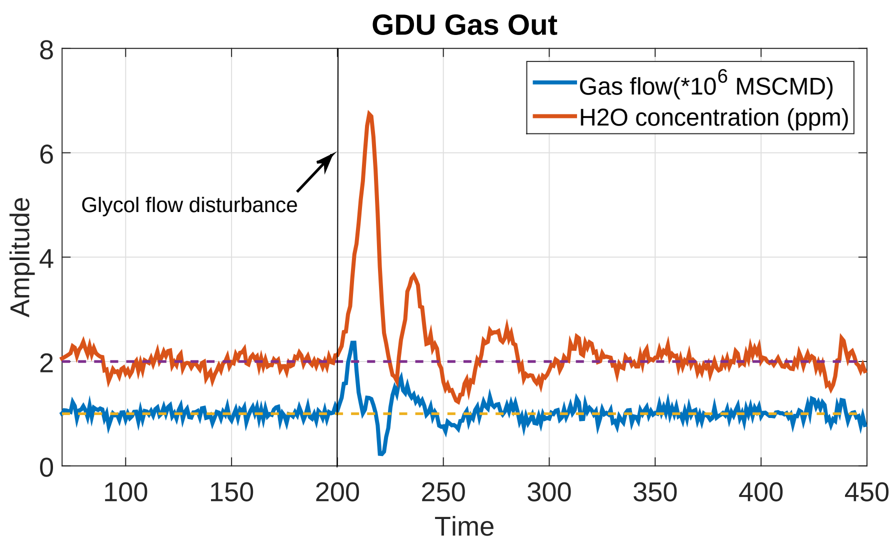


Figure 5.6: GDU Gas outlet responses for a glycol filter chock

It is clearly seen that, the GDU model (responses shown in Fig. 5.6) responds to the glycol filter chock exactly as expected of a real gas dehydration process. The inclusions of the white noise in the measurement parameters are to represent the measurement noise commonly found in real applications.

5.3.1.3 Hydrocarbon Dew pointing Unit (HCDPU) Model Validation

To assess the model response of the HCDP, the flow set point of *FIC-5* is stepped up from 1.2 to 1.7 *MMSCMD* at sample time 240. It is expected that, at the time when the *IGV* decreased the angle opening in order to decrease the load demand through the turbo expander, there will be a slight reduction in pressure and then a small overshoot as expected due to the load reduction. The delay of pressure stream fluctuation is due to the fact that the pressure sensor *PIC-2* is physically located in the downstream of the condensate flush drum while the *IGV* is located in the inlet of the expander.

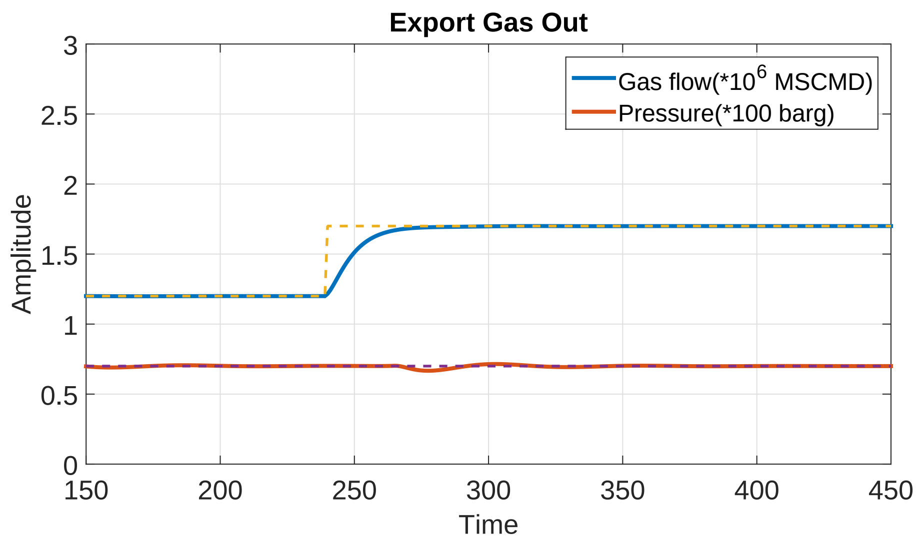


Figure 5.7: HCDP Gas outlet responses with a step disturbance in gas flow

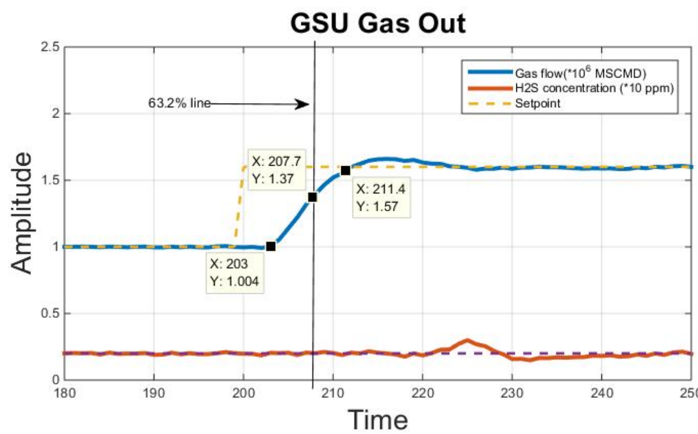
The HCDP model responses shown in figure 5.7 react to a step disturbances on gas flow rate as expected of a real hydrocarbon dew-pointing process. Please note, the trends are presented without the white noise because the measurement noise are too small in the real application.

5.3.2 Model Validation by Comparisons with a Real Industrial Process

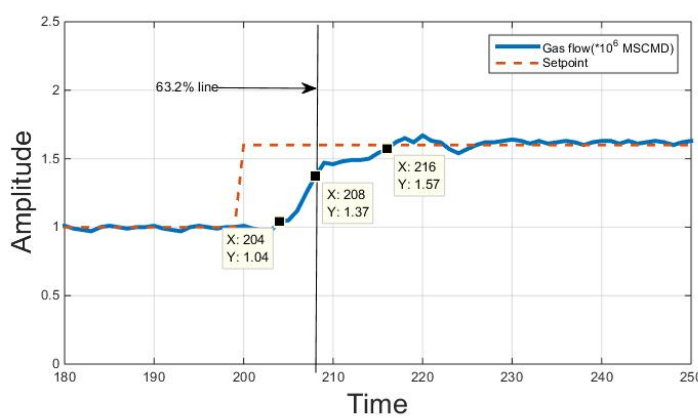
Secondly, the obtained process models of the GSU, GDU and HCDP will be validated by comparison with a real industrial process, PDO Harweel site in Oman, for the same forced input.

5.3.2.1 Gas Sweetening Unit (GSU) Model Validation

Fig. 5.8a, below captures the simulation results of the GSU model stimulated by a step increment of 20% in the throughput gas flow. The model response is compared with a digitised real GSU response for almost the same size step increment taken from PDO Harweel site in Oman shown in Fig. 5.8b. The actual GSU real process responses are presented in Fig. C.1 in Appendix C.



(a) Model response



(b) Digitised real process response

Figure 5.8: GSU Gas outlet responses with a set point increment of 20% in gas flow rate (Real process responses are presented in Appendix C)

Table 5.2: Model and Process Comparison Table of GSU

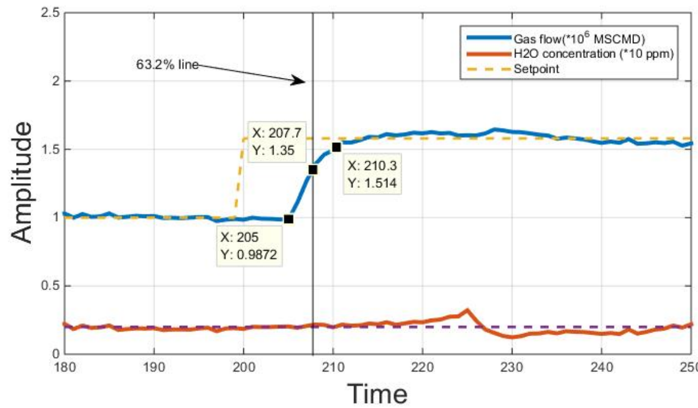
	Model	Real Process	Error %
Time Delay τ_d	3	4	25%
Time constant τ	4.7	4	7.5%
5% Settling time τ_{st}	8.4	12	30%
Gain K	7.68	8.56	10%

It is noticeable from the trends, presented in Fig. 5.8, and the GSU model and real process comparison table (Table 5.2) that the behaviours and dominant time constants of the gas flow rate and the H_2S concentration are close for the model and real system data. Bearing in mind that the developed models represent generic processes and dynamics and not specific units.

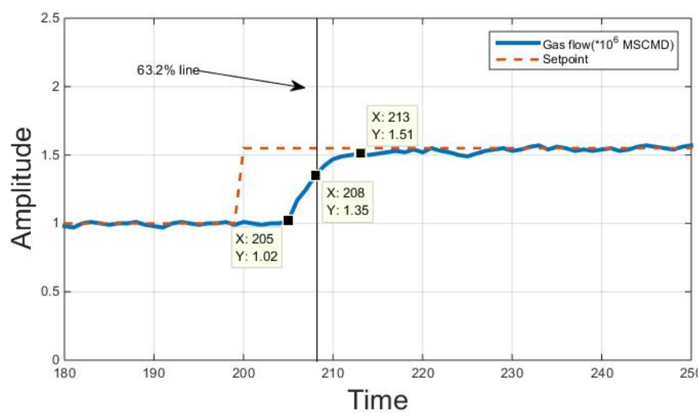
5.3.2.2 Gas Dehydration Unit (GDU) Model Validation

Fig. 5.9a trends the simulation results of the GDU model stimulated by a step increment of 20% in the throughput gas flow. The model behaviour is compared with a digitised real GDU response for almost the same size step increment taken from the PDO Harweel site in Oman shown in Fig. 5.9b. The actual GDU real process responses are presented in Fig. C.2 in Appendix C.

It is clear from GDU validation figures presented in Fig. 5.9, and the GDU model and real process comparison table (Table 5.3) that the model responses for the gas flow rate and the water content load in the gas are close to the real process and thus provide a suitable generic representation.



(a) Model response



(b) Digitised real process response

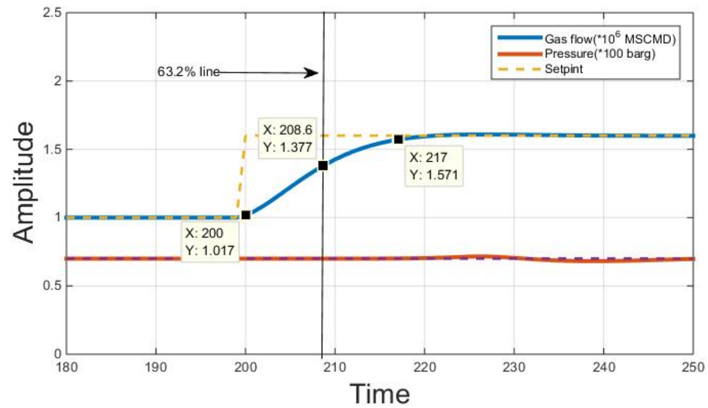
Figure 5.9: GDU Gas outlet responses with a set point increment of 20% in gas flow rate (Real process responses are presented in Appendix C)

Table 5.3: Model and Process Comparison Table of GDU

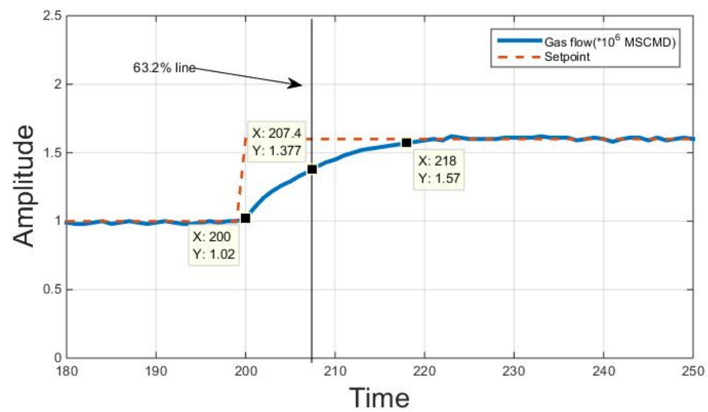
	Model	Real Process	Error %
Time Delay τ_d	5	5	0%
Time constant τ	2.7	3	10%
5% Settling time τ_{st}	5.3	8	33%
Gain K	10.5	9	16%

5.3.2.3 Hydrocarbon Dew pointing Unit (HCDPU) Model Validation

The HCDP model behaviour is shown in Fig. 5.10a for a step disturbance on gas flow rate. The model response is compared with a digitised real HCDP response for almost the same size step increment taken from PDO Harweel site in Oman shown in Fig. 5.10b. The actual HCDP real process responses are presented in Fig. C.1 in Appendix C.



(a) Model response



(b) Digitised real process response

Figure 5.10: HCDP Gas outlet responses with a set point increment of 20% in gas flow rate (Real process responses are presented in Appendix C)

It is noticeable from the trends, presented in Fig. 5.10, and the HCDP model and real process comparison table (Table 5.4) that the behaviours and dominant time constants of the gas flow rate and pressure are close for the model and real system data. Bearing in mind that the developed models represent generic processes and dynamics and not specific units.

Table 5.4: Model and Process Comparison Table of HCDP

	Model	Real Process	Error %
Time Delay τ_d	0	0	0%
Time constant τ	8.6	7.4	16%
5% Settling time τ_{st}	17	18	5.5%
Gain K	4.5	5.5	18%

5.4 Summary

Large scale series processes are rather common in the upstream oil and gas industry. Consequently, representative models are a key demand for control and automation engineers to test and verify different control approaches and strategies. The chapter delivers simple and easy to understand process models based on transfer functions for a complex gas processing operations. Processes like gas sweetening and gas dehydration are deemed as difficult control tasks for both process and control engineers. Henceforth, the presented models aim to ease these control challenges by providing an authentic framework for engineers to design, analyse and evaluate different control solutions. The developed models of the gas treatment train processes were verified and validated against real process responses to the same disturbances taken from PDO Harweel site in Oman. The models were proved to reproduce the systems behaviours of each process and hence achieve the main objective.

The model provides good opportunity for process control engineers to test a variety of process disturbances, malfunctions, and load changes on the process operation and verify the impact with different control system designs. A key aim is to design a control system to solve a major industrial problem that is 'the disturbance growth in a series connected processes' and 'control system operator dependency' affecting the series connected processes in LSS.

Next chapter will focus on analysing a variety of process disturbances, malfunctions, and load changes on the gas train process operation and verifying the utility of the model for capturing key industrial scenarios. Chapter (7), will then investigate the use of these models and scenarios as a base to test the control concepts and proposals introduced in chapter (4).

Chapter 6

DISTURBANCES IMPACT ANALYSIS

The core aims of this chapter are to analyse the influence of disturbances in a natural gas processing train in the upstream oil and gas plants and to authenticate the representative model that can be used for developing and testing a swift and anticipatory control system. The impacts of two different causes of process disturbances on a gas phase train comprising three main processes connected in series are presented. The analysis provides answers about how feed disturbances and process unit failures affect series connected processes and more specifically gas sweetening, gas dehydration and hydrocarbon dew-pointing units.

There is an obvious importance for upstream oil and gas companies in confronting the control system weaknesses in order to cope with the increasing level of process complexity, demanding product specifications, profitability, safety, and environmental sustainability challenges and of course, to ensure they meet production revenue targets. Accordingly, process control systems need to act quickly, and whenever possible use anticipation, to reduce the impact of disturbances rather than relying just on simple reactive feedback schemes. Today, the majority of the existing upstream oil and gas plants utilises classical PID control algorithm for the process control. Unfortunately, PID can't deal with process constraints, does not implicitly include feedforward information and has a great difficulty in controlling multivariable and complex dynamics systems [38]. Nowadays, the majority of the gas processing operations must be accomplished in the upstream production phase in a challenging environment and with an increasing difficulty of product specifications. Consequently, the process control engineers have to be vigilant in monitoring process disturbances, which have the potential to deviate process operation towards unstable or unsafe regions. Thus implying the need of new control approaches to cope with the process complexity.

This chapter demonstrates the influence of disturbances on a series connected LSS (Large Scale Systems) such as upstream oil and gas fields. These plants constitute a number of processes connected in series and physically distributed over a large area. The common causes of major process disturbances in upstream production fields are equipment failures and feed disturbances [2]. Such disturbances are capable to cause substantial deviations of the process and possibly cause violation of safety and operation constraints. In series connected systems, where one process output is the feed to a successor process, the impact of disturbances can quickly escalate. The expected consequences when one or more antagonistic condition develops at the same time are a higher risk of a major disruption that may lead to overall process shut down.

The disturbance analysis employed the validated model representing typical gas train processes in upstream oil and gas fields, developed in chapter (5), as the base element to analyse a variety of process malfunctions, disturbances and load changes on the gas processing train. In addition, verify their consequences on the entire process. The process model encompasses three main processes of the natural gas treatment operation. These are gas sweetening, gas dehydration and hydrocarbon condensate removal processes.

Knowledge about how different disturbances and process malfunctions affects the gas processing train are indeed valuable for process control engineers. There is a necessity to develop control methodologies that can tackle the disturbance growth issue in series connected processes such as those described in chapter (4). Henceforth, the key long term task is to design a specific control system that can considerably reduce the frequency of plant shutdowns and at the same time decrease the operating costs, by properly controlling the disturbance growth in the process. Both of these improvements are also expected to reduce energy fluctuations in the process hence saves fuel.

Section 6.1 provides analysis and discussions about process disturbances caused by the feed changes as well as the malfunction of process units. While, section 6.2 present a summary of the findings.

6.1 Analysis of Process Disturbances

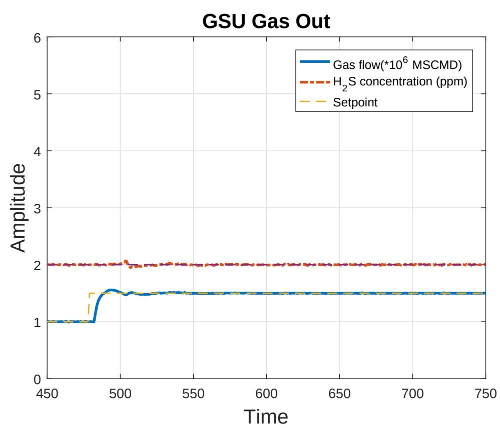
The significance of a disturbance on the process depends essentially on its magnitude and the location where it happens. For instance, process disorders can be caused by a process unit malfunction or a sudden feed change. The consequences of process disturbances may not stop with a process shutdown only, but can lead to a disastrous situation. Consequently, there is a need to analyse different disruption scenarios that may arise due to different process disturbances and evaluate their effects.

The multivariable interactive control loops, in the existing oil and gas plants, are controlled by mean of SISO loops and control room operators . This type of control systems can be easily represented by a decentralised non-cooperative multivariable generalised predictive controller (GPC). Hence, decentralised GPC controllers will be utilised for the disturbance analysis.

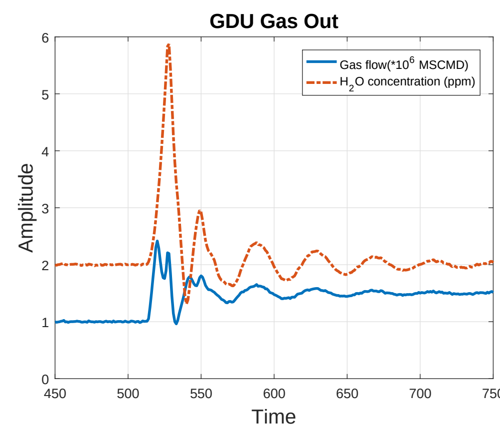
6.1.1 Feed Disturbance

Process disturbances due to feed changes are common on upstream oil and gas fields. Feed disturbance can be simply initiated by plant operators, when changing process set points, or by an automated operation of process units like pumps, valves, compressors, etc. Practically, a well tuned PID control system supported by an experienced plant operator is capable to handle most of these disruptions to some extent. Nevertheless, there are circumstances when the feed disturbances have the potential to trigger a substantial process upset. Generally, these situations require complex procedures to be followed, which normal operators may be less adept to handle. In the context of this analysis, the disruptive nature of sudden feed changes is a critical issue for a series connected processes with multi input multi output (MIMO) loops.

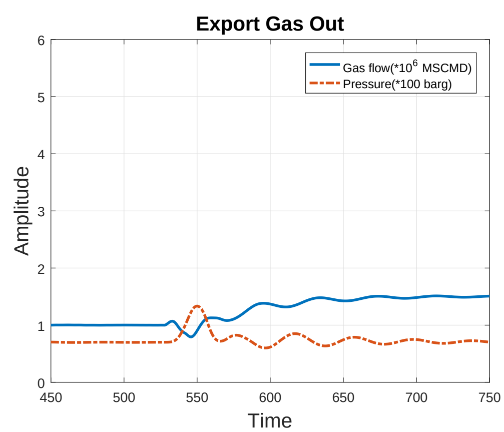
To test the impact of a sudden feed change in the whole gas processing train, a 50% step up had been introduced to the gas flow setpoint of the GSU. Figures 6.1a, 6.1b, and 6.1c illustrate the impact of feed disturbances on each system of the series connected processes (GSU, GDU, and HCDP respectively).



(a) GSU Gas outlet response



(b) GDU Gas outlet response



(c) HCDP Gas outlet response

Figure 6.1: Gas train processes response as a result of the process feed disturbance trigered by a 50% step increase in the GSU gas flow reference

At the time both GSU control loops, gas flow rate and H_2S concentration in the gas, seem insignificantly affected by the feed disturbance, however the controlled variables of the successor processes GDU and HCDP were significantly affected. Both GDU control loops, gas flow rate and H_2O concentration in the gas, experienced a sustained oscillatory disturbance for a quite long time as seen in Fig. 6.1b. GDU gas throughput is badly affected by the feed disturbance on the predecessor process. The gas flow increases to almost 2.5 *MMSCMD* and drops down to one *MMSCMD* before it undergoes a slow decaying oscillation until it settles at the new gas flow rate. Such phenomena can cause disastrous flow waves inside the pipelines causing hammering effects against valves, flanges, measuring equipment, etc. Sometimes damage can be immediate and catastrophic when valves or flanges break and subsequent loss of hazardous containment occurs. From an operational point of view, an abrupt oscillation in the gas flow rate upsets the operation stability of the GDU glycol contactor causing valuable glycol carry over with gas as explained by Branan [11]. During the oscillatory operation period of the contactor column, the product is specified as 'off specifications' and normally flared till the operation stabilises again, hence wasting valuable resources.

As a consequence of the GDU gas flow disturbance, the water load on gas also fluctuates for almost the same period of time. Presence of water in the pressurised gas pipelines can form gas hydrate across valves or pipe elbows and completely blocks the flow of gas [23]. Moreover, due to the corrosive effects of water, there is also an increased risk of materials corrosion in contact with natural gas and condensed water causing damages to the pipeline and equipment [6].

The effects of the feed disturbance originating in the GSU gas flow rate are far more excessive in the subsequent HCDP process. Considering Fig. 6.1c, moderate and extended fluctuations are noticeable in the export gas flow rate. The gas pressure trend shows a rapid increase from 70 *barg* to 130 *barg* followed by a reduction of 80 *barg*. The oscillation cycle continues for a long period of time before it stabilises. These large flow and pressure fluctuations in the turbo expander discharge can lead to a surge situation and cause a complete breakdown to the machine internal parts [54]. In fact, pressure surge has a larger effect on turbo expanders than centrifugal compressors as stated by Kidnay et al. [40].

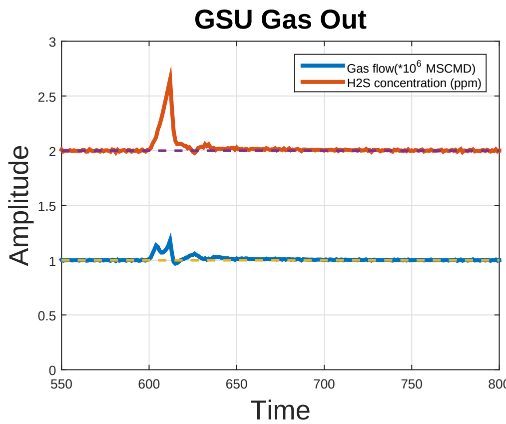
6.1.2 Process Unit Malfunction

Process disturbances caused by a process malfunction or a sudden unit shut down are a major issue facing oil and gas companies. Practically speaking, the effects vary from a minor missed production targets to a total plant shut down depending on the criticality of the affected units on the process and the fault type. Process unit malfunction is often an outcome of poor maintenance or a harsh environment or simply a human mistake. It is worth mentioning that most oil and gas production plants are located either in deserts, where they experience high ambient temperature changes between day and night as well as sand storm's, or in offshore environments, where the operations are limited in space and fronting fickle ocean weather. The disruptive nature caused by a process unit malfunction is more problematic in a series connected processes with multi input multi output (MIMO) loops.

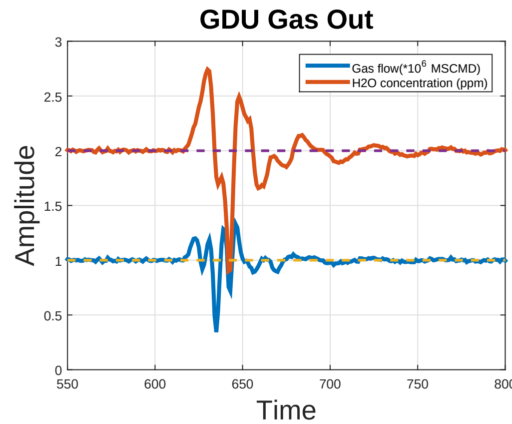
In order to test the consequences of a sudden process unit malfunction in the whole gas processing train, a 10% sulfinol solvent filter chock had been introduced to the solvent control loop of the GSU. Figures 6.2a, 6.2b, and 6.2c show the significance of a process unit malfunction disturbance on each system of the series connected processes (GSU, GDU, and HCDP respectively).

GSU trends presented in Fig. 6.2a show a sharp increase of H_2S concentration in the GSU gas output by nearly 40% of it is initial reference value as a direct result of the solvent filter chock. The gas flow rate through GSU has increased also by 25% relative to its reference value, driven by a sudden reduction in the solvent flow through the GSU absorber. Gas flow with H_2S concentration of 4 *ppm* or higher is considered harmful to the downstream processes due to the corrosiveness of H_2S in the presence of water and dangerous due to the toxic nature of H_2S [51].

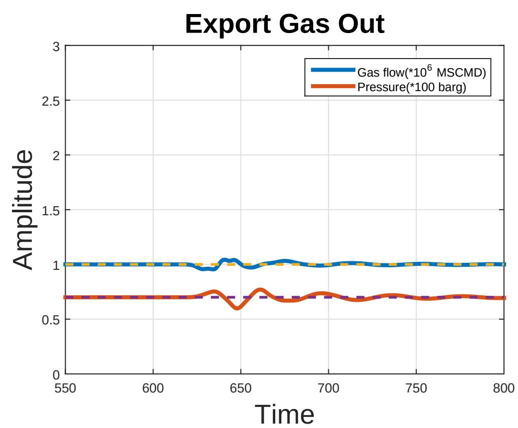
Both GDU control loops, gas flow rate and H_2O concentration in the gas, experi-



(a) GSU Gas outlet response



(b) GDU Gas outlet response



(c) HCDP Gas outlet response

Figure 6.2: Gas train processes response as a result of process unit malfunction triggered by a 10% solvent filter chock in the GSU

enced elongated and extreme fluctuations as trended in Fig. 6.2b. GDU gas throughput was seriously affected by the solvent flow disturbance on the predecessor process. The gas flow undergoes a massive fluctuations with a maximum cycle amplitude of 0.75 *MMSCMD* which is 75% of its reference value. As in feed disturbance, the product will be flared due to it is being “off specifications” during the instability period and the risk of hammering flow is more likely due to the massive fluctuations in the gas flow rate. Repetitive disturbances of this nature may cause damage to valve packing or cause cracks on flange bolts leading to loss of hazardous containment.

Large fluctuations of the water vapour concentration trend clearly indicates that a considerable amount of glycol had been pumped to the contactor during the gas flow rate disturbance and maybe it had been carried over to the downstream processes. Similarly, as in feed disturbance and due to system instability, there is a possibility of increasing water load in the gas which may cause hydrate issues and material corrosion in the downstream processes.

Despite the bad disturbance effects on the GDU process, HCDP process variables were not affected much. Fig. 6.2c shows slight variations on the gas flow rate and a moderate variations in the gas pressure in between 75 *barg* and 60 *barg*.

6.1.3 Real Process Disturbance Data

It is of great difficulty to get a real process disturbance figures to validate the obtained model disturbance trends due to *data confidentiality and sensitivity*. Nevertheless, the generic process model itself was validated and verified against a real process data in section (5.3). For the reader, the key point is that the proposed model gives authentic responses to real scenarios and thus provides a suitable test bed for control investigations.

6.2 Summary

The gas train model provided in chapter (5), has been utilised as a benchmark model to examine the significance of different disturbance types on a gas processing train. The impact of two different causes of process disturbances on a 'gas phase train' have been studied: 'Feed disturbance', initiated by a set-point change on GSU gas flow rate, and 'process unit malfunction', triggered by a unit failure on GSU solvent flow. Both disturbance types cause significant impacts on the successor process. However, the influence on GSU where both disturbances originated, and HCDP the third process in raw are different for each disturbance type. A feed disturbance on GSU has a bad influence on the pressure loop in the HCDP while it does not upset GSU loops much. Unlike the feed disturbance, the process unit malfunction disturbs the GSU but is found to have minor impacts on HCDP loops.

The next step in this research study is to look in more detail at development of new control structures. The results gained in this study will be exploited to develop the control system for the 'gas phase train' as it was presented in chapter (4) which is expected to reduce process shutdown occasions. As it was proven by this analysis, the system functionality deteriorates substantially when one unit fails or the feed disturbances lead to a system instability. The proposed control system in brief, aims to enhance (rather than replace) the current classical control system in the existing oil and gas plants by integrating the process safeguarding system and cost effective MPC's into a classical PID control system. Process safeguarding will enable a prompt response to disturbances caused by unit failures and enhance optimality.

The control system should satisfy the typical control objectives. Those are the controlled variables must be kept within 0.5% of their setpoints at steady state and the settling time should be as fast as possible with maximum overshot less than 10% to prevent oscillatory operation. The control system need to address process disturbances and to consider the operational constraints as well. The new control structure must also inexpensively integrate the team experience and operational knowledge within it. The approach should require as little retrofitting as possible, that is to build on existing infrastructure and expertise as much as possible, as this reduces cost, training requirements and simplifies validation.

Chapter 7

CONTROL SYSTEM DESIGN

This chapter presents and implements a feasible control structure solution based on MPC for the two control problems, discussed in chapter (3), affecting gas phase train in the existing oil and gas production plants. These problems are: control system operator dependency [2] and disturbance growth in a series connected process [31, 8]. In reality, many industries do not necessarily need new control algorithms, but rather improved usability of existing technologies to allow a limited workforce of varying experience to easily commission, operate and maintain these valued applications. This work examines the integration of small size MPC's with the classical PID control system to handle interactive control loops in three series gas treatment processes.

Upstream gas plants typically encompass a large physical area, with tens of compressors, pumps, vessels and hundreds of measuring sensors, control instruments and valves. Companies employs number of staff to work as control room operators. Their main task is to monitor the process deviation and amend the controllers reference values via a Distributed Control System (DCS) network to achieve safe and profitable optimal plant operation. The plant control optimisation and problem solution are totally dependent on the respective operators' efficiency and significantly, also on their speed of observation at the time a process deviates from one operation scenario to another as proven by Jipp et al. (2011) [37]. Operators have a propensity for working inside their customary range of familiarity and their choices can be overstated by the control room environment and the sudden assigned obligations and duties.

Most of the upstream oil and gas production plants are primarily utilising established PID control laws to manage process variables. The risk here arises from the absence of coordination between controllers on the grounds that every controller needs to adapt alone in meeting its goals with the exception of the situations where a cascade approach is applied. Additionally, PID cannot easily deal with process constraints, does not implicitly include feedforward information and has a great difficulty in controlling multivariable and complex dynamics systems [38] such as control of fractionation columns, compressor surge control or crude stabiliser column control. These units contain a number of interactive control loops and accordingly, it is often hard to tune SISO loops to control such processes adequately. Nevertheless, in practice these process are often controlled using simple control strategies with one consequence being that their performance and stability are sensitive to disturbances and load changes. Therefore, a pragmatic control approach for brownfield processes, where most of the gas treatment processes are accomplished, is needed. Practically, a successful approach must build on existing infrastructure and expertise.

The chapter starts by illustrating the proposed feasible control solution of the gas train followed by a brief description and solution to the MIMO loop interaction challenges. The overall controller methodology is then presented step by step starting by PID controllers design in section 7.3 followed by inner loop controllers design and matrix fraction description equation computation in section 7.4. MPC algorithim construction is shown in section 7.5 accompanied by the design of the feedforward loops and constraints. Section 7.7 presents the control analysis and simulation plans. While, the following two sections provides the experimental results of the proposed control structure performance in confronting sudden feed change disturbance and process unit malfunction to analyse control performance (section 7.8) and constraint handling (section 7.9). Section 7.10 revisits the pre set thesis aims and discusses the achievements. Finally, discussions and conclusions are presented in the last section.

7.1 Proposed Control System

There are many control system structure proposals in the literature - and indeed already being used in practice - which are likely to be feasible for greenfield projects but not necessarily for brownfield ones. The feasibility of retro-fitting a new control structure is influenced by factors like project cost, system simplicity, process safety, running cost, and anticipated gains compared with the existing control system. Forbes et al. (2015) [26] concluded that “Many industries do not necessarily need better algorithms, but rather improved usability of existing technologies to allow a limited workforce of varying expertises to easily commission, use and maintain these valued applications”. Critically, from an operational standpoint, the feasible control solution to enhance the current classical control system in the existing oil and gas plants must also inexpensively integrate the team experience and operational knowledge within it.

Chapter (4) provides what is considered to be a more pragmatic alternative. The concept, of the feasible solution, integrates small size MPC’s with the classical control system to handle the interactive control loops in each process. The proposed control system, as it is sketched in Fig. 7.1, integrates MPC as a master controller in the existing classical control of each subsystem. The MPC receives system measurements from the process sensors to compute the subsystem optimal control actions and provide local control goals as set-points (SP) for the critical PID controllers only (high interaction control loops) while accounting for all process interactions. The MPC also receives system units status from the process safeguarding system to dynamically update the system constraints. However, a key proposal is that the MPC shares information like the next control move with its neighbour controllers to enhance the disturbance rejection and consequently the plant-wide optimal performance.

The proposed control system is designed on a cascade strategy and thus provides a flexible system control almost like a decentralised structure in dealing with disturbances and unit failures, and at the same time improves the closed loop performance

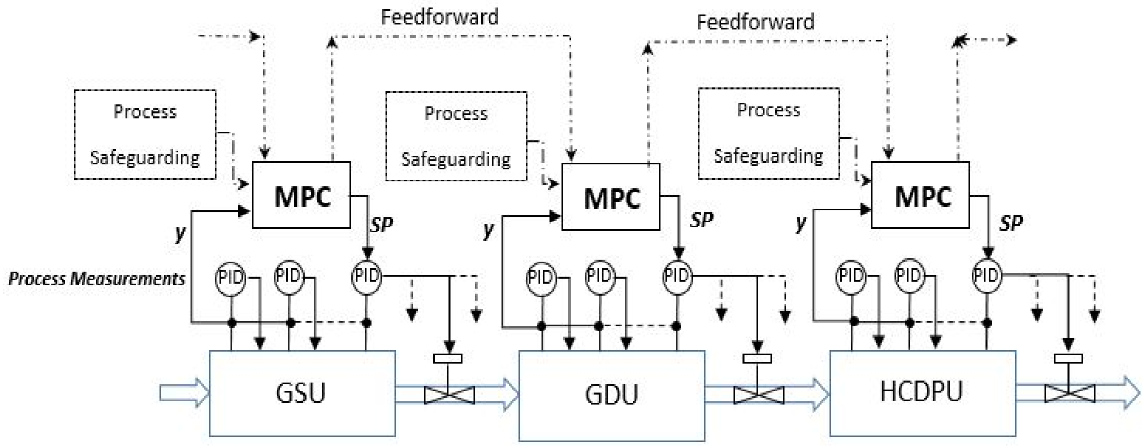


Figure 7.1: Integration of MPC with classical control

and the plant-wide optimal operation. The MPC's are designed to regulate the critical loops only while the rest of the uncritical PID loops will continue to function in a decentralised fashion. This minimises any design and set up costs, reduces demand on the communication network and simplifies any associated real time optimisations. The improved local control will reduce the need for control room operator interactions with their associated weaknesses. The one way communication from the process safeguarding enables prompt response to disturbances caused by unit failures, while the communications with adjacent MPC's in effect enables feed-forward to reduce the impact of process disturbances and enhance optimality.

7.2 Challenges and Solutions of MIMO Loops

Gas processing trains encompass three or more complex dynamic processes connected in series. In practice these processes are coupled and contain a number of interactive control loops which are usually to be controlled by conventional PID control laws. The potential drawback being that their performance and stability are sensitive to disturbances and load changes [38]. Despite the vast array of PID tuning methods [67, 64], tuning MIMO PID controllers is still difficult and may not give good solutions [38].

Poorly tuned interacting controllers severely limits the best achievable closed loop performance and thus incur extra operational costs [14].

In the other side, MPC has become a standard approach due to its ability to deal with process constraints and multivariable systems. Accordingly, it is popularity in the chemical process industries has increased steadily [26]. However, there are also drawbacks to the use of a single MPC to control either an entire MIMO system in a centralised fashion; or a MIMO subsystems in a decentralised approach which were thoroughly discussed in chapter (4).

One obvious solution is to break up the control problem into subsystems and then separate SISO loops from the MIMO ones. SISO loops normally have no or low interactions with other loops. Henceforth, it will continue to be controlled by PID's as usual. Whereas the control of all MIMO loops in each subsystem will be indirectly allocated to a local MPC which in turn works as a master controller to regulate slave PID controllers that manipulates interactive control variables. Local MPC's cooperates with the neighbouring system controllers by communicating their predicted process outputs $(\underset{\to k}{\mathbf{y}})_n$ in order to account for interactions between coupled processes.

7.3 PID Controllers Setting

The control strategy of each subsystem incorporates two SISO PID controllers in the inner control loops and one small MPC of dimension (2X2) in the outer loop. These PID controllers, categorised as critical PID's, regulates the intermediate flow control valves between the subsystems. They were designed by aid of 'MATLAB' software and their settings are listed in table 7.1.

Table 7.1: PID Controllers Settings

Unit	Tag No	Description	K_p	K_i
GSU	FIC-1	GSU Outlet Flow	-0.09	-0.005
	QIC-1	H_2S Concentration	0.05	0.004
GDU	FIC-3	GDU Outlet Flow	-0.02	-0.005
	QIC-2	H_2O Concentration	0.02	0.001
HCDP	FIC-5	Export Flow	0.06	0.15
	PIC-2	Export Pressure	-0.25	-0.05

7.4 Inner Loops PID Controllers Design

The master MPC's in each system are multivariable Generalised Predictive Controllers (GPC) whose prediction is based on a matrix fraction description (MFD). Hence, in order to illustrate the problem of controlling multivariable processes with different dead times by PID's and MPC, a representative LMFD (Left Matrix Fraction Description) equations representing the inner loop control of each system must be computed first. Two 'MATLAB' codes were written for this purpose. The first creates LMFD equations from a continuous process model (Appendix A). While, the second creates LMFD equations to represent a model with it's relevant SISO PID controllers (Appendix B). The computation steps to obtain the systems LMFD equations are illustrated in the following subsections.

7.4.1 GSU

The GSU process, shown in Fig 5.2, has two variables that have to be controlled: the throughput gas flow measured by the flow meter *FIC-1* and the acid concentration in the gas outlet measured by the process analyser *QIC-1*. The manipulated variables are the absorber gas outlet flow through *FCV-1* and the absorber sulfinol input flow through *FCV-2*. The specification of the acid concentration in the outlet gas is fixed by operational goals and must be kept within 0.5% of its setpoint at steady state. The dynamics of the process are described as follows:

$$\begin{pmatrix} Y_1 \\ \\ Y_2 \end{pmatrix} = \begin{pmatrix} \frac{-13.5}{18.6s+1}\, e^{-2s} & \frac{16.7}{23.5s+1}\, e^{-6s} \\ \\ \frac{7.3}{9.5s+1}\, e^{-13s} & \frac{20}{15.4s+1}\, e^{-6s} \end{pmatrix} \begin{pmatrix} U_1 \\ \\ U_2 \end{pmatrix} \tag{7.1}$$

Where Y_1 and Y_2 corresponds to the outlet gas flow rate and acid concentration in the gas, whereas U_1 and U_2 corresponds to absorber gas outlet flow and sulfinol input flow respectively.

The discrete transfer matrix for a sampling time of one minute is:

$$G_{GSU} = \begin{pmatrix} \frac{-0.7066z^{-1}}{1-0.9477z^{-1}}\, z^{-2} & \frac{0.7294z^{-1}}{1-0.9001z^{-1}}\, z^{-6} \\ \\ \frac{0.6957z^{-1}}{1-0.9583z^{-1}}\, z^{-13} & \frac{1.257z^{-1}}{1-0.9371z^{-1}}\, z^{-6} \end{pmatrix} \tag{7.2}$$

After defining the GSU model in the discrete form, gas flow and acidic gas concentration PID controllers are then constructed by the *PID* command in 'MATLAB'. Please refer to (Appendix B) for the detailed 'MATLAB' code file, specifically written for the gas train processes.

The absorber gas throughput PID controller C_{FIC1} is given by:

$$C_{FIC1} = \frac{-0.09z + 0.085}{z - 1} \tag{7.3}$$

and the acid concentration in the gas PID controller C_{QIC1} is given by:

$$C_{QIC1} = \frac{0.05z - 0.046}{z - 1} \tag{7.4}$$

Then, the next step is to assign the PID controllers to the model. This is done by using *connect* command in 'MATLAB' as it is shown in the 'MATLAB' code file presented in (Appendix B). Thereafter, the left matrix fraction description equations (LMFD) can be extracted from the discrete state space system.

LMFD is the most popular transfer matrix representation of MIMO processes as it can be easily obtained by performing step or pulse tests to the plant. The MIMO transfer matrix of a CARIMA model is given by:

$$\mathbf{T}(z^{-1}) = \mathbf{A}(z^{-1})^{-1}\,\mathbf{B}(z^{-1})\,z^{-1} \tag{7.5}$$

Given a rational matrix $\mathbf{T}(z^{-1})$, the problem (eq. 7.5) can be solved, as described by Camacho et al. [13], by making matrix $\mathbf{A}(z^{-1})$ equal to a diagonal matrix with diagonal elements equal to the least common multiplier of the denominators of the corresponding row of the transfer function ($\mathbf{T}(z^{-1})$). Then, matrix $\mathbf{B}(z^{-1})$ can be easily calculated by:

$$\mathbf{B}(z^{-1}) = \mathbf{A}(z^{-1})\,\mathbf{T}(z^{-1})\,z \tag{7.6}$$

So, the resulting matrices of $\mathbf{A}(z^{-1})$ and $\mathbf{B}(z^{-1})$ will be in the following forms:

$$\mathbf{A}(z^{-1}) = \begin{pmatrix} A_{11} & 0 \\ 0 & A_{22} \end{pmatrix}$$

and

$$\mathbf{B}(z^{-1}) = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix}$$

Hence, the CARIMA model that represents the process with the inner loop control, shown in Fig 7.2, is:

$$\mathbf{A}(z^{-1})\,\mathbf{y} = \mathbf{B}(z^{-1})\,\mathbf{u}$$

Please note that, the MPC control signals ($\mathbf{u}$) manipulates the reference of the PID controllers ($\mathbf{r}$) as it is illustrated in Fig. 7.2.

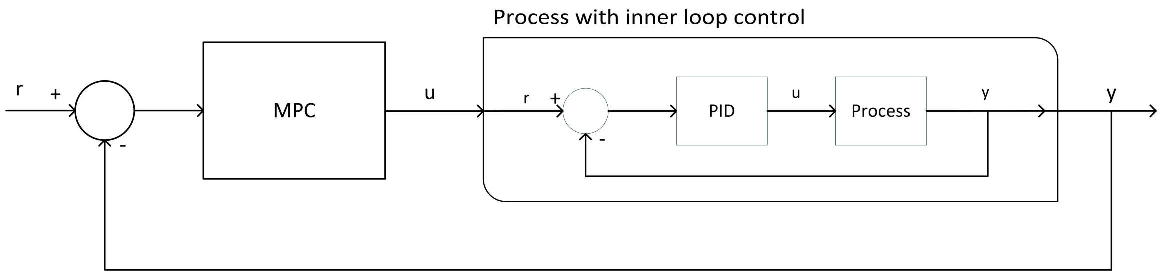


Figure 7.2: Process with Inner Loop Control

LMFD of the GSU model with the relevant inner loops PID controllers were computed by the purposely designed 'MATLAB' code to generate the LMFD equations of process models with their relevant SISO PID controllers. The 'MATLAB' code file is presented in (Appendix B). The generated LMFD equations of the GSU process model with the relevant inner loops PID controllers are:

$$
\begin{aligned}
A_{11}(z^{-1}) &= 1 - 5.6167z^{-1} + 13.1475z^{-2} - 16.4168z^{-3} + 11.5329z^{-4} - 4.3219z^{-5} \\
&\quad +0.6750z^{-6} \\
A_{22}(z^{-1}) &= 1 - 5.6167z^{-1} + 13.1475z^{-2} - 16.4168z^{-3} + 11.5329z^{-4} - 4.3219z^{-5} \\
&\quad +0.6750z^{-6} \\
B_{11}(z^{-1}) &= (0 + 0.0636z^{-1} - 0.2952z^{-2} + 0.5479z^{-3} - 0.5085z^{-4} + 0.2360z^{-5} \\
&\quad -0.0438z^{-6})z^{-2} \\
B_{12}(z^{-1}) &= (0 + 0.0348z^{-1} - 0.1637z^{-2} + 0.3079z^{-3} - 0.2896z^{-4} + 0.1361z^{-5} \\
&\quad -0.0256z^{-6})z^{-6} \\
B_{21}(z^{-1}) &= (0 - 0.0656z^{-1} + 0.3143z^{-2} - 0.6017z^{-3} + 0.5760z^{-4} - 0.2757z^{-5} \\
&\quad +0.0528z^{-6})z^{-13} \\
B_{22}(z^{-1}) &= (0 + 0.0629z^{-1} - 0.2909z^{-2} + 0.5381z^{-3} - 0.4976z^{-4} + 0.2300z^{-5} \\
&\quad -0.0425z^{-6})z^{-6}
\end{aligned}
$$

7.4.2 GDU

The GDU system, shown in Fig 5.3, has two variables that have to be controlled: the throughput gas flow measured by *FIC-3* and the water load in the gas outlet measured by the process analyser *QIC-2*. The manipulated variables are the contactor gas outlet flow through *FCV-3* and the contactor lean glycol input flow through *FCV-4*. The specification of the water content concentration in the outlet gas is fixed by operational goals and must be kept to within 0.5% of its setpoint at steady state. The dynamics of GDU are represented by the following model:

$$\begin{pmatrix} Y_1 \\ \\ Y_2 \end{pmatrix} = \begin{pmatrix} \frac{-8}{15s+1}\, e^{-3s} & \frac{19}{30.3s+1}\, e^{-7s} \\ \\ \frac{6.2}{13.5s+1}\, e^{-13s} & \frac{10}{16.7s+1}\, e^{-7s} \end{pmatrix} \begin{pmatrix} U_1 \\ \\ U_2 \end{pmatrix} \tag{7.7}$$

Where Y_1 and Y_2 corresponds to the outlet gas flow rate and water concentration in the gas. U_1 and U_2 corresponds to glycol contactor gas outlet flow and glycol input flow respectively.

The discrete transfer matrix for a sampling time of one minute is:

$$G_{GDU} = \begin{pmatrix} \frac{-0.5159z^{-1}}{1-0.9355z^{-1}}\, z^{-3} & \frac{0.4427z^{-1}}{1-0.9286z^{-1}}\, z^{-7} \\ \\ \frac{0.6168z^{-1}}{1-0.9675z^{-1}}\, z^{-13} & \frac{0.5812z^{-1}}{1-0.9419z^{-1}}\, z^{-7} \end{pmatrix} \tag{7.8}$$

The glycol contactor gas throughput PID controller C_{FIC3} is given by:

$$C_{FIC3} = \frac{-0.02z + 0.015}{z - 1} \tag{7.9}$$

While the water concentration in the gas PID controller C_{QIC2} is given by:

$$C_{QIC2} = \frac{0.02z - 0.019}{z - 1} \tag{7.10}$$

Thereafter, calculation of the LMFD equations representing the GDU model with the relevant inner loops PID controllers gives:

$$
\begin{aligned}
A_{11}(z^{-1}) &= 1 - 5.7516z^{-1} + 13.7837z^{-2} - 17.6176z^{-3} + 12.6663z^{-4} - 4.8569z^{-5} \\
&\quad +0.7760z^{-6} \\
A_{22}(z^{-1}) &= 1 - 5.7516z^{-1} + 13.7837z^{-2} - 17.6176z^{-3} + 12.6663z^{-4} - 4.8569z^{-5} \\
&\quad +0.7760z^{-6} \\
B_{11}(z^{-1}) &= (0 + 0.0103z^{-1} - 0.0471z^{-2} + 0.0859z^{-3} - 0.0781z^{-4} + 0.0354z^{-5} \\
&\quad -0.0064z^{-6})z^{-3} \\
B_{12}(z^{-1}) &= (0 + 0.0123z^{-1} - 0.0587z^{-2} + 0.1116z^{-3} - 0.1061z^{-4} + 0.0504z^{-5} \\
&\quad -0.0096z^{-6})z^{-7} \\
B_{21}(z^{-1}) &= (0 - 0.0089z^{-1} + 0.0407z^{-2} - 0.0746z^{-3} + 0.0682z^{-4} - 0.0311z^{-5} \\
&\quad +0.0057z^{-6})z^{-13} \\
B_{22}(z^{-1}) &= (0 + 0.0116z^{-1} - 0.0554z^{-2} + 0.1055z^{-3} - 0.1005z^{-4} + 0.0479z^{-5} \\
&\quad -0.0091z^{-6})z^{-7}
\end{aligned}
$$

7.4.3 HCDP

The HCDP process, shown in Fig 5.4, has two variables to be controlled to maintain the product quality, these are: unit pressure measured by *PIC-2* which is located at the gas outlet of the condensate flush drum and the load demand on the unit measured by *FIC-5*. The manipulated variables are: the re-compressor outlet flow measured through *FCV-5* and the expander inlet flow through *IGV* (Inlet Guide Vanes). The dynamics of the Turbo Expander are represented by the following model:

$$
\begin{pmatrix} Y_1 \\ \\ Y_2 \end{pmatrix} = \begin{pmatrix} \frac{0.2e^{-s}}{2s^2+4s+1} & \frac{1}{2s+1} \\ \\ \frac{0.3e^{-0.5s}}{0.4s^2+s+1} & \frac{-0.3e^{-1.3s}}{0.1s^2+3s+1} \end{pmatrix} \begin{pmatrix} U_1 \\ \\ U_2 \end{pmatrix} \tag{7.11}
$$

Where Y_1 and Y_2 corresponds to the export gas flow rate and gas pressure of the condensate flush drum, whereas U_1 and U_2 corresponds to compressor outlet flow and the expander inlet flow respectively.

The discrete transfer matrix is:

$$G_{HCDP} = \begin{pmatrix} \frac{0.009108z^{-1}+0.006533z^{-2}}{1-1.29z^{-1}+0.3679z^{-2}}\ z^{-2} & \frac{0.06139z^{-1}+0.04031z^{-2}}{1-0.9475z^{-1}+0.2865z^{-2}} \\ \\ \frac{0.2212z^{-1}}{1-0.7788z^{-1}}\ z^{-1} & \frac{-0.04362z^{-1}-0.002914z^{-2}}{1-0.8449z^{-1}+3.059e-07z^{-2}}\ z^{-3} \end{pmatrix} \tag{7.12}$$

The export gas flow rate PID controller C_{FIC5} is given by:

$$C_{FIC5} = \frac{-0.06z + 0.015}{z-1} \tag{7.13}$$

While the expander gas outlet pressure PID controller C_{PIC2} is given by:

$$C_{PIC2} = \frac{-0.25z + 0.225}{z-1} \tag{7.14}$$

Calculation of the LMFD equations representing the GDU model with the relevant inner loops PID controllers gives:

$$\begin{aligned}
A_{11}(z^{-1}) &= 1 - 5.8494z^{-1} + 14.8344z^{-2} - 21.3224z^{-3} + 19.0258z^{-4} - 10.8133z^{-5} \\
&\quad +3.8324z^{-6} - 0.7765z^{-7} + 0.0691z^{-8} - 0.0001z^{-9} \\
A_{22}(z^{-1}) &= 1 - 5.8494z^{-1} + 14.8344z^{-2} - 21.3224z^{-3} + 19.0258z^{-4} - 10.8133z^{-5} \\
&\quad +3.8324z^{-6} - 0.7765z^{-7} + 0.0691z^{-8} - 0.0001z^{-9} \\
B_{11}(z^{-1}) &= (0 + 0.0005z^{-1} - 0.0012z^{-2} + 0.0005z^{-3} + 0.0005z^{-4} - 0.0005z^{-5} \\
&\quad +0.0001z^{-6})z^{-2} \\
B_{12}(z^{-1}) &= (0 - 0.0553z^{-1} + 0.2755z^{-2} - 0.5819z^{-3} + 0.6765z^{-4} - 0.4688z^{-5} \\
&\quad +0.1944z^{-6} - 0.0448z^{-7} + 0.0044z^{-8}) \\
B_{21}(z^{-1}) &= (0 + 0.0037z^{-1} - 0.0111z^{-2} + 0.0098z^{-3} + 0.0010z^{-4} - 0.0054z^{-5} \\
&\quad +0.0020z^{-6} + 0.0002z^{-7} - 0.0001z^{-8})z^{-1} \\
B_{22}(z^{-1}) &= (0 + 0.0109z^{-1} - 0.0527z^{-2} + 0.1077z^{-3} - 0.1207z^{-4} + 0.0795z^{-5} \\
&\quad -0.0303z^{-6} + 0.0058z^{-7} - 0.0002z^{-8} - 0.0001z^{-9})z^{-3}
\end{aligned}$$

7.5 MPC Algorithm

All MPC's in Fig. 7.1 are multivariable Generalised Predictive Controllers (GPC) whose prediction is based on a MFD. The proposed control algorithm for each MPC in the process sup-systems, presented in Fig. 7.1, is:

$$\underset{\rightarrow k+1}{\mathbf{y}}^{[i]} = H\Delta \underset{\rightarrow k}{\mathbf{u}}^{[i]} + P\Delta \underset{\leftarrow k-1}{\mathbf{u}}^{[i]} + Q \underset{\leftarrow k}{\mathbf{y}}^{[i]} + \underset{\leftarrow k}{\mathbf{D}_n}^{[i]} \tag{7.15}$$

where:

- $\underset{\rightarrow k+1}{\mathbf{y}}$ the vector of output predictions, $\Delta \underset{\rightarrow k}{\mathbf{u}}$ the vector of optimised input predictions, $\Delta \underset{\leftarrow k-1}{\mathbf{u}}$ is a vector of past control increments and $[i]$ represents the process being controlled whether it is GSU, GDU, or HCDPU.
- H, P, and Q are prediction matrices (see equation 2.18).
- $\underset{\leftarrow k}{\mathbf{D}_n}$ is the feed forward term representing the disturbances caused by the neighbouring systems' interactions. Feed-forward term ($\mathbf{D}_n$) is defined in section (7.5.1).

The GPC control law is then determined from a minimisation of a two norm measure of predicted performance:

$$\underset{\Delta \underset{\rightarrow k}{\mathbf{u}}}{min} \quad J = \|\underset{\rightarrow k}{\mathbf{r}}^{[i]} - \underset{\rightarrow k}{\mathbf{y}}^{[i]}\|_2^2 + \lambda\|\Delta\underset{\rightarrow k}{\mathbf{u}}^{[i]}\|_2^2 \tag{7.16}$$

Consequently, the GPC control law is defined by the first element of $\Delta u_k = \mathbf{e}_1^T \Delta \underset{\rightarrow}{\mathbf{u}}$, $\mathbf{e}_1^T = [I, 0, 0, ..., 0]$:

$$\Delta \mathbf{u}_k = \mathbf{e}_1^T (H^T H + \lambda I)^{-1} H^T [\underset{\rightarrow k}{\mathbf{r}}^{[i]} - P\underset{\leftarrow k}{\mathbf{y}}^{[i]} - Q\Delta \underset{\leftarrow k-1}{\mathbf{u}}^{[i]} - \underset{\leftarrow k}{\mathbf{D}_n}^{[i]}] \tag{7.17}$$

Please note that, The MPC control signals ($\mathbf{u}$) equals to ($\mathbf{r}_{PID}$) the reference of the internal PID controllers.

7.5.1 Feed forward loops ($\boldsymbol{D}_n$)

The SISO PID control scheme, currently used to operate the oil and gas upstream plants, does not have a feed forward built into their algorithms that measures disturbances in advance. Instead the control system depends on a human operator to observe, and sometimes predict, process disturbances and compensate for the errors by amending PID controllers set-points. Generally, operators have great knowledge about their plant which enables them to predict, for a short horizon, the plant's future path. Actually, this type of control is a reactive strategy rather than a predictive one and it is not enough to operate the process in a safe and optimal manner, as discussed earlier in chapter (3). As an alternative, the feed forward option needs to be based on a mathematical model of the process that can measure the disturbances and predict their associated effects. Advanced knowledge about feed disturbances will enable the control algorithm to properly control the process.

Advance knowledge provided by integration of the feedforward loops in the control algorithm are expected to improve the speed and accuracy of the control actions. A well thought out feedforward control law will substantially reduce the effects of disturbances on the successor or predecessor systems. Hence, reducing valve hysteresis, equipment wear and tear and maintenance costs. Nevertheless, the major anticipated benefits of the feedforward control include considerable reduction in energy consumption as well as enhanced stability and reliability of the process.

The main aim here is to design a simple and systematic control algorithm and at the same time efficient one which is easily be understood by the industrial control engineers and operation team. In fact, the main reasons preventing uptake of MPC control schemes in the upstream oil and gas plants are their complexity and difficulty to troubleshoot. Taking account of this perspective, the feedforward law should be as simple as possible, without compromising the efficiency, in order to reduce the complexity of the overall control algorithm.

Referring to eq. (7.15), the feed forward term $\mathbf{D}_n$ is designed based on the process reaction to any inputs or disturbances the system might receive. Typically, gas flow rates should match for each process in the train. Predicted process outputs, forwarded by predecessor MPC's, $(\underset{\rightarrow k}{\mathbf{y}})_n$ are continuously used to estimate the future interaction between subsystems. Scaling factor matrices ($\mathbf{L}$) account for the severity of that process interaction on the current system, hence:

$$\mathbf{D}_n = \mathbf{L}^{[i]}[(\underset{\rightarrow k}{\mathbf{y}})_n - \underset{\rightarrow k}{\mathbf{r}}] \tag{7.18}$$

where $\underset{\rightarrow}{\mathbf{r}}$ is the future reference of the current process.

The scaling factor matrices ($\mathbf{L}$) are influenced by the strength of interactions between the relevant subsystems and can be computed by modelling the disturbance effects in the series processes. Gas quality of a predecessor process does not influence the successor system behaviour but the gas flow rate does. Gas flow rate is the common controlled variable in all gas train processes. Fluctuations of the gas flow rate in a predecessor process have the potential to cause a sequence of disturbances in the successor processes. To demonstrate the effects, an almost 50% disturbance had been introduced to the GSU gas flow rate; and the effects on the successor processes gas flow rates are trended in Fig. 7.3.

Gas train process disturbance simulation showed that, the disturbance in the GDU gas flow rate is about 82% of the GSU gas flow rate peak magnitude where the disturbance was generated. Whereas, HCDPU gas flow rate was disturbed by about 25% of the GDU gas flow rate peak magnitude. Hence, a representative scaling factor for each process can be designed based on this results. Simple design of scaling factors are preferred to reduce the overall control algorithm complexity. The simplest and efficient, efficiency will be demonstrated in later suctions, scaling factors found to be:

$$\mathbf{L}^{[GDU]} = \begin{pmatrix} 0.82 & 0 \\ & \\ 0 & 0 \end{pmatrix}, \; and \quad \mathbf{L}^{[HCDPU]} = \begin{pmatrix} 0.25 & 0 \\ & \\ 0 & 0 \end{pmatrix} \tag{7.19}$$

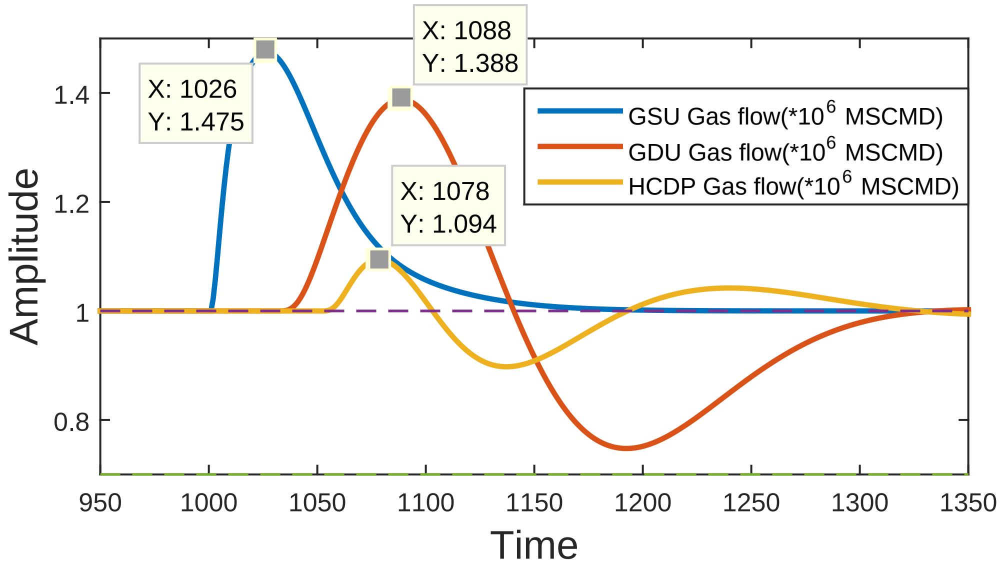


Figure 7.3: Process disturbance simulation of the gas train

7.5.2 Process constraints

Process constraints can be applied on control input increments, control input amplitude and process output signal. These constraints can be described, respectively, by:

$$\underline{\Delta \mathbf{u}} \leq \Delta \mathbf{u}_k \leq \overline{\Delta \mathbf{u}}\,, \quad \forall k$$
$$\underline{\mathbf{u}} \leq \mathbf{u}_k \leq \overline{\mathbf{u}}\,, \quad \forall k$$
$$\underline{\mathbf{y}} \leq \mathbf{y}_k \leq \overline{\mathbf{y}}\,, \quad \forall k$$

Process constraints need to be included in the GPC optimisation, in order to continually compare the optimal predictions (8.25) with their limits over the prediction horizon in the cost function J. As described in section (2.6), the constraints acting on a process can be represented in terms of d.o.f. ($\Delta \mathbf{u}$). To incorporate the proposed control algorithm with the feedforward term ($\underset{\leftarrow k}{\mathbf{D}_n}$) in the constraints inequalities, lets express the output upper and lower constraints in the following form:

$$\underbrace{\begin{bmatrix} I \\ -I \end{bmatrix}}_{C_y} \underset{\rightarrow}{\mathbf{y}} \leq \underbrace{\begin{bmatrix} \overline{y} \\ -\underline{y} \end{bmatrix}}_{d_y} \tag{7.20}$$

Then, substitute $\underset{\rightarrow}{\mathbf{y}}$ from (8.25) into (7.20) which gives:

$$C_y \; H \underset{\rightarrow k}{\Delta \mathbf{u}} + C_y \; P \underset{\leftarrow k-1}{\Delta \mathbf{u}} + C_y \; Q \underset{\leftarrow k}{\mathbf{y}} + C_y \; \underset{\leftarrow k}{\mathbf{D}_n} \leq d_y \tag{7.21}$$

Then, the three sets of inequalities, input rate (2.64), input (2.70) and output (7.21), in a one compact form as follows:

$$\underbrace{\begin{bmatrix} C_{\Delta u} \\ C_u E \\ C_y H \end{bmatrix}}_{CC} \underset{\rightarrow}{\Delta \mathbf{u}} \leq \underbrace{\begin{bmatrix} d_{\Delta u} \\ d_u \\ d_y \end{bmatrix} - \begin{bmatrix} 0 \\ C_u L \\ 0 \end{bmatrix} \mathbf{u}_{k-1} - \begin{bmatrix} 0 \\ 0 \\ C_y P \end{bmatrix} \underset{\leftarrow k-1}{\Delta \mathbf{u}} - \begin{bmatrix} 0 \\ 0 \\ C_y Q \end{bmatrix} \underset{\leftarrow k}{\mathbf{y}}}_{dd} - \begin{bmatrix} 0 \\ 0 \\ C_y \end{bmatrix} \underset{\leftarrow k}{\mathbf{D}_n} \tag{7.22}$$

This is a convenient compact form in which the constraints inequalities are separated into constant part (CC) and time varying parts (dd) which updated every sample. Where the top block represent the input rate constraints, the middle block represents the input constraints and the bottom block represent the output constraints.

7.6 Control Algorithm Flow Chart

The control algorithm steps are explained by means of a flow chart shown in Fig. 7.4. The future inputs are computed to ensure convergence within the specified control horizon period while considering the process constraints. Also the disturbances caused by the neighbouring systems are being taken into account.

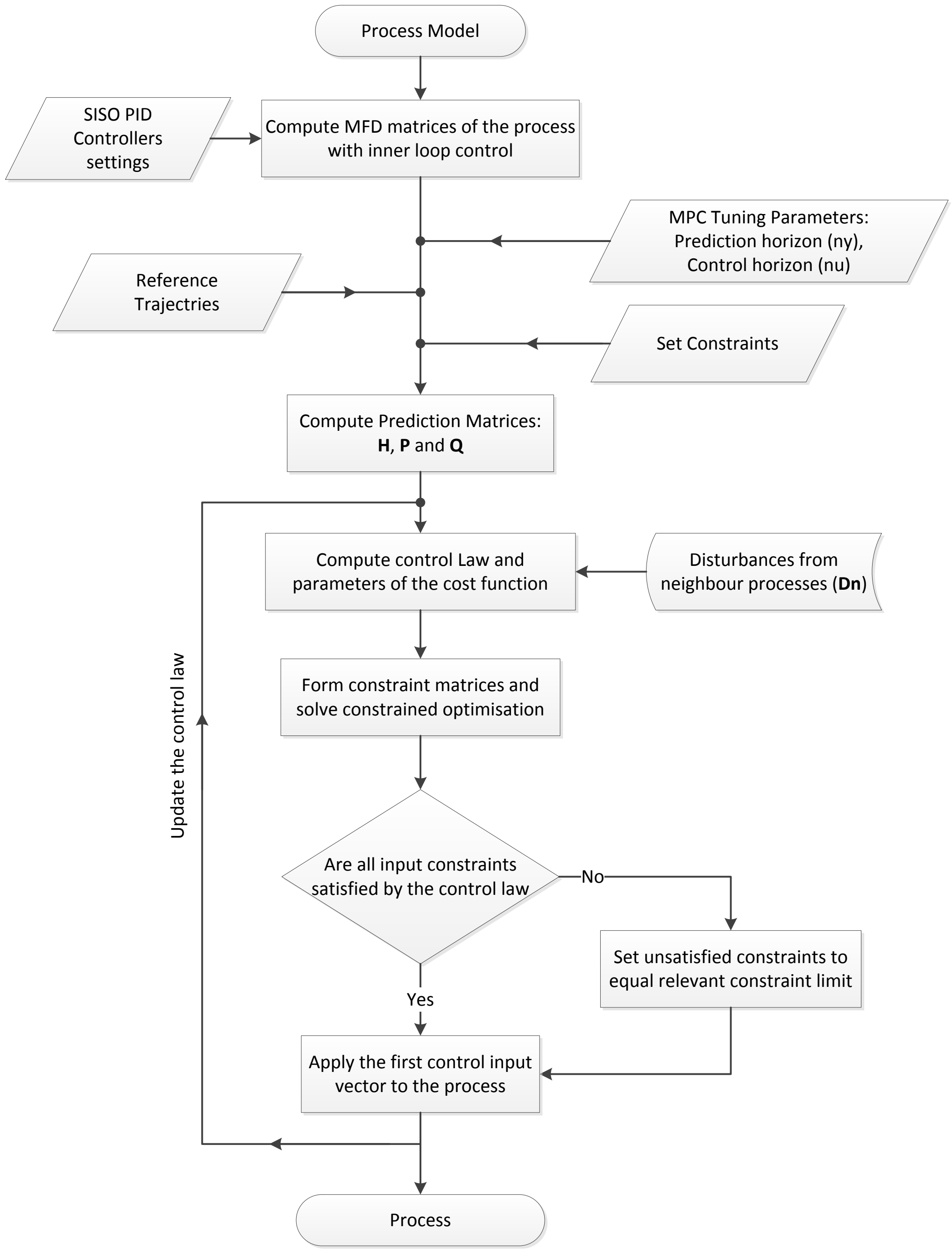


Figure 7.4: Flow chart of control algorithm

7.7 Control Analysis and Simulation Plan

The proposed control algorithm will then undergo a set of simulations for evaluation purposes. Different simulation scenarios that reflects the real process situations were carefully chosen to properly test and evaluate the proposed control algorithm in controlling the whole gas train processes. Process analysis and simulations map is presented in table 7.2 below:

Table 7.2: Control algorithm simulation plan

Type of Analysis	**Simulation**	**Results**		
		GSU	**GDU**	**HCDP**
Wide Process Control	Feed Disturbance	Fig. 7.5	Fig. 7.6	Fig. 7.7
	Process Disturbance	Fig. 7.8	Fig. 7.9	Fig. 7.10
Wide Process Control with Constraints	Process Disturbance	Fig. 7.11	Fig. 7.12	Fig. 7.13
	Feed Disturbance	Fig. 7.14	Fig. 7.15	Fig. 7.16

7.8 Wide Process Control Performance Analysis

The proposed control methodology was tested on the gas phase train model developed in chapter (5). The proposal was examined for two main causes of process disturbances (a sudden feed change and a process unit malfunction). The results are then compared against the current conventional control strategy that rely on a number of SISO PID controllers with the control room operator. At the same time, the comparison also highlights the benefits gained by adding and utilising the feed forward loops to the process control strategy.

7.8.1 *Feed Disturbance*

Process disturbances due to feed changes are common on upstream oil and gas plants and can be easily initiated by plant operators when changing process set points, or by an automated operation of process units like pumps, valves, compressors, etc. In practice, a well tuned PID control system supported by experienced plant operators is capable of handling most of these disturbances to some extent. However, there are circumstances when the feed disturbances have the potential to cause a significant process upset due to the complex interactions of the underlying process. The disruptive nature of sudden feed changes is more of an issue for a series connected processes with multi input multi output (MIMO) loops.

In order to analyse and compare the performance of the proposed control structure with the conventional one at a time of a sudden feed change, a 50% step up had been introduced to the gas flow setpoint of the GSU. Thereafter, the process responses of the conventional control system (operator + SISO PID), the proposed control system without feedforward (MPC + SISO PID), and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparisons between the three different control strategies. The consequences on each process of the gas train are presented in Fig. 7.5 for GSU; Fig. 7.6 for GDU; and Fig. 7.7 for HCDPU.

In summary, comparing the proposed control structures (with and without the feedforward) against the conventional control, the results show that the MPC's in the proposed control structures took prompt actions at the time of disturbance to regulate slave PID controllers set points simultaneously while accounting for all process interactions. Looking to the GSU variables presented in Fig. 7.5, it is noticeable that all control systems were capable to absorb the feed disturbance and properly control the unit. Conversely, the case is different in the GDU Fig. 7.6, and the HCDPU Fig. 7.7; where the proposed control structures (with and without the feedforward) are distinguished by their ability in reducing interactions, unlike the conventional control system. In other hands, the results also proves the benefits of adding feedforward loops to the proposed control structure by means of reduced overshoots and faster settling times in the GDU and the HCDPU.

Hereafter, to digest the outcomes presented in the figures, a detailed discussion of each process unit, controlled by three different control strategies, in response to the gas train throughput feed disturbance of +50% are presented in the following sub sections.

7.8.1.1 Feed disturbance

The GSU was exposed to a feed disturbance at sample 1000 where the reference of the gas flow increased from 1 *MSCMD* to 1.5 *MSCMD*. Therefore, the gas flow rate increased by 500,000 *SCMD* which is practically considered as a huge step up. In real life, operators will only increase by a maximum step of 0.2 *MSCMD*, during start up, or 0.1 *MSCMD*, at high flow rate, to account for disturbances in the whole gas train processes.

7.8.1.2 Impact of feed disturbance on GSU

The top set of Fig. 7.5 represents the GSU under conventional control. Both trends, the gas flow rate and gas quality, seems properly controlled with a maximum overshot of around 0.1 *MSCMD* in the gas flow rate.

The second set represents the GSU controlled by the proposed control system without feedforward (MPC + PID). Both controlled trends indicates very smooth control with no overshoots.

The third set represents the GSU controlled by the proposed control system with feedforward (MPC + FF + PID). The responses are identical to the second set because the disturbance were originated in the GSU, hence there are no feedforward information.

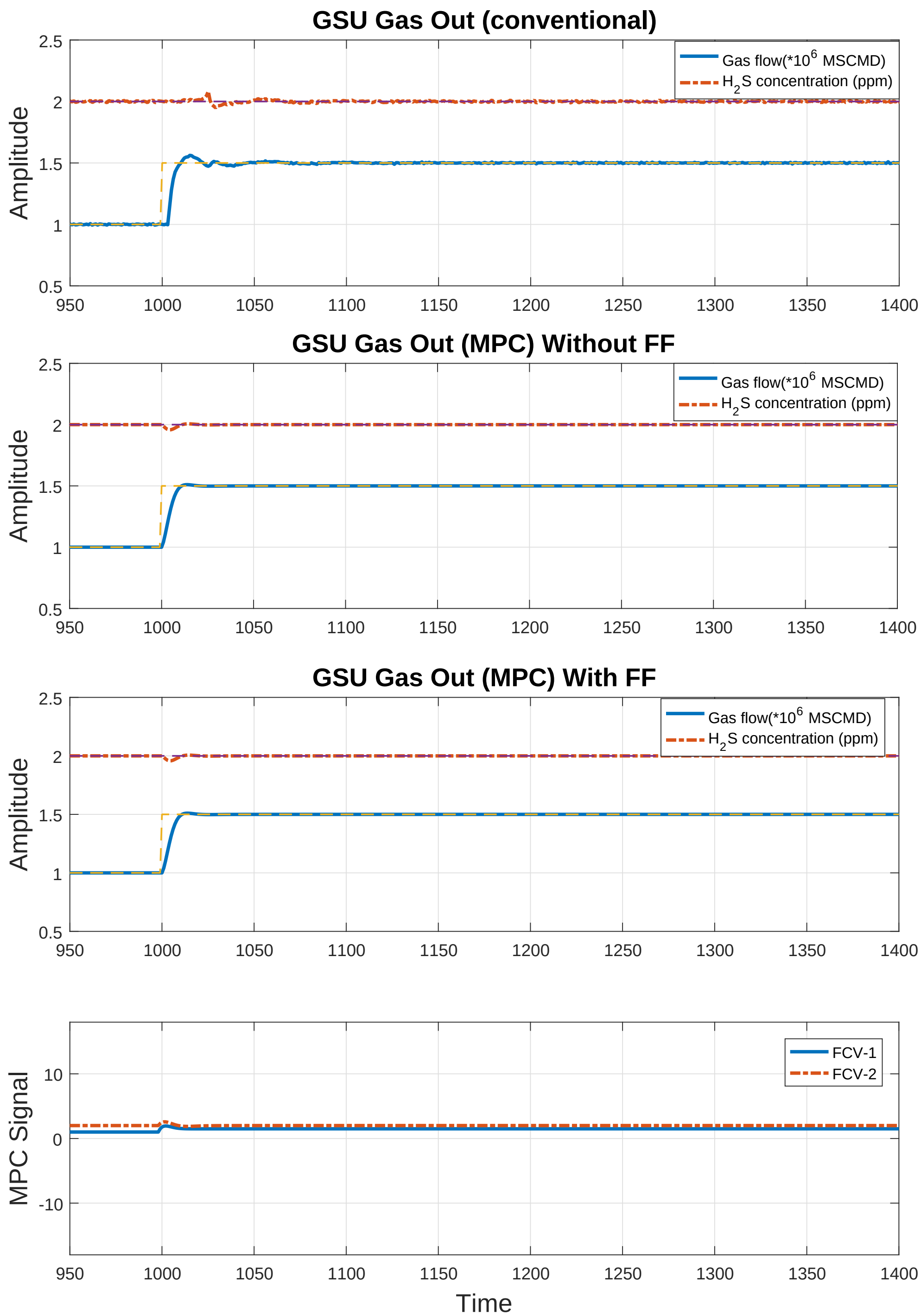


Figure 7.5: Comparison of GSU Process responses as a result of the 50% step increase in the (GSU) gas flow reference.

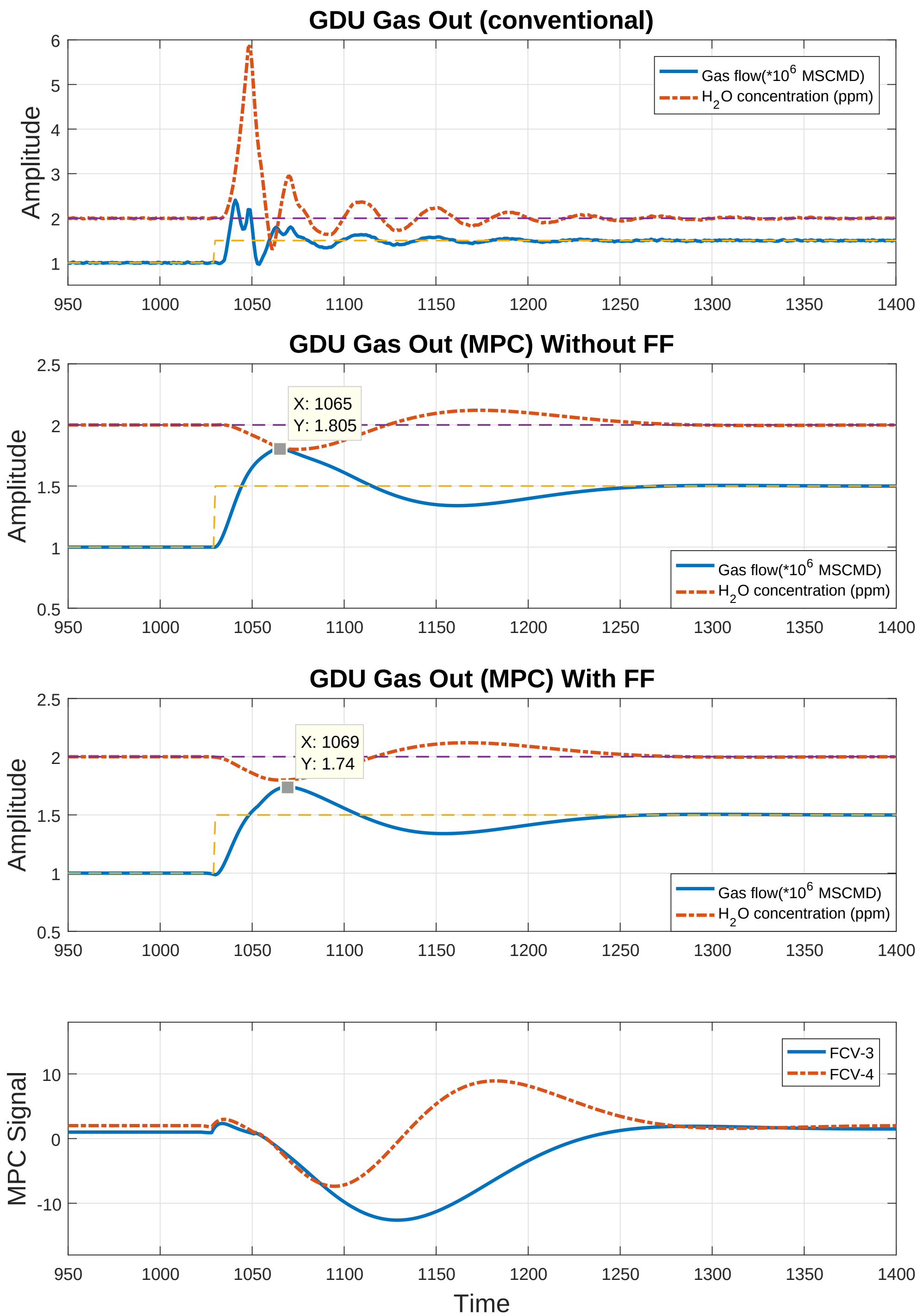


Figure 7.6: Comparison of GDU Process responses as a result of the 50% step increase in the (GSU) gas flow reference.

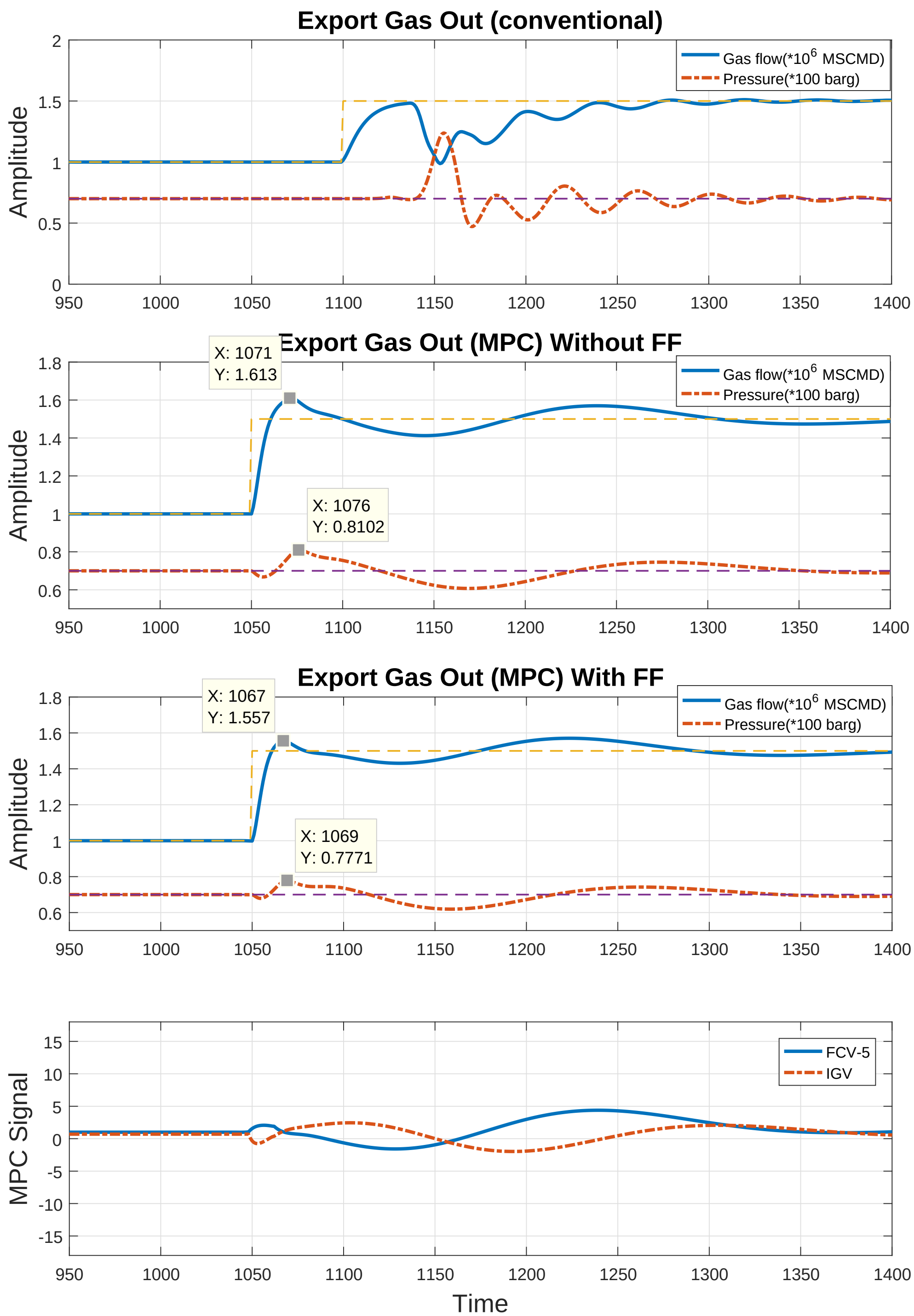


Figure 7.7: Comparison of HCDP Process responses following a 50% step increase in the (GSU) gas flow reference.

The fourth set shows the MPC control signal in the proposed control system with feedforward. MPC control signal slightly increased at the time of the disturbance and then idealised. This indicates that, MPC changes the reference value, behaving like an operator, while the main control task is carried out by the internal control loops.

7.8.1.3 Impact of feed disturbance on GDU

The top set of Fig. 7.6 represents the GDU under conventional control. As a response to the feed disturbance, the gas flow rate increased sharply to around 2.25 *MSCMD* and then dropped down to 1 *MSCMD* before it settles in a decaying oscillation to the new reference value. The water load in the gas also undergoes a massive disturbance, in response to the gas fluctuation which caused unbalanced operation of the unit.

The second set represents the GDU controlled by the proposed control system without feedforward (MPC + PID). The gas flow rate smoothly stepped up to the new reference with minimum process disturbance. As a result, the water load trend shows a minor disturbance only.

The third set represents the GDU controlled by the proposed control system with feedforward (MPC + FF + PID). The gas flow rate trend slightly reduced before the disturbance hit the GDU which indicates that the controller utilised the advanced knowledge provided by the feed forward loop. Compared with the second set, The gas flow overshoot was reduced from 20.3% to 16% which, in consequence, enhanced the settling time.

The fourth set shows the MPC control signal in the proposed control system with feedforward. MPC control signals, for both loops, altered the internal control loop references immediately after the feed disturbance on the GSU and before the disturbance shock reaches the GDU. This indicates that, the MPC controller was prepared for the disturbance. Hence, the outcome is a smooth and tailored control signal which, indeed, is beyond human operator capability.

7.8.1.4 Impact of feed disturbance on HCDP

The top set of Fig. 7.7 represents the HCDP unit under conventional control. As a response to the feed disturbance, the gas flow rate increased to around 1.5 *MSCMD* and then dropped down to 1 *MSCMD* before it gradually increased with oscillation to the new reference value. The gas pressure increased from 70 *bar* to 130 *bar*, considered dangerous pressure, before it settled in a decaying oscillation.

The second set represents the HCDP unit controlled by the proposed control system without feedforward (MPC + PID). The situation is totally different here. The gas flow rate smoothly stepped up to the new reference with minimum process disturbance. As a result, the pressure trend shows a minor disturbance only, with a maximum pressure of 81 *bar*.

The third set represents the HCDP unit controlled by the proposed control system with feedforward (MPC + FF + PID). In this case, the gas flow overshoot was only 3.8%, that's within the 5% settling time, compared to 7.53% in the second set. Also, the pressure trend overshoot was reduced from 15.74% to 11%. In other hands, both trends settling times were improved.

The fourth set shows the MPC control signal in the proposed control system with feedforward. Once again, MPC control signals altered the internal control loop references immediately after the disturbance being detected on the GDU and before it reaches the HCDP. This ensures that, the MPC controller was prepared for the disturbance and the outcome is a smooth control signals for both controlled variables.

7.8.1.5 Summary of feed disturbance impact on gas train

The following table summarises the feed disturbance results on the gas train processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

Table 7.3: Summary of feed disturbance impact on gas train

Unit			GSU	GDU	HCDP
Gas flow rate	% Overshoot	Operator + SISO PID	7	53	34
		MPC + SISO PID	0	20	7.5
		MPC + FF +SISO PID	0	16	3.8
	Settling time	Operator + SISO PID	13	125	170
		MPC + SISO PID	13	170	200
		MPC + FF +SISO PID	13	140	180
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	3	200	79
		MPC + SISO PID	0	10	15
		MPC + FF +SISO PID	0	10	11
	Settling time	Operator + SISO PID	0	165	210
		MPC + SISO PID	0	150	240
		MPC + FF +SISO PID	0	150	180

7.8.2 Process Unit Malfunction

Process disturbances caused by a process malfunction or a sudden unit shut down are a major issue facing oil and gas companies. Practically speaking, the effects vary from a minor missed production targets to a total plant shut down depending on the criticality of the affected units on the process and the fault type. Process unit malfunction is often an outcome of poor maintenance or harsh environment or simply a human mistake. It is worth mentioning that most oil and gas production plants are located either in deserts where they experience high ambient temperature changes between day and night and sand storm’s or in offshore environments where the operations are limited in space and fronting fickle ocean weather. The disruptive nature caused by a process unit malfunction is more problematic in a series connected processes with multi input multi output (MIMO) loops.

In order to compare the performance of the proposed control structure with the conventional one at a time of a sudden process unit malfunction, a 10% sulfinol solvent filter chock had been introduced to the solvent control loop of the GSU. Thereafter, the process responses of the conventional control system (SISO PID + operator), the proposed control system without feedforward (MPC + SISO PID), and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparison between the three different control strategies. The result consequences on GSU, GDU, and HCDPU are presented sequentially in figures 7.8, 7.9, and 7.10.

Once again, the MPC's in the proposed control structures (with and without the feedforward) took prompt actions at the time of process disturbance to regulate slave PID controllers set points simultaneously while accounting for all process interactions. In summary, GSU trends presented in Fig. 7.8 shows that, in the case of the conventional control there are a sharp increase of H_2S concentration by nearly 40% of its initial reference value and spikes on the gas flow rate as a direct result of the solvent filter chock. Whereas, the proposed solutions (with and without the feedforward) show a smooth control with no spikes in both trends. The proposed control structures (with and without the feedforward) in both GDU Fig. 7.9, and HCDPU Fig. 7.10 shows a smooth and neat control trends, unlike the spiky trends in the conventional control case.

The following sub sections provide discussion about each process unit, under three control strategies, in response to the GSU sulfinol solvent flow disturbance by mean of filter chock of 10%.

7.8.2.1 Process disturbance

The GSU was exposed to a process disturbance at sample 1000 where a 10% sulfinol solvent filter chock had been introduced to the solvent control loop.

7.8.2.2 Impact of process disturbance on GSU

The top set of Fig. 7.8 represents the GSU with conventional control. The gas quality trend show a sharp increase of H_2S concentration by nearly 40% of its initial reference value as a direct result of the disturbance. The gas flow rate had spikes with magnitude of 1.25 *MSCMD*.

The second set represents the GSU controlled by the proposed control system without feedforward (MPC + PID). Both controlled trends indicates smooth control with a maximum overshoots of 25% on the gas flow rate and less than 10% on the gas quality.

The third set represents the GSU controlled by the proposed control system with feedforward (MPC + FF + PID). The responses are identical to the second set because the disturbance were originated in the GSU, hence there are no feedforward information.

The fourth set shows the MPC control signal in the proposed control system with feedforward. MPC gradually changed the reference value of the gas quality internal loop controller as a response of the disturbance. This action indicates that, MPC changes the reference value, behaving like an operator, while the main control task is carried out by the internal control loops.

7.8.2.3 Impact of process disturbance on GDU

The top set of Fig. 7.9 represents the GDU under conventional control. Both controlled variables, the gas flow rate and the water load on the gas, undergoes steep short frequency oscillations with $\pm 50\%$ overshoot. In reality, such unbalanced operation well lead to shut down the unit.

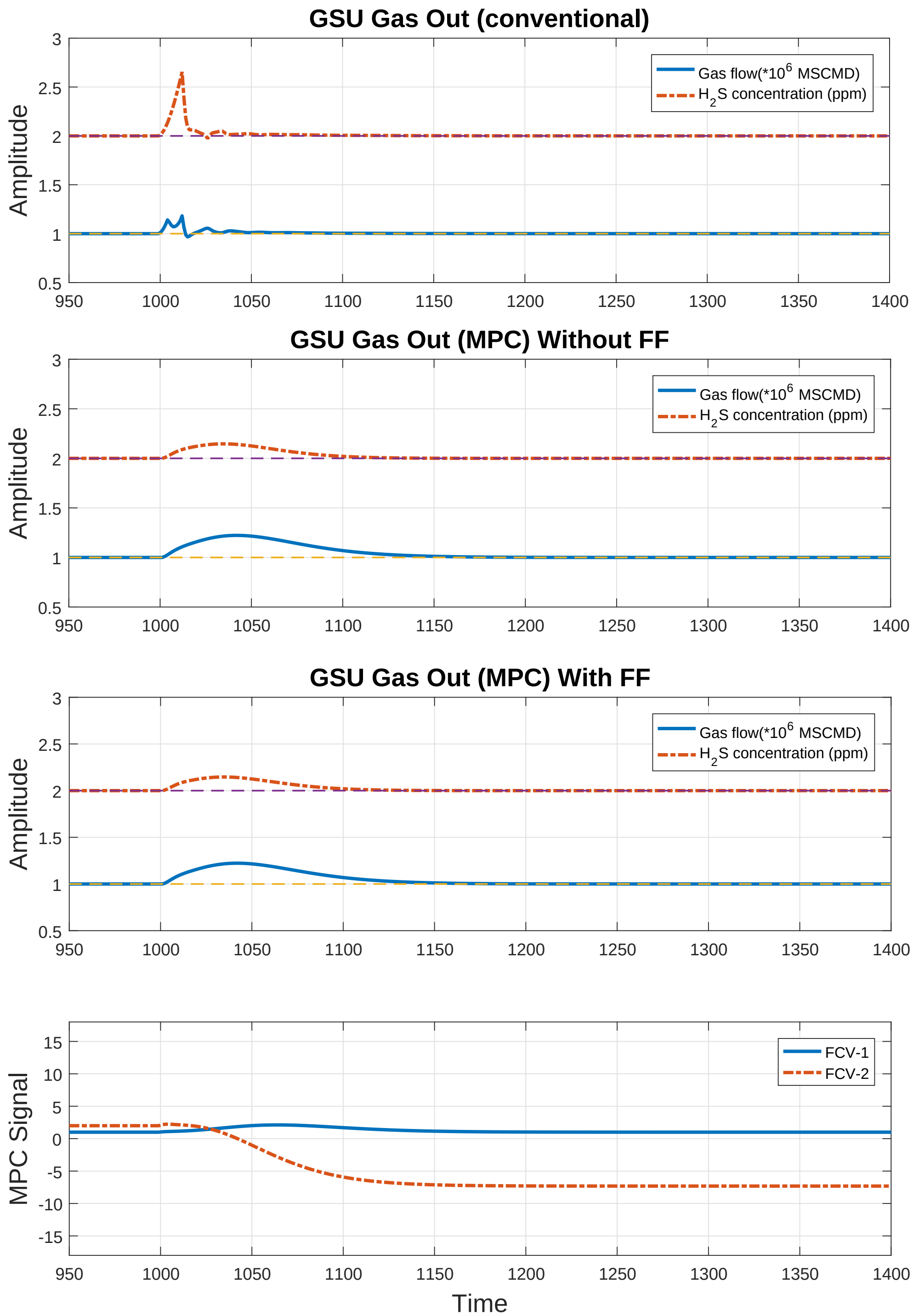


Figure 7.8: Comparison of GSU Process responses as a result of the 10% solvent filter chock in the (GSU).

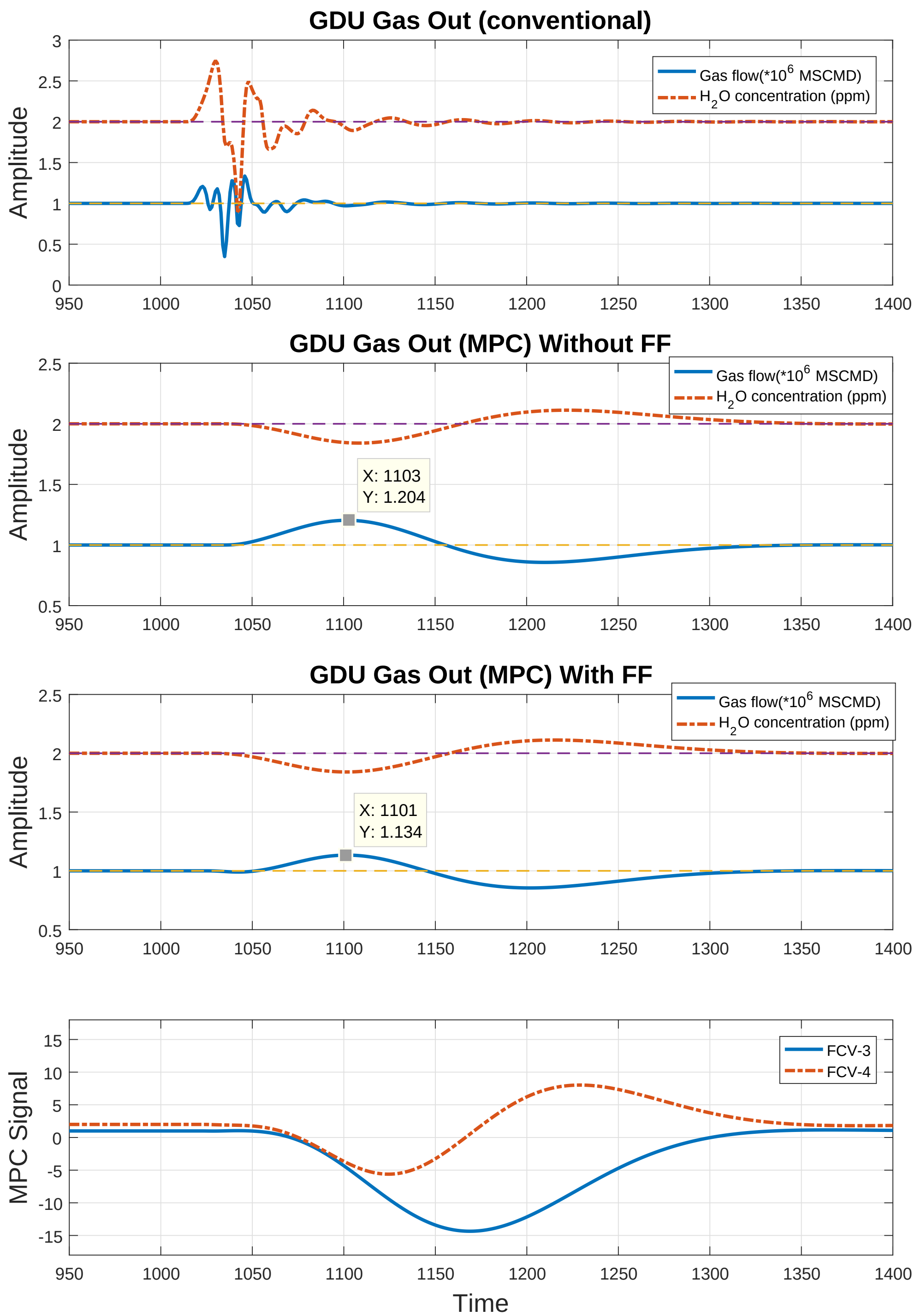


Figure 7.9: Comparison of GDU Process responses as a result of the 10% solvent filter chock in the (GSU).

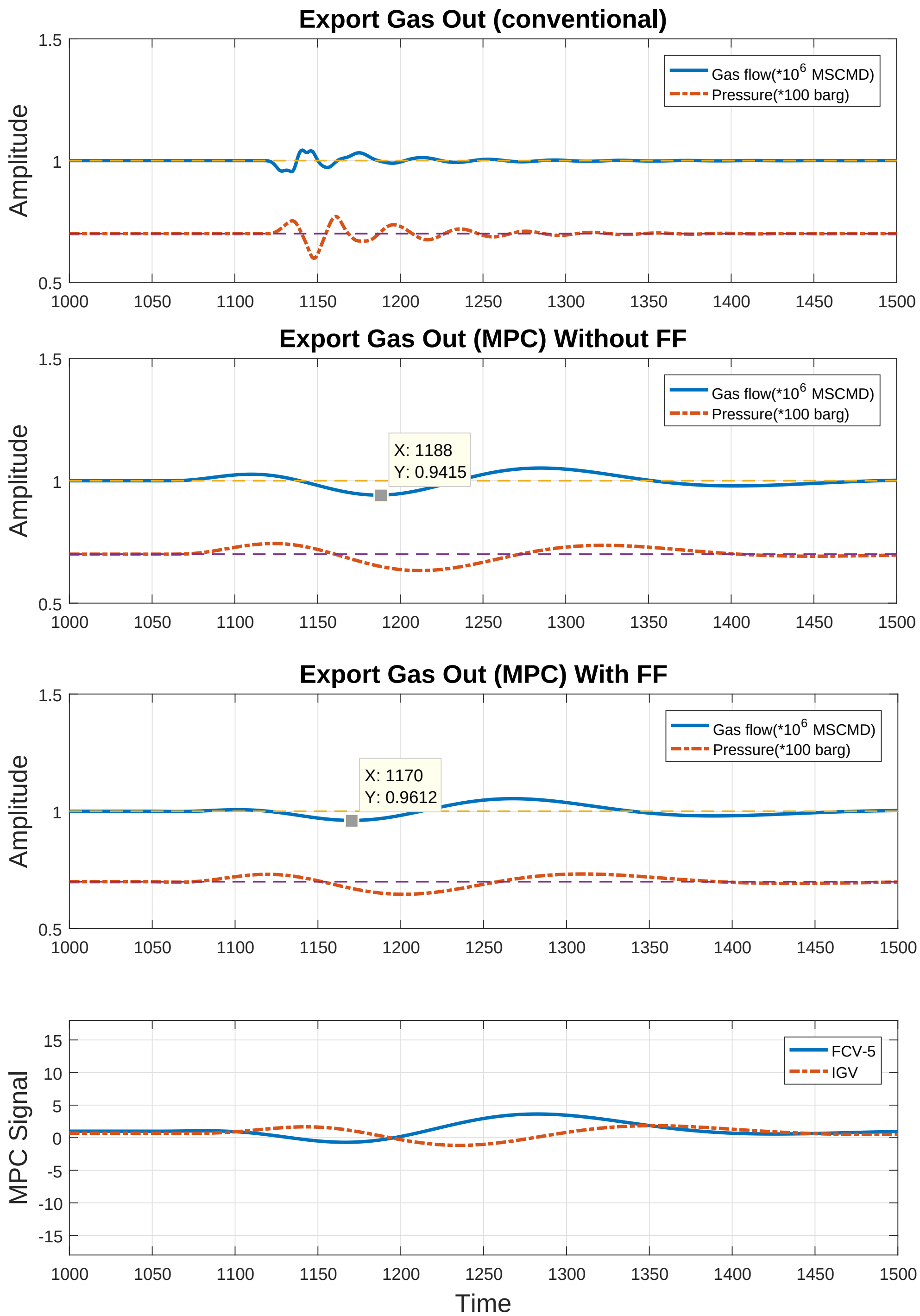


Figure 7.10: Comparison of HCDPU Process responses as a result of the 10% solvent filter chock in the (GSU).

The second set represents the GDU controlled by the proposed control system without feedforward (MPC + PID). The situation is totally different here. The gas flow rate were smoothly controlled with minimum process disturbance. As a consequence, the water load trend show a minor disturbance effect only.

The third set represents the GDU controlled by the proposed control system with feedforward (MPC + FF + PID). The gas flow rate trend slightly reduced before the disturbance hit the GDU which indicates that the controller utilised the advanced knowledge provided by the feed forward loop. Compared with the second set, the gas flow overshoot was reduced from 20.4% to 13.4% which, in consequence, speeds up the settling time.

The fourth set shows the MPC control signal in the proposed control system with feedforward (MPC + FF + PID). MPC control signals, for both loops, altered the internal control loop references just before the disturbance shock reaches the GDU. This indicates that, the MPC controller was prepared for the disturbance. Hence, the outcome is a smooth and tailored control signal which, indeed, is beyond human operator capability.

7.8.2.4 Impact of process disturbance on HCDP

The top set of Fig. 7.10 represents the HCDP unit under conventional control. As a response to the process disturbance, the gas flow rate undergoes a small magnitude decaying oscillations. Similarly, the gas pressure oscillates between 60 *bar* and 75 *bar* before it stabilised back at 70 *bar*.

The second set represents the HCDP unit controlled by the proposed control system without feedforward (MPC + PID). The gas flow rate is smoothly controlled with minimum disturbances. In consequence, the pressure trend show a minor disturbance only, with a maximum pressure of less than 80 *bar*.

The third set represents the HCDP unit controlled by the proposed control system with feedforward (MPC + FF + PID). The gas flow rate is smoothly controlled with less oscillations, compared to the second set, which indicates that the controller utilised the advanced knowledge provided by the feed forward loop. In this case, the gas flow undershoot was around 3.9%, that's within the 5% settling time, compared to 5.9% in the second set. Also, the pressure trend shows a minor disturbance only, with a maximum pressure of less than 75 *bar*. In other hands, both trends settling times were improved.

The fourth set shows the MPC control signal in the proposed control system with feedforward (MPC + FF + PID). Once again, MPC control signals altered the internal control loop references just after the disturbance being detected on the GDU and before it reaches the HCDP. This ensures that, the MPC controller was prepared for the disturbance and the outcome is a smooth control signals for both controlled variables.

7.8.2.5 Summary of process disturbance impact on gas train

Table 7.4 summarises the process disturbance results on the gas train processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

7.8.3 Discussion

Alongside the good control performance at the time of the disturbances, it is also noticeable from 'MPC Signal' trends in all units that, the processes are exclusively controlled by PID's during stable operations. However, at the time of the disturbances, MPC's takes the lead and command corrective actions. This means that the MPC behaves like an operator. During normal plant operation it is difficult for the operators to spot process deviations, due to large number of process control loops, until one of the alarm thresholds is triggered. At this point of time, it is too late for correcting actions and the situation will be like fire fighting. Unlike human operators, MPC works like a

Table 7.4: Summary of process disturbance impact on gas train

Unit			GSU	GDU	HCDP
Gas flow rate	% Overshoot	Operator + SISO PID	20	70	5
		MPC + SISO PID	25	20	5.8
		MPC + FF +SISO PID	25	13	3.9
	Settling time	Operator + SISO PID	30	60	50
		MPC + SISO PID	90	200	100
		MPC + FF +SISO PID	90	190	0
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	35	55	15
		MPC + SISO PID	10	10	6
		MPC + FF +SISO PID	10	9	4
	Settling time	Operator + SISO PID	35	165	100
		MPC + SISO PID	60	150	140
		MPC + FF +SISO PID	60	150	0

watch dog. When the process starts to deviate, and before the disturbance escalates, a small and smooth corrective signal will be enough to stabilise the process. Therefore, the results prove that the proposed control structure is capable to operate the plant thus eliminating the operator role. The results also prove the ability of the control structure to properly control the interactions between different processes in the plant during disturbances. The second outcome of this observation unveils a major advantage of the proposed control structure regarding the system availability during power failure. The MPC control layer is generally located in the auxiliary room in the control buildings, while the PID controllers are located in the process itself, therefore in the transmitters or valves housing. These different locations are normally powered from two different sources for safety reasons. So, if the MPC fails due to a power failure or a power dip in the control building, the internal loop controllers, PID's, will continue to operate the plant safely. Table 7.5 lists a summary of pros and cons of the different control strategies used in the study.

Table 7.5: Control Comparison Summary

<table>
<tr><th>Control Strategy</th><th colspan="2">Summary</th></tr>
<tr><td rowspan="2">Operator + SISO PID (Conventional Control)</td><td>Pros</td><td>Easy to design and troubleshoot</td></tr>
<tr><td>Cons</td><td>1- No coordination between controllers
2- Require a human operator presence to handle interactions between MIMO control loops during process disturbances
3- Operational and safety constraints can’t easily be set
4- Reactive control strategy</td></tr>
<tr><td rowspan="2">MPC + SISO PID (No Operator)</td><td>Pros</td><td>1- Does not depend on Operator
2- Efficient in dealing with MIMO and complex loops within the system
3- Constraints can easily be included in the optimisation
4- Reactive but can predict future process responses, so that it can professionally de-escalate disturbances effects
5- Can handle wider ranges of disturbances compared with the conventional control strategies
6- The control system builds on the existing field infrastructure
7- Saves power and reduces wastage due to off-specifications product
8- Significantly reduces process shutdowns occasions</td></tr>
<tr><td>Cons</td><td>1- MPC might be new to the operational crew
2- Instrumentations and control engineers will need training and hands on courses for MPC</td></tr>
<tr><td rowspan="2">MPC + FF + SISO PID (No Operator)</td><td>Pros</td><td>Same as (MPC + SISO PID) plus:
1- Can handle interactions between processes
2- Reduce overshoots and reduces process settling times
3- Provide anticipated control</td></tr>
<tr><td>Cons</td><td>1- MPC might be new to the operational crew
2- Instrumentations and control engineers will need training and hands on courses for MPC</td></tr>
</table>

7.9 Wide Process Control with Constraints

The process control performance was largely enhanced by implementing decentralised cooperative small MPC's in the control structure. Nevertheless, the process wide control performance can be further improved to maximise plant optimality, hence increase profitability rate, by inclusion of the process constraints in the control strategy. As discussed earlier, one major advantage of MPC is its systematic ability in dealing with multivariable constraints as they can simply be incorporated into the optimisation of the performance index. In gas train processes, there are number of operation and safety constraints such as maximum gas flow rate, maximum pressure and of course constraints that bound the quality of the processed gas. Integration of these constraints in the optimisation of the cost function ensures an optimal control input trajectory with respect to the system constraints.

In general, the most profitable operation points, of oil and gas plants, lie close to the constraint lines. For example, operating the plant at its maximum capacity, therefore close to the upper limit of the output constraint, increases the production rate but also makes the control system more vulnerable to disturbances. Hence, to avoid constraints violation, plants are usually operated at a recommended safe margin to account for any disturbances. Unlike plants operated by conventional control systems, that depend on PID schemes, plants with MPC control systems can be operated closer to the constraint limits offering superior control and maximising profits.

In order to illustrate the effectiveness of the inclusion of constraints in the proposed control structure, two different major process disturbance situations were examined under the following constraints and controllers settings:

- The prediction (n_y) and control (n_u) horizons of GSU, GDU and HCDP are 40 and 10 respectively.

- Constraints settings are:

  $0 \leq Gas\ flow\ rate\ (Output) \leq 3\ MSCMD$; $-3 \leq \Delta\mathbf{U} \leq 3$; $-50 \leq \mathbf{U} \leq 50$;
  $0 \leq H_2S\ (GSU\ 2^{nd}\ Output) \leq 6\ ppm$; $0 \leq H_2O\ (GDU\ 2^{nd}\ Output) \leq 6\ ppm$;
  $0 \leq Gas\ Pressure\ (HCDP\ 2^{nd}\ Output) \leq 100\ barg$

7.9.1 Major Process Unit Malfunction

Constraints violations are very likely to happen when the process is operated close to the constraint limits. Consider a situation where the plant is operated at it's maximum capacity and suddenly a major disturbance occurs, eg. a unit failure, which has the potential to cause unbalanced operation to the entire process series. Hence, to analyse the gas train control system behaviour during such scenarios, a disturbance of 50% sulfinol solvent filter chock had been introduced to the solvent control loop of the GSU while the gas train is operated at 2.8 *MSCMD* (very close to the maximum constraint at 3 *MSCMD*). Thereafter, the process responses of the conventional control system (SISO PID + operator) and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparison between both control strategies. The result consequences on GSU, GDU, and HCDP unit are presented sequentially in figures 7.11, 7.12 and 7.13.

To summarise the outcomes, Looking to the GSU discharge trends, the MPC responded systematically to the deviation in the gas quality as a result of the major disturbance. Even though the process were operated very close to the maximum gas flow constraints, when the disturbance strikes, the control system was able to ensure smooth and safe operation without violating the constraints. The control system efficiency in handling constraints plus the feedforward communication eases the disturbance effects on the successor processes and supported their controllers to manage the process with minimum control interventions as seen in GDU and HCDP trends.

The following sub sections provide discussion about each process unit, under both control strategies, in response to the GSU sulfinol solvent major flow disturbance of

50% filter chock.

7.9.1.1 Process disturbance

The GSU was exposed to a major process disturbance, while the gas train is operated close to the maximum constraint of the gas flow rate, at sample 1000. A 50% sulfinol solvent filter chock had been introduced to the solvent control loop.

7.9.1.2 Impact of process disturbance on GSU

The top set of Fig. 7.11 represents the GSU under conventional control. The disturbance caused the sulfinol flow to the absorber to drop by half which caused the sudden increase in the gas acidity. At the same time, the gas flow rates through the absorber increased due to the reduction in the opposing sulfinol flow. Clearly, the maximum gas flow constraint were violated by a large magnitude for more than 15 samples. This scenario will lead to the GSU being shut down by the safe guarding system.

The second set represents the GSU controlled by the proposed control system with feedforward (MPC + FF + PID). Even though, the process was operating close to the constraints, both trends were controlled within their operating envelops without violating constraints. The gas flow rate was capped just under the constraints threshold.

The third set shows the MPC control signal in the proposed control system with feedforward. The control system response was quick and effective. MPC gradually changed the reference value of the gas quality internal loop controller as a response to the disturbance.

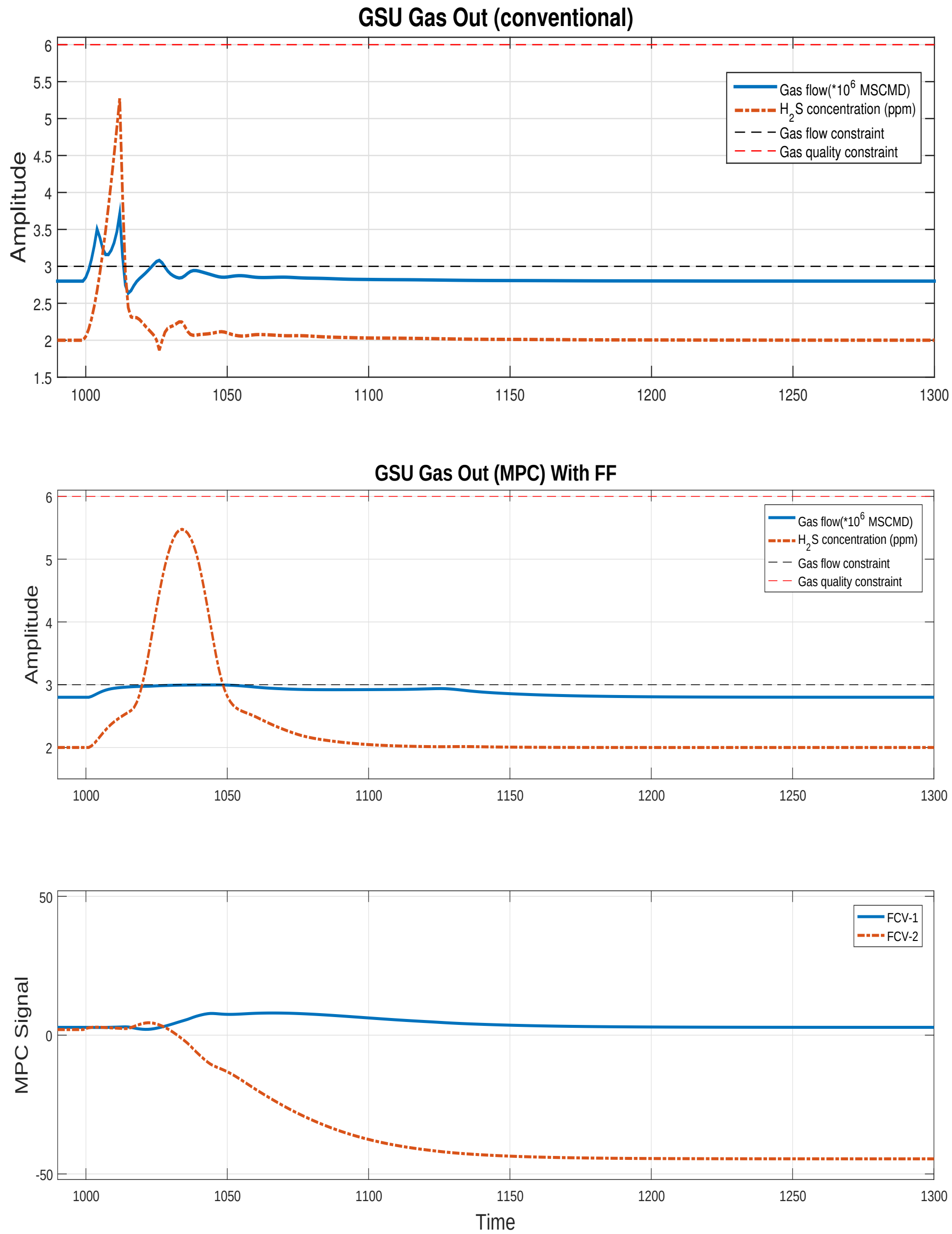


Figure 7.11: Comparison of GSU process responses as a result to the 50% solvent filter chock disturbance in the (GSU). The top set represent the GSU trends under the conventional control (Operator + PID). The second set is the GSU results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

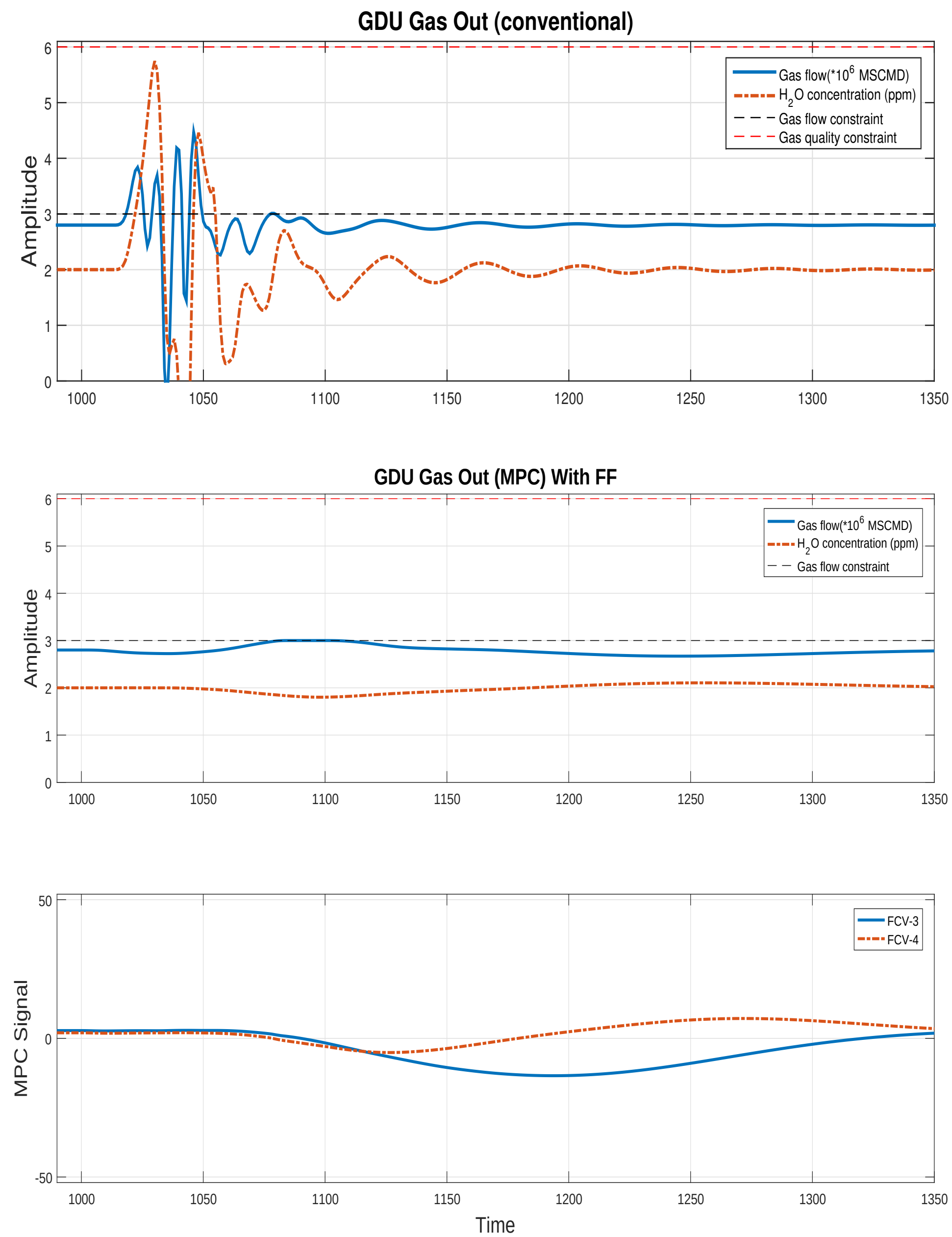


Figure 7.12: Comparison of GDU process responses as a result to the 50% solvent filter chock disturbance in the (GSU). The top set represent the GDU trends under the conventional control (Operator + PID). The second set is the GDU results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

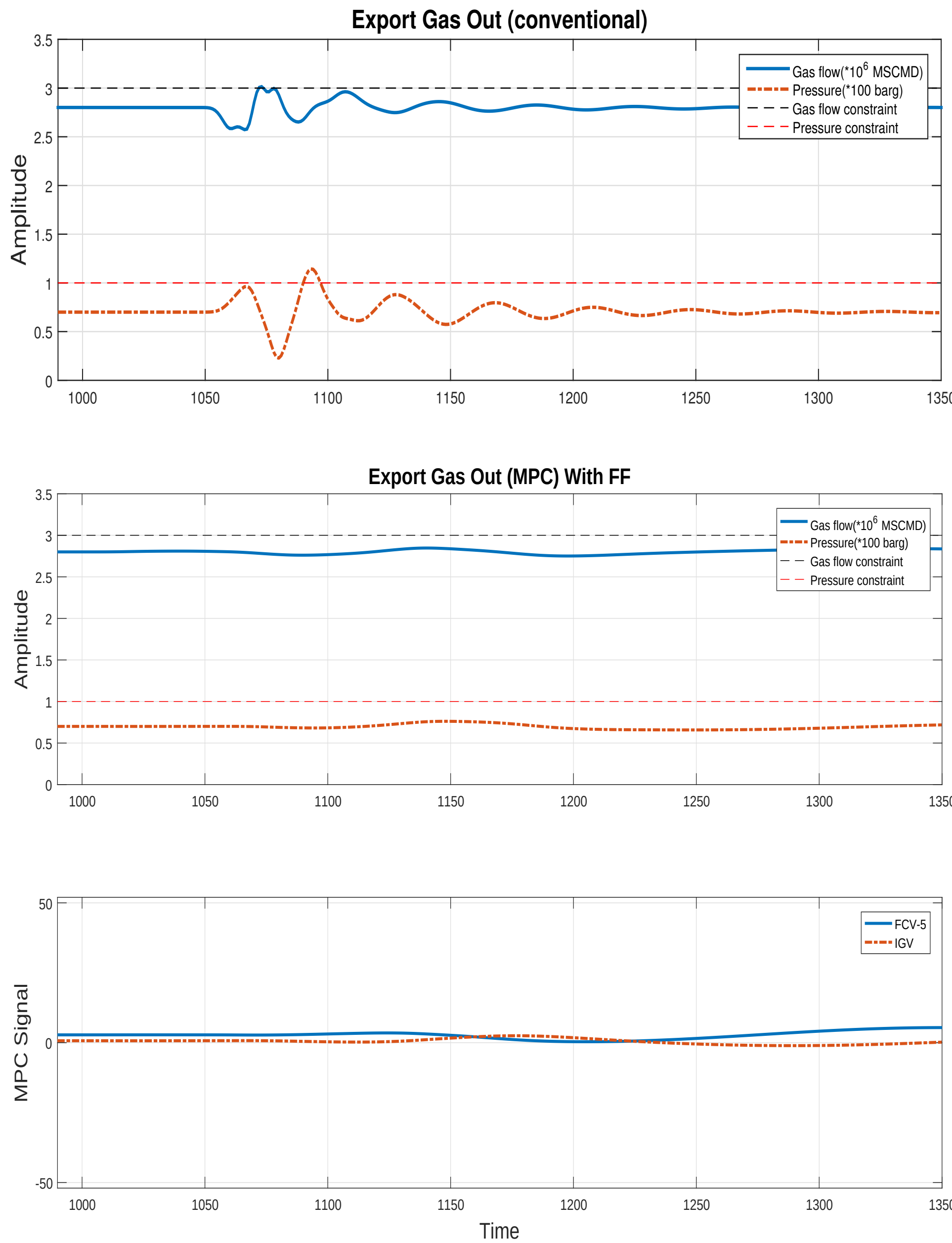


Figure 7.13: Comparison of HCDP process responses as a result to the 50% solvent filter chock disturbance in the (GSU). The top set represent the HCDP trends under the conventional control (Operator + PID). The second set is the HCDP results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

7.9.1.3 Impact of process disturbance on GDU

The top set of Fig. 7.12 represents the GDU under conventional control. The outcome is a sluggish control with maximum and minimum output constraints of both loops being violated in many occasions. Once again, this scenario will lead to the GDU being shut down by the safe guarding system.

The second set represents the GDU controlled by the proposed control system with feedforward (MPC + FF + PID). Both controlled trends shows smooth control with minimum signs of disturbance. The gas flow rate trend slightly reduced before the disturbance hit the GDU which indicates the controller cooperation, in providing and utilising the advanced information, by the feed forward loop. Constraint handling in the GSU played a major role in stabilising the successor process GDU by capping the gas flow rate constant under the constraint limit which, actually, stopped the disturbance oscillations. The GDU gas flow rate was successfully controlled without violating the constraints. In response to the good control performance of the gas flow rate, the GDU contactor operation was not disturbed which indicated by the gas quality trend.

The third set shows the MPC control signal in the proposed control system with feedforward. MPC control signals, for both loops, altered the internal control loop references just before the disturbance shock reaches the GDU. This indicates that, the MPC controller was prepared for the disturbance. Hence, the outcome is a smooth and tailored control signal which, indeed, is beyond human operator capability.

7.9.1.4 Impact of process disturbance on HCDP

The top set of Fig. 7.13 represents the HCDP unit under conventional control. Clearly, the maximum gas pressure constraint was violated and the pressure control is oscillatory with a magnitude of 80 *bar*. This scenario will lead to the HCDP process being shut down by the safe guarding system.

The second set represents the HCDP unit controlled by the proposed control system with feedforward (MPC + FF + PID). There are almost no signs of the disturbance in the third successor process. Both flow and pressure trends indicates stable operation. That's due to the good control performance in the predecessor processes GSU and GDU.

The third set shows the MPC control signal in the proposed control system with feedforward. MPC control signals, for both loops, altered the internal control loop references just before the disturbance shock reaches the HCDP unit. This indicates that, the MPC controller was prepared for the disturbance. Hence, the outcome is a smooth and tailored control signal which, indeed, is beyond human operator capability.

7.9.1.5 Summary of major process disturbance impact on gas train

Table 7.6 summarises the major process disturbance results on the gas train processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

Table 7.6: Summary of major process disturbance impact on gas train

Unit			GSU	GDU	HCDP
Gas flow rate	% Overshoot	Operator + SISO PID	36	100	7
		MPC + FF +SISO PID	7	7	1.8
	Settling time	Operator + SISO PID	40	140	80
		MPC + FF +SISO PID	55	70	0
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	165	190	64
		MPC + FF +SISO PID	170	4	8
	Settling time	Operator + SISO PID	50	300	150
		MPC + FF +SISO PID	80	0	50

7.9.2 Major Feed Disturbance

Major feed disturbances are also capable to cause constraints violation. Hence, to examine the gas train control system behaviour during such scenarios, a large setpoint change had been introduced to the GSU gas flow rate. The setpoint was stepped up from 1.5 *MSCMD* to 2.8 *MSCMD* (very close to the maximum constraint at 3 *MSCMD*). Thereafter, the process responses of the conventional control system (opereator + SISO PID) and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparisons between both control strategies. The consequences on each process of the gas train are presented in Fig. 7.14 for GSU; Fig. 7.15 for GDU; and Fig. 7.16 for HCDP unit.

In summary, looking to the GSU discharge trends, the MPC responded systematically to the major feed disturbance without violating the gas flow maximum constraint, even though the new setpoint of gas flow rate is very close to the maximum constraint. The control system efficiency in handling constraints plus the feedforward communication eases the disturbance effects on the successor processes and supported their controllers to operate the process without violating the constraints as seen in GDU and HCDP trends.

Hereafter, a detailed discussion of each process unit, controlled by both control strategies conventional and proposed, in response to the gas train feed major disturbance of around +90% are presented in the following sub sections.

7.9.2.1 Feed disturbance

The GSU was exposed to a large feed disturbance at sample 1000 where the gas flow rate reference value stepped up from 1.5 *MSCMD* to 2.8 *MSCMD* to analyse the proposed control system behaviour in handling constraints.

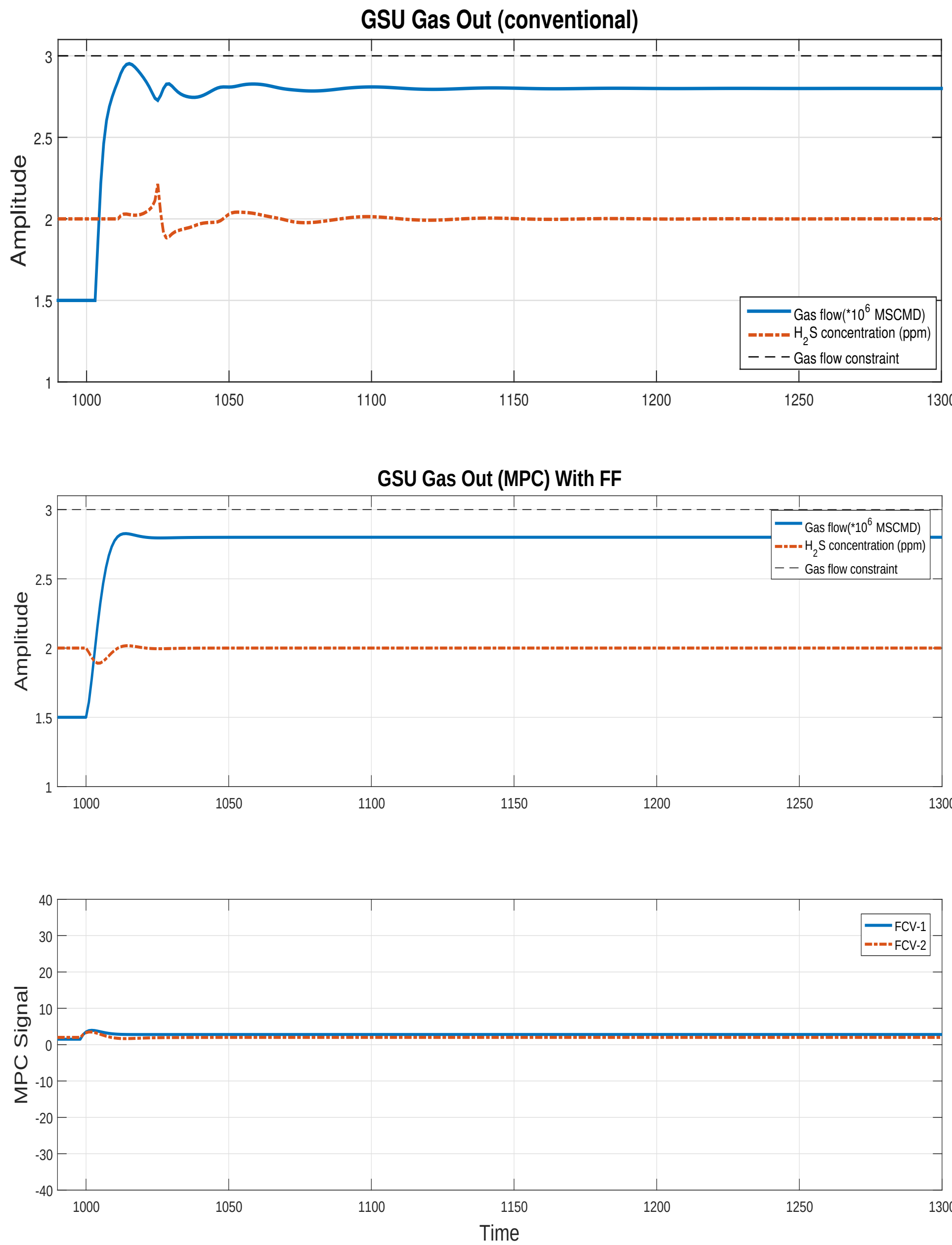


Figure 7.14: Comparison of GSU process responses as a result to the major feed disturbance. The top set represent the GSU trends under the conventional control (Operator + PID). The second set is the GSU results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

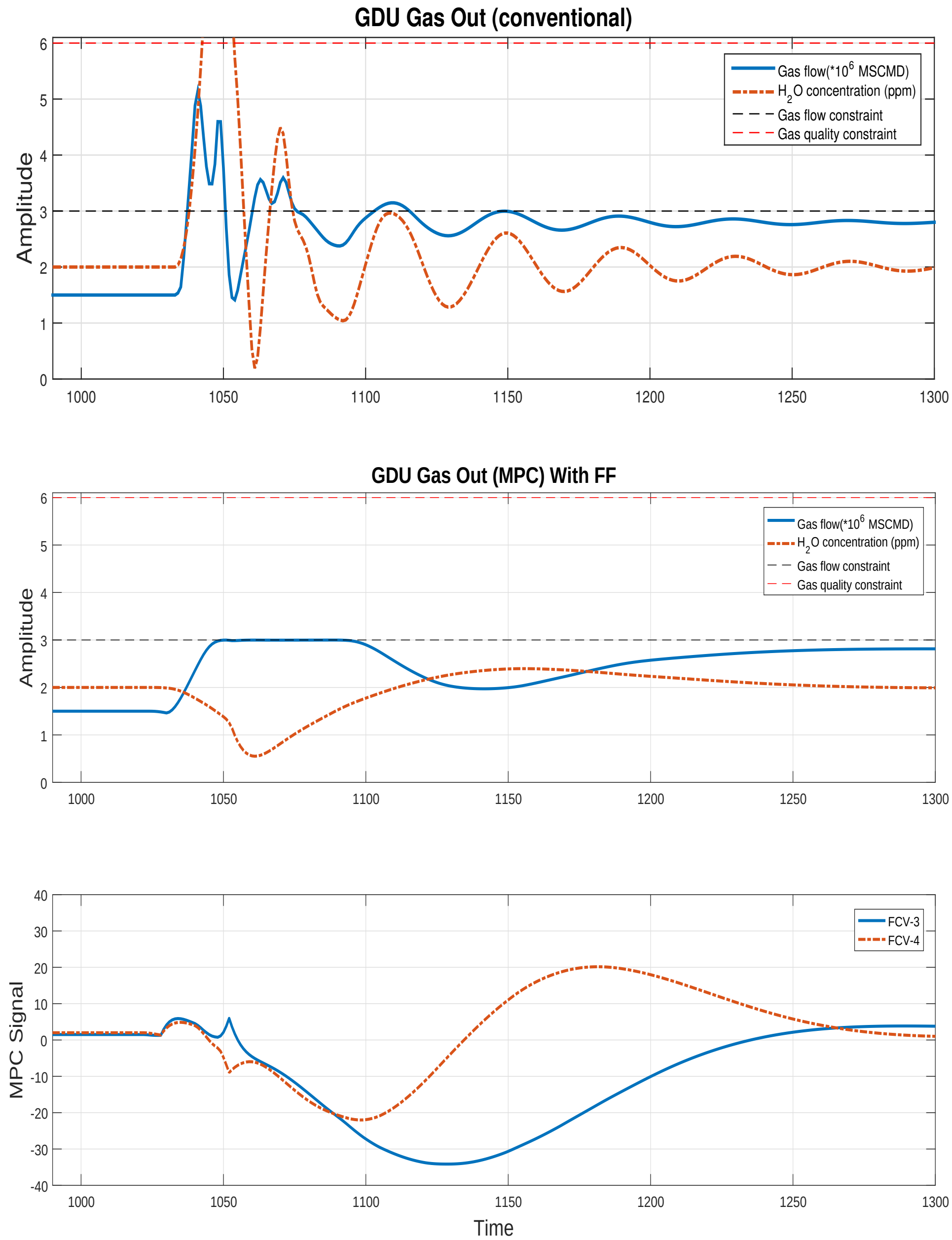


Figure 7.15: Comparison of GDU process responses as a result to the major feed disturbance in the (GSU). The top set represent the GDU trends under the conventional control (Operator + PID). The second set is the GDU results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

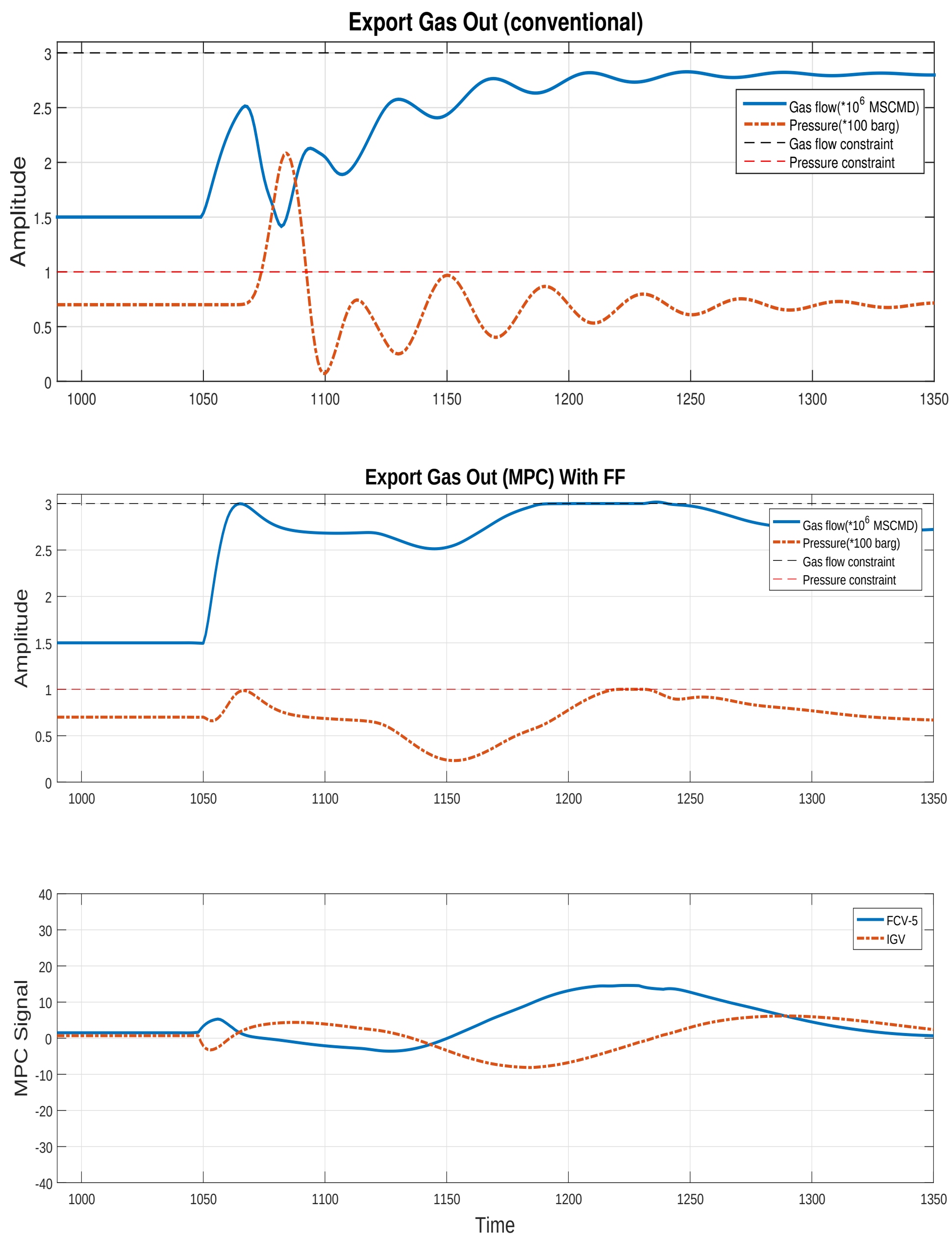


Figure 7.16: Comparison of HCDP process responses as a result to the major feed disturbance in the (GSU). The top set represent the HCDP trends under the conventional control (Operator + PID). The second set is the HCDP results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

7.9.2.2 Impact of feed disturbance on GSU

The top set of Fig. 7.14 represents the GSU under conventional control. Both trends, the gas flow rate and gas quality, seems to be properly controlled with overshoot without violating the constraints.

The second set represents the GSU controlled by the proposed control system with feedforward (MPC + FF + PID). Both controlled variables were capable to absorb the feed disturbance and properly controlled the unit without violating the constraints. When the gas flow rate starts to increase, the controller immediately pumped extra solvents to the absorber to insure the quality of the processed gas during the disturbance. This can be seen in the MPC signal trend and the resulted action on the processed gas quality trend.

The third set shows the MPC control signal in the proposed control system with feedforward. MPC control signal increased at the time of the disturbance and then idealised, while the main control task is carried out by the internal control loops.

7.9.2.3 Impact of feed disturbance on GDU

The top set of Fig. 7.15 represents the GDU under conventional control. The outcome is a sluggish control with maximum output constraints of both loops being violated in many occasions. Once again, this scenario will lead to the GDU being shut down by the safe guarding system.

The second set represents the GDU controlled by the proposed control system with feedforward (MPC + FF + PID), while the MPC control signal is presented in the third set. Looking to the gas flow trend, a noticeable reduction is observed before the disturbance actually reaches the system. That's due to the advance disturbance knowledge provided by the feedforward loop. The reduction to the water load in the gas is due to the fact that the controller pre-pumped extra glycol to the contactor just before the disturbance. At the time when the disturbance wave reached the GDU, the gas flow rate increased to the maximum constraint without violating it. As a direct result to the raise in the gas flow rate, the water load in the gas starts to increase as well. The controller reduced the gas flow rate to support the control of the gas quality. Thereafter, Both trends stabilised at their reference values. The GDU gas flow rate was successfully controlled without violating the constraints. The performance of the control structure is remarkable to maintain balanced operation of the GDU contactor.

7.9.2.4 Impact of feed disturbance on HCDP

The top set of Fig. 7.16 represents the HCDP unit under conventional control. Clearly, the maximum gas pressure constraint were largely violated and the pressure control is rather oscillatory. This scenario will lead to the HCDP unit being shut down by the safe guarding system.

The second set represents the HCDP unit controlled by the proposed control system with feedforward (MPC + FF + PID), while the MPC control signal is presented in the third set. The gas flow rate smoothly stepped up to the new reference value and then reduced to 2.5 *MSCMD* before it increased towards the constraint threshold without violating the constraints. In consequence, the pressure trend were capped twice at maximum constraint without violating it.

7.9.2.5 Summary of major feed disturbance impact on gas train

Table 7.7 summarises the major feed disturbance results on the gas train processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

Table 7.7: Summary of major feed disturbance impact on gas train

Unit			GSU	GDU	HCDP
Gas flow rate	% Overshoot	Operator + SISO PID	6	115	75
		MPC + FF +SISO PID	1.8	28	10
	Settling time	Operator + SISO PID	15	190	200
		MPC + FF +SISO PID	10	140	210
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	13	250	200
		MPC + FF +SISO PID	5	60	71
	Settling time	Operator + SISO PID	30	225	230
		MPC + FF +SISO PID	0	165	220

7.10 Review of thesis pre-set aims

The research aimed to develop an inexpensive feasible control system for the existing upstream oil and gas plants to target the disturbance growth in the series connected processes and the system dependency on operators. It is clear from the simulations results that the proposed control structure was capable to address both issues. The proposed control structure satisfies the typical control objectives, addresses process disturbances, considers operational constraints and can be integrated on the existing infrastructure which reduces cost and training requirements. An achievement summary of pre-set aims is listed down:

- **Feasible control concept**. A simple in structure, easy and inexpensive to implement control concept were developed in section 4.2. The control strategy was based on breaking the control problem into smaller parts and performed by splitting the MPC into smaller systems and dedicating it to control critical interactive loops only which makes it easier to troubleshoot and judge the behaviour of each MPC separately. Control performance was then enhanced by inclusion of feedforward loops in the algorithm.

The concept satisfies the typical control objectives, addresses the process control challenges and considers operational constraints. Further more, the control concept inexpensively integrates the team experience and operational knowledge within it by keeping the current control practice and just building on it. By building on the plants existing infrastructure, the approach requires a little retrofitting only. Which in turn, reduces cost, training requirements and simplifies validation.

- **Process model**. A representative and validated gas train process model were developed in chapter 5. The developed model reflects the realistic upstream oil and gas operations. The model could also be of benefit to studies on Large Scale Systems (LSS) in general.

- **Control system design**. A simple and inexpensive control system, based on the control concept, was developed and analysed on chapter 7. The main targeted control challenges were:

  1- *The disturbance growth in the series connected processes*. Simulation analysis presented in sections 7.8 and 7.9 proves that the developed control system is capable to quickly anticipate and tackle disturbance growth in the series connected processes. Which significantly reduces the frequency of plant shut downs and also saves on operating costs by properly controlling the disturbance growth in the process. These improvements goes beyond to reduce energy fluctuations in the process and saves fuel.

  2- *The system dependency on operators*. As discussed in chapter 3, the performance of the control room operator sometimes imposes a constraint on the overall control system performance. The proposed control structure was proved, by the simulations results in sections 7.8 and 7.9, to provide control system totally independent from control room operator interventions. The analysis showed that, omitting the control room operators role from the control decisions, superiorly improved the performance of the control system as well as the disturbance rejection.

- **Implementation simplicity and ease of validation**. Implementation of the developed control structure is simple and easy. The proposed control structure builds MPC layer on top of the existing PID control loops and uses the existing signal transmission cables. The implementation will be carried out on the instrument auxiliary room by copying plants signals from the DCS to a computer loaded with process models and the designed MPC algorithms. Thereafter, the MPC's control signals needs to be rooted to the setpoint channels of specific PID control loops via soft Auto/Manual switch in the DCS (To allow operator manual control and to aid comparisons between MPC and operator control as well).

7.11 Summary

The process control performance was largely enhanced by implementing decentralised cooperative small MPC's in the control structure. The results of smart integration of MPC with the conventional PID control system affectedly limits the disturbance influence in the process. Amalgamation of the feedforward loops in the control algorithm improved the speed and accuracy of the control actions in confronting disturbances. Nonetheless, the process wide control performance was further improved by inclusion of the process constraints in the control strategy. As a result, the MPC actions improved the plant performance beyond what a skilled and experienced operator can achieve. The results also prove the ability of the proposed control structure to reduce the disturbance effects in the series connected processes and to handle process constraints. Therefore, reducing the system dependency on operators.

Splitting the MPC into smaller systems and dedicating it to control critical interactive loops only, makes it easier to troubleshoot and to judge the behaviour of each

MPC separately. But the biggest benefit of the proposed solution is the control system availability improvement during failure of one or more MPC's. All process controlled variables will be under control even though one, or more, MPC is turned off for some reason (a set-up error for example) or if the MPC failed due to a power failure in the control building. The internal loop controllers (PID's), normally located in the process itself (therefore in the transmitter or valve housing), will continue to operate the plant.

The designed control algorithm is simple, systematic and easy to be understood without compromising the control efficiency. Compared with the current available solutions in the literature [53], the proposed control solution is cheaper because it builds up on the original plant control system structure. Also it is simpler to implement because the supervisory MPC control layer is small in size. Furthermore, it can be added to the existing control structure in the instrument auxiliary room without disturbing the current field arrangements. The MPC system model is quite easy to develop for a small dimension problems, as well as the control algorithms. Nevertheless, it almost delivers the same benefits and does not omit the team operational experience and maintenance skills. In addition, it's performance can be easily validated in the DCS by altering the cascade mode between auto and manual.

Chapter 8

CASE STUDY

The proposed control system was successfully implemented in the previous chapter to control the gas train processes in the upstream oil and gas fields. The proposed control system was purposely designed to tackle the disturbance growth in a series connected systems and to omit, or limit, the control room operator role in the control decisions. The success of the proposed control system in achieving the pre-set objectives was evaluated by the system response to a number of disturbance simulation scenarios. But, the arising questions that one might ask are: can this control methodology used to control other interactive processes? would it perform well? etc... This chapter is designated to answer such questions and aims to examine the transferability of the proposed control system, designed in the previous chapter, by implementing it in a different process.

The chapter starts by illustrating the process model of the case study in section 8.1. Section 8.2 presents process model analyses. The overall controller methodology is then presented step by step starting from PID controllers design in section 8.3 followed by inner loop controllers design and matrix fraction description equation computations in section 8.4 and ended by MPC algorithim design in section 8.5. Section 8.6 presents the control analysis and simulation plans. While, the following two sections provides the experimental results of the proposed control structure performance in confronting sudden feed change disturbance and process unit malfunction to analyse control performance (section 8.7) and constraint handling (section 8.8). Finally, discussions and conclusions are presented in the last section.

8.1 Case Study Process

Consider the two columns gas treatment process presented in Fig. 8.1 below:

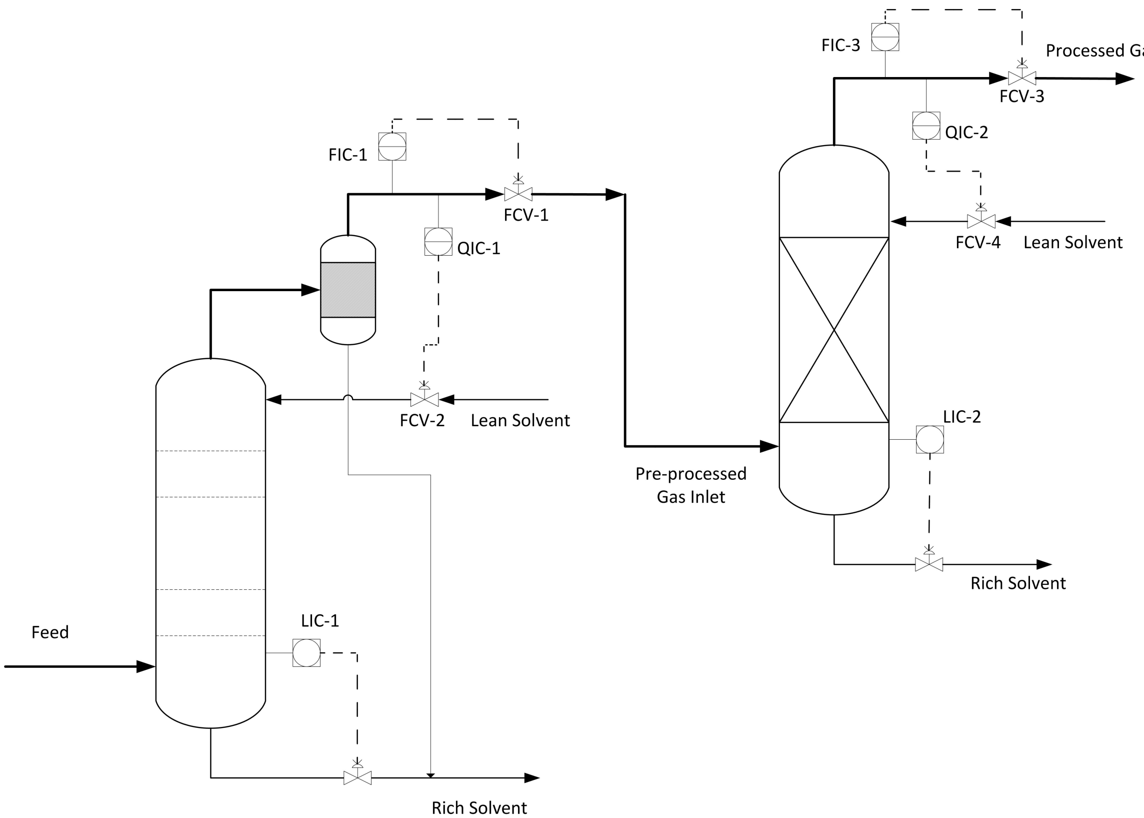


Figure 8.1: Two columns gas treatment process. Row gas feed will be treated in the first column and then purified in the second column.

The process treats and purify a row gas feed in two sub-processes. The first process model is given by:

$$G_{Column1} = \begin{pmatrix} \frac{12}{16s+1}\, e^{-s} & \frac{-18}{21s+1}\, e^{-3s} \\ \\ \frac{6}{11s+1}\, e^{-7s} & \frac{-19}{14s+1}\, e^{-3s} \end{pmatrix} \tag{8.1}$$

While the second process model is:

$$G_{Column2} = \begin{pmatrix} \frac{-6}{31s+1}\ e^{-4s} & \frac{-8}{17s+1}\ e^{-5s} \\ \\ \frac{5}{9s+1}\ e^{-7s} & \frac{16}{13s+1}\ e^{-5s} \end{pmatrix} \tag{8.2}$$

8.2 Simple Process Model Analysis

The main aim of this section is to analyse the process behaviour and the functional relationship between process variables of each unit in the two columns gas treatment process presented in Fig. 8.1.

8.2.1 Column one process

To evaluate column one model behaviour, a disturbance of 40% on solvent flow stream has been introduced to the system at sample time 200. Column one process responses are presented in Fig. 8.2.

Referring to column one in Fig. 8.1, row hydrocarbon gas enters the bottom of the column where the acid gas components are removed in a counter-current contact with the solvent flowing downwards from the top. The disturbance limits the solvent flow to the column and hence the gas flow through the column kicked off due to the reduction on the opposing flow. In response, the acidic gas increased sharply, as expected, driven by the sudden rise in the gas volumetric flow rate and the reduction of the solvent flow rate. Please note that, the inclusions of the white noise in the measurement parameters are to represent the measurement noise commonly found in real applications.

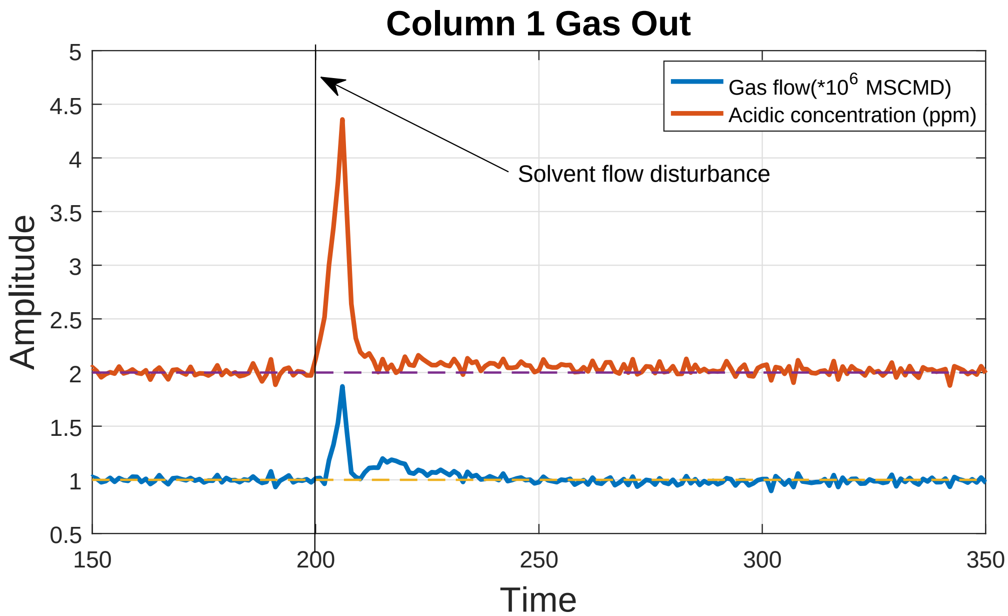


Figure 8.2: Column one gas outlet responses for a solvent flow disturbance

8.2.2 Column two process

In order to evaluate the model response of column two model, a disturbance of 30% on rich solvent flow stream, at the bottom outlet of the column, has been introduced to the system at sample time 200. Column two process responses are presented in Fig. 8.3.

The disturbance limits the solvent flow to the down stream solvent regeneration package (not shown in Fig. 8.1) and causes disturbances to the regenerated solvent quality which describes the sharp increase in the water load in the gas. Hence, the control system pumps extra lean solvent to the contactor column to control it. Gas flow fluctuations takes longer time to settle because the disturbance affects both operations in the system: the solvent regeneration package and the export gas dehydration.

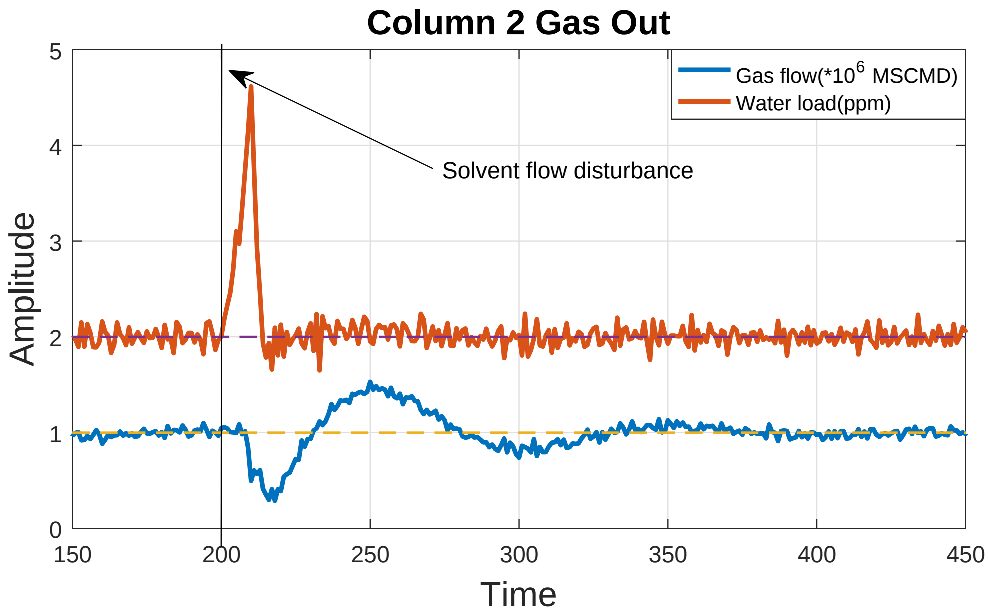


Figure 8.3: Column two gas outlet responses for a solvent flow disturbance

8.3 PID Controllers Design

The control strategy of each subsystem incorporates two SISO PID controllers in the inner control loops and one small MPC of dimension (2X2) in the outer loop. These PID controllers, categorised as critical PID's, regulates the intermediate flow control valves between the subsystems.

PID controllers can be tuned using the SIMC tuning rules [69]. For a first order process model with a delay of the form:

$$g = \frac{k}{\tau_1 s + 1}\, e^{-\theta s} \tag{8.3}$$

the PI controller parameters can be found by adjusting the desired time constant of the process (τ_c) only as follows:

$$\begin{aligned} K_p &= \tfrac{1}{k}\tfrac{\tau_1}{\tau_c+\theta} \\ \tau_i &= min\{\tau_1,\ 4(\tau_c+\theta)\} \end{aligned} \tag{8.4}$$

8.3.1 Column One PID Controllers Design

The first input first output transfer function of column one process (8.1) is:

$$g_{11} = \frac{12}{16s+1}\, e^{-s} \tag{8.5}$$

This transfer function has the following parameters: $k = 12$, $\tau_1 = 16$ and $\theta = 1$. The desired closed loop response time τ_c is 10. So, tuning the PID using the SIMC rules (8.4) gives:

$$\begin{gathered} The\ proportional\ gain\ (K_p) = \tfrac{1}{k}\tfrac{\tau_1}{\tau_c+\theta} = \tfrac{1}{12}\tfrac{16}{10+1} = 0.1212 \\ \tau_i = min\{16,\ 4(10+1)\} = 16 \\ The\ integral\ gain\ (K_i) = \tfrac{1}{\tau_i} = \tfrac{1}{16} = 0.0625 \end{gathered} \tag{8.6}$$

The second input second output transfer function of column one process (8.1) is:

$$g_{22} = \frac{-19}{14s+1}\, e^{-3s} \tag{8.7}$$

This transfer function has the following parameters: $k = -19$, $\tau_1 = 14$ and $\theta = 3$. The desired closed loop response time τ_c is 10. So, the tuning become:

$$\begin{gathered} The\ proportional\ gain\ (K_p) = \tfrac{1}{k}\tfrac{\tau_1}{\tau_c+\theta} = \tfrac{1}{-19}\tfrac{14}{10+3} = -0.0567 \\ \tau_i = min\{14,\ 4(10+3)\} = 14 \\ The\ integral\ gain\ (K_i) = \tfrac{1}{\tau_i} = \tfrac{-1}{14} = -0.0714 \end{gathered} \tag{8.8}$$

8.3.2 Column Two PID Controllers Design

The first input first output transfer function of column two process (8.2) is:

$$g_{11} = \frac{-6}{31s+1}\, e^{-4s} \tag{8.9}$$

This transfer function has the following parameters: $k = -6$, $\tau_1 = 31$ and $\theta = 4$. The desired closed loop response time τ_c is 10. So, tuning the PID using the SIMC rules

(8.4) gives:

$$\begin{aligned} The\ proportional\ gain\ (K_p) &= \tfrac{1}{k}\tfrac{\tau_1}{\tau_c+\theta} = \tfrac{1}{-6}\tfrac{31}{10+4} = -0.369 \\ \tau_i &= min\{31,\ 4(10+4)\} = 31 \\ The\ integral\ gain\ (K_i) &= \tfrac{1}{\tau_i} = \tfrac{-1}{31} = -0.0323 \end{aligned} \tag{8.10}$$

The second input second output transfer function of column two process (8.2) is:

$$g_{22} = \frac{16}{13s+1}\ e^{-5s} \tag{8.11}$$

This transfer function has the following parameters: $k = 16$, $\tau_1 = 13$ and $\theta = 5$. The desired closed loop response time τ_c is 10. So, the tuning become:

$$\begin{aligned} The\ proportional\ gain\ (K_p) &= \tfrac{1}{k}\tfrac{\tau_1}{\tau_c+\theta} = \tfrac{1}{16}\tfrac{13}{10+5} = 0.0542 \\ \tau_i &= min\{13,\ 4(10+5)\} = 13 \\ The\ integral\ gain\ (K_i) &= \tfrac{1}{\tau_i} = \tfrac{1}{13} = 0.0769 \end{aligned} \tag{8.12}$$

8.3.3 Summary of PID Controllers Setting

PID controllers were designed by SIMC method and their settings are listed in Table 8.1 below:

Table 8.1: PID Controllers Settings

Unit	**Tag No**	**Description**	**K$_p$**	**K$_i$**
First Process	FIC-1	First Column Outlet Flow	0.1212	0.0625
	QIC-1	First Column Outlet Gas Quality	-0.0567	-0.0714
Second process	FIC-3	Second Column Outlet Flow	-0.369	-0.0323
	QIC-2	Second Column Outlet Gas Quality	0.0542	0.0769

8.4 Inner Loops PID Controllers Design

The master MPC's in each system are multivariable Generalised Predictive Controllers (GPC) whose prediction is based on a matrix fraction description (MFD). Hence, in order to illustrate the problem of controlling multivariable processes with different dead times by PID's and MPC, a representative LMFD (Left Matrix Fraction Description) equations representing the inner loop control of each system must be computed first. Two 'MATLAB' codes were written for this purpose. The first creates LMFD equations from a continuous process model (Appendix A). While, the second creates LMFD equations to represent a model with it's relevant SISO PID controllers (Appendix B). The computation steps to obtain the systems LMFD equations are illustrated in the following subsections.

8.4.1 Column One Process

Column one process, shown in Fig 8.1, has two variables that have to be controlled: the throughput gas flow measured by the flow meter ***FIC-1*** and the column outlet gas quality measured by the process analyser ***QIC-1***. The manipulated variables are the column gas outlet flow through ***FCV-1*** and the column solvent input flow through ***FCV-2***. The dynamics of the process are described as follows:

$$\begin{pmatrix} Y_1 \\ \\ Y_2 \end{pmatrix} = \begin{pmatrix} \frac{12}{16s+1}\, e^{-s} & \frac{-18}{21s+1}\, e^{-3s} \\ \\ \frac{6}{11s+1}\, e^{-7s} & \frac{-19}{14s+1}\, e^{-3s} \end{pmatrix} \begin{pmatrix} U_1 \\ \\ U_2 \end{pmatrix} \tag{8.13}$$

Where Y_1 and Y_2 corresponds to the outlet gas flow rate and quality. Whereas U_1 and U_2 corresponds to the column gas outlet flow and solvent input flow respectively.

The discrete transfer matrix for a sampling time of one minute is:

$$G_{Column1} = \begin{pmatrix} \frac{0.727z^{-1}}{1-0.9394z^{-1}}\ z^{-1} & \frac{-0.8371^{-1}}{1-0.9535z^{-1}}\ z^{-3} \\ \\ \frac{0.5214z^{-1}}{1-0.9131z^{-1}}\ z^{-7} & \frac{-1.31z^{-1}}{1-0.9311z^{-1}}\ z^{-3} \end{pmatrix} \tag{8.14}$$

After defining column one process model in the discrete form, gas flow and quality PID controllers are then constructed by the *PID* command in 'MATLAB'. Please refer to (Appendix B) for the detailed 'MATLAB' code file.

Column one gas throughput PID controller C_{FIC1} is given by:

$$C_{FIC1} = \frac{0.1212z - 0.0587}{z-1} \tag{8.15}$$

and the outlet gas quality PID controller C_{QIC1} is given by:

$$C_{QIC1} = \frac{-0.0567z - 0.0147}{z-1} \tag{8.16}$$

Then, the next step is to assign the PID controllers to the model. This is done by using *connect* command in 'MATLAB' as it is shown in the 'MATLAB' code file presented in (Appendix B). Thereafter, the left matrix fraction description equations (LMFD) can be extracted from the discrete state space system.

LMFD is the most popular transfer matrix representation of MIMO processes as it can be easily obtained by performing step or pulse tests to the plant. The MIMO transfer matrix of a CARIMA model is given by:

$$\mathbf{T}(z^{-1}) = \mathbf{A}(z^{-1})^{-1}\ \mathbf{B}(z^{-1})\ z^{-1} \tag{8.17}$$

Given a rational matrix $\mathbf{T}(z^{-1})$, the problem (eq. 8.17) can be solved, as described by Camacho et al. [13], by making matrix $\mathbf{A}(z^{-1})$ equal to a diagonal matrix with diagonal elements equal to the least common multiplier of the denominators of the corresponding row of the transfer function $\mathbf{T}(z^{-1})$. Then, matrix $\mathbf{B}(z^{-1})$ can be easily calculated by:

$$\mathbf{B}(z^{-1}) = \mathbf{A}(z^{-1})\ \mathbf{T}(z^{-1})\ z \tag{8.18}$$

So, the resulting matrices of $\mathbf{A}(z^{-1})$ and $\mathbf{B}(z^{-1})$ will be in the following forms:

$$\mathbf{A}(z^{-1}) = \begin{pmatrix} A_{11} & 0 \\ 0 & A_{22} \end{pmatrix}$$

and

$$\mathbf{B}(z^{-1}) = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix}$$

Hence, the CARIMA model that represents the process with the inner loop control, shown in Fig 8.4, is:

$$\mathbf{A}(z^{-1})\ \mathbf{y} = \mathbf{B}(z^{-1})\ \mathbf{u}$$

Please note that, the MPC control signals ($\mathbf{u}$) manipulates the reference of the PID controllers ($\mathbf{r}$) as it is illustrated in Fig. 8.4.

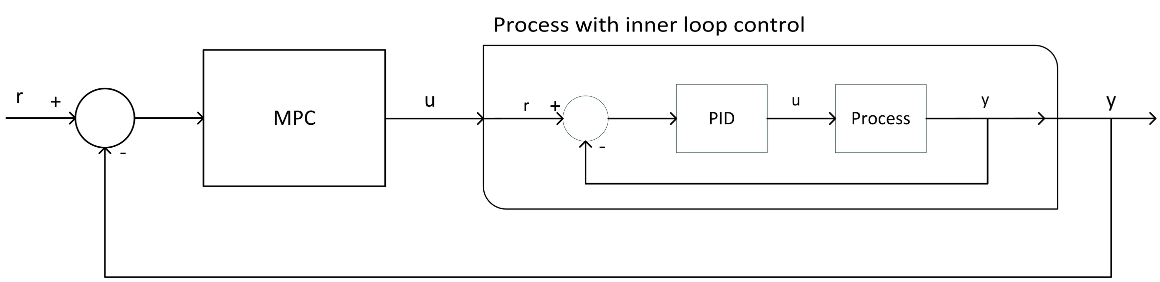


Figure 8.4: Process with Inner Loop Control

LMFD of column one process model with the relevant inner loops PID controllers are computed by the purposely designed 'MATLAB' code to generate the LMFD equations of process models with their relevant SISO PID controllers. The 'MATLAB' code file is presented in (Appendix B). The generated LMFD equations of column one process model with the relevant inner loops PID controllers are:

$$
\begin{aligned}
A_{11}(z^{-1}) &= 1 - 5.5747z^{-1} + 13.0737z^{-2} - 16.5106z^{-3} + 11.8415z^{-4} - 4.5722z^{-5} \\
&\quad +0.7423z^{-6} \\
A_{22}(z^{-1}) &= 1 - 5.5747z^{-1} + 13.0737z^{-2} - 16.5106z^{-3} + 11.8415z^{-4} - 4.5722z^{-5} \\
&\quad +0.7423z^{-6} \\
B_{11}(z^{-1}) &= (0 + 0.0881z^{-1} - 0.3738z^{-2} + 0.6311z^{-3} - 0.5279z^{-4} + 0.2175z^{-5} \\
&\quad -0.0350z^{-6})z^{-1} \\
B_{12}(z^{-1}) &= (0 + 0.0475z^{-1} - 0.1673z^{-2} + 0.2081z^{-3} - 0.0944z^{-4} - 0.0037z^{-5} \\
&\quad +0.0098z^{-6})z^{-3} \\
B_{21}(z^{-1}) &= (0 + 0.0632z^{-1} - 0.2723z^{-2} + 0.4635z^{-3} - 0.3885z^{-4} + 0.1596z^{-5} \\
&\quad -0.0255z^{-6})z^{-7} \\
B_{22}(z^{-1}) &= (0 + 0.0743z^{-1} - 0.2599z^{-2} + 0.3226z^{-3} - 0.1470z^{-4} - 0.0054z^{-5} \\
&\quad +0.0154z^{-6})z^{-3}
\end{aligned}
$$

8.4.2 Column Two Process

Column two process, shown in Fig 8.1, has two variables that have to be controlled: the throughput gas flow measured by *FIC-3* and the column outlet gas quality measured by the process analyser *QIC-2*. The manipulated variables are the column gas outlet flow through *FCV-3* and the column solvent input flow through *FCV-4*. The dynamics of column two are represented by the following model:

$$
\begin{pmatrix} Y_1 \\ \\ Y_2 \end{pmatrix} = \begin{pmatrix} \frac{-6}{31s+1}\, e^{-4s} & \frac{-8}{17s+1}\, e^{-5s} \\ \\ \frac{5}{9s+1}\, e^{-7s} & \frac{16}{13s+1}\, e^{-5s} \end{pmatrix} \begin{pmatrix} U_1 \\ \\ U_2 \end{pmatrix} \tag{8.19}
$$

Where Y_1 and Y_2 corresponds to the outlet gas flow rate and quality. Whereas, U_1

and U_2 corresponds to the column gas outlet flow and solvent input flow respectively.

The discrete transfer matrix for a sampling time of one minute is:

$$G_{Column2} = \begin{pmatrix} \frac{-0.1905z^{-1}}{1-0.9683z^{-1}}\ z^{-4} & \frac{-0.457z^{-1}}{1-0.9429z^{-1}}\ z^{-5} \\ \\ \frac{0.5258z^{-1}}{1-0.8948z^{-1}}\ z^{-7} & \frac{1.185z^{-1}}{1-0.926z^{-1}}\ z^{-5} \end{pmatrix} \tag{8.20}$$

Column two gas throughput PID controller C_{FIC3} is given by:

$$C_{FIC3} = \frac{-0.369z + 0.3367}{z - 1} \tag{8.21}$$

While the outlet gas quality PID controller C_{QIC2} is given by:

$$C_{QIC2} = \frac{0.0542z + 0.0227}{z - 1} \tag{8.22}$$

Thereafter, calculation of the LMFD equations representing column two process model with the relevant inner loops PID controllers gives:

$$\begin{aligned}
A_{11}(z^{-1}) &= 1 - 5.5974z^{-1} + 13.1388z^{-2} - 16.5587z^{-3} + 11.8195z^{-4} - 4.5306z^{-5} \\
&\quad +0.7285z^{-6} \\
A_{22}(z^{-1}) &= 1 - 5.6267z^{-1} + 13.2783z^{-2} - 16.8247z^{-3} + 12.0726z^{-4} - 4.6508z^{-5} \\
&\quad +0.7513z^{-6} \\
B_{11}(z^{-1}) &= (0 + 0.0703z^{-1} - 0.3289z^{-2} + 0.6154z^{-3} - 0.5750z^{-4} + 0.2682z^{-5} \\
&\quad -0.0499z^{-6})z^{-4} \\
B_{12}(z^{-1}) &= (0 - 0.0248z^{-1} + 0.0835z^{-2} - 0.0940z^{-3} + 0.0282z^{-4} + 0.0153z^{-5} \\
&\quad -0.0083z^{-6})z^{-5} \\
B_{21}(z^{-1}) &= (0 - 0.1940z^{-1} + 0.9215z^{-2} - 1.7502z^{-3} + 1.6617z^{-4} - 0.7886z^{-5} \\
&\quad +0.1497z^{-6})z^{-7} \\
B_{22}(z^{-1}) &= (0 + 0.0642z^{-1} - 0.2178z^{-2} + 0.2472z^{-3} - 0.0757z^{-4} - 0.0401z^{-5} \\
&\quad +0.0222z^{-6})z^{-5}
\end{aligned}$$

8.5 MPC Design

The MPC's are multivariable Generalised Predictive Controllers (GPC) whose prediction is based on a MFD. Similarly as in chapter 7, the proposed control algorithm for each MPC in the process sup-systems is:

$$\underset{\rightarrow k+1}{\mathbf{y}}^{[i]} = H\Delta \underset{\rightarrow k}{\mathbf{u}}^{[i]} + P\Delta \underset{\leftarrow k-1}{\mathbf{u}}^{[i]} + Q \underset{\leftarrow k}{\mathbf{y}}^{[i]} + \underset{\leftarrow k}{\mathbf{D}_n}^{[i]} \tag{8.23}$$

where:

- $\underset{\rightarrow k+1}{\mathbf{y}}$ the vector of output predictions, $\Delta \underset{\rightarrow k}{\mathbf{u}}$ the vector of optimised input predictions, $\Delta \underset{\leftarrow k-1}{\mathbf{u}}$ is a vector of past control increments and $[i]$ represents the process being controlled whether it is column one or column two.
- H, P, and Q are prediction matrices (see equation 2.18).
- $\underset{\leftarrow k}{\mathbf{D}_n}$ is the feed forward term representing the disturbances caused by the neighbouring systems' interactions. Feed-forward term ($\mathbf{D}_n$) was defined in analogous way to the gas train processes shown in section (7.5.1). As presented in eq. (7.18)

  $$\mathbf{D}_n = \mathbf{L}^{[i]}[(\underset{\rightarrow k}{\mathbf{y}})_n - \underset{\rightarrow k}{\mathbf{r}}]$$

  with

  $$\mathbf{L}^{[Column\ one]} = \begin{pmatrix} 0.80 & 0 \\ \\ 0 & 0 \end{pmatrix}$$

The GPC control law is then determined from a minimisation of a two norm measure of predicted performance:

$$\min_{\Delta \underset{\rightarrow k}{\mathbf{u}}} \quad J = \|\underset{\rightarrow k}{\mathbf{r}}^{[i]} - \underset{\rightarrow k}{\mathbf{y}}^{[i]}\|_2^2 + \lambda \|\Delta \underset{\rightarrow k}{\mathbf{u}}^{[i]}\|_2^2 \tag{8.24}$$

Consequently, the GPC control law is defined by the first element of $\Delta u_k = \mathbf{e}_1^T \Delta \underset{\rightarrow}{\mathbf{u}}$, $\mathbf{e}_1^T = [I, 0, 0, ..., 0]$:

$$\Delta \mathbf{u}_k = \mathbf{e}_1^T (H^T H + \lambda I)^{-1} H^T [\underset{\rightarrow k}{\mathbf{r}}^{[i]} - P \underset{\leftarrow k}{\mathbf{y}}^{[i]} - Q\Delta \underset{\leftarrow k-1}{\mathbf{u}}^{[i]} - \underset{\leftarrow k}{\mathbf{D}_n}^{[i]}] \tag{8.25}$$

Please note that, The MPC control signals ($\mathbf{u}$) equals to ($\mathbf{r}_{PID}$) the reference of the internal PID controllers.

8.6 Control Analysis and Simulation Plan

The proposed control algorithm, developed in chapter (7), will again be evaluated in the case study process. Different simulation scenarios that reflects the real process situations were carefully chosen to properly test and evaluate the proposed control algorithm in controlling the two columns gas treatment process. Process analysis and simulations map is presented in table 8.2.

Table 8.2: Case study Control algorithm simulation plan

Type of Analysis	**Simulation**	**Results**	
		Column 1	**Column 2**
Wide Process Control	Feed Disturbance	Fig. 7.5	Fig. 7.6
	Process Disturbance	Fig. 7.8	Fig. 7.9
Wide Process Control with Constraints	Process Disturbance	Fig. 7.11	Fig. 7.12
	Feed Disturbance	Fig. 7.14	Fig. 7.15

8.7 Wide Process Control Performance Analysis

The proposed control methodology was tested on the two columns gas treatment process. The proposal was examined for two main causes of process disturbances (a sudden feed change and a process unit malfunction). The results are then compared against the current conventional control strategy that rely on a number of SISO PID controllers with the control room operator. At the same time, the comparison also highlights the benefits gained by adding and utilising the feed forward loops to the process control strategy.

8.7.1 Feed Disturbance

In order to analyse and compare the performance of the proposed control structure with the conventional one at a time of a sudden feed change, a 50% step up had been introduced to the gas flow setpoint of the column one. Thereafter, the process responses of the conventional control system (operator + SISO PID), the proposed control system without feedforward (MPC + SISO PID), and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparisons between the three different control strategies. The consequences on each process of the two columns gas treatment process are presented in Fig. 8.5 for column one and Fig. 8.6 for column two.

In summary, comparing the proposed control structures (with and without the feedforward) against the conventional control, the results show that the MPC's in the proposed control structures took prompt actions at the time of disturbance to regulate slave PID controllers set points simultaneously while accounting for all process interactions. Looking to column one variables presented in Fig. 8.5, it is noticeable that all control systems were capable to absorb the feed disturbance and properly control the unit. Conversely, the case is different in column two Fig. 8.6; where the proposed control structures (with and without the feedforward) are distinguished by their ability in reducing interactions, unlike the conventional control system. In other hands, the results also proves the benefits of adding feedforward loops to the proposed control structure by means of reduced overshoots and faster settling times in column two.

Hereafter, a detailed discussion of each process unit, controlled by three different control strategies, in response to the throughput feed disturbance of +50% are presented in the following sub sections.

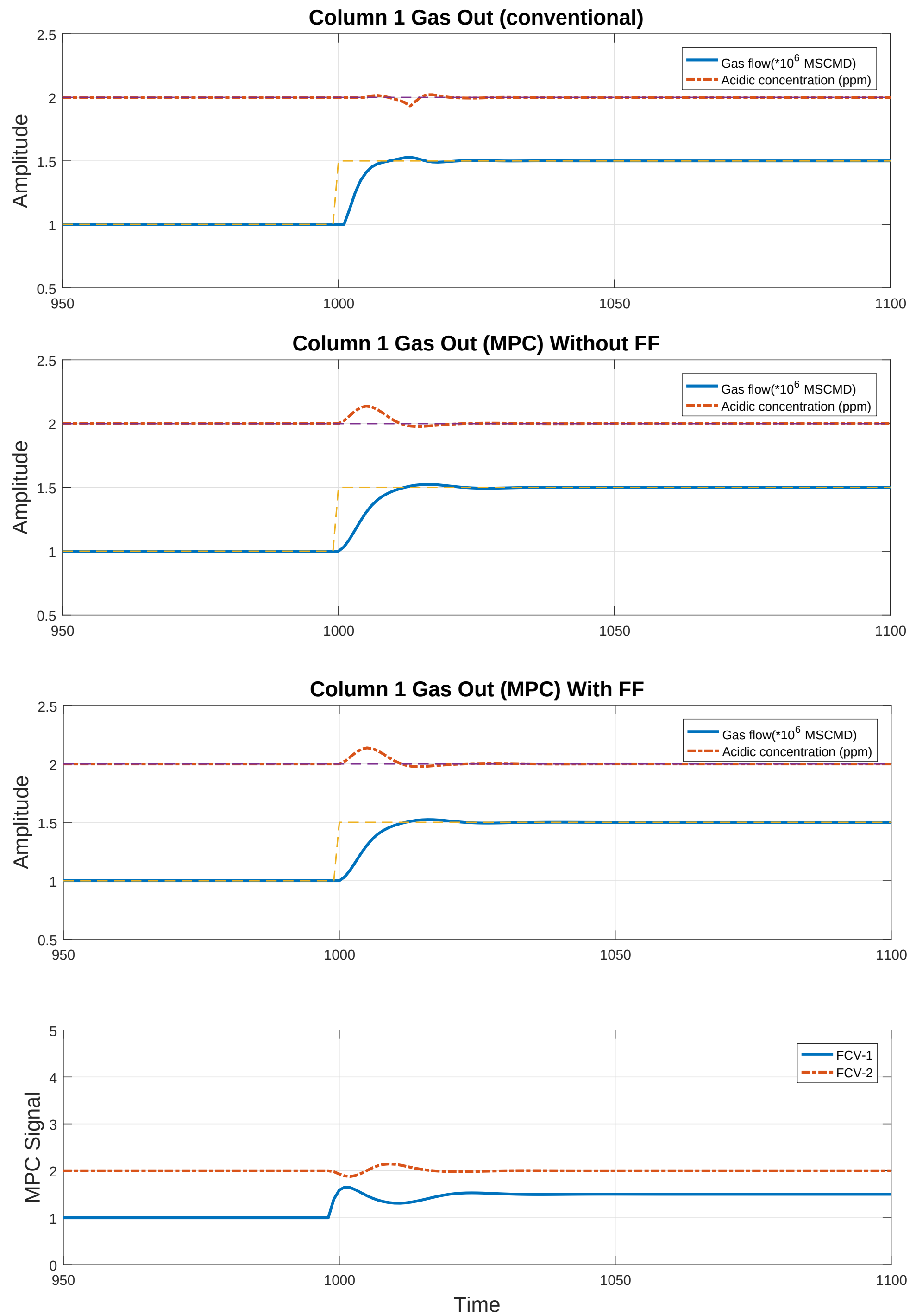


Figure 8.5: Comparison of column one process responses as a result of the 50% step increase in the gas flow reference

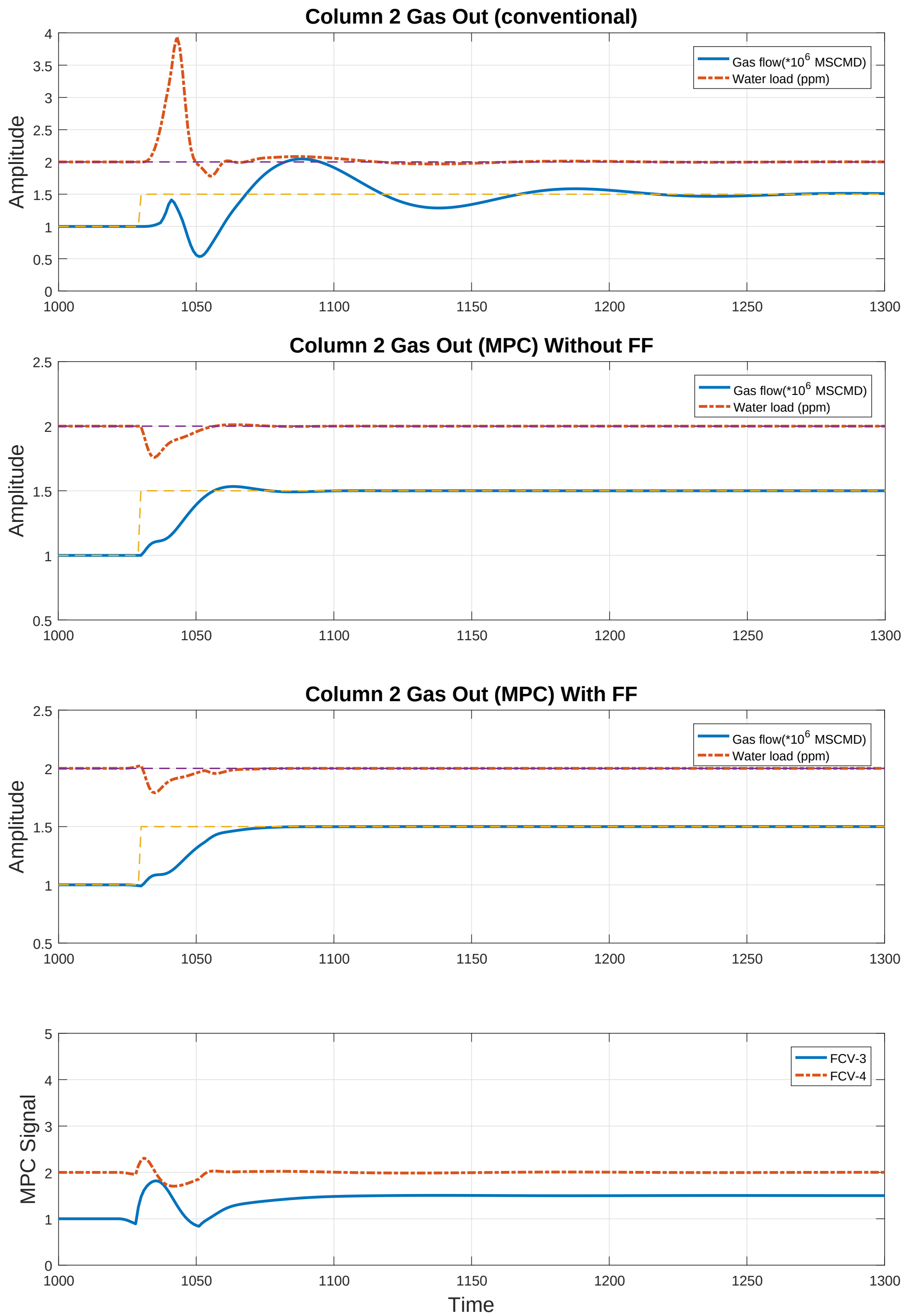


Figure 8.6: Comparison of column two process responses as a result of the 50% step increase in column one gas flow reference.

8.7.1.1 Feed disturbance

Column one was exposed to a feed disturbance at sample 1000 where the reference of the gas flow increased from 1 *MSCMD* to 1.5 *MSCMD*. Therefore, the gas flow rate increased by 500,000 *SCMD* which is practically considered as a huge step up. In real life, operators will only increase by a maximum step of 0.2 *MSCMD*, during start up, or 0.1 *MSCMD*, at high flow rate, to account for disturbances in the whole gas train processes.

8.7.1.2 Impact of feed disturbance on Column one

The top set of Fig. 8.5 represents column one process with conventional control. Both trends, the gas flow rate and gas quality, seems properly controlled with a maximum overshot of around 0.1 *MSCMD* in the gas flow rate.

The second set represents column one controlled by the proposed control system without feedforward (MPC + PID). Both controlled trends indicates very smooth control with minor overshoots.

The third set represents column one being controlled by the proposed control system with feedforward (MPC + FF + PID). The responses are identical to the second set because the disturbance were originated in column one, hence there are no feedforward information.

The fourth set shows the MPC control signal in the proposed control system with feedforward. MPC control signal of the gas flow rate increased at the time of the disturbance and then idealised at the new setpoint, while the quality control signal responds to the change in the gas flow rate and then idealised at it's original position. This indicates that, MPC changes the reference value, behaving like an operator, while the main control task is carried out by the internal control loops.

8.7.1.3 Impact of feed disturbance on column two

The top set of Fig. 8.6 represents column two with conventional control. As a response to the feed disturbance, the gas flow rate fluctuated between 0.5 *MSCMD* and 2 *MSCMD* before it gradually settled to the new reference value. The water load in the gas also increased by 100% of it is setpoint, in response to the gas disturbance which may cause unbalanced operation of the unit.

The second set represents column two controlled by the proposed control system without feedforward (MPC + PID). The gas flow rate smoothly stepped up to the new reference with minimum process disturbance. As a result, the water load trend shows a minor disturbance only.

The third set represents column two controlled by the proposed control system with feedforward (MPC + FF + PID). The gas flow rate trend slightly reduced before the disturbance hit the process which indicates that the controller utilised the advanced knowledge provided by the feed forward loop. Compared with the second set, The gas flow rate stepped up to the new reference value without overshoot which, in consequence, enhanced the settling time.

The fourth set shows the MPC control signal in the proposed control system with feedforward. MPC control signals, for both loops, altered the internal control loop references immediately after the feed disturbance on the predecessor process and before the disturbance shock reaches column two. This indicates that, the MPC controller was prepared for the disturbance. Hence, the outcome is a smooth and tailored control signal which, indeed, is beyond human operator capability.

8.7.1.4 Summary of feed disturbance impact on two columns process

Table 8.3 summarises the feed disturbance results on two columns gas treatment process processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

Table 8.3: Summary of feed disturbance impact on two columns process

Unit			Column 1	Column 2
Gas flow rate	% Overshoot	Operator + SISO PID	3	67
		MPC + SISO PID	2	4
		MPC + FF +SISO PID	2	0
	Settling time	Operator + SISO PID	11	160
		MPC + SISO PID	13	25
		MPC + FF +SISO PID	13	27
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	6	98
		MPC + SISO PID	7.5	10
		MPC + FF +SISO PID	7.5	8
	Settling time	Operator + SISO PID	10	30
		MPC + SISO PID	13	20
		MPC + FF +SISO PID	13	15

8.7.2 Process Unit Malfunction

In order to compare the performance of the proposed control structure with the conventional one at a time of a sudden process unit malfunction, a 15% solvent filter chock had been introduced to the solvent control loop of column one. Thereafter, the process responses of the conventional control system (SISO PID + operator), the proposed control system without feedforward (MPC + SISO PID), and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparison between the three different control strategies. The result consequences on columns one and two processes are presented sequentially in figures 8.7 and 8.8.

Once again, the MPC's in the proposed control structures, with and without the feedforward, took prompt actions at the time of process disturbance to regulate slave PID controllers set points simultaneously while accounting for all process interactions. In summary, column one trends presented in Fig. 8.7 shows that, in the case of the conventional control the acidic gas concentration increased by nearly 20% of its initial reference value and the gas flow rate increased by 25% for a while as a direct result of the solvent filter chock. Whereas, the proposed solutions (with and without the feedforward) show a smooth control with no spikes in both trends. The proposed control structures (with and without the feedforward) in column two Fig. 8.8 show a smooth and neat control trends, unlike the spiky trends in the conventional control case.

The following sub sections provide discussion about each process unit, under three control strategies, in response to column one solvent flow disturbance by mean of filter chock of 15%.

8.7.2.1 Process disturbance

Column one was exposed to a process disturbance at sample 1000 where a 15% solvent filter chock had been introduced to the solvent control loop.

8.7.2.2 Impact of process disturbance on column one

The top set of Fig. 8.7 represents column one with conventional control. The gas quality trend show a sharp increase of acidic gas concentration by nearly 20% of its initial reference value as a direct result of the disturbance. The gas flow rate had spikes with magnitude of around 1.25 *MSCMD*.

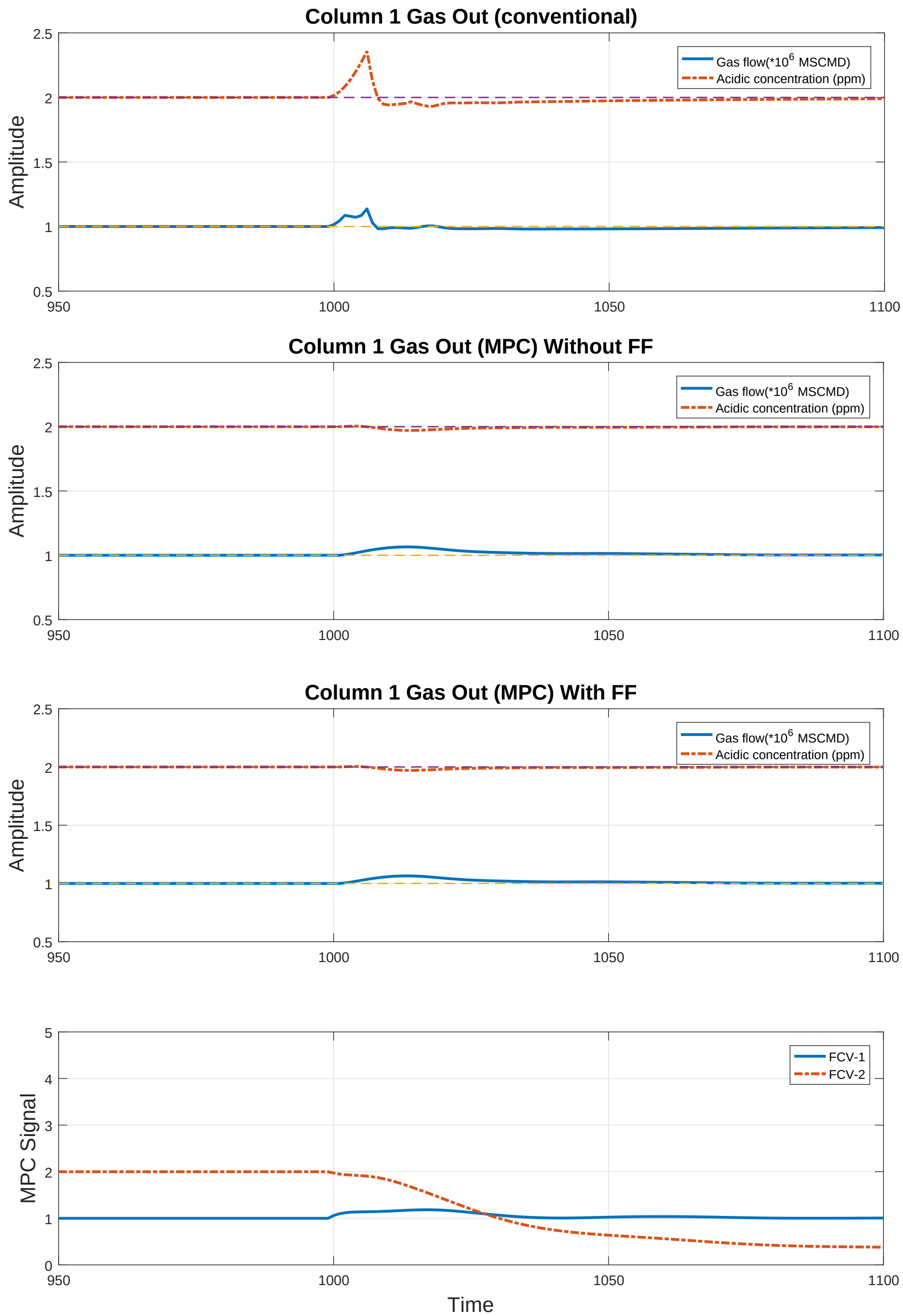


Figure 8.7: Comparison of column one process responses as a result of the 15% solvent filter chock.

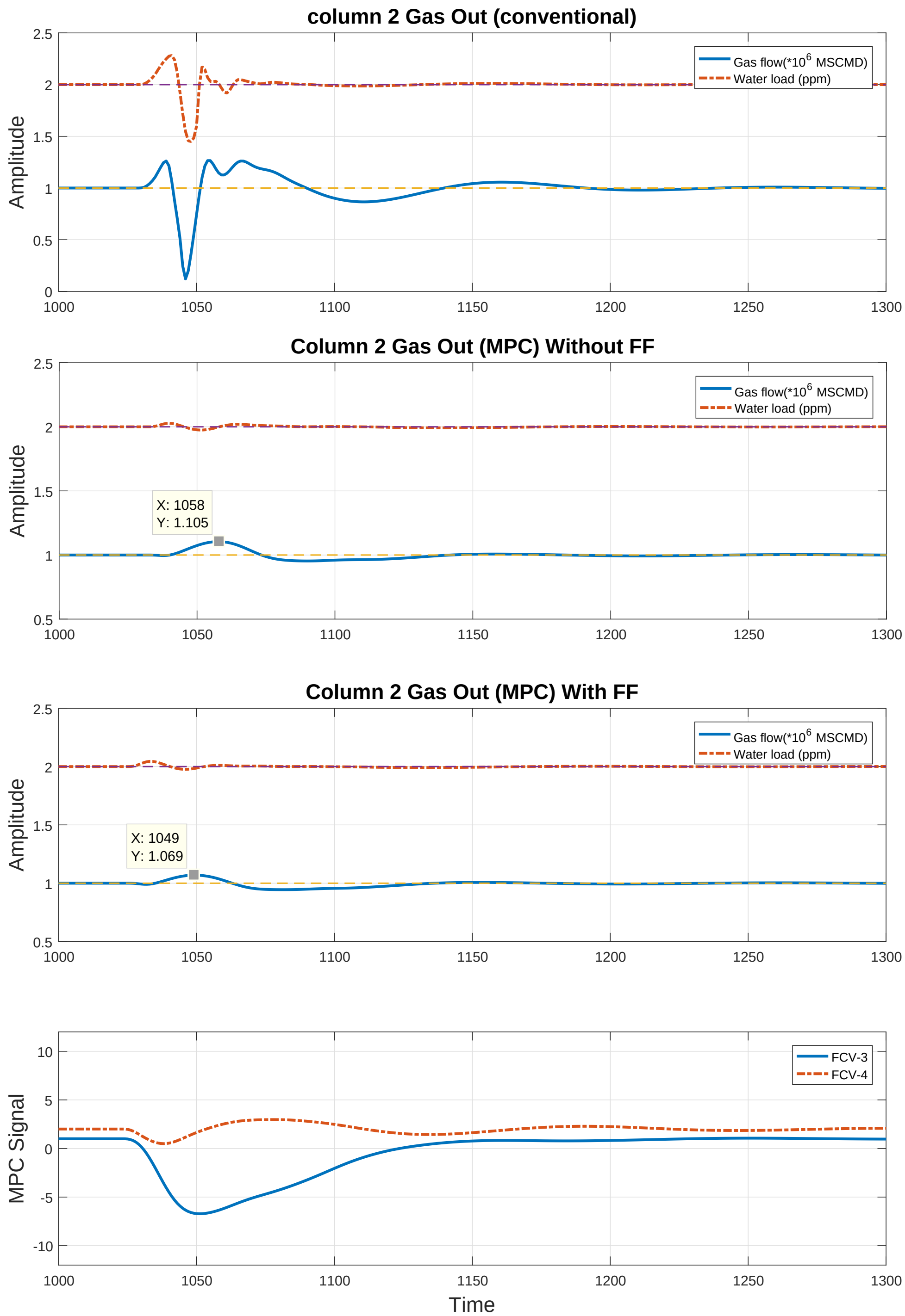


Figure 8.8: Comparison of column two process responses as a result of the 15% solvent filter chock in column one.

The second set represents column one process controlled by the proposed control system without feedforward (MPC + PID). Both controlled trends indicates smooth control with a maximum overshoots of 10% on the gas flow rate.

The third set represents column one controlled by the proposed control system with feedforward (MPC + FF + PID). The responses are identical to the second set because the disturbance were originated in column one, hence there are no feedforward information.

The fourth set shows the MPC control signal in the proposed control system with feedforward. MPC gradually changed the reference value of the gas quality internal loop controller as a response of the disturbance. This action indicates that, MPC changes the reference value, behaving like an operator, while the main control task is carried out by the internal control loops.

8.7.2.3 Impact of process disturbance on column two

The top set of Fig. 8.8 represents column two process with conventional control. Both controlled variables, the gas flow rate and the water load on the gas, undergoes steep short frequency oscillations. In reality, such unbalanced operation well lead to shut down the unit.

The second set represents column two process controlled by the proposed control system without feedforward (MPC + PID). The situation is totally different here. The gas flow rate were smoothly controlled with minimum process disturbance. As a consequence, the water load trend show a minor disturbance effect only.

The third set represents column two controlled by the proposed control system with feedforward (MPC + FF + PID). Compared with the second set, the gas flow overshoot was reduced from 10.5% to 7% which indicates that the controller utilised the advanced knowledge provided by the feed forward loop.

The fourth set shows the MPC control signal in the proposed control system with feedforward (MPC + FF + PID). MPC control signals, for both loops, altered the internal control loop references just before the disturbance shock reaches column two. This indicates that, the MPC controller was prepared for the disturbance. Hence, the outcome is a smooth and tailored control signal which, indeed, is beyond human operator capability.

8.7.2.4 Summary of process disturbance impact on two columns process

Table 8.4 summarises the process disturbance results on the two columns gas treatment processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

Table 8.4: Summary of process disturbance impact on two columns process

Unit			Column 1	Column 2
Gas flow rate	% Overshoot	Operator + SISO PID	20	85
		MPC + SISO PID	10	10
		MPC + FF +SISO PID	10	6.9
	Settling time	Operator + SISO PID	11	140
		MPC + SISO PID	15	35
		MPC + FF +SISO PID	15	27
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	20	25
		MPC + SISO PID	1	1
		MPC + FF +SISO PID	1	1
	Settling time	Operator + SISO PID	30	35
		MPC + SISO PID	0	0
		MPC + FF +SISO PID	0	0

8.8 Wide Process Control with Constraints

In order to illustrate the effectiveness of the inclusion of constraints in the proposed control structure, two different major process disturbance situations were examined under the following constraints and controllers settings:

- The prediction (n_y) and control (n_u) horizons of column one and two processes are 40 and 15 respectively.

- Constraints settings are:
  $0 \leq Gas\ flow\ rate\ (Output) \leq 3\ MSCMD$; $\quad -3 \leq \Delta\mathbf{U} \leq 3$; $\quad -30 \leq \mathbf{U} \leq 30$;
  $0 \leq Acidic\ concentration\ (Column\ one\ Output) \leq 4\ ppm$;
  $0 \leq Water\ load\ (Column\ two\ Output) \leq 4\ ppm$;

8.8.1 Major Process Unit Malfunction

Constraints violations are very likely to happen when the process is operated close to the constraint limits. Consider a situation where the plant is operated at it's maximum capacity and suddenly a major disturbance occurs which has the potential to cause unbalanced operation to the entire process series, for example a unit failure. Hence, to analyse the gas train control system behaviour during such scenarios, a disturbance of 50% solvent filter chock had been introduced to the solvent control loop of column one while the process is operated at 2.8 *MSCMD* (very close to the maximum constraint at 3 *MSCMD*). Thereafter, the process responses of the conventional control system (SISO PID + operator) and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparison between both control strategies. The result consequences on columns one and two are presented sequentially in figures 8.9 and 8.10. To summarise the outcomes, Looking to column one discharge trends, the MPC responded systematically to the deviation in the gas quality as a result of the major disturbance. Even though the process were operated very close to the maximum gas flow constraints, when the disturbance strikes, the control system was able to ensure smooth and safe operation without violating the constraints. The control system efficiency in handling constraints plus the feedforward communication eases the disturbance effects on the successor process and supports it's control system to manage the process with minimum control interventions as seen in column two trends. The following subsections provide discussion about each process unit, under both control strategies, in response to column one solvent major flow disturbance of 50% filter chock.

8.8.1.1 Process disturbance

Column one was exposed to a major process disturbance, while the process is operated close to the maximum constraint of the gas flow rate, at sample 1000. A 50% solvent filter chock had been introduced to the solvent control loop.

8.8.1.2 Impact of process disturbance on column one process

The top set of Fig. 8.9 represents column one process under conventional control. The disturbance caused the solvent flow to the column to drop by half which caused the sudden increase in the gas acidity. At the same time, the gas flow rates through the column increased due to the reduction in the opposing solvent flow. Clearly, the maximum gas flow constraint were violated by a large magnitude for a considerable time. This scenario will lead to column one being shut down by the safe guarding system.

The second set represents column one controlled by the proposed control system with feedforward (MPC + FF + PID). Even though, the process was operating close to the constraints, both trends were controlled within their operating envelops without violating constraints. The gas flow rate was capped just under the constraints threshold.

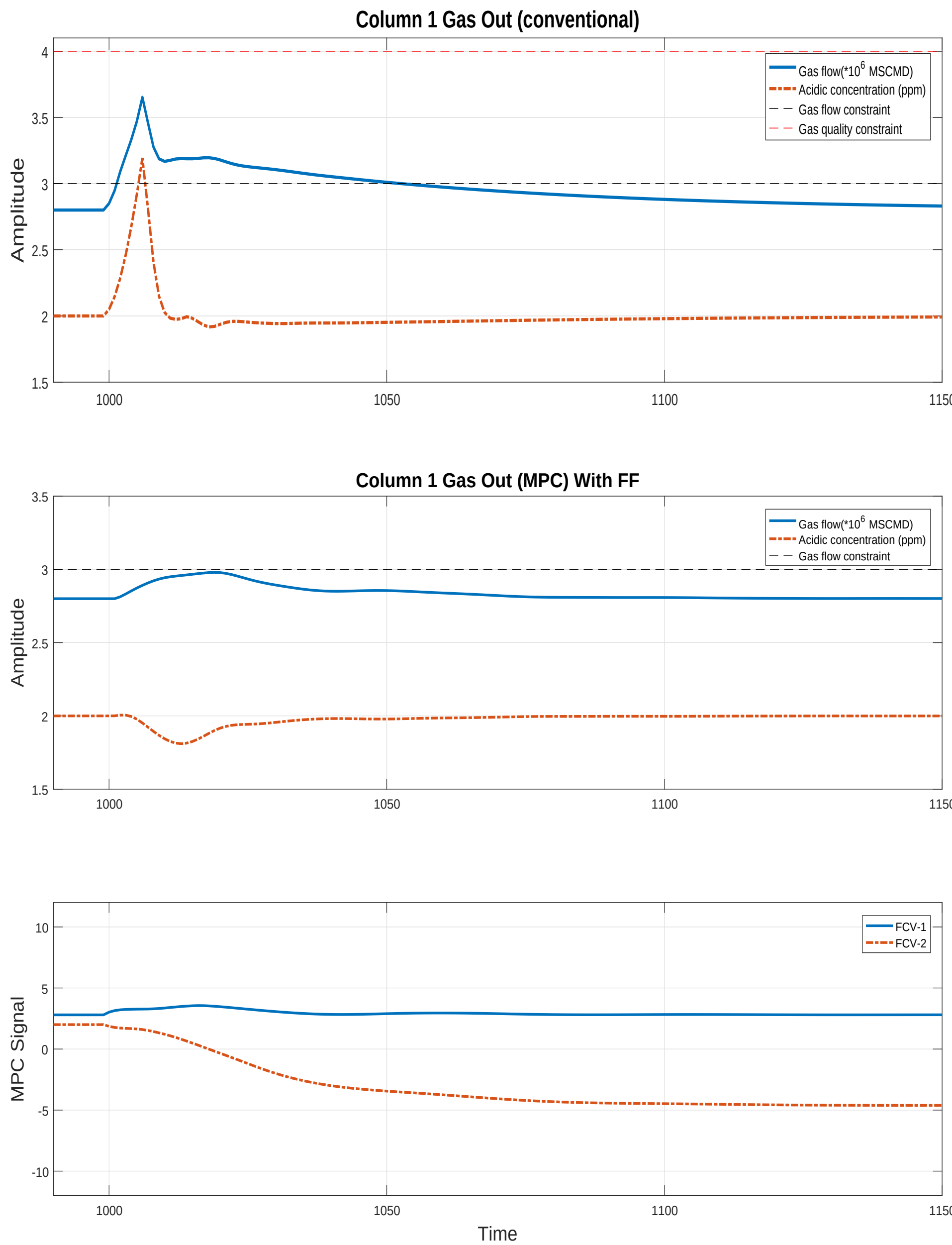


Figure 8.9: Comparison of column one process responses as a result to the 50% solvent filter chock disturbance. The top set represent column one trends under the conventional control (Operator + PID). The second set is column one results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

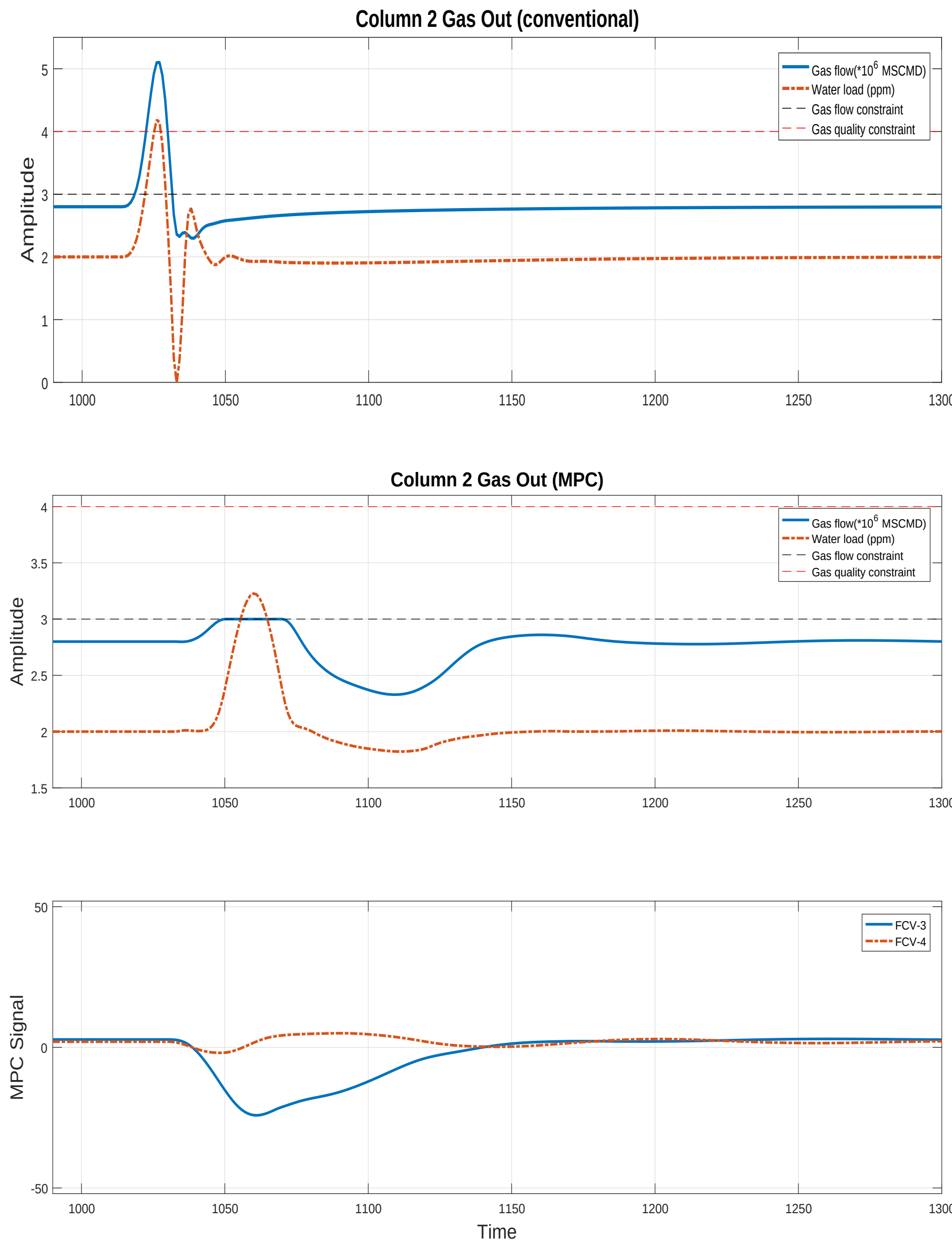


Figure 8.10: Comparison of column two process responses as a result to the 50% solvent filter chock disturbance in column one. The top set represent column two trends under the conventional control (Operator + PID). The second set is column two results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

The third set shows the MPC control signal in the proposed control system with feedforward. The control system response was quick and effective. MPC gradually changed the reference value of the gas quality internal loop controller as a response to the disturbance.

8.8.1.3 Impact of process disturbance on column two

The top set of Fig. 8.10 represents column two process under conventional control. The outcome is a sluggish control with maximum constraints of both loops being violated. Once again, this scenario will lead to column two process being shut down by the safe guarding system.

The second set represents column two process controlled by the proposed control system with feedforward (MPC + FF + PID). The gas flow rate trend slightly reduced before the disturbance hit the GDU which indicates the controllers cooperation, in providing and utilising the advanced information, by the feed forward loop. Constraint handling in column one played a major role in stabilising the successor process, column two, by capping the gas flow rate constant under the constraint limit which, actually, stopped the disturbance oscillations. Column two gas flow rate was successfully controlled without violating the constraints.

The third set shows the MPC control signal in the proposed control system with feedforward. MPC control signals, for both loops, altered the internal control loop references just before the disturbance shock reaches column two. This indicates that, the MPC controller was prepared for the disturbance. Hence, the outcome is a smooth control signal which, indeed, is beyond a human operator capability.

8.8.1.4 Summary of major process disturbance impact on two columns process

Table 8.5 summarises the major process disturbance results on the two columns gas treatment processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

Table 8.5: Summary of major process disturbance impact on two columns process

Unit			Column 1	Column 2
Gas flow rate	% Overshoot	Operator + SISO PID	32	80
		MPC + FF +SISO PID	7	18
	Settling time	Operator + SISO PID	75	40
		MPC + FF +SISO PID	30	80
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	60	105
		MPC + FF +SISO PID	10	62
	Settling time	Operator + SISO PID	20	30
		MPC + FF +SISO PID	15	80

8.8.2 Major Feed Disturbance

Major feed disturbances are also capable to cause constraints violation. Hence, to examine the control system behaviour during such scenarios, a large setpoint change had been introduced to column one gas flow rate. The setpoint was stepped up from 1.5 *MSCMD* to 2.8 *MSCMD* (very close to the maximum constraint at 3 *MSCMD*). Thereafter, the process responses of the conventional control system (opereator + SISO PID) and the proposed control system with feedforward (MPC + FF + SISO PID) were presented side by side for each process to aid comparisons between both control strategies. The consequences on each process of the gas train are presented in Fig. 8.11 for column one and Fig. 8.12 for column two.

In summary, looking to column one discharge trends, the MPC responded systematically to the major feed disturbance without violating the gas flow maximum constraint, even though the new setpoint of gas flow rate is very close to the maximum constraint. The control system efficiency in handling constraints plus the feedforward communication eases the disturbance effects on the successor process and supported it's control system to operate the process without violating the constraints as seen in column two trends.

Hereafter, a detailed discussion of each process unit controlled by both control strategies, conventional and proposed, in response to the gas train throughput major disturbance of around +90% are presented in the following sub sections.

8.8.2.1 Feed disturbance

Column one process was exposed to a large feed disturbance at sample 1000 where the gas flow rate reference value stepped up from 1.5 *MSCMD* to 2.8 *MSCMD* to analyse the proposed control system behaviour in handling constraints.

8.8.2.2 Impact of feed disturbance on column one process

The top set of Fig. 8.11 represents column one process under conventional control. Both trends, the gas flow rate and gas quality, seems to be properly controlled without violating the constraints.

The second set represents column one process controlled by the proposed control system with feedforward (MPC + FF + PID). Both controlled variables were capable to absorb the feed disturbance and properly controlled the unit without violating the constraints.

The third set shows the MPC control signal in the proposed control system with feedforward. MPC control signal increased at the time of the disturbance and then idealised, while the main control task is carried out by the internal control loops.

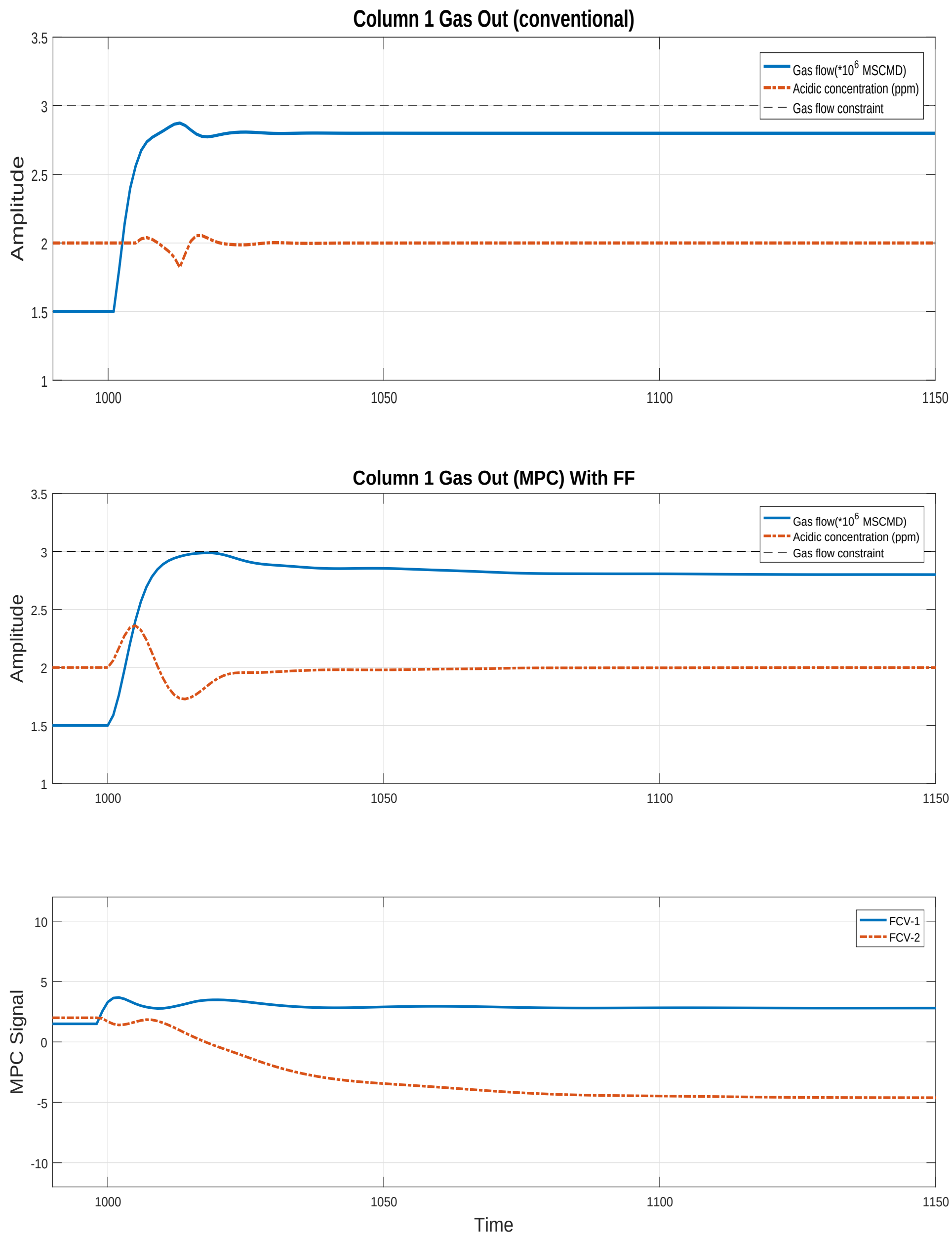


Figure 8.11: Comparison of column one process responses as a result to the major feed disturbance. The top set represent column one trends under the conventional control (Operator + PID). The second set is column one results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

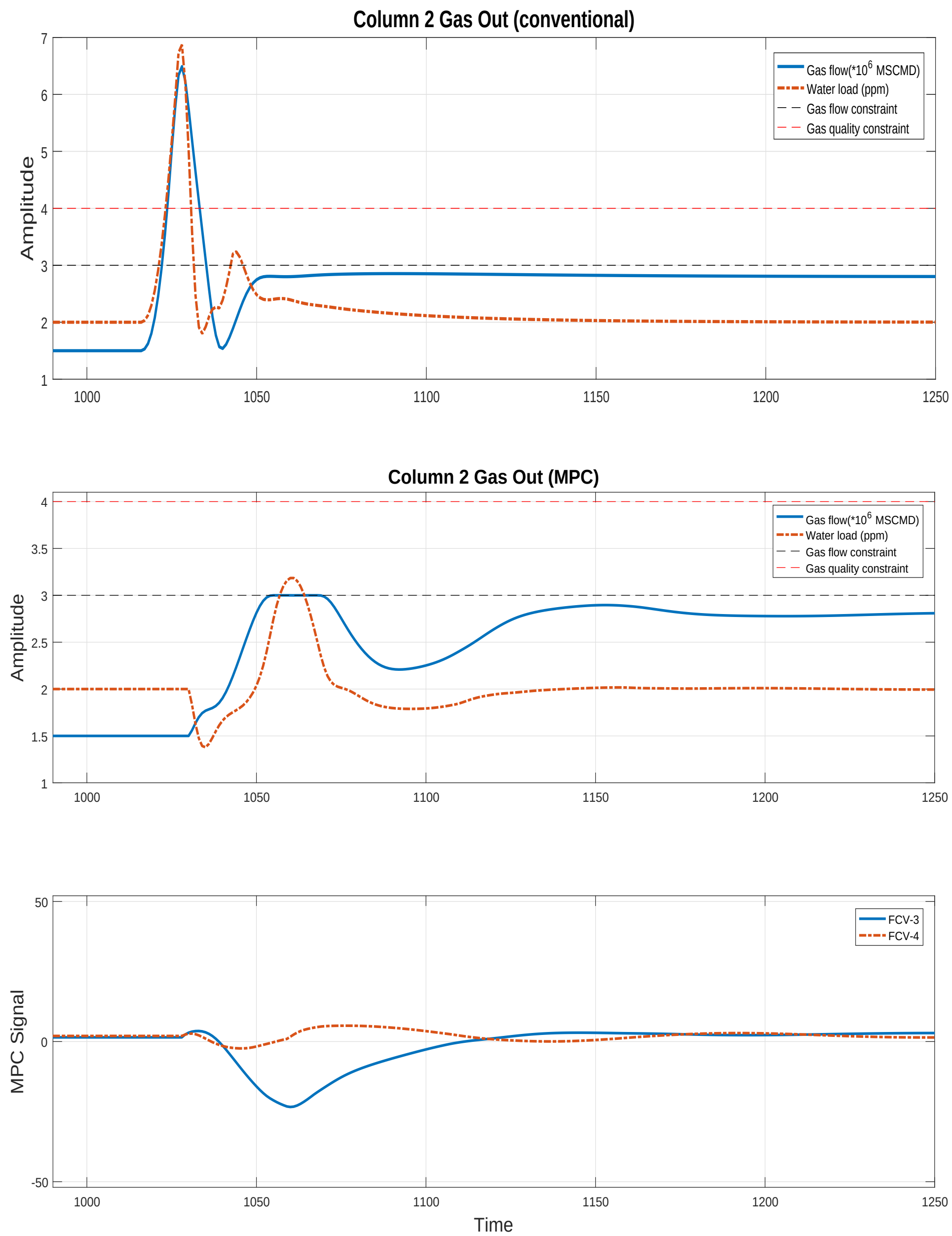


Figure 8.12: Comparison of column two process responses as a result to the major feed disturbance on column one. The top set represent column two trends under the conventional control (Operator + PID). The second set is column two results under the proposed control structure (MPC + FF + PID), while the third set represents the MPC control signal in the proposed control.

8.8.2.3 Impact of feed disturbance on column two process

The top set of Fig. 8.12 represents column two process under conventional control. Both controlled variables increased largely with violation to their maximum output constraints. Once again, this scenario will lead to column two process being shut down by the safe guarding system.

The second set represents column two process controlled by the proposed control system with feedforward (MPC + FF + PID), while the MPC control signal is presented in the third set. Looking to the water load trend, The reduction to the water load in the gas is due to the fact that the controller pre-pumped extra solvent to the column just before the disturbance. At the time when the disturbance wave reached column two, the gas flow rate increased to the maximum constraint without violating it. As a direct result to the raise in the gas flow rate, the water load in the gas starts to increase also.

The controller reduced the gas flow rate to support the control of the gas quality. Thereafter, Both trends stabilised at their reference values. Column two gas flow rate was successfully controlled without violating the constraints. The performance of the control structure is remarkable to maintain balanced operation of column two process.

8.8.2.4 Summary of major feed disturbance impact on two columns process

Table 8.6 summarises the major feed disturbance results on the two columns gas treatment processes and compares the benefit of the proposed control systems (non operator dependent) over the conventional one (operator + SISO PID).

Table 8.6: Summary of major feed disturbance impact on two columns process

Unit			Column 1	Column 2
Gas flow rate	% Overshoot	Operator + SISO PID	3	135
		MPC + FF +SISO PID	7	19
	Settling time	Operator + SISO PID	20	30
		MPC + FF +SISO PID	25	75
2^{nd} controlled variable	% Overshoot	Operator + SISO PID	10	245
		MPC + FF +SISO PID	20	55
	Settling time	Operator + SISO PID	20	60
		MPC + FF +SISO PID	22	70

8.9 Summary

This chapter aimed to examine the transferability of the earlier designed control system, in chapter 7. The chapter also provide assurance that the proposed control system can be used to control other interactive processes.

The proposed control methodology was tested in a two columns gas treatment process. The results on process control performance were indicative which proves the transferability of the new control system. The results also prove the ability of the proposed control structure to reduce the disturbance effects in the series connected processes and to handle process constraints. The process wide control performance was further improved by inclusion of the feedforward loops in the control algorithm, which speeds up the control actions in confronting disturbances. Accordingly, reducing the system dependency on operators.

Alongside the good control performance at time of disturbances, it is also noticeable from 'MPC Signal' trends in all units that, the processes are exclusively controlled by PID's during stable operations. However, at time of disturbances, MPC's takes the lead and command corrective actions. This means that the MPC behaves like an operator. During normal plant operation it is difficult for the operators to spot process deviations, due to large number of process control loops, until one of the alarm threshold is triggered. At this point of time, it is too late for a correcting actions and the situation will be like a fire fighting. Unlike human operators, MPC works like a watch dog. When the process starts to deviate, and before the disturbance escalates, a small and smooth corrective signal will be enough to stabilise the process. Therefore, the results prove that the proposed control structure is capable to operate the plant with eliminating the operator role. The results also prove the ability of the control structure to properly control the interactions between different processes in the plant during disturbances.

The designed control algorithm is simple, systematic and easy to be understood without compromising the control efficiency. Compared with the current available solutions in the literature [53], the proposed control solution is cheaper because it builds up on the original plant control system structure. Also it is simpler to implement because the supervisory MPC control layer is small in size. Furthermore, it can be added to the existing control structure in the instrument auxiliary room without disturbing the current field arrangements. The MPC system model is quite easy to develop for a small dimension problems, as well as the control algorithms. Nevertheless, it almost delivers the same benefits and does not omit the team operational experience and maintenance skills. In addition, it's performance can be easily validated in the DCS by altering the cascade mode between auto and manual.

Chapter 9

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The final chapter is organised as follows: section 9.1 presents the conclusion of the thesis. The conclusions are divided into subsections concluding the main themes of the thesis. While the future work proposals are presented in section 9.2.

9.1 Conclusions

Upstream oil and gas plants are complex processes, which comprises a number of interactive systems. Most, if not all, of these plants are controlled by the conventional SISO PID controllers. Therefore, these processes are most susceptible to major control upsets during disturbances due to the reactive control theme of the PID algorithm as well as the lack of coordination between subsystem controllers. Feed disturbance and disturbances related to equipment failure can cause escalating control disruption affecting all predecessor and successor sub-processes. There is always a constant push towards a higher product quality and continuous good operation safety records with lower operation cost initiated by the escalating product quality specifications that become stricter, tight environmental regulations, and demands for productivity growth. Therefore, oil and gas producers are confronting a strong competitive environment nowadays. Hence, extracting greater value from the current manufacturing assets becomes a major challenge.

This thesis brought much needed attention to the control challenges facing upstream oil and gas production plants, especially the existing ones, and discussed different solutions to handle their control challenges. The thesis targeted two main control issues affecting the current upstream oil and gas fields. These are the disturbance growth in the series connected process, and the control system dependency on operators.

Advanced control literature includes a vast number of methods, which provide important ways to improve production situations. Novel control strategies offer a potential to implement more advanced control algorithms but in reality, most industrial engineers prefer to select a robust and transparent process control structure that uses simple controllers such as PID's. In the other hand, model based predictive control (MPC) is one of the most successful solutions for multivariable processes. MPC has become a standard approach and its popularity in the chemical process industries has increased steadily due to its ability to deal with process constraints, multivariable and complex dynamics systems. Nevertheless, it is main weaknesses are the algorithm complexity and the elongated computation time needed for prediction and optimisation. The control structure of the existing upstream production plants needs to simply and inexpensively encompass MPC features such as predictions, optimizations, coordination and constraint handling as well as PID features like simplicity and ease of troubleshoot. The thesis presented a friendly inexpensive control system upgrade based on MPC for the **existing** upstream oil and gas plant (brownfield). The solution was based on developing a control system with improved disturbance rejection techniques by cheaply integrating MPC in the current process PID control system.

The thesis starts by identifying the upstream oil and gas operations and discusses the associated control challenges that provides the research questions. Then, presents a general theoretical background of model predictive control in chapter 2. The chapter starts with a generic historical introduction about MPC followed by an overview describing the features and main principles of MPC. The chapter thereafter discusses

MPC core components and provides a brief description about MPC algorithms evolution. Then, presents the basic concepts of predictions accompanied by the basic MPC algorithms, that provides a common theoretical framework necessary for arguments in this thesis. The chapter also provides description about constraint handling in MPC.

9.1.1 Research problem and solution

Upstream oil and gas operations description and the associated control challenges that form the research problems were presented in chapter 3. These control challenges were the control system operator dependency and series connected process disturbance growth. Oil and gas production plants confront regular increase in complexity with time, while the organisations' managements drive towards a reduction in manning. Therefore, the control system must be able to anticipate the effects of current control inputs on the future plant operation directions. Process high and low threshold alarms can be set as constraints to the control system which consequently forces the system to weight and judge each control input to satisfy the constraints. The initial task was to develop an auto strategy which takes these decisions and therefore is equivalent to an expert control room operator. Consequently, the plant will be operated in safe and optimal manner. The prime contribution of this thesis is the development of the feasible control concept for upstream oil and gas fields presented in section 4.2. Unlike the currently available control strategies in the industry, the concept builds on existing infrastructure and expertise that reduces cost, training requirements and simplifies validation. Moreover, by utilising the existing structures, the MPC output trends can be easily compared against operator's manual set-points in the classical control by switching the MPC mode in the DCS from cascade to manual. In addition, the implementation of the new control strategy is straightforward because it takes place in the instrument auxiliary room, hence it does not disturb the field arrangements by any means.

9.1.2 Process model

In order to investigate the proposed control approach and compare it against different control structures it is necessary to have a suitable benchmark model reflecting the realistic upstream oil and gas operations. A verified model for the gas phase operation in upstream oil and gas plants suitable for system analysis and control design investigations was developed in chapter 5. The developed process models are simple, easy to understand and based on transfer functions. These models would also be of benefit to Large Scale System (LSS) and system interactions control research fields. The process models capture the three main gas treatment processes found in most upstream oil and gas processing plants: gas sweetening, gas dehydration, and hydrocarbon dew-pointing. The models provide a realistic process representation to test and verify different process control approaches, specifically those which deals with highly interactive control loops. Therefore, the models offer good opportunity for process control engineers to test a variety of process disturbances, malfunctions, and load changes on the process operation and verify the impact with different control system designs. Thereafter, the gas train model had been utilised to examine the significance of different disturbance types on a gas processing train. The impact of two different causes of process disturbances on a 'gas phase train' have been studied in chapter 6. The analysed process disturbances are 'Feed disturbance' initiated by a setpoint change on GSU gas flow rate and 'process unit malfunction', triggered by a unit failure on GSU solvent flow. Both disturbance types cause significant impacts on the successor process as shown in sections 6.1.1 and 6.1.2. However, the influence on GSU where both disturbances originated, and HCDP the third process in raw are different for each disturbance type. A feed disturbance on GSU has a bad influence on the pressure loop in the HCDP while it does not upset GSU loops much. Unlike the feed disturbance, the process unit malfunction disturbs the GSU but is found to have minor impacts on HCDP loops.

9.1.3 Controller design

Disturbance analysis proved that the system functionality deteriorates substantially when one unit fails or the feed disturbances lead to a system instability. The results gained from the disturbance analysis were exploited to implement and look in more depth at the developed control concept for the 'gas phase train' as it was presented in section 4.2. The proposed control system aims to enhance (rather than replace) the current classical control system in the existing oil and gas plants by integrating the process safeguarding system and cost effective MPC's into a classical PID control system. The design of the feasible control concept was demonstrated in chapter 7. The chapter examined the integration of small size MPC's with the classical PID control system in handling interactive control loops in the three series gas treatment processes. The process control performance was largely enhanced by implementing decentralised cooperative small MPC's in the control structure. The results of smart integration of MPC with the conventional PID control system affectedly limits the disturbance influence in the process. Amalgamation of the feedforward loops in the control algorithm improved the speed and accuracy of the control actions in confronting disturbances. Nonetheless, the process wide control performance was further improved by inclusion of the process constraints in the control strategy. As a result, the MPC actions improved the plant performance beyond what a skilled and experienced operator can achieve. The results also prove the ability of the proposed control structure to reduce the disturbance effects in the series connected processes and to handle process constraints. Accordingly, reducing the system dependency on operators. Splitting the MPC into smaller systems and dedicating it to control critical interactive loops only, makes it easier to troubleshoot and to judge the behaviour of each MPC separately. But the biggest benefit of the proposed solution is the control system availability improvement during failure of one or more MPC's. All process controlled variables will be under control even though one, or more, MPC is turned off for some reason (a set-up error for example) or if the MPC failed due to a power dip in the control building. The internal loop controllers (PID's), normally located in the process itself (therefore in the transmitter or valve housing), will continue to operate the plant.

The success of the proposed control system in achieving the pre-set objectives draw an important question about the transferability of the proposed control methodology to control other interactive processes. Well, the thesis provided assurance that the proposed control system can be successfully implemented in different interactive processes by testing it in a different process. The proposed control methodology was tested in a two columns gas treatment process. The results on process control performance were indicative which proves the transferability of the new control system. The results also prove the ability of the proposed control structure to reduce the disturbance effects in the series connected processes and to handle process constraints. Alongside the good control performance at time of disturbances, it is also noticeable from 'MPC Signal' trends in all units that, the processes are exclusively controlled by PID's during stable operations. However, at time of disturbances, MPC's takes the lead and command corrective actions. This means that the MPC behaves like an operator. During normal plant operation it is difficult for the operators to spot process deviations, due to large number of process control loops, until one of the alarm threshold is triggered. At this point of time, it is too late for a correcting actions and the situation will be like a fire fighting. Unlike human operators, MPC works like a watch dog. When the process starts to deviate, and before the disturbance escalates, a small and smooth corrective signal will be enough to stabilise the process. Therefore, the results prove that the proposed control structure is capable to operate the plant with eliminating the operator role. The results also prove the ability of the control structure to properly control the interactions between different processes in the plant during disturbances.

9.1.4 Final remark

As a final remark, the designed control algorithm is simple, systematic and easy to be understood without compromising the control efficiency. Compared with the current available solutions, the proposed control concept is cheaper because it builds up on the original plant control system structure. Also it is simpler to implement because the supervisory MPC control layer is small in size. Furthermore, it can be added to the existing control structure in the instrument auxiliary room without disturbing the current field arrangements. The MPC system model is quite easy to develop for a small dimension problems, as well as the control algorithms. Nevertheless, it almost delivers the same benefits and does not omit the team operational experience and maintenance skills. In addition, it's performance can be easily validated in the DCS by altering the cascade mode between auto and manual.

9.2 Future Research Directions

The main future direction of the work described in this thesis is the practical implementation of the proposed control concept. Successful completion of this task require accurate model development for the underlying process. A simple process identification method can be used to develop a precise enough process model. Where, the system characteristics are solely identified from the response to a known forcing input. Bear in mind, the interests should be primarily focused on the process interactive loops only because most other control loops can be satisfactorily controlled by SISO PID's.

Nevertheless, three key obstacles were identified in order to progress the practical implementation. These are:

- **Site Management**. Even though, process modelling on site seems simple and straightforward but in reality the situation is not that easy. Site mangers might refuse to authorise the modelling for different reasons. Site managers have their own tasks and targets and they will resist any steps that may lead to process disturbance and hence production deferments. The way forward is by persuading strong managers by the long term benefits.

- **Operational Team**. Operators could also resist the identification process and even the implementation. There reasons could vary from as simple as extra challenges to their daily tasks; to real valid ones if they feel that the success of the proposed concept could stepdown their important roles and the possibility of losing their jobs. Hence, it is very important to assure the work force that the control system upgrade aims to support their roles and to enhance their decisions.

- **Technical issues**. Clear technical plan of the control system upgrade should be identified first. The plan needs to clearly identify all related technical issues such as whether to install the MPC's in the current DCS server or on a server by its own. What about the computational load if the MPC's installed in the DCS server? If installed in different server how are we going to establish communications between DCS and MPC? Actually, there are no direct answers to these questions and hence need to be addressed on site.

Appendix A

MATLAB PROGRAM FILE TO CREATE LMFD EQUATIONS FROM A CONTINUOUS PROCESS MODEL

A left matrix fraction description (LMFD) of a process model can be obtained by using the following MATLAB code. Consider the 2X2 GSU model given by:

$$G_{GSU} = \begin{pmatrix} \frac{-0.7066z^{-1}}{1-0.9477z^{-1}}\ z^{-2} & \frac{0.7294z^{-1}}{1-0.9001z^{-1}}\ z^{-6} \\ \\ \frac{0.6957z^{-1}}{1-0.9583z^{-1}}\ z^{-13} & \frac{1.257z^{-1}}{1-0.9371z^{-1}}\ z^{-6} \end{pmatrix} \tag{A.1}$$

In order to compute the GSU model LMFD equations, the continuous model will first be converted to a discrete model with descending power (z^{-1}). LMFD is then obtained by "making matrix $\mathbf{A}(z^{-1})$ equal to a diagonal matrix with diagonal elements equal to the least common multiple of the denominators of the corresponding row of the transfer function" [13]. Here is the MATLAB code:

Gas Sweetening Model

```
g11=tf(-13.5,[18.6 1]); delay11=2;
g12=tf(16.7,[23.5 1]); delay12 =6;
g21=tf(7.3,[9.5 1]);delay21 =13;
g22=tf(20,[15.4 1]);delay22 =6;
```

```
G=[g11,g12;g21,g22];    % G is matrix form of transfer function.
```

To convert G to discrete with descending power (z^-1) and sampling time of 1 minute

```
Ts=1;
% Delay can be added to gd(ij) after convertion.
% In this case 1/Ts = 1; therefore the delay = 1*g(ij)
g11d=c2d(g11,Ts);[n,d,Ts]=tfdata(g11d);g11d=tf(n,d,Ts,'variable','z^-1');
g12d=c2d(g12,Ts);[n,d,Ts]=tfdata(g12d);g12d=tf(n,d,Ts,'variable','z^-1');
g21d=c2d(g21,Ts);[n,d,Ts]=tfdata(g21d);g21d=tf(n,d,Ts,'variable','z^-1');
g22d=c2d(g22,Ts);[n,d,Ts]=tfdata(g22d);g22d=tf(n,d,Ts,'variable','z^-1');

Gd=[g11d,g12d;g21d,g22d];
% G is matrix form of descrete transfer function (z^-1).
```

Please Note:

A(z^-1) is a diagonal matrix with A11= Least Common denominator of row and so on.
Bij(z^-1) is a matrix of numerators corresponds to Aij multiplied by (z^1)

```
A=[]; B=[];
[NUM11,DEN11] = tfdata(Gd(1,1),'v');
[NUM12,DEN12] = tfdata(Gd(1,2),'v');
[NUM21,DEN21] = tfdata(Gd(2,1),'v');
[NUM22,DEN22] = tfdata(Gd(2,2),'v');

A11=conv(DEN11,DEN12);  %A11(z^-1) matrix
A22=conv(DEN21,DEN22);  %A22(z^-1) matrix
```

```
As=max([size(A11,2),size(A22,2)]);
A(1,1:2:2*As) = [A11];
A(2,2:2:2*As) = [A22];

delay11=round(delay11/Ts);delay11=[zeros(1,delay11) 1];
% Delay = 1*2= 2, therfore z^(-2)
delay12=round(delay12/Ts);delay12=[zeros(1,delay12) 1];
% Delay = 1*6= 6, therfore z^(-6)
delay21=round(delay21/Ts);delay21=[zeros(1,delay21) 1];
% Delay = 1*13= 13, therfore z^(-13)
delay22=round(delay22/Ts);delay22=[zeros(1,delay22) 1];
% Delay = 1*6= 6, therfore z^(-6)

B11=conv(NUM11(:,2:end),DEN12); B11=conv(B11,delay11);
% NUMij(:,2:end) because: B(Z^-1) matrix is multiplied by z^1
B12=conv(NUM12(:,2:end),DEN11); B12=conv(B12,delay12);
% NUMij(:,2:end) because: B(Z^-1) matrix is multiplied by z^1
B21=conv(NUM21(:,2:end),DEN22); B21=conv(B21,delay21);
% NUMij(:,2:end) because: B(Z^-1) matrix is multiplied by z^1
B22=conv(NUM22(:,2:end),DEN21); B22=conv(B22,delay22);
% NUMij(:,2:end) because: B(Z^-1) matrix is multiplied by z^1

Bs=max([size(B11,2),size(B12,2),size(B21,2),size(B22,2)]);
B(1,1:2:2*Bs) = [B11 zeros(1,Bs-size(B11,2))];
B(1,2:2:2*Bs) = [B12 zeros(1,Bs-size(B12,2))];
B(2,1:2:2*Bs) = [B21 zeros(1,Bs-size(B21,2))];
B(2,2:2:2*Bs) = [B22 zeros(1,Bs-size(B22,2))];
```

Appendix B

LMFD OF A MODEL WITH IT'S RELEVANT SISO PID CONTROLLERS

Here is a MATLAB code to obtain LMFD equations to represent a model with it's relevant SISO PID controllers. The code is based on GSU continuous model. The code first converts the continuous model to a discrete model with descending power. Then, builds and connects the PID controllers. Thereafter, the code obtain the LMFD equations.

Gas Sweetening Model

```
g11=tf(-13.5,[18.6 1])*exp(tf([-2 0],1));
g12=tf(16.7,[23.5 1])*exp(tf([-6 0],1));
g21=tf(7.3,[9.5 1])*exp(tf([-13 0],1));
g22=tf(20,[15.4 1])*exp(tf([-6 0],1));

G=[g11,g12;g21,g22];  %G is matrix form of transfer function.
```

To convert G to discrete with descending power (z^-1) and sampling time of 1 minute

```
Ts=1; % sampling time = 1 second
g11d=c2d(g11,Ts);[n,d,Ts]=tfdata(g11d);g11d=tf(n,d,Ts,'variable','z^-1');
g12d=c2d(g12,Ts);[n,d,Ts]=tfdata(g12d);g12d=tf(n,d,Ts,'variable','z^-1');
```

```
g21d=c2d(g21,Ts);[n,d,Ts]=tfdata(g21d);g21d=tf(n,d,Ts,'variable','z^-1');
g22d=c2d(g22,Ts);[n,d,Ts]=tfdata(g22d);g22d=tf(n,d,Ts,'variable','z^-1');

Gd=[g11d,g12d;g21d,g22d];
% G is matrix form of descrete transfer function (z^-1).

Gs=Gd;


%                  e       u
%          r --->O-->[ C1 ]---[ Gs ]-+---> y
%              - |                   |
%                +<------------------+


Kp1=-0.09; Ki1=-0.005; Kp2=0.05; Ki2=0.004;
C1=[pid(Kp1,Ki1,0,0,Ts),0; 0,pid(Kp2,Ki2,0,0,Ts)];

C1.u = 'e';
C1.y = 'u';
Gs.u = 'u';
Gs.y = 'y';
Sum = sumblk('e = r - y',2);

SYS= connect(Gs,C1,Sum,'r','y');

[A2,B2,C2,D2]=ssdata(SYS);
[b1,a1]=ss2tf(A2,B2,C2,D2,1);
[b2,a2]=ss2tf(A2,B2,C2,D2,2);
```

```
A=[]; B=[];

A(1,1:2:14) = [a1];  %A11(z^-1) matrix
A(2,2:2:14) = [a2];  %A22(z^-1) matrix

B11=b1(1,:);
B12=b2(1,:);
B21=b1(2,:);
B22=b2(2,:);

B(1,1:2:14) = [B11];
B(1,2:2:14) = [B12];
B(2,1:2:14) = [B21];
B(2,2:2:14) = [B22];
```

Appendix C

REAL PROCESS RESPONSES TO A STEP CHANGE IN THE FEED GAS

Here are the real process responses to a step increment of 20% in the throughput gas flow (i.e. in the GSU feed). The process responses were then digitised in order to validate the process models. The digitised real process responses of the three systems (GSU, GDU and HCDP) were utilised in section 5.3.2 for model validation by comparison with a real industrial process.

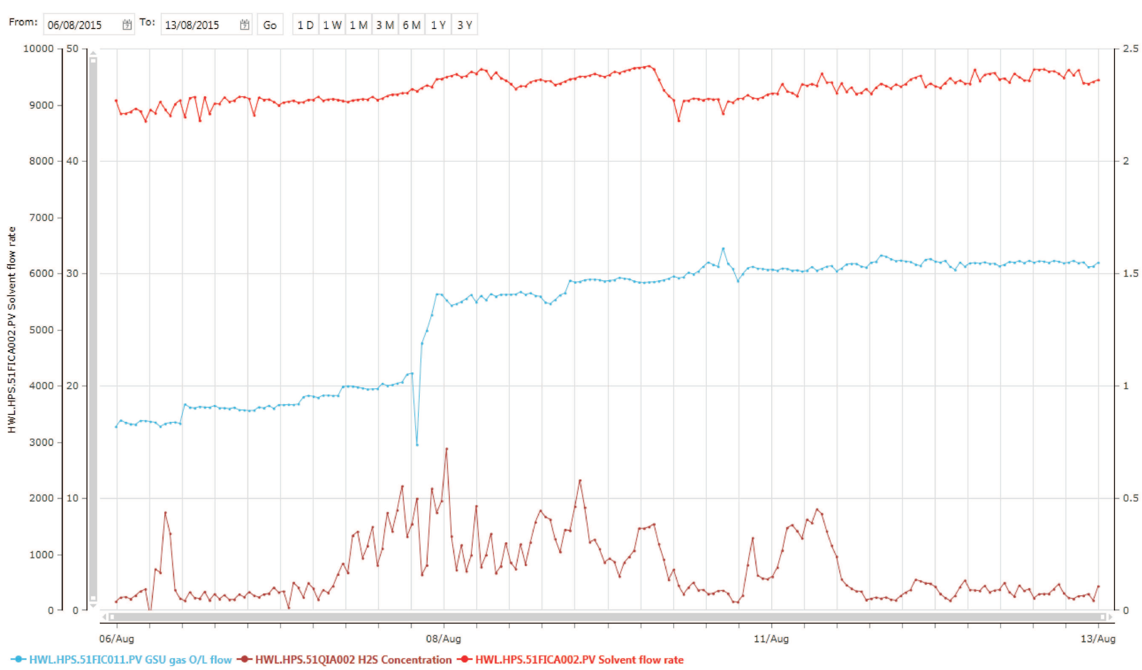


Figure C.1: PDO Harweel GSU. Blue: Gas flow rate (*Range 0 - 2.5 MMSCMD*), Brown: H_2S concentration (*Range 0 - 50 ppm*), Red: Solvent flow rate (*Range 0 - 10000 m^3/d*)

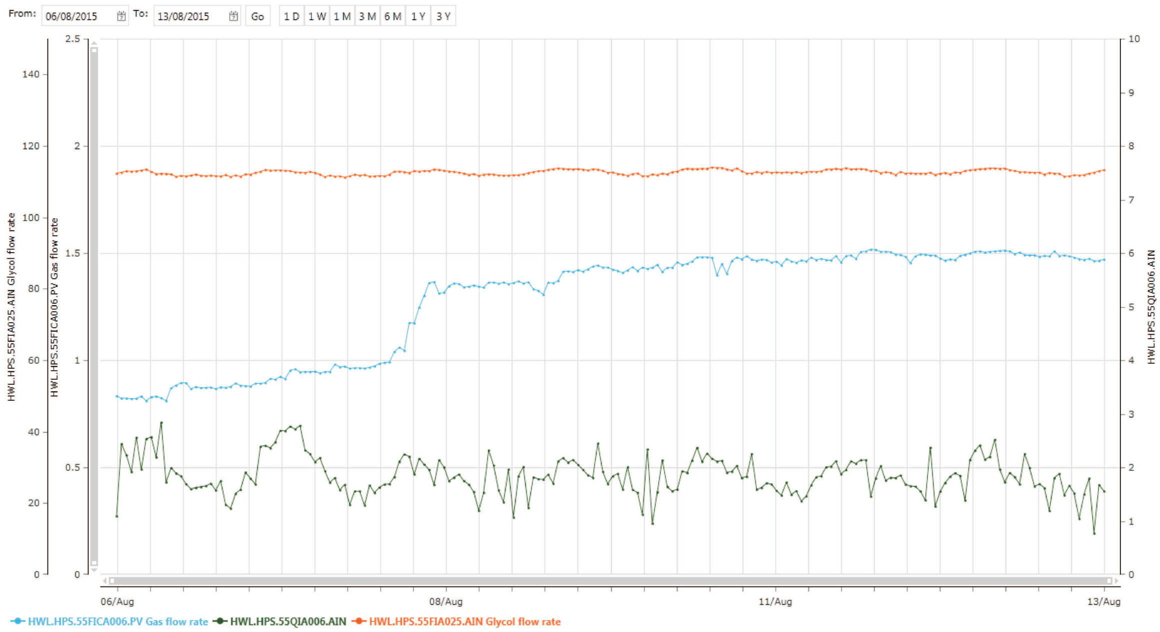


Figure C.2: PDO Harweel GDU. Blue: Gas flow rate (*Range 0 - 2.5 MMSCMD*), Green: H_2O concentration (*Range 0 - 10 ppm*), Red: Glycol flow rate (*Range 0 - 140 m^3/d*)

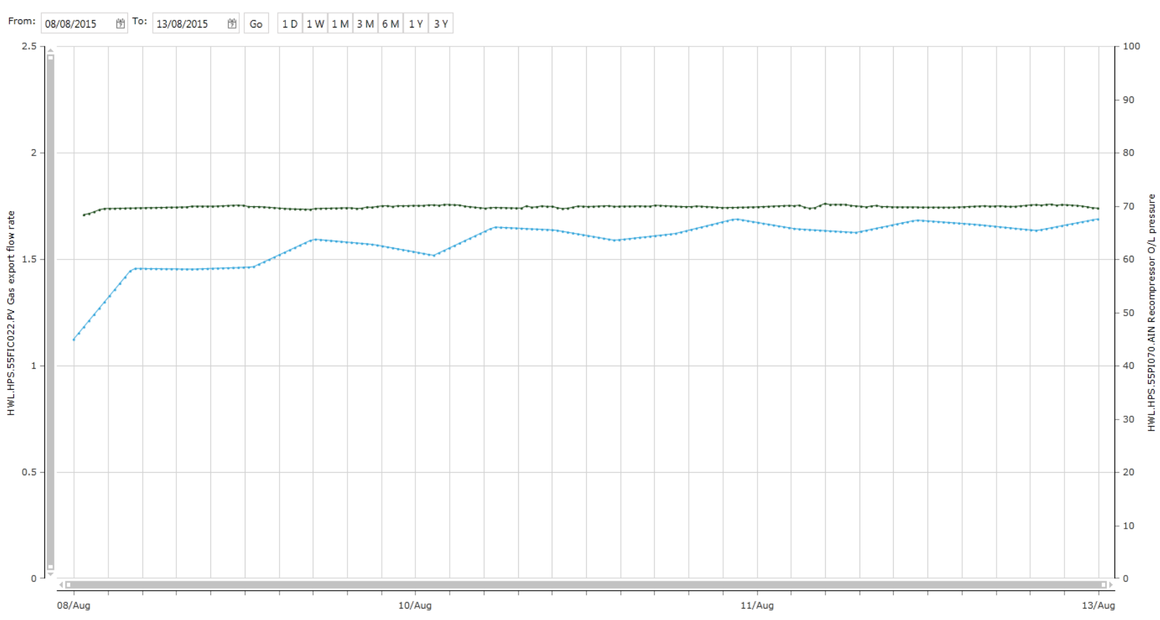


Figure C.3: PDO Harweel HCDP. Blue: Export Gas flow rate (*Range 0 - 2.5 MMSCMD*), Green: Recompressor outlet Gas pressure (*Range 0 - 100 barg*)

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