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ON LIGHTS-OUT PROCESS CONTROL IN THE MINERALS PROCESSING INDUSTRY

by

Laurentz Eugene Olivier

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SUMMARY

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Laurentz Eugene Olivier

Promoter:	Prof. I. K. Craig
Department:	Electrical, Electronic and Computer Engineering
University:	University of Pretoria
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The concept of lights-out process control is explored in this work (specifically pertaining to the minerals processing industry). The term is derived from lights-out manufacturing, which is used in discrete component manufacturing to describe a fully automated production line, i.e. with no human intervention. Lights-out process control is therefore defined as the fully autonomous operation of a processing plant (as achieved through automatic process control), without operator interaction.

Process control theory has developed very far to the current status of advanced controllers able to perform optimisation and even planning functions on complex, possibly nonlinear, processes. The advances in digital technologies have enabled the industrial implementation of many of these automation strategies, to the point where the processing industry is achieving all-time highs in production with less need for human intervention in the process. This trend leads to the natural questioning of the possibility of fully automated, lights-out, process control.

Model predictive control (MPC) is the most successful advanced control technology used in industry today. The implementation and successful operation of an MPC is discussed in the lights-out control

setting. Other enabling technologies that are required for implementation of lights-out control are discussed and a framework for lights-out process control is presented.

The minerals processing industry is used as a case study in this work to illustrate the current status and possible advancement towards lights-out process control. To this end, a survey was conducted regarding the degree of automation in the minerals processing industry. The objectives of the survey included gauging the extent to which minerals processing operations are automated, how often and why operators intervene in the process, what inhibits further automation, and what the prospects are for total process automation.

The survey results, along with available literature, were used to identify some key requirements for lights-out control. One major requirement for maintaining controller performance automatically is maintaining the quality of the available plant model (if the controller makes use of the plant model or plant model parameters). This is achieved through detecting and correcting for significant model-plant mismatch. If the controller and plant can sufficiently be represented by transfer functions, a closed-form expression for the mismatch can be used. This expression is derived and applied in this work. If the controller does not have a transfer function a partial correlation analysis is proposed.

Another prerequisite, specifically for lights-out operation, is the need for active fault-tolerant control (FTC), as the occurrence of a process fault usually necessitates operator intervention in the process. Once a process fault has entered the system the process may not be controllable any longer. For complex nonlinear systems, a constrained controllability analysis is not a trivial task. This work presents a stochastic method for evaluating the ability of the controller to regulate the plant outputs while adhering to the input constraints. To not confuse this evaluation with the well-known input-output controllability, state controllability, or functional controllability analyses the term regulatability analysis will be used.

Even if process regulatability has been proven, it is still of concern whether the plant can operate economically with the diagnosed fault. For a certain class of faults it would be more economical to shut the plant down and repair the fault as soon as possible. A methodology for the economically driven decision to shut the plant down is therefore presented.

The methods developed are applied to a nonlinear run-of-mine ore milling circuit simulation with the vision of lights-out process control. Run-of-mine ore refers to ore taken directly from the mine, without any pre-processing.

Other considerations such as market changes and the social impact of lights-out process control are also discussed. Based on available literature regarding the automation of jobs, the current status in the processing industry, as well as the survey on the status of automation in the minerals processing industry, it seems as though lights-out process control, at least for simple linear processes, may become a reality within the next 20 years.

OPSOMMING

RAKENDE "LIGTE-UIT"-PROSESBEHEER IN DIE MINERAALPROSESSERINGSBEDRYF

deur

Laurentz Eugene Olivier

Promotor:	Prof. I. K. Craig
Departement:	Elektriese, Elektroniese en Rekenaar-Ingenieurswese
Universiteit:	Universiteit van Pretoria
Graad:	Philosophiae Doctor (Elektroniese Ingenieurswese)

Sleutelwoorde:	Beheerbaarheid, ekonomiese verrigting, foutbestand, foutdeteksie en -isolasie, gevorderde beheer, ligte-uit-prosesbeheer, mineraalprosessering, modelvoorspellende beheer, onbehandelde erts, toestandsafskatting

Die konsep van ligte-uit-prosesbeheer word ondersoek in hierdie werkstuk (met spesifieke betreking tot die mineraalprosesseringsbedryf). Die uitdrukking is afgelei van ligte-uit-vervaardiging, wat in die industrie van diskrete komponentvervaardiging gebruik word om 'n totaal geoutomatiseerde produksielyn te beskryf waar geen menslike interaksie nodig is nie. Ligte-uit-prosesbeheer is dus gedefinieer as die totale geoutomatiseerde werking van 'n prosesseringsaanleg (met behulp van outomatiese prosesbeheer), sonder die teenwoordigheid van 'n operateur.

Prosesbeheerteorie het al baie ver gevorder tot waar dit tans moontlik is vir gevorderde beheerders om optimerings- en beplanningsdoelwitte te bereik vir komplekse, moontlik nie-lineêre, prosesse. Die vooruitgang van digitale tegnologie het dit ook moontlik gemaak om baie van die gevorderde beheerstrukture in die industrie te implementeer, tot op die punt waar die prosesseringsbedryf tans spog met rekord-hoë produksieuitsette wat bereik word met al hoe minder ingryping deur operateurs. Hierdie tendens laat 'n mens natuurlik bevraagteken of totaal geoutomatiseerde ligte-uit-prosesbeheer moontlik is.

Modelvoorspellende beheer (MVB) is die mees suksesvolle gevorderde beheerstrategie wat tans in die industrie gebruik word. Die implementering en suksesvolle bedryf van MVB word bespreek in die milieu van ligte-uit-prosesbeheer. Ander tegnologieë wat nodig is om ligte-uit-beheerimplementering moontlik te maak, word ook bespreek en ’n raamwerk vir so ’n ligte-uit-beheerder word voorgelê.

Die mineraalprosesseringsbedryf word gebruik as ’n gevallestudie in hierdie werkstuk om die huidige toestand en die moontlike vooruitgang na ligte-uit-prosesbeheer te illustreer. Volgens hierdie doelwit is ’n opname gemaak van die mate van automatisering van prosesse in die mineraalprosesseringsbedryf. Die doelwitte van die opname sluit in om te bepaal in watter mate prosesse in die mineraalprosesseringsbedryf geoutomatiseerd is, hoe dikwels en hoekom operateurs ingryp in die proses, wat verdere outomatisasie verhoed, en wat die vooruitsig is vir totale outomatisasie van prosesse.

Die resultate van die opname is tesame met die beskikbare literatuur gebruik om te identifiseer wat die sleutelbenodigdhede is om ligte-uit-prosesbeheer ’n realiteit te maak. Een van die hoofbenodigdhede vir outomatiese handhawing van die beheerder se verrigting is outomatiese handhawing van die kwaliteit van die beskikbare prosesmodel (indien die beheerder gebruik maak van die prosesmodel of die parameters daarvan). Dit word gedoen deur vas te stel of daar ’n wesenlike verskil is tussen die aanleg en die beskikbare model van die aanleg, en dan ook te kompenseer vir so ’n verskil. ’n Uitdrukking word voorgelê vir hierdie verskil in die geval waar die beheerder met ’n oordragsfunksie voorgestel kan word. Indien die beheerder nie ’n oordragsfunksie het nie, word van ’n parsiële korrelasie-analise gebruik gemaak.

’n Verdere voorvereiste, spesifiek vir ligte-uit-verwerking, is aktiewe foutbestande beheer, aangesien die teenwoordigheid van foute in die stelsel dit gewoonlik nodig maak dat die operateur moet ingryp. Wanneer ’n fout die stelsel begin affekteer, mag dit onmoontlik word om die stelsel verder te beheer. Vir komplekse nie-lineêre prosesmodelle is die evalusie van die beheerbaarheid met perke op die insette nie ’n eenvoudige taak nie. ’n Stogastiese metode word voorgelê in hierdie werkstuk om hierdie evaluering te voltooi. Dit is dus nodig om te weet of die beheerder die uitsitte binne perke kan hou indien daar ook perke op die insette geplaas is. Hier word verwys na ’n evaluering van reguleerbaarheid eerder as ’n evaluering van beheerbaarheid, sodat hierdie metode nie verwar word met die welbekende evaluerings vir inset-uitsetbeheerbaarheid, toestandsbeheerbaarheid, of funksionele beheerbaarheid nie.

Selfs indien die beheerbaarheid van ’n proses verseker is, is dit steeds nodig om te evalueer of die proses vanuit ’n ekonomiese oogpunt nog in bedryf moet bly. Vir ’n sekere tipe fout is dit meer ekonomies om die proses te stop en die fout so gou moontlik reg te maak. ’n Metode vir so ’n ekonomies gedrewe evaluering word ook voorgestel.

Die metodes wat ontwikkel is, word dan toegepas op ’n simulasie van ’n maalkring wat onbehandelde erts maal en wat deur ’n nie-lineêre model beskryf word.

Ander oorwegings rakende ligte-uit-prosesbeheer, soos die verandering van markte en die sosiale impak, word ook bespreek. Gebaseer op beskikbare literatuur rakende die outomatisering van arbeid, die huidige stand van sake in die prosesseringsbedryf, en ook die resultate van die opname rakende die mate van outomatisasie in die mineraalprosesseringsbedryf, blyk dit dat ligte-uit-prosesbeheer, minstens vir eenvoudige lineêre prosesse, waarskynlik ’n realiteit sal word binne die volgende 20 jaar.

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LIST OF ABBREVIATIONS

APC	Advanced process control
CDKF	Central difference Kalman filter
CSW	Cumulative sum of weights
CV	Controlled variable
DCS	Distributed control system
DV	Disturbance variable
EKF	Extended Kalman filter
EWMA	Exponentially weighted moving average
FDI	Fault detection and isolation
FTC	Fault-tolerant control
FT-NMPC	Fault-tolerant nonlinear model predictive control
GLR	Generalised likelihood ratio
IMC	Internal model control
MIMO	Multiple-input multiple-output
MPC	Model predictive control
MPM	Model-plant mismatch
MV	Manipulated variable
NL-GLR	Nonlinear generalised likelihood ratio
NMPC	Nonlinear model predictive control
NRMSE	Normalised root mean square error
OECD	Organisation for economic cooperation and development
OEM	Original equipment manufacturer
PCA	Principal component analysis
PDF	Probability density function
PID	Proportional-integral-derivative
QTA	Qualitative trend analysis
ROM	Run-of-mine
SMC	Sequential Monte Carlo
SIR	Sampling importance resampling
SISO	Single-input single-output
UKF	Unscented Kalman filter

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CHAPTER 1 INTRODUCTION

Digital technology has improved manufacturing systems dramatically, up to the current advent of the fourth industrial revolution. Within this framework technological advancements are currently in part developed under the banner "Industry 4.0" (Allgöwer 2014). Some manufacturing plants are even operated without human intervention, which is called lights-out manufacturing (Baker and Merchant 1993). Process control is likewise advancing rapidly, and fully automated production is becoming a reality. Fully automated production is termed lights-out process control, and is the focus of this work.

Figure 1.1 shows the layout of a generalised control loop. Any controller has objectives, which may include simple control objectives such as the regulation of controlled variables (CVs) to setpoint, or simply keeping them within bounds, as well as more advanced optimisation objectives such as minimising the process energy usage or maximising the economic performance. Based on the controller objectives and the process outputs a control signal is generated and serves as the exogenous input to the plant (or process). The process may also be perturbed by external disturbances (which could be measured [d] or unmeasured [d^*]), and the process outputs [y] are measured. The processing of plant data could simply be the transduction of measurements into a usable form, or any more complex operation, some of which will be described later in this work.

The generalised control loop of Figure 1.1 forms the basis on which the methods discussed and developed in this thesis will build. This structure will later be expanded into a framework for lights-out process control, which is one of the contributions of this work.

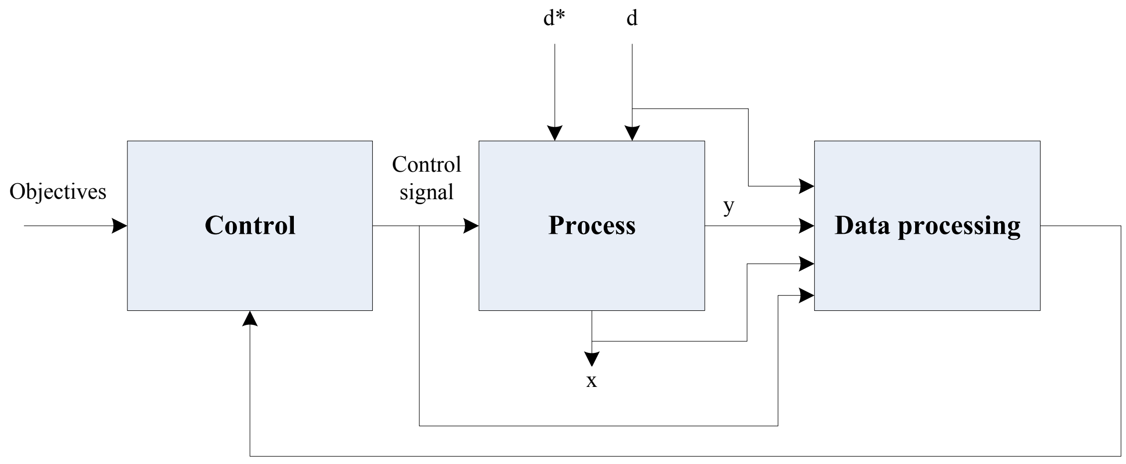

Figure 1.1. Block diagram of a generalised control loop.

1.1 CONTEXT OF THE PROBLEM

Automatic feedback control systems have been in use for more than 2000 years (Bennett 1996), with some of the earliest known examples being water clocks as described by Vitruvius around 270 B.C. The development of control theory and the progress in implementations were however very slow until the development of the centrifugal flyball governor by James Watt in 1788, which was used for regulating the speed of steam engines (Bennett 1979). Over the following century there were extensive efforts made to improve the Watt governor, and thousands of patents were granted around the world. In 1868 James Clark Maxwell published a now famous paper entitled “On Governors” in which he described linear differential equations for various governor mechanisms (Maxwell 1867 - 1868).

The kindling supplied by these developments led to what is known as the first (1760 to ∼1840) and then the second (∼1840 to 1914) industrial revolutions that predominantly included the replacement of human and animal muscle power with machine power. Even though the first half of the 20th century saw widespread industrial application of temperature, pressure, and flow control (Bennett 1996), the rapid development of digital technology since the 1960s truly made modern process control possible. The modern control system may comprise digital computer-based advanced process control (APC) systems that operate industrial processes profitably, while maintaining safety margins, satisfying product quality restrictions, and preventing violation of environmental constraints.

The advancement of digital technology has progressed along a, now famous, Moore’s Law trajectory that describes how the number of transistors in integrated circuits grew exponentially over time (Brock and Moore 2006). This dramatic increase in computing power has enabled the application of ever more complex algorithms, and more complex tasks are now being automated. Brynjolfsson and McAfee (2014) notes that the second machine age, an age where human mental power is being replaced by digital technologies, has already begun. This advancement of computing power has also advanced the field of process control.

The most successful form of advanced control employed today is model predictive control (MPC) (Bauer and Craig 2008, Samad 2016). Implementing linear MPC controllers is seen as a routine task for modern control practitioners, and MPC is often used to improve the plant economic performance (Qin and Badgwell 2003, Craig, Aldrich, Braatz, Cuzzola, Domlan, Engell, Hahn *et al.* 2011). MPC is conceptually simple, and can easily deal with complex systems with many inputs and outputs. Input and output constraints are also generally straightforward to include. These traits have contributed to the popularity of MPC technology (Mayne 2014). Because of its success, MPC is used in this work to illustrate the impact of digital technologies on APC.

Developments in MPC technology coupled with the developments in digital technology, indicates that the process industry appears to be evolving towards *lights-out process control*, i.e. fully automated process plants in which no human intervention or supervision is needed. In fact, fully automated (lights-out) process control is already a reality on some relatively simple process plants that do not require much more than baselayer proportional-integral-derivative (PID) control to function as required (The Linde Group 2016, Solar and Benefit 2016). This work, in part, examines if the same will also be possible in future for more complex plants (specifically within the minerals processing industry) on which MPC controllers are routinely implemented today.

The term “lights-out process control” is adapted from “lights-out manufacturing,” which was introduced in the 1980s for discrete manufacturing processes (Jaikumar 1986). Initial advantages of this fully automated manufacturing approach included additional productivity with minimal impact on labour costs, as capital equipment could be utilised at night when workers went home for the evening. This enabled the lights to literally be switched off with the factory operational, hence the term “lights-out.”

Unlike the discrete manufacturing processes of the 1980s, operations in the process industry are mostly continuous and already run 24/7/365. APC is regarded as a mature technology without which the process industry cannot operate (Craig *et al.* 2011). In this light there is a natural drive towards increasing automation in processing plants as automation tends to reduce variability of process variables which leads to increased profits (Xu, Huang and Akande 2007), it reduces operating costs (Brann, Thurman and Mitchell 1996), and leads to improved safety (as human error is one of the principal causes of accidents (Lees 2012)) and reliability (Bauer and Craig 2008). It is therefore envisioned that gradually production personnel will be fewer and more sophisticated, while processing systems will become more automated and efficient (Baker and Merchant 1993). It is noted in Samad and Cofer (2001) that petroleum refining personnel are decreasing, while refinery output is increasing. This shows the effect of automation on production.

The drive towards increasing automation is also occurring in industries other than the process industry, e.g. in the air transportation industry. Kelly, Folds and Sobhi (1993) notes that automated aircraft are the safest ever flown, even with a smaller crew owing to the reduction in overall workload in the cockpit. Samad and Cofer (2001) describes how aircraft crews of 5 were required sixty years ago with domain over aircraft bearing, navigation, and status monitoring. These crews were gradually reduced while the domain decreased with improved technology, and modern crews of 2 are a good example of the type of system described by the architecture of Antsaklis, Passino and Wang (1989): operation is largely automated with an operator (the pilot) to intervene if needed.

The minerals processing industry is used in this work as a case study to illustrate the status of automation, and how some of the key technologies required for lights-out control may be applied. Minerals processing operations are under increased pressure to perform with escalating energy costs and increasingly stringent environmental regulations (Craig *et al.* 2011), with process control as one of the widely recognised tools in overcoming these challenges (see e.g. Matthews and Craig (2013)). Advanced control strategies are required, but Hodouin (2011) notes that the peripheral control tools are as important as the controller itself. Peripheral control tools refer to all the tools in the control loop (other than the controller itself) that contribute to improved operation.

1.2 RESEARCH OBJECTIVE

Given the current state of automatic process control theory and industrial applications, one may naturally ask whether lights-process control is a possibility, or whether it will become possible in the near future. In essence this work presents a treatise pertaining to this question as it applies to the minerals processing industry.

First of all the objective is to determine the current state of automatic process control, i.e. how far is control (implementations and theory) on the road to lights-out production? The second objective that couples with the first, is to identify the enabling technologies that need to be implemented in order for a process to run lights-out, and to provide a framework for a lights-out process controller.

Key requirements for the implementation of a lights-out process controller should be identified, discussed, and illustrated. The objective is to demonstrate the working of these methods on a nonlinear simulation of a minerals processing operation.

1.3 RESEARCH CONTRIBUTION

The main contributions of this study are:

- A review of the development of automatic process control to the current state of advanced controllers performing optimisation and planning functions for complex nonlinear processes;
- Providing an introduction to lights-out process control and presenting a framework for the implementation of such a controller;
- Presenting the results of a survey regarding the degree of automation in the minerals processing industry (including the main limitations to further automation, as well as the prospects of lights-out process control in this industry);

- Giving a detailed overview of some of the key concepts required for lights-out control implementations, including model quality analysis, active fault-tolerant control, controllability analysis for a faulty system, and an economic performance analysis for a faulty system; and
- Presenting a simulation study for a nonlinear grinding mill circuit to illustrate the implementation of the key concepts introduced for lights-out process control.

The following publications resulted from this study:

- L.E. Olivier and I.K. Craig, Model-plant mismatch expression for classically controlled systems, *In: Proceedings of the 19th IFAC World Congress, Cape Town, South Africa*, pp. 11500 – 11505, 2014.
- L.E. Olivier and I.K. Craig, Development and application of a model-plant mismatch expression for linear time-invariant systems, *Journal of Process Control*, 32, pp. 77 – 86, 2015.
- L.E. Olivier and I.K. Craig, Fault-tolerant Nonlinear MPC using Particle Filtering, *In: Proceedings of the 11th IFAC Symposium on Dynamics and Control of Process Systems, including Biosystems (DYCOPS-CAB), Trondheim, Norway*, pp. 177 – 182, 2016.
- L.E. Olivier and I.K. Craig, Should I shut down my processing plant? – An analysis in the presence of faults, submitted to *Journal of Process Control*, April 2016.
- L.E. Olivier and I.K. Craig, The degree of automation in the minerals processing industry – A survey on the road to lights-out process control, submitted to *Journal of Process Control*, August 2016.

The following publications resulted from prior work that is related to this study:

- L.E. Olivier, I.K. Craig, and Y.Q. Chen, Fractional order and BICO disturbance observers for a run-of-mine ore milling circuit, *Journal of Process Control*, 22, pp. 3 – 10, 2012.

- L.E. Olivier, B. Huang, and I.K. Craig, Dual particle filters for state and parameter estimation with application to a run-of-mine ore mill, *Journal of Process Control*, 22, pp. 710 – 717, 2012.

- L.E. Olivier and I.K. Craig, Model-plant mismatch detection and model update for a run-of-mine ore milling circuit under model predictive control, *Journal of Process Control*, 23, pp. 100 – 107, 2013.

Although not forming part of the core of this thesis, the publication below was also generated during this study:

- J.D. Le Roux, L.E. Olivier, M.A. Naidoo, R. Padhi, and I.K. Craig, Throughput and product quality control for a grinding mill circuit using nonlinear MPC, *Journal of Process Control*, 42, pp. 35 – 50, 2016.

1.4 ORGANISATION

This thesis is organised as follows:

- Chapter 2 discusses the concept of lights-out process control and how process control has evolved into its current state. The chapter then describes what impact the advances in digital technologies has had on MPC technology. The technologies required for lights-out process control are discussed and a framework for a lights-out process control installation is given.

- Chapter 3 presents the results of a survey regarding the degree of automation in the minerals processing industry. The survey explores the current status of automation in the industry, the main limitations to further automation, and the prospects of lights-out process control. The results of the survey form part of the justification for the work that follows.

- Chapter 4 provides further details on the key enabling technologies required for lights-out process control.

- Chapter 5 presents a simulation study of a run-of-mine (ROM) ore milling circuit in a lights-out process control framework. The key enabling technologies presented in Chapter 4 are applied to the nonlinear milling circuit process.

- Chapter 6 concludes the work. The main points addressed in the thesis are summarised, and the prospects of lights-out process control in the minerals processing industry are stated.

CHAPTER 2 TOWARDS LIGHTS-OUT PROCESS CONTROL

The process industry appears to be heading towards lights-out process control, i.e. processes are increasingly automated and require less human intervention. Production is at record levels, but the median income is falling and fewer jobs are available (Brynjolfsson and McAfee 2012).

This chapter explores the impact of digital technologies on advanced process control. MPC is used as a case study for this discussion, owing to its success in the process industry (Qin and Badgwell 2003). The current trends observed in industry are introduced and discussed, with Industry 4.0 being one example.

Some specific lights-out process control issues are discussed, such as the prospects of lights-out process control, and the technologies required to make it a reality. A framework for lights-out process control is also presented. The likely impact of lights-out process control is discussed, with reference to the design methodology required for such controllers.

2.1 THE IMPACT OF DIGITAL TECHNOLOGIES ON ADVANCED PROCESS CONTROL

The exponential growth of computing, of which the most famous paradigm is known as Moore's Law, is well documented (see e.g. Cavin, Lugli and Zhirnov (2012)). Combinatorial effects are obtained when coupling this growth with the increased networking of computing devices, also known as the "internet of things." The extent of this expansion is very large, and it is estimated that as many as 50 billion devices will be connected by 2020 (Perera, Zaslavsky, Christen and Georgakopoulos 2014).

This section discusses the impact these advances in digital technologies has on the advanced process control field, in particular where human mental power is being replaced by digital technologies when establishing and maintaining APC systems in the form of MPC controllers. MPC is selected as it is the most successful advanced control strategy currently employed in the process industry (Bauer and Craig 2008, Qin and Badgwell 2003).

2.1.1 Establishing and maintaining a successful model predictive controller

The impact of advances in digital technologies on MPC technology can be considered through analysing the steps taken to establish and maintain a successful MPC controller for an industrial process. These steps are (adapted from Darby and Nikolaou (2012) and Qin and Badgwell (2003)):

1. **Economic motivation of MPC:**
   This step includes compiling an economically driven motivation for the MPC project (Bauer and Craig 2008). This evaluation should justify the project cost based on the economic returns over the lifetime of the project.

2. **Obtain seed models and do preliminary MPC configuration:**
   It is crucial for the success of any advanced controller to ensure the health of the baselayer regulatory control loops upon which it resides. This task is completed in the pretest phase, and may include maintenance and repair of actuators and sensors, updating of regulatory control philosophies, and tuning of regulator control loops. For some implementations a significant portion of the benefits derived from implementing an MPC controller comes from this step (see e.g. Muller (2016)).
   A conceptual design for the MPC is also completed during this step, which includes selecting the optimisation strategy, the number of MPCs, and choosing the manipulated variables (MVs), controlled variables (CVs), and disturbance variables (DVs) for each. The seed models (initial models) are obtained which may include performing some manual plant steps, or they may be obtained from historic data and/or process simulators.

3. **Plant testing:**
   Data is generated for model identification, typically through automatic step testing software

(although manual plant tests may also be performed). Ideally all the parameters that will be used as MVs will be adjusted, and all measured DVs will also be varied if possible.

This step may take a long time depending on the size of the control installation, and plant testing is therefore seen as an expensive exercise. Much focus has been placed in the recent past on performing plant tests optimally and automatically to minimise the disruption to optimal production and to limit the engineering effort (Zhu, Patwardhan, Wagner and Zhao 2013).

If proper seed models are available (as may be derived from sufficient process knowledge, historical data, or a plant simulator) plant testing can be done in closed-loop with a relatively minor effect on plant operation.

In addition, modern digital technology makes it possible to perform plant tests remotely with associated time and cost savings.

4. **Model and controller development:**

   Plant models are identified from the data obtained in the previous step. Models should be checked for consistency with process physics, and models may be validated against plant simulators if they are available.

   The design of the MPC(s) is then completed. Sometimes the final design can differ substantially from the conceptual design depending on the outcomes of plant testing. Initial controller parameters are specified (e.g. control and prediction horizons, penalization weights for control violations or excessive MV moves, and optimization weights). Dynamic process simulators are a good place to test and tune the MPC if they are available (Qin and Badgwell 2003).

5. **Controller commissioning and user training:**

   The MPC is now deployed on the actual plant. Depending on the amount of controller simulations that were performed in the previous step (as well as the simulator quality) the MPC may be close to optimal. With little simulation the MPC may still require substantial tuning and testing during the commissioning phase. Commissioning includes monitoring the controller performance in the presence of DVs, how CV and MV movements are traded off against each other, and how aggressive the controller is in responding to CV limit violations or in finding the optimal operating region. Initial controller parameters specified in the previous step are now refined.

   Operator training forms part of this phase, and because the operator is currently the main MPC customer, sufficient training is critical for the success of the MPC project.

6. **Controller monitoring and maintenance:**
   This step includes the use of tools that detect performance degradation as well as the cause(s) of degradation, to identify issues to operating personnel, to adapt the underlying plant models, and to retune the MPC controller. MPC performance is monitored (Xu *et al.* 2007) and controller maintenance undertaken when some measure of performance degradation is detected.
   At some point in time the MPC performance may not be maintainable any longer without plant re-identification. This often signals the start of an APC revamp project, which starts again from step 1.

For plants that can be sufficiently described with linear models, steps 3, 4, and most of step 5 are considered routine. Control practitioners seem to have little difficulty in completing MPC projects within this category (Camacho and Bordons 2012). The focus for vendors has turned much more towards implementing MPC projects in a streamlined fashion such that configuration, plant testing, and commissioning times are minimised. Many practitioners have therefore strived towards streamlining steps 3, 4, and 5 into one, reducing the disruption to production. Such a method is described in Zhu *et al.* (2013) and commercial implementation details can be seen in Golightly (2014).

For a mainly linear plant therefore creating a new MPC controller is relatively straightforward using modern software tools. Maintaining APC benefits over extended periods of time however is much more difficult. This difficulty could be because of easily correctable problems such as poor baselayer maintenance, operational changes, lack of training for new operators, or more problematic requirements such as automatically diagnosing and updating process models.

Process simulators have enabled more efficient operator training, baselayer performance monitoring (Huang and Shah 2012) and automatic tuning (Pavković, Polak and Zorc 2014) help to maintain baselayer performance, process models are maintained through detecting the presence of poor models (Badwe, Gudi, Patwardhan, Shah and Patwardhan 2009) and updating the models appropriately (Olivier and Craig 2013). The automated tools that can help with addressing these difficulties are further discussed in Section 2.2.2.

Changing operating conditions, lack of operator expertise, changes in plant equipment, and controller technology that is not yet robust result in MPC performance deterioration being of growing concern among end-users. This situation prompted Hodouin (2011) to make the argument that peripheral control tools are at least as important as the controller itself. Peripheral control tools include all the elements in the control loop (excluding the controller itself) that contribute to improving controller performance, such as fault detection and isolation systems (Zhang and Jiang 2008), data reconciliation procedures (Narasimhan and Jordache 2000), observers, soft sensors (Lin, Recke, Knudsen and Jørgensen 2007), optimisers, and model parameter tuners. The focus of Hodouin (2011) was also on minerals processing operations, but most of the arguments made there are valid for the process industry as a whole.

In summary, digital technologies and theoretical advances have made automated modelling and controller design tools possible that make it easier, quicker and hence cheaper to establish a successful MPC controller, and to keep it running for longer. In addition, automated tools are increasingly blurring the distinction between the technologies required to establish an MPC controller and those required to maintain MPC performance for extended periods of time. With increased automation of MPC operation and maintenance, the role of the plant operator is likely to evolve from continuously monitoring and intervening, to a manager-by-exception who may not necessarily be geographically close to the plant (Brann *et al.* 1996).

Few examples of such systems already exist for the processing industry, where operators manage plants with little to no interactions. Details on such implementations are however largely missing from academic literature although remote plant monitoring is performed by some users and vendors. For example, Linde has a remote monitoring center in New Jersey, from which it monitors the company's network of over 70 atmospheric and process gas plants throughout the U.S., Canada and Mexico (The Linde Group 2013).

2.1.2 Related industry trends

The advances in digital technology and the increased interconnectivity of devices have brought about three main initiatives, related to the future of manufacturing and automatic process control. These are Industry 4.0 (Brettel, Friederichsen, Keller and Rosenberg 2014) that began in Germany, the Smart Manufacturing Leadership Coalition (SMLC) (Smart Manufacturing Leadership Coalition 2012) that originated in the USA along with its Smart Process Manufacturing steering committee, and the Industrial Internet of Things (Raferty 2016) promoted by the Industrial Internet Consortium.

Industry 4.0 refers to the 4th industrial revolution. This is the combination of "cyber-physical systems," the "internet of things," and "cloud computing" in order to create self-configuring real-time optimised processes that allow for customised, modularised, and adaptive production that is energy efficient, resource efficient, safe, and reliable. A dominant characteristic of Industry 4.0 is that processing equipment communicate all along the supply chain. A framework for such an interconnected smart factory in the Industry 4.0 context is given in Wang, Wan, Zhang, Li and Zhang (2016).

But what might the role of advanced control, and specifically MPC, be within the framework of Industry 4.0? Allgöwer (2014) notes that optimising control plays an important role in realising the Industry 4.0 goals of processing that is optimal, energy efficient, safe, and reliable. In fact the power of MPC-driven optimisation for process improvements has led to a recent focus on economic MPC (Ellis, Durand and Christofides 2014) and distributed, cooperative MPC (Stewart, Venkat, Rawlings, Wright and Pannocchia 2010). Allgöwer and co-workers see these technologies as contributing largely toward achieving the aims of Industry 4.0.

The motivation for the SMLC are largely in line with those of Industry 4.0. The main inspiration of SMLC is that an integrated smart manufacturing enterprise (including suppliers, original equipment manufacturers (OEMs), and companies up to the supply chain) that is knowledge enabled, and model rich, will be able to improve decision making and drive action, beyond what could be achieved by optimisation of the underlying parts.

The Industrial Internet of Things is also concerned with the interconnection of everything along the value chain; manufacturing, connected vehicles, transportation optimisation, instrumented agriculture, smart cities etc. The Industrial Internet Consortium is working with industry to set the standards and best practices for this industrial internet. Many automation companies form part of the consortium members.

Another related trend is big data analytics (Qin 2014) that can play a significant role in establishing and maintaining successful MPC controllers. The concepts included within big data analytics can help to obtain seed models for plant testing, to develop soft-sensors, to detect sensor or actuator failure, to monitor the health of regulatory and advanced controllers, and to signal the need for maintenance when significant performance degradation is noted.

Incorporating the concepts of big data analytics into the MPC framework is an active research topic. One main focus is on providing theoretical guarantees for stability and constraint satisfaction in the light of poor quality of the available real-time data. Goebel and Allgöwer (2014a) and Goebel and Allgöwer (2014b) have for example proposed algorithms that use subspace clustering techniques to extract the core of predicted input trajectories off-line, in order to formulate simplified on-line MPC algorithms.

2.2 LIGHTS-OUT PROCESS CONTROL DEVELOPMENTS

This section presents some additional evidence for the trend of increased automation in the process industry. The technologies required to realise a lights-out process control strategy are listed, and a framework for such a controller is presented.

2.2.1 The replacement of process plant operators with automation

One issue to consider is what is likely to happen to the jobs of process operators. Frey and Osborne (2013) analysed the susceptibility to computerisation (automation) of 702 different occupations. The model used by Frey and Osborne (2013) gives higher probabilities of computerisation for jobs that require repetitive (routine) tasks. Their overall conclusion is that 47 % of total US employment is in the high risk category, meaning that associated occupations are potentially automatable over perhaps a decade or two. This number is even higher in the developing world, where the overall figure is reported at 67 %. What is striking from a process control perspective is that many of the most susceptible jobs are those of plant operators; Table 2.1 provides a selected list in descending order of the probability of computerisation. Although minerals processing plant operators are not singled out in the analysis, it is expected that their susceptibility to computerisation should be close to those of the operators shown.

The data of Frey and Osborne (2013) were grouped by country in the development report of The World Bank Group (2016), as is illustrated in Figure 2.1. The unadjusted values shown in Figure 2.1 correspond to those in Frey and Osborne (2013). The adjusted values account for the slower pace of technology adoption in poorer countries, according to the technology adoption lag model of Comin and Hobijn (2010).

Table 2.1. The susceptibility to computerisation of process plant operator jobs (adapted from Frey and Osborne (2013)).

Rank	Occupation	Probability of computerisation
614	Nuclear power reactor operators	0.95
529	Stationary engineers and boiler operators	0.89
516	Metal-refining furnace operators and tenders	0.88
491	Plant and system operators, all other	0.86
487	Chemical plant and systems operators	0.85
486	Power plant operators	0.85
471	Rolling machine setters, operators and tenders, metal and plastic	0.83
429	Gas plant operators	0.78
389	Petroleum pump system operators, refinery operators, and gaugers	0.71
339	Wastewater treatment plant and system operators	0.61

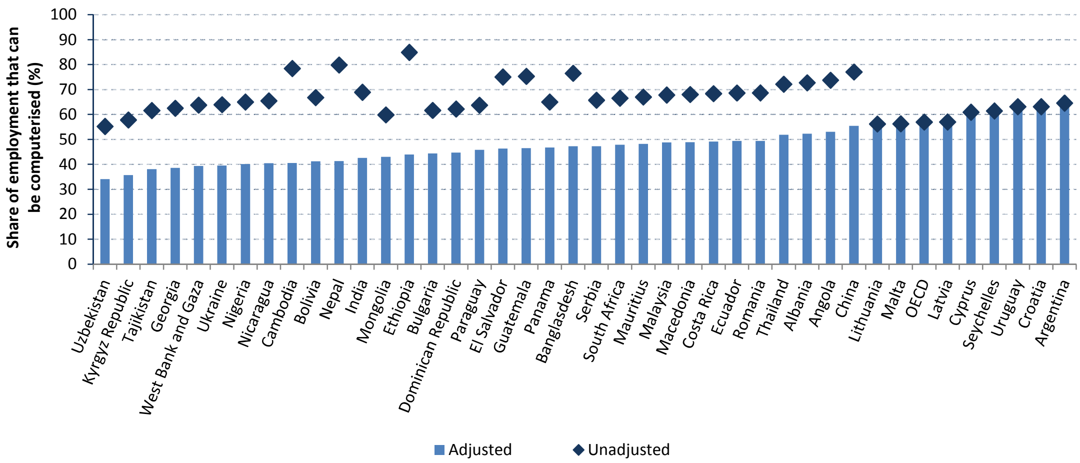

Figure 2.1. Jobs susceptible to automation (over perhaps the next decade or two (Frey and Osborne 2013)) listed by country; adapted from The World Bank Group (2016), with permission.

The model of Frey and Osborne (2013) was recently criticised in Arntz, Gregory and Zierahn (2016) for following an occupation-based approach, i.e. they assume that whole occupations rather than single job-tasks are automated by technology. The study of Arntz *et al.* (2016) show that only 9 % of occupations in Organisation for Economic Cooperation and Development (OECD) countries can be automated. The study however agrees with Frey and Osborne (2013) that low qualified workers are likely to bear the brunt of computerisation as the automatability of their jobs is higher compared to highly qualified workers. The tasks that operators have to perform also generally fall into the tasks that Arntz *et al.* (2016) show to be more probable of replacement by digital technologies. Whether the entire job of the plant operator will be made obsolete by digital technologies is not certain, but many of the tasks performed by operators will be replaced by digital technologies. Some of these tasks include: routine process adjustments because of changes in the operating region, reacting to recurring disturbances that enter the process, and reacting to faults that may arise.

Autor (2015) notes that although automation substitutes for labour, it typically also complements labour and raises output in ways that lead to higher demand for labour. It is for this reason that expert commentators often overstate the extent of machine substitution for human labour. It is also mentioned in Arntz *et al.* (2016) that jobs can evolve with the introduction of new technologies, and that all the jobs listed in Frey and Osborne (2013) may not cease to exist, but will look quite different over time. One example listed by Autor (2015) is the evolution of the job of a bank teller after the introduction of automatic teller machines. The introduction of these machines reduced the operating cost of a bank branch which resulted in more branches opening up. The tellers in modern banks are more focused on personalised service and even marketing as opposed to simply cashing cheques and counting out money. The introduction of teller machines have therefore increased the number of bank tellers, although their tasks have changed significantly.

With fewer operator tasks, production personnel will gradually become fewer and more skilled, having to deal with an increasingly diverse array of tasks. This forms part of a broader trend highlighted by the changing structure of the supply and demand for skills in Acemoglu and Autor (2011). As an example, Figure 2.2 shows male wages in the United States over time for the period 1963 – 2008 for various skill levels. It is evident from this figure that the market is increasingly rewarding skills as measured by the level of education achieved. In contrast, the wages of those having the education level typically required of an operator have been almost stagnant in real terms over the last four decades. This figure also shows how lower educated workers have bore the brunt of the changing digital landscape as agreed

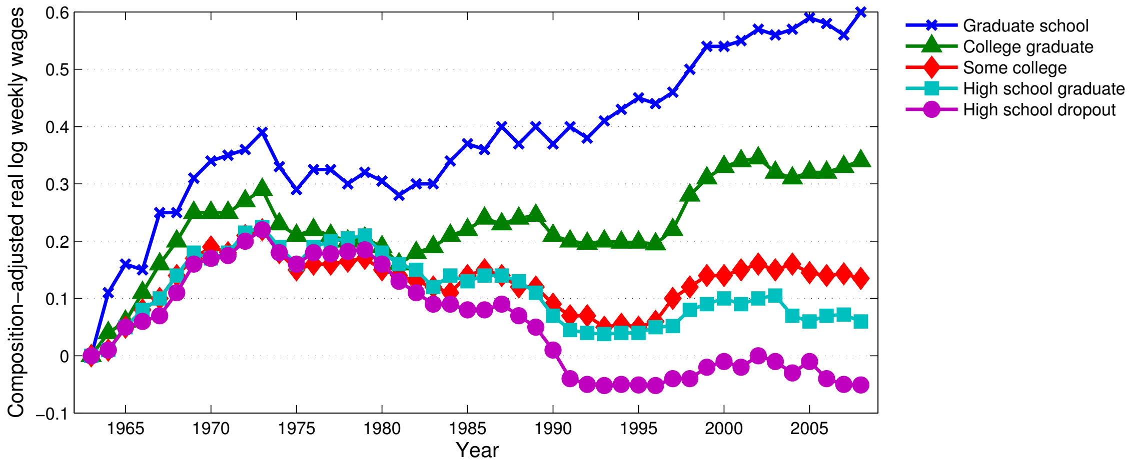

Figure 2.2. Real, composition adjusted log weekly wages over time for full-time male workers at different levels of education. The data source is March current population survey data for earnings for the years 1963 – 2008. The real log weekly wage for each education group is the weighted average of the relevant composition adjusted cells using a fixed set of weights equal to the average employment share of each group. Nominal wage values are deflated using a Personal Consumption Expenditure deflator. Adapted from Acemoglu and Autor (2011), with permission.

by Frey and Osborne (2013) and Arntz *et al.* (2016).

Brynjolfsson and McAfee (2012) noted that production is at record levels, and yet the median income is falling and fewer jobs are available. This situation was also noted for petroleum refining by Samad and Cofer (2001), where refinery personnel are decreasing, but refinery output is increasing. In Rotman (2013) it is stated that new technologies, such as improved analytics, big data, and artificial intelligence, are automating many routine tasks. In Frey and Osborne (2013) it is exactly the amount of routine tasks that operators perform that contribute to the high probabilities listed for their replacement by automation.

The replacement of the bulk of operator actions by automation is likely to happen over the next 20 years. This time-frame is supported by the analysis horizon of (Arntz *et al.* 2016) and also in part by the survey results following in Chapter 3. In fact for processes where the plant can be sufficiently represented by linear models, i.e. where the control problem is simpler and better understood, operating in a lights-out fashion may become a reality within the next 20 years. This is despite the criticism of the Frey and Osborne (2013) model in Arntz *et al.* (2016), because the actions that operators generally perform for plants in this category are regarded as routine. Even Arntz *et al.* (2016) agrees that these actions are automatable over the next 20 years. What exactly theses actions are in minerals processing plants will be highlighted later in Chapter 3.

2.2.2 Requirements for lights-out process control

The general aim of autonomous control is listed by Passino (1993) as the desire to have the control system performing well under significant uncertainties in the system and its environment for extended periods of time, and for the control system to compensate for significant system failures without external intervention. Successful implementation of this desire on a processing plant satisfies the original vision of lights-out manufacturing, and such an implementation may be referred to as lights-out process control. The successful implementation of these objectives also encompass the important actions currently performed by operators on industrial minerals processing plants.

2.2.2.1 Handling of disturbances and changes in the operating region

Proper handling of disturbances and changes in operating region may seem like a straightforward requirement, but it is the foundation of a proper controller configuration. These are classical control problems, but without addressing them properly lights-out process control cannot happen. It will be shown later in this work that control installations on industrial plants do not always even meet these requirements, which commonly results in the need for the operator to intervene.

Handling of disturbances is one of the hallmarks of feedback control. When dealing with strong disturbances however, feedback regulation may not be sufficient to achieve satisfactory disturbance rejection performance (Yang, Li, Chen and Li 2010). It is then necessary to include the disturbance rejection requirement into the controller design. This can be achieved through controller tuning for disturbance rejection (Seborg, Edgar and Mellichamp 2003), or through a more advanced method such as a disturbance observer (Olivier, Craig and Chen 2012a).

Even though a disturbance observer can be used along with MPC (Yang *et al.* 2010), disturbances can also be compensated for through estimating the disturbance magnitude and compensating directly for it in the MPC objective function (Muske and Badgwell 2002).

Many linear model-based controllers do not handle changes in operating region well. This is generally true for highly nonlinear systems, where direct modelling of the nonlinearity and the deployment of an explicit nonlinear model-based control strategy (see e.g. Allgöwer and Zheng (2012)) should be used. Deriving an appropriate nonlinear model is however not a straightforward task (Nelles 2013), and the decision to use a nonlinear model should not be taken lightly. However, if the operating region changes significantly during normal operation and the process is sufficiently nonlinear, nonlinear control methods are required.

Again, for plants where the entire operating region can be sufficiently represented by linear models the control problem is easier to solve.

2.2.2.2 Autonomous controller maintenance

The requirements for lights-out process control also need to include tools that can perform the functions described in step 6 of section 2.1.1 autonomously, i.e. automated surveillance of controller performance, as well as autonomous maintenance through automated adaptation of plant models and retuning of controllers. These tasks have been, and still are, a significant point of focus for academics and vendors alike (see e.g. Van den Hof (2013)).

Advanced control strategies are however generally also dependent on proper baselayer control integrity. Huang and Shah (2012) gives a comprehensive overview of how single-input single-output (SISO) control loop performance monitoring may be done. Ko and Edgar (2004) defined a minimum variance control performance metric as a function of the PID controller settings. This benchmark gives a realistic performance assessment metric of an existing PID loop.

Once improper baselayer performance has been detected, the control engineer may update the corresponding controller(s), or an auto-tuning PID algorithm may be employed (see e.g. Pavković *et al.* (2014) and Neçaibia and Ladaci (2014)) if the improper baselayer performance is owing to improper tuning. One major cause of improper tuning is a change in the plant dynamics. Examples of the sources of changes in plant dynamics are maintenance or equipment changes as well as changes in operating conditions or parameters. As soon as the plant dynamics change, the controller designed based on the original dynamics will produce sub-optimal control moves. An automated detection and correction scheme for such differences is therefore of concern.

Improper performance can however also be owing to hardware issues such as valve stiction or transmitter problems. Methods exist to detect valve stiction (Choudhury, Shah, Thornhill and Shook 2006), and compensation can be done either through tuning (Mohammad and Huang 2012) or through modification of the controller output signal such as adding pulses to overcome the stiction (Hägglund 2002). The best remedy however for valve stiction is overhaul of the valve which might sometimes only be done during a plant shutdown.

Model-based control has proven to be very successful at achieving good control performance. The performance of the model-based controller is however very dependent on the quality of the process model that is available (Camacho and Bordons 2012). Process models need to be advanced enough to accurately represent the process, but simple enough for inclusion in the controller formulation. The accuracy of process models also degrades over time, and proper model maintenance is a key element in maximising APC benefits. Traditionally the model is maintained through full process re-identification, which is a costly and time-consuming exercise (Conner and Seborg 2005). Automated detection (Badwe *et al.* 2009, Olivier and Craig 2015) and compensation (Olivier and Craig 2013) of model-plant mismatch (MPM) is required to maintain controller performance in the lights-out control framework. Some vendor tools (e.g. Golightly (2014)) make MPC controllers more conservative, and hence robust, when model mismatch is suspected, leaving the APC still operational, but with a more conservative approach to optimisation, until the mismatch can be corrected. Effective process modelling for control is also the focus of Van den Hof (2013).

Auto-tuning of MPC is not yet common, but some examples do exist in the literature. Approaches based on multi-objective optimization are presented in Liu and Wang (2000) and Vega, Francisco and Tadeo (2008).

2.2.2.3 Reconfigurable fault-tolerant control

It is also required of the lights-out process controller to adapt to faults that may arise in the process. A functional architecture for fully autonomous control was introduced by Antsaklis *et al.* (1989). This article already mentions the need for fault detection and isolation (FDI) as well as adaptability to handle significant uncertainties. The article does however still envision an operator in the loop with which the control system should communicate.

There is a distinction between passive fault-tolerant control (FTC) and active FTC (Jiang and Yu 2012), where passive FTC has the objective to tolerate faults. One can rather say that the controller accommodates faults. This approach to controller design can be likened to robust controller design. Active FTC aims at reconfiguring the control strategy to achieve optimal performance in the presence of faults (Zhang and Jiang 2008). This is more in line with what a human operator would try to achieve when faults are present. Active FTC is therefore one of the major keys to lights-out process control becoming a reality in the processing industry.

Active FTC rests upon the proper detection, isolation, and identification of a fault (Chen and Patton 2012). Fault detection is making the binary decision that something has gone wrong; fault isolation is determining the location of the fault; fault identification (also referred to as fault diagnosis) is determining, or usually estimating, the size and nature of the fault.

Once a fault has been identified the active FTC will adapt to handle the fault the best it can. MPC is regarded to be well suited to active FTC as many faults can easily be incorporated into the MPC formulation simply by adjusting the MPC optimisation problem constraints (Patton 2015). A stuck actuator, for example, can be represented by adjusting the MV limits, and the MPC will automatically use the available MVs to still minimise the objective function.

There is however a certain class of faults for which the controller will not be able to keep the plant within output limits. An automated analysis will then be needed to evaluate the plant controllability. An input-output controllability analysis, as described in Skogestad and Postlethwaite (2005), is sufficient for linear systems. For nonlinear systems the analysis is not trivial. The well functioning linear methods (e.g. that of Skogestad and Postlethwaite (2005)) are based on frequency domain analysis techniques, which may only be valid for nonlinear systems at particular operating points. Other functional approaches exist, but the results can be difficult to obtain and the scope limited (Yuan, Chen and Zhao 2011). Simulation based approaches are often prescribed for nonlinear systems (Skogestad and Postlethwaite 2005:165), and the Monte Carlo based approach of Olivier and Craig (2016b) is one useful example.

Even after the plant controllability has been verified the economic operability of the process needs to be established. Again there may be a class of faults for which the process can be controlled, but the economic performance of the process may have been compromised to the extent that it would be more economical to shut the plant down, repair the fault, and start back up than it would be to continue operation with the fault. This decision is currently typically made by plant management, but an automated approach as would be required for lights-out control is described in Olivier and Craig (2016b).

2.2.2.4 Additional requirements for plant-wide lights-out process control

The requirements listed above may be incorporated to achieve lights-out process control of a unit operation. Additional requirements are needed to expand the concept into a plant-wide control framework (Skogestad 2000). These requirements include the proper selection of controlled variables for process regulation, supervisory control, and optimisation as well as process throughput management. Skogestad (2004) presents a systematic procedure for the selection of a control structure to achieve these aims. Another approach to this vertical integration requirement is cascaded MPC as proposed by Lu (2015).

Horizontal integration of up- and down-stream units is also required. These requirements are not different in general from the requirements to expand current control strategies into the plant-wide control arena, but they are essential to achieve the aims of Industry 4.0 and the SMLC.

2.3 A FRAMEWORK FOR LIGHTS-OUT PROCESS CONTROL

Reconfigurable fault-tolerant control is one of the important technologies required for lights-out process control. The frameworks required for both contain many parallels, meaning that a reconfigurable FTC framework is a good starting point for formulating a lights-out process control framework. A framework for reconfigurable FTC is shown in Zhang and Jiang (2008). Consolidating the need for reconfigurable fault-tolerant control with the general aims of lights-out process control may be achieved with a structure as presented in Figure 2.3.

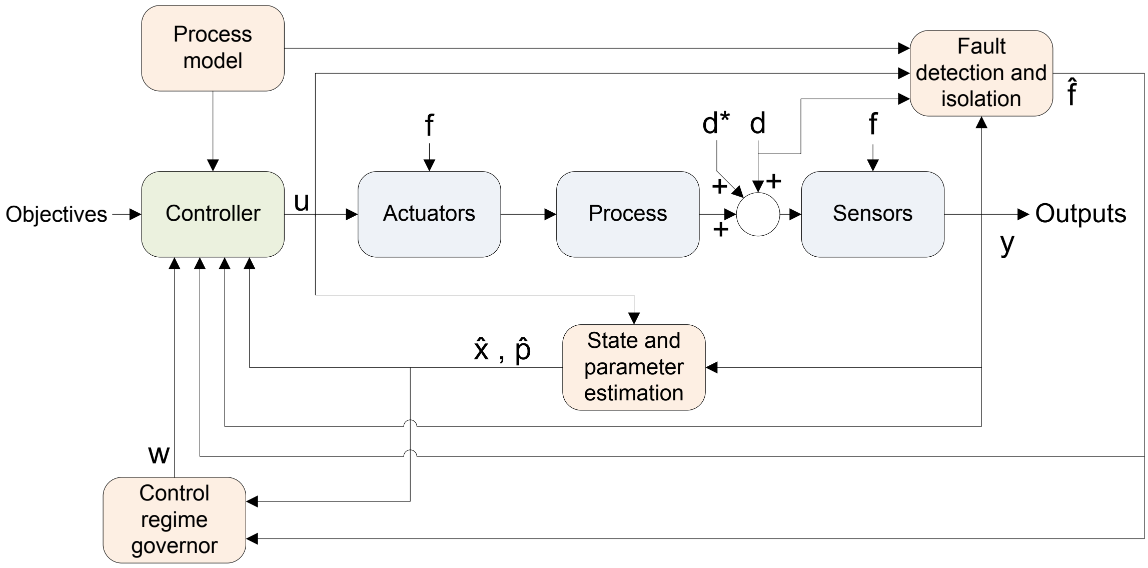

Figure 2.3. Framework for lights-out process control in a processing plant.

The controller is shown in green, the plant elements are shown in blue, and the peripheral tools required to achieve lights-out process control along with the (optional) process model are shown in light orange.

In this structure reference is specifically made to *Objectives* rather than *Setpoints* as planning and optimisation functions may also be handled by the controller. The controller supplies the control moves (u), implemented by the actuators that affect the plant. Measured disturbances are represented by d, unmeasured disturbances by d^*, and the outputs by y. Actuators and sensors are specifically shown as they are sources for faults. Plant input and output data are analysed by the fault detection and isolation block, the results of which are passed to the controller. State estimation is important for the advanced controller and parameter estimation is required to directly compensate for changes in operating conditions. The estimated states and parameters are represented by $\hat{x}$ and $\hat{p}$ respectively.

The control regime governor is required to determine the control objectives based on the faults. In the presence of certain faults achievement of certain control objectives may not be possible. In these situations the control regime governor should adapt the control objectives (w) to ensure that the plant operates close to the best achievable performance given the limitations. Adjusting control objectives could include changing optimization targets, adjusting controller limits, or adjusting tuning parameters.

An optimal action for the control regime governor on a processing plant may also be to shut the plant down (or more commonly an individual unit or subsection of the plant) in order to fix current faults. This action is never an option on for example an aviation automation system, where the objective must always be to keep the plant active. This is one major difference between total automation as applied to a processing plant and aviation, an area in which fault-tolerant control has seen widespread application (see for example Zhang and Jiang (2008) or Kale and Chipperfield (2005)).

The process model is an optional element in this framework. Model-based control has proven to be very successful in the process industry, and most of the work presented in this thesis will focus on model-based algorithms. Advanced control is however possible without an explicit process model (e.g. fuzzy-logic or statistical process control), as is fault detection and isolation for which many data-driven approaches exist. The model is however included to illustrate its importance in this work.

Considering Figure 2.3 it is noticeable that the controller to be used in a lights-out control setting is not a standard model-based controller. The controller must be able to incorporate fault detection and isolation information, as well as being able to reconfigure its objectives based on the information supplied by the control regime governor.

2.4 LIKELY IMPACT OF LIGHTS-OUT PROCESS CONTROL

Conjecture regarding the impact of lights-out process control in the minerals processing industry is not at the core of this work. Some general observations in light of other publications are however briefly presented in this section.

The impact of increased levels of automation, also in the minerals processing industry, is likely to be profound. Even if the findings of Frey and Osborne (2013) are overestimating the impact, the number of operating tasks that can be automated (Arntz *et al.* 2016) is significant. A survey conducted by the Citi Group (published in Oxford Martin School and Citi (2016)) showed that 85 % of the Citi Group's clients believed that automation will lead to major challenges with regards to labour and wealth distribution.

Automation and related topics are also increasingly being discussed in political circles. For example, the 2016 economic report of the President of the United States explores concerns that increased automation in the workplace threatens to displace elements of the conventional labour force (Obama and The Council of Economic Advisers 2016). In addition, the related topic of Industry 4.0 is receiving significant attention from politicians in Europe, especially in Germany (Davies 2015).

Given the high percentage of jobs that the World Bank reports is susceptible to automation (along the results of Frey and Osborne (2013)), one might expect that unemployment could increase dramatically over the next couple of decades. Autor (2015) however notes that although automation substitutes for labour, it typically also complements labour and raises output in ways that lead to higher demand for labour. It is for this reason that expert commentators often overstate the extent of machine substitution for human labour. The Citi Group report also investigated the policies that are most likely to be effective in offsetting the risks of automation impacting on labour and wealth distribution. The results showed that investment in education, the encouragement of entrepreneurship, and active labour market policies are expected to be the most effective. It is interesting to note that education is mentioned as the primary countermeasure, given the trend of wages in the US for different levels of qualification given in Acemoglu and Autor (2011) (see Figure 2.2).

Even though some caution exists in the labour market to fully automated systems, 76 % of respondents to the Citi Group survey still labelled themselves "techno-optimists." This speaks to the prospects for automation with regards to increased productivity, decreased downtime, and increased profits. The World Bank Group (2016) reports that the pessimism concerning the global outlook is not because of digital technologies, but in spite of them.

Automation is also regarded as one of the major contributors to overcoming the difficulties currently faced in the processing industry (Craig *et al.* 2011). This has to do with the major contributions to optimal operations that automation has produced in the past.

The design premise for establishing a lights-out control system is inherently different from the current practice for designing advanced controllers. Currently the primary customer for an APC is the plant operator. As such, the main measures of success of an APC include whether the operator is content with the controller operation and what the on-line time of the controller is.

Without an operator to satisfy, the APC design should focus on the maximisation of plant economic performance. Some practitioners are already exploring an approach where only parts of a larger APC controller can be switched off or that can have MV limits adjusted by the operator.

In the lights-out control framework a (currently very important) safety barrier is removed from the processing system, the intelligent human operator. A lights-out processing plant would therefore require additional safeguards to ensure that the automation system reacts appropriately to all possible scenarios. Currently safety systems in the processing industry are commonly designed by making use of a safety integrity level analysis, or a layer of protection analysis (see e.g. Exida (n.d.)). The safeguards required for lights-out operations would need to be considered when these analyses are completed.

2.5 CHAPTER CONCLUSION

Much progress has already been made on the path to complete lights-out process operations, and it is likely to become increasingly difficult and expensive to achieve further autonomy. This is especially true for operations that employ advanced controllers such as MPC.

As levels of autonomy increase controllers have to become more sophisticated. Approaching total automation one may ask whether the tasks that the controller have to perform would not necessarily be performed better by a human operator. Take the failure of a measurement instrument as a simple example. If a controller is not sophisticated enough to identify the failure of the instrument, it may make absurd control moves to try and regulate the measured value to its setpoint. A human operator would easily be able to identify a process reading that does not make sense as an instrument problem, and would not make changes that would have adverse effects on the process.

Some tasks are therefore seen as being more easily completed by a human than a machine. If the final stretch towards total automation falls within this category one may reach a point of diminishing returns, where efforts to achieve increased levels of automation do not outweigh the improved performance achieved by this automation.

This view should however not inhibit the efforts for establishing the technologies that would increase the levels of automation in the processing industry. An analogy to facial recognition is listed here as illustration. Previously there was a view that computer algorithms would not be able to match humans in the task of facial recognition. This has however not stopped the development of automated facial recognition systems and O'Toole, Phillips, Jiang, Ayyad, Pénard and Abdi (2007) shows an example of such a system that can outperform humans when illumination levels change.

In summary, it is apparent that automatic control, and MPC technology in particular, will play an increasingly important role in the future of the minerals processing industry (and in fact in the process industry as a whole). As far as lights-out manufacturing is concerned, there are already a number of process operations that practice lights-out manufacturing with some remote oversight – typically with baselayer process control. For process plants that are mostly linear and under MPC control, near lights-out operation, also with some remote oversight, is likely to become more widespread within the next decade or so.

CHAPTER 3 DEGREE OF AUTOMATION IN THE MINERALS PROCESSING INDUSTRY

3.1 CHAPTER INTRODUCTION

The minerals processing industry is used in this work as a case study. This chapter pertains specifically to minerals processing, but parallels to the processing industry as a whole will be drawn where applicable. Minerals processing operations are under increased pressure to perform with escalating energy costs and increasingly stringent environmental regulations (Craig *et al.* 2011), with process control as one of the widely recognised tools in overcoming these challenges (see e.g. Matthews and Craig (2013) for a demand side management approach to energy optimisation for a minerals processing unit operation).

A simplified overview of the metallurgical extraction process, adapted from Hodouin (2011), is shown in Figure 3.1. Grinding ore into a fine product is generally the first step in the metallurgical extraction process (Craig and MacLeod 1995). The process of crushing and grinding the ore into small fragments is known as comminution, and comminution of metal-bearing ore is primarily required to liberate minerals and to make them amenable to the subsequent metallurgical extraction steps (Marsden and House 1992). These liberated minerals are then separated through a process such a flotation or leaching. At this step further regrinding may be specified as needed. In the separation process the rejects are removed and the final product, the valuable metals, are extracted from the concentrate through some recovery process such as electrometallurgy or pyrometallurgy.

A survey regarding the degree of automation in the minerals processing industry was conducted. The

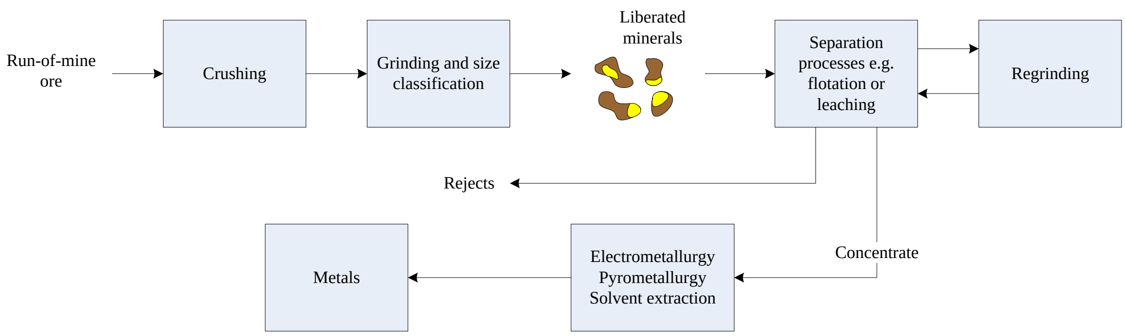

Figure 3.1. Simplified metallurgical extraction process, adapted from Hodouin (2011), with permission.

survey included questions related to the amount of process interaction required from operators, the main automation challenges, and the prospects for lights-out process control in the industry. The questionnaire used to conduct the survey is included in its entirety in Addendum A, such that the reader may see all the information provided to survey respondents.

A survey on the control and economic concerns of grinding mill circuits is presented in Wei and Craig (2009b). The survey presented here is not limited to grinding mill circuits, and does not focus specifically on economic performance assessment (see Bauer and Craig (2008) or Wei and Craig (2009a) for an example in the minerals processing context). Some of the results of this survey are however in line with Wei and Craig (2009b) and comparisons will be drawn where applicable.

Another survey regarding control in the processing industry is presented in Bauer and Craig (2008). The survey described in Bauer and Craig (2008) focusses on economic performance assessment and control pertaining to the processing industry in general, but some of the advanced control results will also be compared to the results from the survey described in this chapter where applicable.

3.2 SURVEY RESULTS

This section presents the results of the survey regarding the degree of automation in the minerals processing industry. The objectives of the survey were to determine:

- The degree to which operations in the minerals processing industry are automated;
- How often operators need to intervene in the process and why;

- What inhibits further automation; and
- What are the challenges on the road to lights-out process control?

The survey was distributed (among others) to academics active in research in the minerals processing industry, control (including advanced control) practitioners and consultants, production personnel working on minerals processing plants, as well as process engineers and metallurgists providing process support. Respondents completed the survey on-line as a web-based questionnaire that was mainly active during the month of March 2015. In total 55 completed questionnaires were received. This number compares favourably with the amount of respondents listed in Bauer and Craig (2008), Wei and Craig (2009b) and Takatsu, Itoh and Araki (1998), even though the reader should interpret results with caution as the number is relatively small for drawing statistically significant conclusions.

For the survey, the respondents were informed that process automation (or automatic process control) indicates any automatic regulation with reduced or minimal human intervention. There was a distinction made between basic control and advanced control; where basic process control is considered to be designed and built with the process itself, to facilitate basic operation, control, and automation requirements. Advanced control is typically added subsequently to address particular performance or economic improvement opportunities. Advanced control is also usually deployed optionally and in addition to basic process control.

Plant personnel were asked to report on the plants they work on. Researchers and consultants (or service providers) were asked to report on the general situation they encounter on plants that they service. Note that each result figure shows the survey question in the figure caption.

Figure 3.2 shows the positions of survey respondents. Noteworthy responses in the “Other” category are Engineering Managers and Project Managers.

Figure 3.3 shows the geographical locations of respondents, and Figure 3.4 shows the commodities that respondents are involved with processing. Most respondents are based in Africa, which is largely owing to the questionnaire distribution.

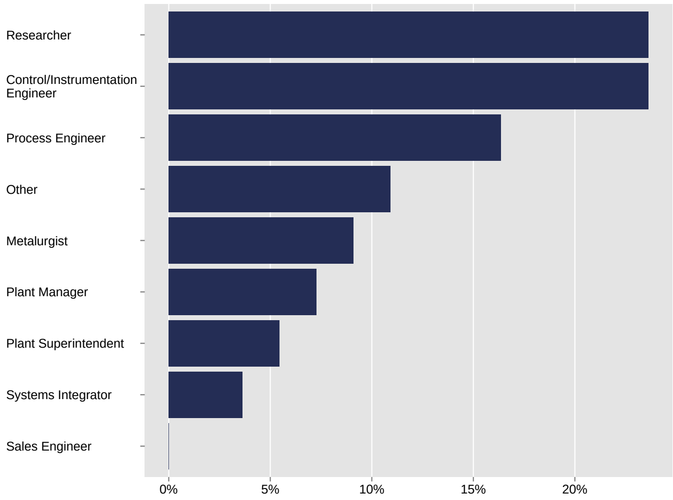

Figure 3.2. Responses to the question: "What is your position?"

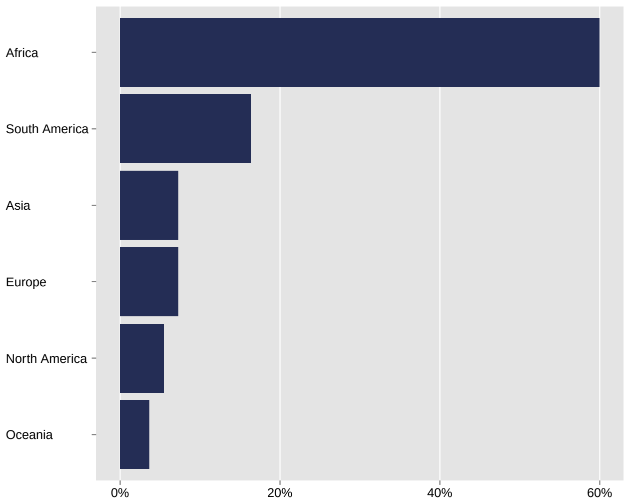

Figure 3.3. Responses to the question: "What is you geographical location?"

3.2.1 How far is the minerals processing industry along the road to lights-out process control?

One of the main indications of the degree of automation of a process is the degree of human intervention in the process. Along this line the number of actions that plant operators are reported to perform is shown in Figure 3.5. Most respondents report that operators perform 1 action per 10 to 30 minutes. Some work has gone into analysis of operator workload with two notable subjective measures being

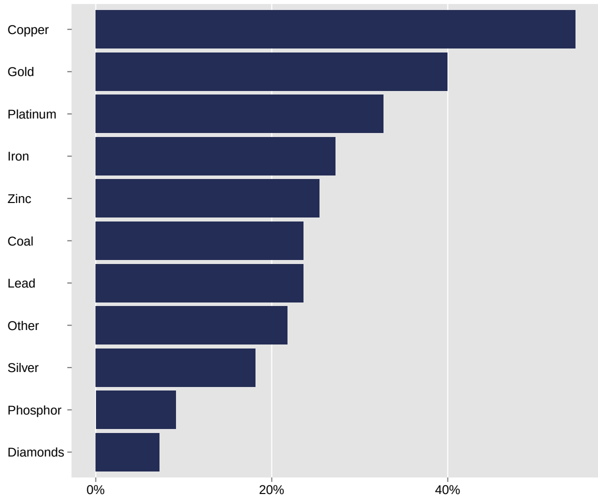

Figure 3.4. Responses to the question: "What commodity do you extract?"

the Subjective Workload Assessment Technique (SWAT) (Reid and Nygren 1988) and the NASA Task Load Index (TLX) (Hart and Staveland 1988). In Connelly (1995) the SWAT technique was used to find that a good workload level for a distributed control system (DCS) operator performing under steady state conditions is about 4.4 control moves per hour. When the plant is experiencing a process transient operators had a moderate workload of 13.6 control moves per hour. An excessive workload was marked at about 18.6 moves per hour. When operator workload increases much higher than this value, operator errors increase to an unacceptable level (Connelly 1995). This result shows that panel operators in the minerals processing industry have acceptable workload levels.

Figure 3.6 shows the perceived level of importance of operator actions, with most respondents rating on the higher end of the scale. The fact that most modern processing operations are completed with the aid of a plant operator indicates that the importance of a plant operator is highly regarded industry-wide.

If operators are performing a fair amount of actions per hour and these actions are very important to the unit operation, the next important question is what these actions are. The results for this question are shown in Figure 3.7 with most respondents stating that these actions are for changes in operating conditions or for normal operational requirements.

When the plant is at steady state the main operating task is to optimise. This means that changes

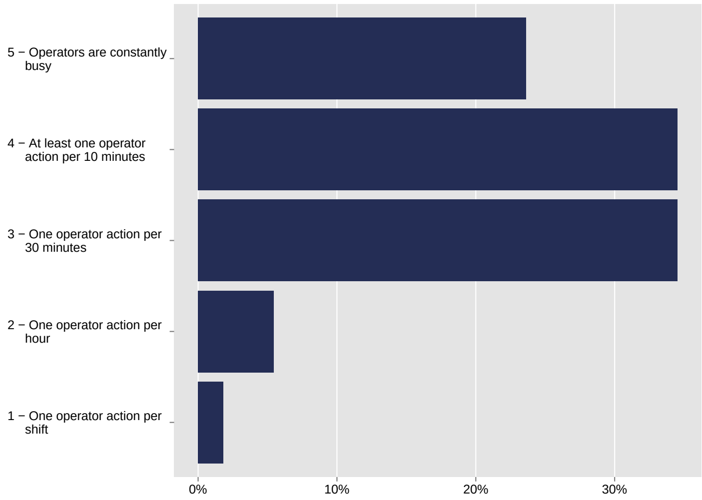

Figure 3.5. Responses to the question: "How many operator actions are required during normal plant operation?"

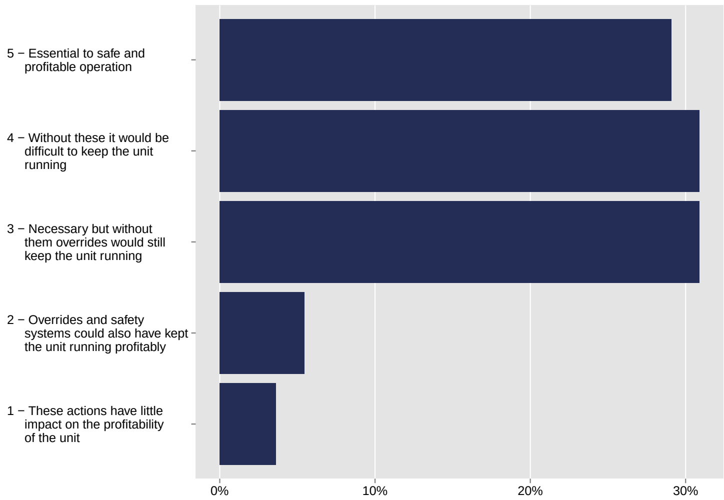

Figure 3.6. Responses to the question: "How important are these operator actions?"

made for normal operational requirements are generally optimisation moves. Operator moves made for changes in operating conditions shows that plants experience frequent transients. The widespread use of control for regulation and optimisation (see Bauer and Craig (2008)) implies that there is much room for improved performance with increased levels of automation.

Coupled with the amount of required operator actions is the amount of control functions that are generally disabled and therefore have to be regulated manually. Respondents indicated a relatively

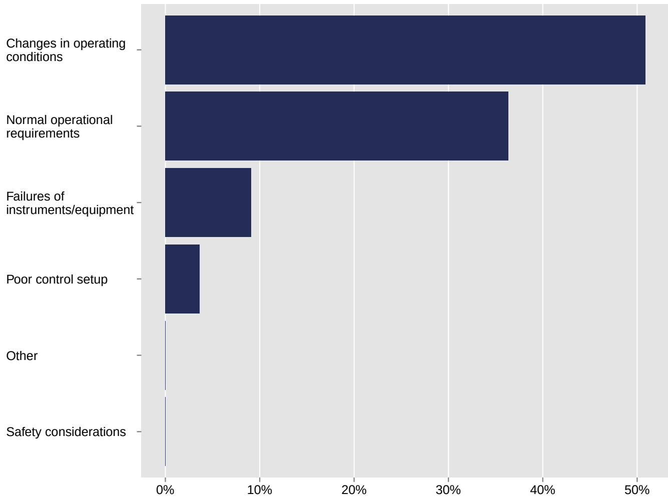

Figure 3.7. Responses to the question: "What is the main reason for operator actions?"

large variance in the amount of times that control functions are disabled on their plants (see Figure 3.8). Respondents were asked to disregard control functions that are not set up properly and are disabled permanently. Other than incorrect control set-up, there can be a wide array of reasons why control functions are disabled corresponding to the difficult nature of controlling minerals processing plants. The difficulty in controlling minerals processing plants are attributed to strong external disturbances, poor process modelling, and difficulty in measuring process variables (Hodouin 2011). The implementation of peripheral control tools (see Hodouin (2011) for the definition and Olivier *et al.* (2012a); Olivier, Huang and Craig (2012b); Olivier and Craig (2013) for implementation examples) to overcome these difficulties may help with alleviating the need for disabling control functions. Faults on instruments and actuating elements (as well as the maintenance thereof) are also large contributors to why control functions are disabled.

The control technologies used by minerals processing plants is shown in Figure 3.9 (respondents were asked to select all applicable technologies that they use). This figure indicates that PID control really is ubiquitous (Samad 2016). This result is interesting to compare with that found in Wei and Craig (2009b) for grinding mills, where PID was also by far the most common. The emergence of MPC as the most common advanced control method is in line with the result reported by Bauer and Craig (2008) for the process industry as a whole.

The scope for lights-out process control on a per-plant basis is related to the relative size of control

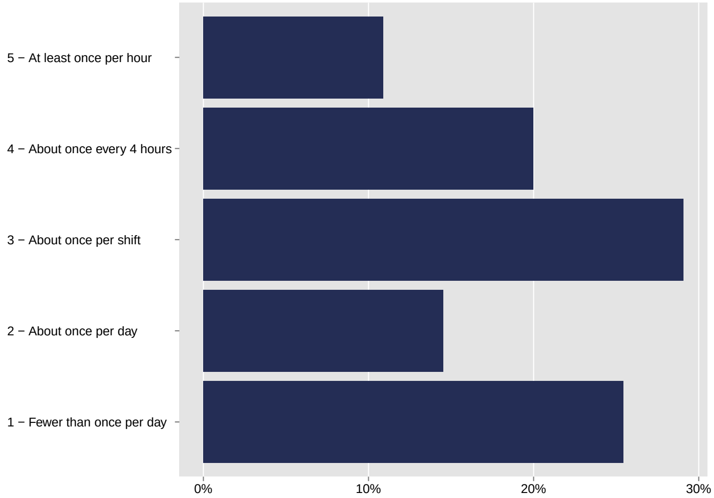

Figure 3.8. Responses to the question: "How often are control functions disabled and operated manually by the operator?"

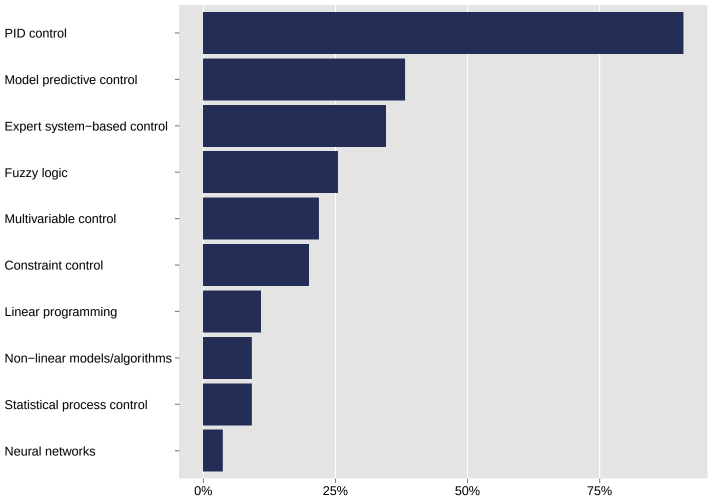

Figure 3.9. Responses to the question: "What types of control technologies does your plant/unit use?"

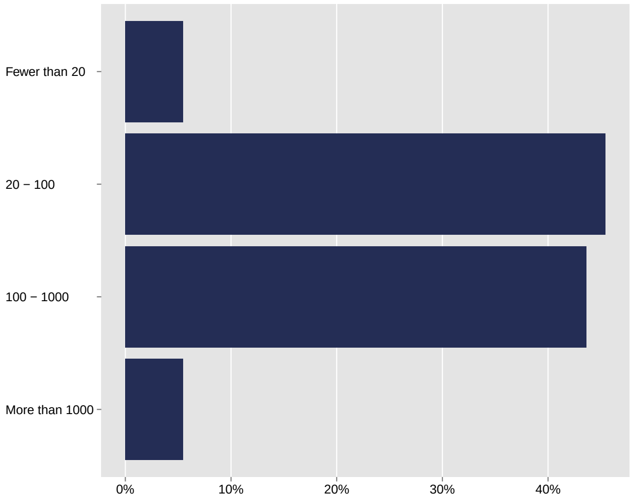

Figure 3.10. Responses to the question: "How many control loops are on your plant?"

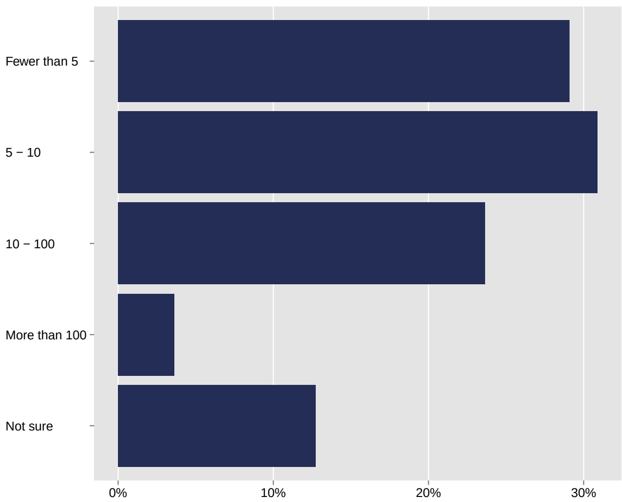

Figure 3.11. Responses to the question: "How many advanced process controllers are on your plant?"

installations typically encountered. Figure 3.10 shows the number of basic controllers and Figure 3.11 shows the number of advanced controllers typically encountered. Here it is interesting to note the amount of advanced controllers implemented per basic control function.

Regarding on-line process measurements (see Figure 3.12); the fact that respondents feel more measurements are made than needed for basic control functions indicates that there is room for implementation of optimising controllers. Optimisation is however generally centred around the most important process variables. Some important process variables are measured manually (see Figure 3.13)

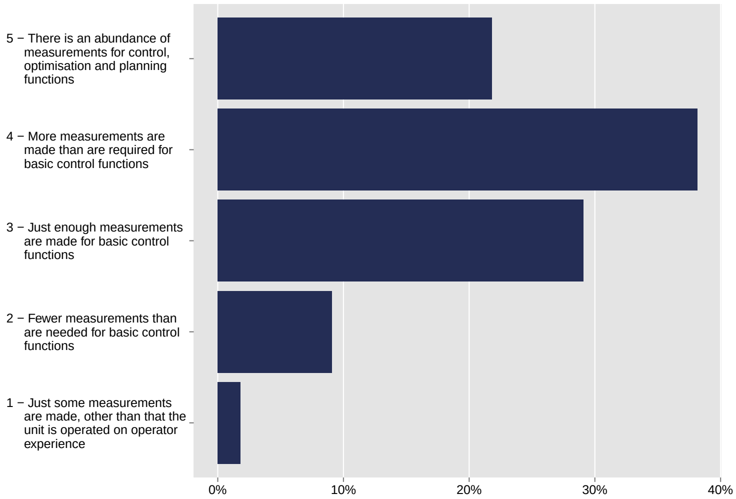

Figure 3.12. Responses to the question: "How many online measurements are made on your plant/unit?"

which corresponds with the statement by Hodouin (2011) that measurements are difficult to make. Probably the most promising way in which the unavailability of on-line measurements can be overcome is through state and parameter estimation. Good overviews of available methods are shown in Haykin (2001) and Arulampalam, Maskell, Gordon and Clapp (2002), and an implementation pertaining to minerals processing is presented in Olivier *et al.* (2012b).

It is shown in Figure 3.14 that most respondents are happy with the performance of their control systems. The main inhibitor of improved control performance is illustrated by Figure 3.15 to be a lack of understanding of the process dynamics; a lack of expertise in operating the system is listed second. Reasons pertaining to automation, namely setting up and maintaining control systems and a lack of on-line measurements, are listed as third and fourth. The main inclusion in the "Other" category is instrument failures. There does not seem to be much of a problem with the actuation of control functions in general.

It is interesting that respondents list the lack of understanding of process dynamics as the main reason for not achieving better control. Much work has gone into modelling processes in the minerals processing industry. An overview of modelling techniques for a variety of minerals processing operations is shown in King (2012). A validated model for a grinding mill circuit is also presented by Le Roux, Craig, Hulbert and Hinde (2013). This model has the focus of being simple enough

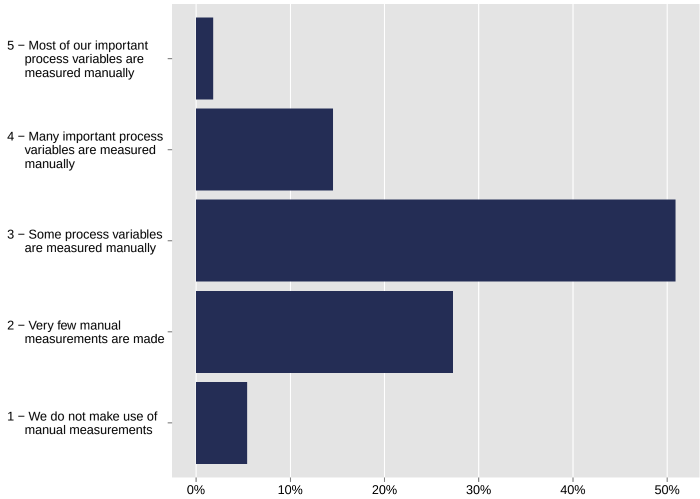

Figure 3.13. Responses to the question: "How many manual measurements are made on your plant/unit?"

for implementing model-based advanced control while providing accurate predictions. Black box modelling has also been used to good effect for MPC (see for example Chen, Zhai, Li and Li (2007)). It does therefore seem that these techniques have not yet found widespread use in industry.

The fact that a lack of expertise in operating the system is listed as the second largest inhibitor of improved control performance also indicates that there is a large scope for increased automation.

Faults are reportedly only detected through their effects by operators as shown in Figure 3.16. This implies that in general fault detection and isolation is a manual action. To a certain extent plants also commonly make use of transmitters and actuators that provide some form of fault feedback. This helps to isolate some common control system failures (Isermann 2006).

Figure 3.17 shows the functions that advanced controllers perform on minerals processing plants. Most respondents expectedly indicated that advanced controllers perform regulation and optimisation tasks. It is less common to see advanced controllers facilitating the switching of control philosophies, or to perform planning functions. Even though advanced planning functions can be automated (Lu 2015), advanced control may also perform basic planning functions, such as managing plant throughput. The fact that few respondents marked "None" on this question indicates the penetration of advanced control into the minerals processing industry.

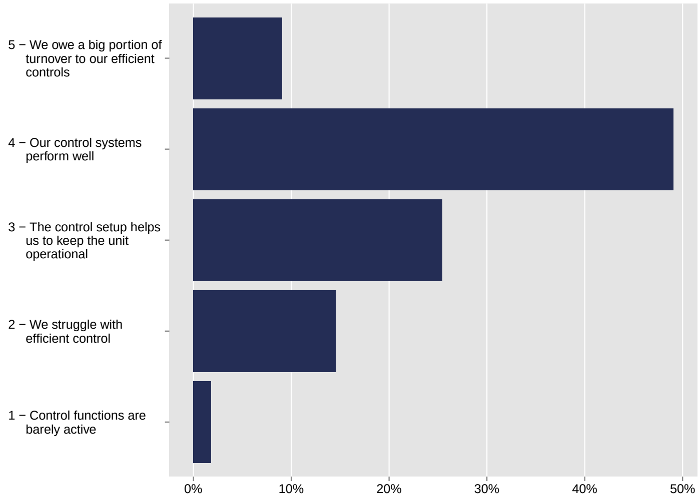

Figure 3.14. Responses to the question: "How efficient would you rate the control setup on your plant/unit to be?"

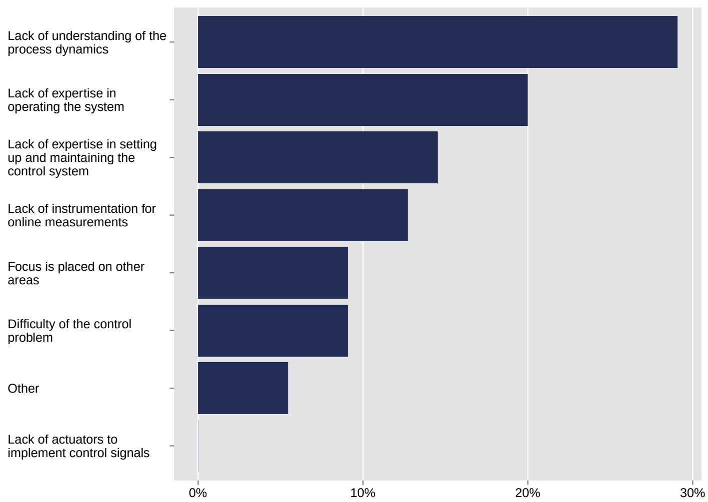

Figure 3.15. Responses to the question: "What do you think is the main factor that inhibits your control system from performing better?"

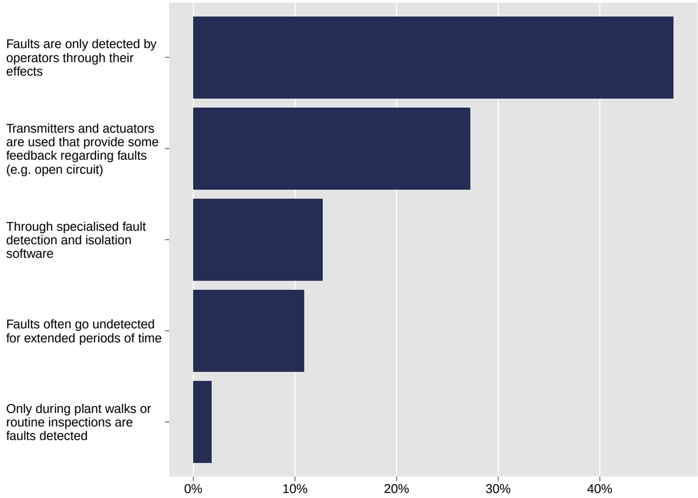

Figure 3.16. Responses to the question: "How are faults on instruments and actuators detected?"

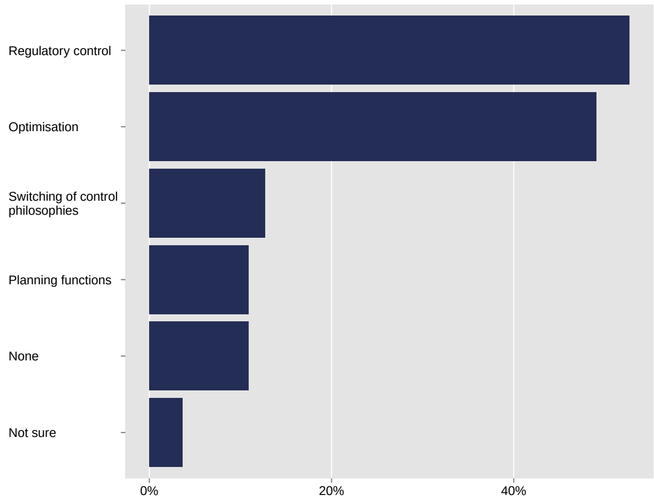

Figure 3.17. Responses to the question: "What functions do advanced controllers perform on your plant/unit?"

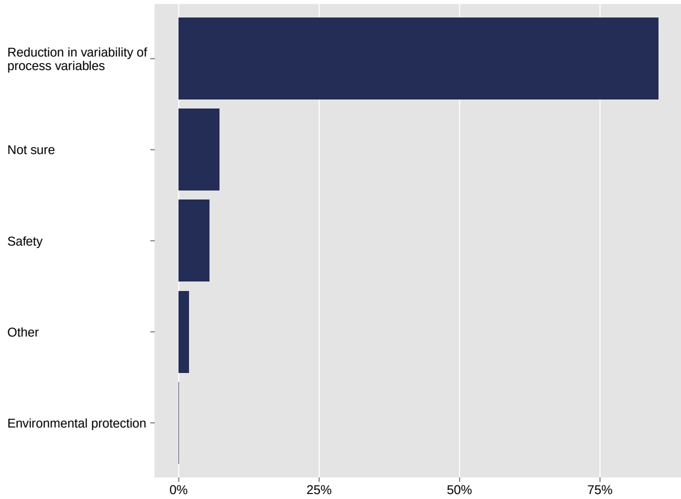

Figure 3.18. Responses to the question: “What is the main benefit you gain from advanced process control?”

Many control implementations and advanced control projects are justified on the promise of reduction in variability of process variables (Xu *et al.* 2007). It is comforting to note that most respondents see such a reduction from their advanced control installations (see Figure 3.18). Even though environmental compliance is listed as one of the main challenges for control in the future of minerals processing by Craig *et al.* (2011), no respondents marked environmental protection as their main benefit from advanced control. This situation may however change in the future.

Figure 3.19 shows the responses as to whether implemented control systems give users the ability to achieve regulatory control functions, optimisation functions, and planning functions (such as specifying the throughput of a unit). The figure shows the number of “yes” responses for each option. As expected all respondents indicated that they achieve regulation through their controls. More than 60 % indicated that they can specify optimisation objectives and just over 50 % indicated that they can specify planning functions. This result does not however indicate that the automated achievement of planning objectives is widespread in minerals processing. A specific plant may have one planning objective achieved through control and many others achieved through manual action, and the respondent would have still answered yes to this question.

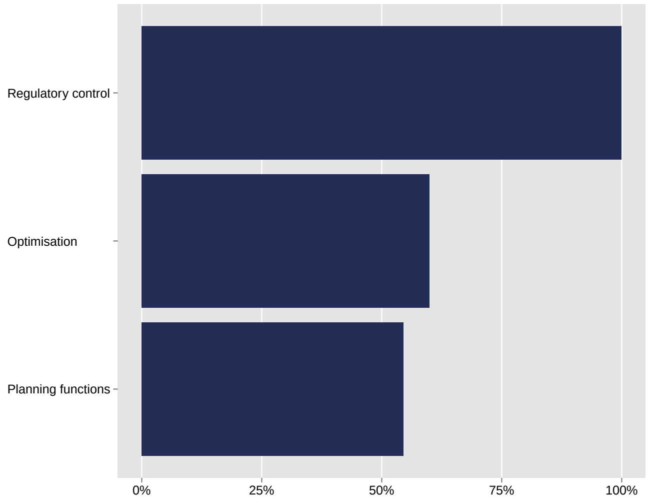

Figure 3.19. Responses to the question: "Does your control system give you the ability to specify objectives on the following control layers?"

3.2.2 The prospect of lights-out process control in the minerals processing industry

The final segment of the survey focussed specifically on total automation, or "lights-out" process control. The statement was made that "It will in future be possible to run our minerals processing plant(s) (or that of our clients) completely autonomously, i.e. with no human intervention." This question couples to the discussion in the previous chapter. Figure 3.20 shows the agreement of respondents with this statement. Almost half of the respondents either agreed or strongly agreed with this statement. About one third of respondents either disagreed or strongly disagreed with the statement.

Respondents were also asked to briefly explain their answer. Respondents in agreement with the statement widely cited the increased sophistication of modern control systems as a tool for achieving increased levels of automation. Efficiency of advanced controllers over manual optimisation actions was also mentioned as a driver towards total automation. Respondents disagreeing with the statement mostly listed large changes in operating conditions (such as feed ore variations), and equipment failures as reasons for their disagreement. Even respondents agreeing with the statement listed equipment failures as a possible stumbling block on the road towards total automation.

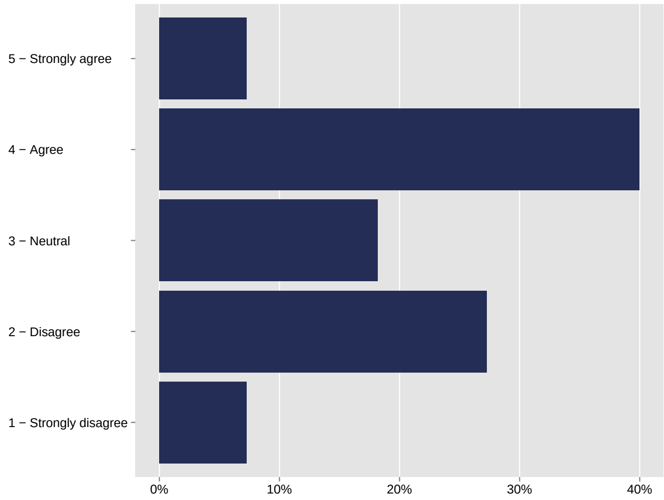

Figure 3.20. Responses to the question: "Please record your level of agreement with the following statement: It will in future be possible to run our minerals processing plant(s) completely autonomously, i.e. with no human intervention."

Lastly, respondents to the survey were asked, if they agreed with the statement regarding total automation, by when they thought it would be possible to run minerals processing plants completely autonomously; Figure 3.21 shows the result. Most respondents indicated that this would be possible within the next 20 years. Considering the amount of time it takes for sound control philosophies and technologies to be widely implemented in industry from the time it was first presented in academic literature, this estimate may not be far fetched. Conversely however, history has shown than new MPC technologies are implemented in industry long before sound theoretical bases for such technologies appear in the academic literature (see e.g. Morari and Lee (1999)). This indication is also in line with the findings presented earlier in this work.

Most of the technologies required for lights-out process control already exist. The effective combination of these technologies and the application on an industrial scale are the next steps, and it seems reasonable to assume that, at least for simpler linear systems, this integration could happen in the next 20 years.

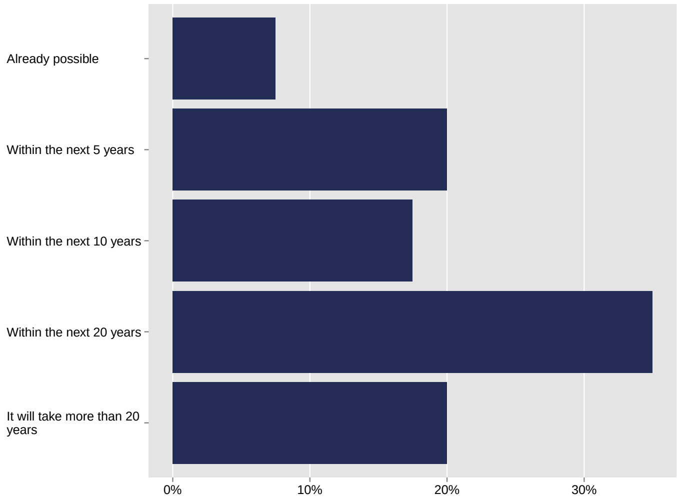

Figure 3.21. Responses to the question: "If you agree with the statement in the previous question, by when do you think it will be possible to run your minerals processing plant(s) completely autonomously?"

3.3 SURVEY RESULTS DISCUSSION

The survey results indicate that most minerals processing plants make use of automatic control to some extent. The application of control ranges in objective from regulation to optimisation and even planning. Operators do however still intervene in the process to a fair extent. The main reasons for operator interventions are to adapt the process to changes in operating conditions, optimisation during normal process operation, and intervention in the presence of failures of instruments or equipment.

Further automation on minerals processing plants will be key in overcoming the challenges that the industry face at present, and in the future (Craig *et al.* 2011). The areas to focus on when increasing the levels of automation should therefore be to automatically handle changes in operating conditions, optimisation, and maintained control in the presence of faults.

Compensation for changes in operating conditions may be done, among others, through parameter estimation (Olivier *et al.* 2012b). Optimisation is already widely applied in the processing industry (Bauer and Craig 2008). The fact that operators still perform optimisation tasks manually in some cases indicates that there is a large scope for optimising control in the minerals processing industry.

Control in the presence of faults may be achieved through active fault-tolerant control (Zhang and Jiang 2008). The survey indicates that the latter has not received much application in minerals processing plants. Survey respondents who believe that lights-out process control is not possible in the minerals processing industry cited the requirement for operator intervention in the presence of equipment or instrumentation faults as one of the main reasons for their opinion.

3.4 CHAPTER CONCLUSION

A survey was conducted regarding the degree of automation in the minerals processing industry. The survey results show the current status of automation in the industry as well as some key focus areas to increase the levels of automation. Increasing the levels of automation will help overcome the challenges faced by the minerals processing industry at present, and in the future.

The focus areas for increased automation are compensation for changes in operating conditions, implementation of optimising control, and control in the presence of instrument and equipment faults. In order to approach lights-out process control the latter will need to see much more application in the industry.

CHAPTER 4 KEY TECHNOLOGIES FOR LIGHTS-OUT PROCESS CONTROL

4.1 CHAPTER INTRODUCTION

This chapter presents more details on some of the key technologies required for lights-out process control. The details on the technologies provided in this chapter, and the illustration of these methods through simulation in the next chapter are not intended to be a complete set of details for all the enabling technologies discussed in Chapter 2. The idea however is to present the core requirements and some enabling methods developed as part of this work.

The situation where only poor process models are available for control is a common one. When there is a notable difference between a process and the available model of the process, it is said that model-plant mismatch (MPM) is present. This situation is not only common, but will usually contribute to deteriorated controller performance. The availability of poor process models is known to be a source of poor control performance, in fact this is listed as one of the most significant reasons for poor control performance in the minerals processing industry by Hodouin (2011). The availability of poor process models is however not limited to the minerals processing industry, and it is for this reason that research into handling MPM has received some focus in the recent past (Badwe *et al.* 2009). Many controller design methods make use of a plant model, which is why addressing MPM is of concern for automated plant operations. Section 4.2 presents some methods for managing MPM.

Once a failure has occurred on a processing plant, be it an actuator failure, a sensor failure, or the failure of a piece of processing equipment, the plant operating performance will likely decrease (Zhang and Jiang 2008), and this easily develops into production stoppages (Blanke, Izadi-Zamanabadi, Bøgh and Lunau 1997). FDI is concerned with detecting that a fault is present, and secondly to isolate the location of the fault. It is also ideally required to determine the magnitude of the fault. Determining, or usually estimating, the fault magnitude is referred to as fault diagnosis or fault identification.

After a fault has entered the system it may be possible to regulate the system through an FTC strategy. Even if an appropriate FTC scheme is in place it may not be possible to regulate the plant for a certain class of faults. A formal analysis would be required to determine whether the plant can be operated after the fault has altered the plant response. A linear controllability analysis, as is presented by Skogestad and Postlethwaite (2005), will be able to say whether the plant is still input-output controllable. Such a controllability analysis is however not as straightforward in the case of nonlinear systems.

The analyses for nonlinear controllability are classified by Yuan *et al.* (2011) as being either analytical or optimisation based. An example of an analytical test is that of functional controllability through the application of repeated Lie derivatives as shown in Haynes and Hermes (1970). This analysis does however quickly become complex, and because the result only shows functional controllability, the interpretation is limited. An optimisation based approach is presented by Perkins and Walsh (1996), where absolute controllability is requested for all possible combinations of uncertainty and disturbances. This analysis is formulated like a min-max optimisation problem (Bemporad, Borrelli and Morari 2003), the solution of which is notoriously conservative (Bemporad 1998, Kerrigan and Maciejowski 2004). In an industrial plant that is perturbed by many disturbances and in which many uncertainties are present the probability that all the worst case disturbances and uncertainties will be present at the same time is very low.

To overcome this conservativeness, and the difficulties in solving nonlinear robust control problems some research has gone into probabilistic methods for analysis and controller design of uncertain systems (Tempo, Calafiore and Dabbene 2012, Calafiore and Campi 2006). The focus then is to identify the probable control performance through a Monte Carlo based analysis, where the uncertain parameter set is sampled from the allowed set. A Monte Carlo based analysis is performed along these lines in this work to assess the probable controllability of the plant in the presence of the identified fault(s). Another advantage of this method is that MV limits (constraints) can be handled directly.

To not confuse this method with a functional controllability, state controllability, or input-output controllability analysis (all of which are sometimes simply referred to as controllability analyses), the term regulatability analysis will be used in this work, with the following definition:

Definition 4.1. A system is defined to be regulatable if $\exists \left[u_{t_0}, \cdots, u_{t_f}\right] \in U$ such that $\left[y_{t_0}, \cdots, y_{t_f}\right] \in Y$ as $t_f \rightarrow \infty$,

where t_0 is the starting time of evaluation, U contains the input constraints and Y contains the output constraints. The evaluation up to $t_f \rightarrow \infty$ is infeasible in practice, and a finite t_f may be selected provided it is sufficiently large to allow the plant to reach steady state.

After it has been established that the system is regulatable, i.e. the plant can still be operated within limits, the question arises whether the plant should still be operated from an economic performance point of view. In other words, is it more economically beneficial to continue to operate with the present fault(s) until the next planned opportunity for repair (the next planned shut-down), or should the plant be shut down as soon as possible, the fault(s) repaired, and started up again.

Control performance assessment is an important asset-management technology to maintain efficient operation of automation systems in processing plants (Jelali 2006). Comparison of the economic operability with a fault present to that without any faults will give an indication of whether efficient operation can be maintained. Optimal economic operability is defined as:

Definition 4.2. A system is said to operate economically optimal if the economic performance of operating in the current mode is at least as great as operating in any other mode, i.e. $\int_0^{t_f} \psi_i.\mathrm{d}t \geq \int_0^{t_f} \psi_j.\mathrm{d}t$ where ψ is the economic performance as a function of time, i represents the current mode of operation, and j represents all other possible modes of operation.

Economic performance assessment of advanced control is well established in the process industry (Bauer and Craig 2008). Comparative economic performance against benchmark control has been presented for example by Zhao, Zhao, Su and Huang (2009) and Julien, Foley and Cluett (2004). In this work however the comparative economic performance with and without faults is the focus.

The regulatability and economic operability analyses will be introduced in this chapter, and illustrated in the following chapter through simulation of a nonlinear ROM ore milling circuit model, controlled by a fault-tolerant nonlinear model predictive controller. Faults are detected and identified by making use of the nonlinear generalised likelihood ratio (NL-GLR) method using particle filters, similar to Olivier and Craig (2016a). The control of the milling circuit is similar to that of Le Roux, Olivier, Naidoo, Padhi and Craig (2016), which makes use of nonlinear MPC to control the slow milling circuit dynamics and a simpler controller to control the fast sump dynamics. In Le Roux *et al.* (2016) a dynamic inversion controller was used to control the sump, but in this work a PI override controller is used for its simplicity and ubiquity. The elements required to achieve this implementation are discussed later in this chapter.

4.2 ADDRESSING MODEL-PLANT MISMATCH

Many controller design methods make use of a plant model. A good plant model usually helps to improve controller performance, but the dynamics of industrial processes can change significantly over time (as is shown for a milling circuit in Craig and MacLeod (1995)). As soon as the plant dynamics change, MPM is present and the controller designed based on the original model will produce sub-optimal control moves. Examples of the sources of changes in plant dynamics are maintenance, equipment changes, and changes in operating conditions or parameters. In order to restore the controller performance the process needs to be re-identified and the controller redesigned, which is a costly and time-consuming exercise (Conner and Seborg 2005). Apart from the formerly mentioned problems, process re-identification also often involves intrusive plant tests that disturb the normal operation of the plant (Badwe *et al.* 2009).

The tools shown in the rest of this section do not specifically handle structural changes to the plant. For such changes extensive model updates may be required (e.g. updating the model order). In such a case full re-identification may be the only viable option.

4.2.1 Addressing model-plant mismatch for classical control systems

The situation addressed in this section includes a variety of controllers, among which the ubiquitous PID controller. When a plant and its controller are sufficiently linear and time-invariant so that they can be represented by transfer functions, and this plant is also under classical control (meaning the controller can also be represented by a transfer function), the MPM can be written as a closed-form

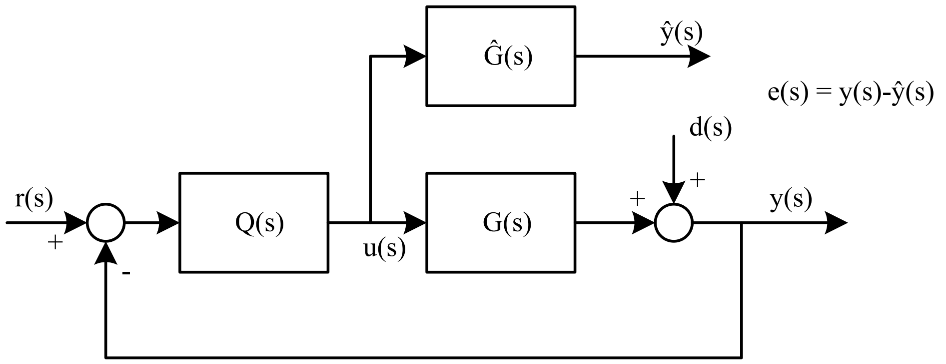

Figure 4.1. Block diagram of a control loop with model outputs being generated.

expression. The MPM expression can be used to identify a representative transfer function of the "true plant" from the currently available plant model.

This closed-form expression for the MPM was first derived in Olivier and Craig (2014) and was successfully applied to industrial data in Olivier and Craig (2015).

PID control is still very predominant in the processing industry as can be seen from Wei and Craig (2009b) and the results of the survey presented in Chapter 3. This implies a large scope for implementation of the expression presented in the following section.

4.2.1.1 Closed-form model-plant mismatch expression

Consider the one degree of freedom, negative feedback control loop shown in Figure 4.1, in which all signals and transfer functions are represented in the Laplace domain. G is the plant that generates the true output $y(s)$, $\hat{G}$ is the model of the plant that generates the model output $\hat{y}(s)$, Q is the controller, $d(s)$ is any disturbance that may be present, and $r(s)$ is the reference signal (setpoint).

The derivation of the MPM expression that follows is done for a general multiple-input, multiple-output (MIMO) system, in which all signals may be vectors and all transfer functions may be matrices. G, $\hat{G}$ and Q are all continuous-time, linear time-invariant (LTI) systems, represented in the Laplace domain. G and $\hat{G}$ have the dimensions $n_y \times n_x$ and Q has the dimensions $n_x \times n_y$. Also, y, $\hat{y}$, r, and v are $n_y \times 1$

vectors, and u is an $n_x \times 1$ vector. For this derivation the number of manipulated variables in the controller must equal the number of controlled variables in the plant, and consequently $n_x = n_y$.

The reference to the Laplace operator (s) will be dropped for ease of representation. Let the residual (e) be the difference between the actual output and the model output as

$$e = y - \hat{y} \tag{4.1}$$

$$e = Gu + d - \hat{G}u \tag{4.2}$$

$$e = \Delta_M u + d \tag{4.3}$$

where $\Delta_M = G - \hat{G}$ is the mismatch. This definition for the mismatch is equivalent to the definition for additive uncertainty presented by Skogestad and Postlethwaite (2005). During this derivation however Δ_M is used to represent uncertainty of any magnitude, as opposed to the weighted uncertainty with a restriction on the maximum singular value in Skogestad and Postlethwaite (2005) ($\bar{\sigma}(\Delta(j\omega)) \leq 1$). The control signal ($u(s)$) is given by

$$u = Q(r - y) \tag{4.4}$$

$$u = Q(r - [Gu + d]) \tag{4.5}$$

$$u = Qr - QGu - Qd \tag{4.6}$$

$$(I + QG)u = Qr - Qd \tag{4.7}$$

$$u = (I + QG)^{-1} Q(r - d) \tag{4.8}$$

$$u = Q(I + GQ)^{-1}(r - d) \tag{4.9}$$

where the push-through rule for matrix manipulation (Skogestad and Postlethwaite 2005:p.68) was used to go from (4.8) to (4.9). The matrix inverse operation of (4.8) requires that the product QG be strictly proper. Substitution of (4.9) into (4.3) then gives

$$e = \Delta_M Q(I + GQ)^{-1}(r - d) + d \tag{4.10}$$

$$e = \Delta_M Q\left(I + \{\Delta_M + \hat{G}\}Q\right)^{-1}(r - d) + d \tag{4.11}$$

$$e = \Delta_M Q\left(I + \Delta_M Q + \hat{G}Q\right)^{-1}(r - d) + d. \tag{4.12}$$

The expression $G = \Delta_M + \hat{G}$ is used to go from (4.10) to (4.11). After this substitution all the terms in (4.11) are known, save for the disturbance if it is unmeasured. Further matrix algebra leads to

$$\begin{aligned}
(e-d)(r-d)^{-1} &= \Delta_M Q \left(I + \Delta_M Q + \hat{G}Q\right)^{-1} && (4.13)\\
(e-d)(r-d)^{-1}\left(I + \Delta_M Q + \hat{G}Q\right) &= \Delta_M Q && (4.14)\\
(e-d)(r-d)^{-1}\left(I + \hat{G}Q\right) &= \Delta_M Q - (e-d)(r-d)^{-1}\Delta_M Q && (4.15)\\
(e-d)(r-d)^{-1}\left(I + \hat{G}Q\right) &= \left[I - (e-d)(r-d)^{-1}\right]\Delta_M Q. && (4.16)
\end{aligned}$$

Rewriting the equation with Δ_M isolated on the left-hand side gives the closed-form mismatch expression as:

$$\Delta_M = \left[I - (e-d)(r-d)^{-1}\right]^{-1}(e-d)(r-d)^{-1}\left(I + \hat{G}Q\right)Q^{-1}. \tag{4.17}$$

This expression may be used to derive the mismatch if the disturbances are known. If the disturbances are however unmeasured or even unknown, data from a period of operation free from significant disturbances can be used (if this is possible), and with $d = 0$ (4.17) becomes

$$\Delta_M = \left[I - er^{-1}\right]^{-1} er^{-1}\left(I + \hat{G}Q\right)Q^{-1}. \tag{4.18}$$

If however unmeasured disturbances cannot be ignored, disturbance estimation techniques (see for example Lee and Ricker (1994)) may be used to account for their values.

The problem with large unmeasured disturbances also plagues classical system identification techniques. This is because the output error (the difference between the measured output and the model output) can be significant in the presence of large disturbances, even if the model is perfect (Zhu 2001).

Usually signals (such as $r(s)$) will not be square for MIMO systems and will consequently not have an inverse in the true sense. This issue is addressed in Addendum B, where the provisions required for applying this expression to MIMO plants are discussed. Sufficient excitation (see Ljung (1999)) is required in either the disturbance or the reference signal in order for the application of (4.17) to be sensible. Without sufficient excitation $\nexists\ (r-d)^{-1}$.

The expression $G = \Delta_M + \hat{G}$ may again be used to obtain the transfer function of the actual plant as

$$G = \left[I - (e-d)(r-d)^{-1}\right]^{-1} (e-d)(r-d)^{-1} \left(I + \hat{G}Q\right) Q^{-1} + \hat{G}. \tag{4.19}$$

If (4.18) is used as the mismatch expression, the plant transfer function is given by

$$G = \left[I - er^{-1}\right]^{-1} er^{-1} \left(I + \hat{G}Q\right) Q^{-1} + \hat{G}. \tag{4.20}$$

Notice from the derivation that there is no mathematical limit on the size of Δ_M. The limit on how large Δ_M may be is therefore only based on the usable data that can practically be extracted, e.g. without control valves saturating. The MPM expression works for single-input single-output as well as multiple-input multiple-output systems.

The requirement for sufficient excitation means that either sufficiently large (and known) changes are required for the independent variables (such as achieved with sizeable setpoint changes), or sufficiently large (and known) disturbances should be present, or both. This limitation is however also present for the MPM detection algorithms presented by Badwe *et al.* (2009); Kano, Shigi, Hasebe and Ooyama (2010), and also for most plant identification methods. The expression handles known disturbances directly, but does not handle unknown disturbances. If it is unavoidable to use data without the presence of large unmeasured disturbances, their values should first be estimated by making use of, for example, a Kalman filter (Kalman 1960a). If this is not possible, the MPM expression described in this section may not yield desirable results.

Identifying the mismatch in the manner proposed in this section is equivalent to identifying the additive uncertainty in the model (Skogestad and Postlethwaite 2005), where the additive model uncertainty is also expressed as the difference between the plant and the model. Another possibility is presented by Böling, Häggblom and Nyström (2004) where the output multiplicative uncertainty is explicitly defined by matching the output of the uncertainty model to the outputs of a set of known models.

4.2.1.2 Application to controller design

Once the mismatch (Δ_M) has been identified correctly, the expression $G = \Delta_M + \hat{G}$ may be used to obtain the representative transfer function of the plant. The representative transfer function of the plant may then be used to redesign the controller.

There are many ways of tuning PI(D) controllers. Some of the more common methods include the Ziegler-Nichols method, the Cohen-Coon method, the internal model control (IMC) tuning relations (Seborg *et al.* 2003), the simplified IMC expansion thereof (Skogestad 2003), Lambda tuning (which is a specific case of the IMC relations), tuning based on the minimisation of the integral error, pole placement, and loop shaping (see Åström and Hägglund (1995) for more examples). Most of these methods however make explicit use either of the plant transfer function or of the model parameters that characterise the transfer function.

There are also many other controller design methods that do not specifically lead to PI(D) controllers but do produce controllers representable by means of transfer functions. These methods include linear quadratic Gaussian (LQG) control, as well as H_2 and H_∞ control, and also MPC in specific instances.

The method chosen for controller design is not so important, what is however important is that the reader appreciates how commonly the plant transfer function is used in controller design. In these cases MPM will cause the controller to perform outside of its original design intent. If the MPM is severe enough this could lead to the dynamic performance specifications not being met or even instability. In such a case the MPM expression presented in the previous section may be used to update the available plant model, and the controller design procedure may be repeated. This will lead to better adherence to the control specifications.

An example of applying the expression to a general MIMO system, as well as an example of applying the expression to industrial data are shown in Addendum C. These are not presented along with the simulation study in the next chapter, as the focus of that study is on a nonlinear model which cannot be handled directly with this MPM expression.

4.2.1.3 Closed-loop identification to handle mismatch for classical control

The main alternative for handling MPM with classical control (to the closed-form expression presented in Section 4.2.1.1), is closed-loop identification. Although the expression of Section 4.2.1.1 is related to closed-loop identification, it does make use of the explicit expression for the mismatch to identify the representative plant model. This implies that the model structure is known *a priori* and can simply be updated through the mismatch expression.

Model identification techniques that make use of closed-loop data have been introduced some time ago (see for example Gustavsson, Ljung and Söderström (1977) or Söderström and Stoica (1989)). A good overview of closed-loop identification is given by Van den Hof (1998), in which different closed-loop identification techniques are discussed and their characteristic properties are compared. The methods described by Van den Hof (1998) are mostly based on statistical approaches and do not make explicit use of the transfer functions representing the system, unlike the method presented in Section 4.2.1.1. A more recent approach to on-line closed loop identification is given in Kruger, Li and Irwin (2006), where the joint plant and controller model is identified using subspace model identification, and thereafter the plant model is separated assuming the controller model is known *a priori*.

4.2.2 Addressing MPM when the controller does not have a transfer function

The most common form of advanced control in the process industry is linear MPC (Bauer and Craig 2008). Unconstrained linear MPC can be represented by a transfer function when the control horizon is constrained. If these conditions are not met, the MPC cannot be represented by a transfer function and the closed-form expression shown in Section 4.2.1.1 is not applicable. Assessing the quality of the underlying MPC model on-line is however still important for sustaining control benefits over the lifetime of the MPC controller.

Once poor models have been detected, the controller performance can be restored through re-identification of the process and redesign of the controller, which is a costly and time-consuming exercise (Conner and Seborg 2005). Apart from the formerly mentioned problems, process re-identification also often involves intrusive plant tests that disturb the normal operation of the plant (Badwe *et al.* 2009).

An alternative to full process re-identification is to firstly identify the elements in the process transfer function matrix that contain significant mismatch, and to only re-identify these. Algorithms for MPM

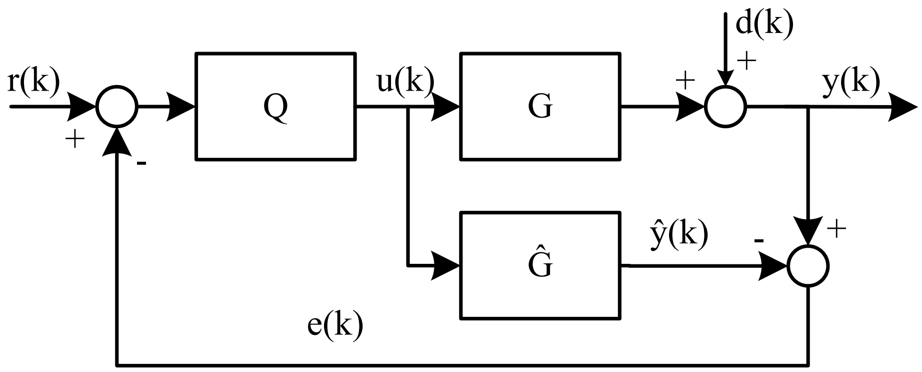

Figure 4.2. Closed-loop IMC structure.

detection have been proposed by Badwe *et al.* (2009) and Kano *et al.* (2010). These algorithms identify the transfer function matrix elements that contain mismatch as well as the significance of the mismatch. This is useful information that can be used to help assess the need for process re-identification. The method of Kano *et al.* (2010) makes use of a statistical test and the stepwise method to try and find the model elements that contribute to the residuals.

In Badwe *et al.* (2009) a partial correlation analysis is used which is briefly presented next. Consider the closed-loop IMC layout shown in Figure 4.2. This layout is almost identical to that shown in Figure 4.1, apart from the model output not forming part of the feedback signal in Figure 4.1. The definitions of all signals in Figure 4.2 are the same as for those in Figure 4.1.

The residuals are again given by equation (4.1), and a correlation between the residuals and the plant inputs indicates the amount of mismatch. The following relations are obtained from Figure 4.2:

$$e = [I+\Delta_M Q]^{-1}\Delta_M Q r + [I+\Delta_M Q]^{-1} d \tag{4.21}$$

$$u = \underbrace{Q[I+\Delta_M Q]^{-1}}_{S_{ru}} r - \underbrace{Q[I+\Delta_M Q]^{-1}}_{S_{du}} d \tag{4.22}$$

where S_{ru} and S_{du} are the input sensitivities from r and d respectively; $\Delta_M = G - \hat{G}$ is the mismatch as defined previously.

At each sampling instant the values of the manipulated variables are calculated by the controller based on the difference between the output and the reference vectors. Depending on the interactions in the model and the design of the controller, correlation may exist between manipulated variables.

This may lead to the detection of spurious correlation or to the non-detection of hidden correlation between residuals and manipulated variables. This would in turn obscure the correct identification of the location of significant MPM. To overcome this Badwe *et al.* (2009) proposed the use of a partial correlation analysis.

Data for analysis should be chosen from a period of time where there is sufficient setpoint excitation. Since models are fitted to the sensitivity functions S_{ru} and S_{du}, the setpoints should be sufficiently exciting to ensure estimation accuracy. In order to ensure that MPM is not incorrectly identified because of disturbances, the disturbance free components of the manipulated variables are required. These are the components of the MVs needed to react to setpoint changes and not for disturbance rejection. The disturbance free components of the MVs are represented as $\hat{u}^r(k)$ and may be obtained as described by Badwe *et al.* (2009). Note that the method does not handle unmeasured disturbances directly. One needs some information about the disturbances if they are not measured. Alternatively one must select a region of data where the plant is not significantly perturbed by unmeasured disturbances.

Next, the component of each MV that is uncorrelated with all other MVs is computed. Each MV may be represented as

$$\hat{u}_i^r(k) = G_{u_i}\tilde{u}^r(k) + \varepsilon_{u_i}(k) \tag{4.23}$$

where G_{u_i} is a model identified between u_i^r and all the other MVs, $\tilde{u}^r$ contains all the other MVs except for u_i, and ε_{u_i} is that component of u_i that is uncorrelated with all other MVs. The estimate of ε_{u_i} is then given by:

$$\hat{\varepsilon}_{u_i}(k) = \hat{u}_i^r(k) - G_{u_i}\tilde{u}^r(k). \tag{4.24}$$

A similar procedure is applied to calculate the component of each residual that is uncorrelated with all other MVs except u_i,

$$e_j(k) = G_{e_j}\tilde{u}^r(k) + \varepsilon_{e_j}(k). \tag{4.25}$$

Here G_{e_j} is the model identified between the residual e_j and all other MVs, except u_i. The estimate for ε_{e_j} is then given by

$$\hat{\varepsilon}_{e_j}(k) = e_j(k) - G_{e_j}\tilde{u}^r(k). \tag{4.26}$$

Non-zero correlation between $\hat{\varepsilon}_{e_j}$ and $\hat{\varepsilon}_{u_i}$ indicates the presence of MPM in the $u_i \rightarrow y_j$ channel.

Next, the course of action to take should be decided once the model elements containing significant mismatch have been detected. One logical option is to re-identify the elements containing significant mismatch via an open-loop step test of the plant. It is however common for at least one of the model elements to be open-loop unstable, which prompts additional considerations in the experiment design.

The use of manual step-tests to re-identify the model does also require some effort on the part of the control engineer, but owing to safety concerns such a supervised method is often advisable.

These drawbacks can, among others, be eliminated through the use of a closed-loop identification procedure. The advantages of using closed-loop identification, as listed by Zhu and Butoyi (2002), include a reduction in the disruption of process operation, and eliminating the need for manual control action.

Irrespective of the way in which the new model is found, the objective is to minimise the magnitude of the residuals produced over the duration of the experiment. Given that the residual is the difference between the plant and model outputs, the modelling objective can be written as

$$\min_{\hat{G}} \sum_{k} \left| y(k) - \hat{G}u(k) \right| \tag{4.27}$$

$$s.t.\ \hat{G} \in \mathbb{G} \tag{4.28}$$

$$\theta_c(\hat{G}) \leq 0 \tag{4.29}$$

$$k_1 \triangleq 0 \tag{4.30}$$

$$k_f \triangleq T \tag{4.31}$$

where $y(k)$ and $\hat{G}u(k)$ (with $k \in [0, \ldots, T]$) are the plant and model outputs respectively. $\theta_c(\hat{G})$ is the set of inequality constraints on $\hat{G}$, and $\mathbb{G}$ is the set of allowed model transfer functions (these constraints are further discussed in Olivier and Craig (2013)). The summation done in (4.27) will tend to zero as $\hat{G} \to G$. This statement is however not free from consideration of disturbances. If unmeasured disturbances affect the plant output during the model re-identification, an incorrect model could result.

Open- and closed-loop identification are discussed in Van den Hof (1998); Shardt and Huang (2011), and an explicit constrained minimisation approach to model update is shown in Olivier and Craig (2013).

If the mismatch that was corrected in this step was significant, i.e. the new process model differs significantly from the old one, it may become necessary to re-tune the MPC objective function weights. This action may be up to the control engineer, but within the framework of lights-out process control an automatic tuning algorithm for MPC may be preferable. Liu and Wang (2000) and Vega *et al.* (2008) present methods based on multi-objective optimisation; Van der Lee, Svrcek and Young (2008) presents a method based on combining the genetic algorithm with multi-objective fuzzy logic.

4.3 FAULT-TOLERANT CONTROL

FTC strategies can broadly be classified as either being passive or active (Zhang and Jiang 2008). With passive FTC the objective is to design the controller such that it is robust enough to handle a class of presumed faults. Active FTC has the objective of isolating faults and adapting the control strategy such that the stability and control performance of the entire system might be maintained.

A fault-tolerant nonlinear model predictive controller (FT-NMPC) is used in this work to regulate the plant under fault conditions. The controller will regulate the plant to the best of its ability, irrespective of whether the regulatability or economic operability conditions are met. The elements of such a controller are discussed in the following sections.

Prakash, Narasimhan and Patwardhan (2005) shows how fault-tolerant control may be implemented in the MPC framework. Reviewing the integration of fault-tolerant control with MPC, it is evident that the design of the state observer is the key to being successful (Deshpande, Patwardhan and Narasimhan 2009). This is because the observer generates outputs based on a proposed set of faults, which may be compared to the plant outputs for fault identification. This is true for model-based FDI, and the requirement of an accurate model for MPC makes model-based FDI the logical choice for use along with MPC.

One promising fault identification method for nonlinear systems, the NL-GLR method (Deshpande *et* *al.* 2009), as used in this work, is based on this idea. Particle filtering is used to implement the state observer.

Particle filtering is an estimation technique based on representing probability densities with weighted samples (particles) (Arulampalam *et al.* 2002). Because this representation does not make any assumption about the form of the distribution, it can be used in general nonlinear, non-Gaussian systems. Particle filters have been used for FDI before, see e.g. Wang and Syrmos (2008). To the knowledge of the author they have however only previously been used in the GLR framework for integration with NMPC by Olivier and Craig (2016a).

The rest of this section describes the elements of the fault-tolerant controller used in the simulation study of the following chapter.

The discussion in the rest of this chapter pertains to the general discrete time state-space representation of a dynamic system

$$x_{k+1} = f\left(x_k, u_k, \theta_k, v_k\right) \tag{4.32}$$

$$y_k = g\left(x_k, u_k, \theta_k, d_k, n_k\right) \tag{4.33}$$

where $x \in \mathbb{R}^n$ is the state vector and $y \in \mathbb{R}^m$ is the output vector, $f(\cdot)$ and $g(\cdot)$ are possibly nonlinear functions describing the state transitions and the outputs respectively, u_k contains the exogenous inputs, θ_k represents the system parameters, $d_k \in D$ represents the modelled disturbances, v_k is the state noise, and n_k is the measurement noise.

4.3.1 Nonlinear model predictive control

Considering the system presented in equations (4.32) and (4.33), the objective of a model predictive controller at each sampling instant is to minimise the scalar performance index

$$\begin{aligned}
\min_{u_k \ldots u_{k+N_c-1}} \quad & J(u_k, \ldots, u_{k+N_c-1}, x_k, r) \\
s.t. \quad & x_{k+1} = f\left(x_k, u_k, \theta_k, v_k\right) \\
& y_k = g\left(x_k, u_k, \theta_k, d_k, n_k\right) \\
& \theta_c(y_k \ldots y_{k+N_p}, u_k \ldots u_{k+N_c-1}) \leq 0
\end{aligned} \tag{4.34}$$

where $x : \mathbb{R} \to \mathbb{R}^{n_x}$ is the state trajectory, $u : \mathbb{R} \to \mathbb{R}^{n_u}$ is the control trajectory, x_k is the state at time step k, r is the reference signal (which may in general specify MV or CV targets), and $\theta_c(\cdot)$ is a possibly nonlinear constraint function.

The performance index (or objective function) to be minimised penalises output values different from the reference values, as well as excessive control moves. This ensures that the output values tend to the reference values without making undue control moves or violating constraints. The flexibility with which control objectives can be incorporated into the objective function is partly why MPC is such a popular technology. The objective function used in this work includes linear optimisation objectives, similar to a variation discussed in Qin and Badgwell (2003) as:

$$J(\cdot) = \sum_{i=1}^{N_p} \left[\|y_{r,i} - \hat{y}_i + D\|_{Q_r}^2 + \|s_i\|_{Q_s}^2 + Q_l y_i \right] + \sum_{i=0}^{N_c - 1} \|\Delta u_i\|_R^2, \tag{4.35}$$

where N_p and N_c are the prediction and control horizons respectively; $\|\cdot\|_Q^2$ is the Q-weighted 2-norm; Q_r, Q_s, Q_l, and R are weighting matrices corresponding respectively to the reference tracking, slack variables for constraint violations, linear optimisation objectives (LP weights), and control movements; y_r is the output reference and $\hat{y}$ is the output prediction. The slack variables are represented by s_i and are defined to be:

$$s_i = \begin{cases} y_i - y_h & ; \quad y_i > y_h \\ y_i - y_l & ; \quad y_i < y_l \\ 0 & ; \quad y_l \leq y_i \leq y_h \end{cases}, \tag{4.36}$$

where y_l and y_h are respectively the output low and high limits. The term, $D = y_k - \hat{y}_k$ (which is constant over the prediction horizon), is included to add integral action (i.e. zero off-set tracking) to the MPC, where y_k is the plant output and $\hat{y}_k$ is the model output at time step k. This conventional feedback procedure assumes the difference between the process and model outputs is because of additive output disturbances, which persist throughout the prediction horizon (Meadows and Rawlings 1997). Although this method can be sensitive to fluctuations in the output, it is a simple yet effective method for compensating the effects of output disturbances.

In the presence of non-stationary disturbances this approach may not work as well. In this case one can augment the system with a constant nonzero disturbance vector (Pannocchia and Rawlings 2003). The state estimation problem is then extended to also estimate the disturbance values, which then eliminates the need for the D-term as described previously. In this work however the simpler approach, using the D-term, is followed.

If any plant output variable does not have a specific reference value, but should rather be minimised, the corresponding entry in the Q_r matrix could be made zero while the corresponding entry in the Q_l matrix is given a positive weighting value (or a negative weight if the value should be maximised).

Qin and Badgwell (2003) notes that including steady-state optimisation objectives into the dynamic optimisation algorithm, as done here, may improve controller performance as long as the steady-state and dynamic objectives do not conflict. As the long as the steady-state optimisation weights are chosen sensibly, this is in fact the case.

The only difference in this formulation between the linear and nonlinear versions of the MPC is whether the output predictions are supplied by propagating the control vector through a linear or nonlinear system function.

In practical applications an MPC generally determines the setpoints for baselayer controls, which are responsible for operating the actuators (commonly control valves) such that the MPC-determined setpoints are achieved. If the baselayer control loops are well tuned and sufficiently fast, their respective closed-loop transfer functions may be assumed to be $T \approx 1$ (Bequette 2003). Their presence may therefore be disregarded from the subsequent data analysis steps described in the following sections.

4.3.2 Fault detection and isolation

Venkatasubramanian, Rengaswamy, Yin and Kavuri (2003a) notes that the desirable characteristics of the fault diagnosis system are:

- Quick detection and diagnosis;
- Isolability (the ability to distinguish between different failures);
- Robustness (specifically to noise and uncertainties);

- Novelty identifiability (i.e. to know when an unknown or novel fault enters the system);
- Classification error estimate;
- Adaptability (e.g. changes in operating point);
- Explanation facility;
- Limited modelling requirements;
- Limited storage and computational requirements; and
- Multiple fault identifiability.

Of course it is very difficult to achieve all of the desirable characteristics simultaneously. Usually if the FDI system becomes more sophisticated to include more features the complexity increases along with computational requirements, and ease of implementation deteriorates. Using a simpler FDI scheme alternatively would lead to missing some of the desirable features.

FDI methods can largely be classified as either being data driven or model-based (Venkatasubramanian *et al.* 2003a, Venkatasubramanian, Rengaswamy, Yin and Kavuri 2003b, Venkatasubramanian, Rengaswamy, Yin and Kavuri 2003c), based on the process knowledge that is required *a priori*. The basic *a priori* knowledge that is required is the set of failures and the relationship between the observations and the failures (Venkatasubramanian *et al.* 2003a).

4.3.2.1 Data driven fault detection and isolation

With data driven FDI the knowledge required is based on past experience of the process. This is referred to as shallow, evidential, or process history-based knowledge (Yang 2004). These methods are often used when there is limited knowledge about the fundamental operating principles of the process, and a large amount of historical data. Data driven methods include neural networks, principal component analysis (PCA), and qualitative trend analysis (QTA).

For data driven methods it is required to transform the historic data into knowledge of the faults. This is referred to as feature extraction, and is necessary for diagnosis later on. This feature extraction process groups data driven methods into qualitative and quantitative methods. QTA is an example of a qualitative method, whereas PCA and neural networks are regarded as quantitative. Venkatasubramanian *et al.* (2003c) gives a more thorough review of data driven FDI approaches.

4.3.2.2 Model based fault detection and isolation

Model-based *a priori* knowledge can also be categorised as being qualitative and quantitative. The model is generally developed based on some fundamental understanding of the process operation. In quantitative models this understanding is captured by model equations relating the system outputs to the system inputs. In qualitative models the relationships are expressed by qualitative functions centred around different units in the process. Observer based methods are quantitative, and methods such as digraphs and fault trees are qualitative. Venkatasubramanian *et al.* (2003a) provides a good overview of quantitative model-based methods, and Venkatasubramanian *et al.* (2003b) gives an overview of qualitative methods.

When using MPC for process control a quantitative process model is required. This makes the use of quantitative model-based FDI a natural choice. Obtaining a quantitative process model is listed as one of the main limitations to quantitative model-based FDI by Venkatasubramanian *et al.* (2003a), but the use of MPC means that such a model will be available. The quality of this model may be another limitation to FDI accuracy, but model maintenance can also be listed as a need for proper MPC functioning.

Deshpande *et al.* (2009) notes that the design of the state observer for fault diagnosis in the MPC framework is the key to being successful. The choice of FDI method and observer to use also depends on whether the system can accurately be represented with linear functions. If the system is strongly nonlinear the problem becomes more complex.

Alcorta Garcia and Frank (1997) provides an overview of methods for observer-based fault diagnosis of nonlinear systems. Most of these methods are based on generating and evaluating the model residuals (the difference between the measured outputs and the model predictions).

4.3.2.3 The nonlinear generalised likelihood ratio method for fault diagnosis

In this work the NL-GLR method of Deshpande *et al.* (2009) is used. The generalised likelihood ratio approach to fault diagnosis was popularised early on by Willsky and Jones (1976) and Narasimhan and Mah (1987). The method was later on expanded to the nonlinear case, and possesses many of the characteristics of the ideal fault diagnosis system listed in Section 4.3.2 (from Venkatasubramanian *et al.* (2003a)). The NL-GLR method is described next.

Consider the innovation sequence calculated from the state observer:

$$\gamma(k) = y(k) - g(\hat{x}_k, \theta_k), \tag{4.37}$$

with $k \in [t, t+N]$. Without any faults the innovation sequence is Gaussian white noise (if the model is a good representation of the plant). If however there are any faults, it is possible to use the test statistic over the innovation sequence window

$$\varepsilon(t,N) = \sum_{k=t}^{t+N} \gamma(k)^T V(k)^{-1} \gamma(k) \tag{4.38}$$

to detect the fault. Note that $V(k)$ is the innovation covariance. The test statistic follows a central chi-squared distribution with zero mean Gaussian noise in the innovation sequence. If this test statistic exceeds a threshold, the fault is confirmed. The threshold and window length are tuning parameters for the fault detection test. There is a trade-off between the speed of fault detection and the accuracy of the detection. If the detection window size is increased the detection accuracy of the fault magnitude will improve, but the time before detection will increase.

Suppose a set of observers is used, each operating with a different postulated fault, and each generates outputs along with the nominal observer (see Figure 4.3 where Y_k represents the plant measurements and U_k represents the plant inputs). The problem of fault isolation is then finding the fault mode observer that best explains the measurement sequence $\{y(t) \ldots y(t+N)\}$ generated over the time window for which the fault was detected. The NL-GLR method can then be stated in mathematical form as:

$$\min_{\hat{b}_{f_j}} \left(J_{f_j}\right) = \sum_{i=t}^{t+N} \gamma_{f_j}^T(i) V_{f_j}(i)^{-1} \gamma_{f_j}(i), \tag{4.39}$$

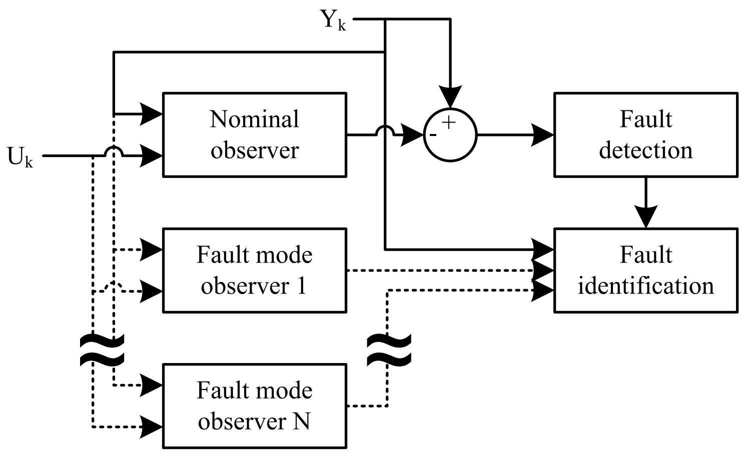

Figure 4.3. Observer bank with different postulated faults for the NL-GLR FDI method.

where $\gamma_{f_j}(i)$ and $V_{f_j}(i)$ are respectively the innovations and innovation covariance matrices generated by the fault mode observer corresponding to fault f_j. The isolated fault corresponds to the fault mode observer for which J_{f_j} is the smallest, with $\hat{b}_{f_j}$ the fault magnitude that produces this minimum value. The fault magnitudes are defined for a variety of faults in the following section.

Because the innovation sequence of (4.37) and the innovation covariance matrix ($V(k)$) appear directly in the Kalman filtering framework, it is natural to make use of the Kalman filter as the state observer (or the extended Kalman filter (EKF) in the nonlinear case). In the linear case the use of the Kalman filter is wholly justified as it is the optimal estimator (Arulampalam *et al.* 2002) (assuming also that the noise is Gaussian). The EKF however, as is often used in the nonlinear case, suffers some known limitations (see Julier and Uhlmann (2004) for a more complete discussion). It is for this reason that particle filtering is rather used in this work as further discussed in Section 4.3.4.3.

The NL-GLR method can also be applied in the presence of non-Gaussian noise (Li and Kadirkamanathan 2001), although the test statistic (equation (4.38)) will follow a different distribution.

4.3.3 Representing faults

There is a set of faults for which fault isolation is a trivial task. Examples include gross sensor faults that may be detected via a simple data validation scheme, and faults for which there are direct measurements available. Many modern sensors will inform the user when they have exceeded the calibration range, and if such a violation is impossible (e.g. a negative level reading, or a temperature that has changed quicker than what is physically possible) it is trivial to state that the sensor has failed at the corresponding condition.

Also consider a flow valve on a line where a flow measurement is made. If the valve is stuck while the controller is trying to manipulate the flow, the flow reading will be a direct indication of the magnitude of the fault. This class of faults is not considered in this work. Focus will be placed on actuator errors where no direct indication is available. Such faults are much more difficult to isolate (Prakash *et al.* 2005). Other faults (including, but not limited to, sensor failure, sensor bias, or sensor drift) can also be included in the set of postulated faults in the observer bank. For completeness these faults are also described.

If the j-th actuator is stuck abruptly at time t then the corresponding plant input can be represented as:

$$u_{u_j}(k) = u(k) + \left[b_{u_j} - e_{u_j}^T u(k)\right] e_{u_j}\sigma(k-t) \tag{4.40}$$

where b_{u_j} represents the constant value at which the j-th actuator is stuck, e_{u_j} is the fault vector with element j equal to one and all other elements equal to zero, and $\sigma(t)$ is the unit step function:

$$\sigma(t) = 0 \text{ if } t < 0;\ \sigma(t) = 1 \text{ if } t \geq 0. \tag{4.41}$$

Similarly, if a bias occurs in the j-th sensor at time t, then the measured output can be represented as:

$$y_{y_j}(k) = g(x_k, \theta_k) + b_{y_j}e_{y_j}\sigma(k-t) + n(k), \tag{4.42}$$

where b_{y_j} is the bias present in the j-th sensor, and $n(k)$ is again the measurement noise. If the j-th sensor fails abruptly at time instant t, then the measurement can be represented as:

$$y_{y_j}(k) = g(x_k, \theta_k) + \left[b_{y_j} - e_{y_j}^T g(x_k, \theta_k)\right] e_{y_j}\sigma(k-t) + n(k), \tag{4.43}$$

where b_{y_j} is the constant output value of the j-th sensor. If there is a drift in the j-th sensor from time t, the measured output can be represented as:

$$y_{y_j}(k) = g(x_k, \theta_k) + b_{y_j}e_{y_j}\zeta(k-t) + n(k), \tag{4.44}$$

where b_{y_j} is the drift slope present in the j-th sensor and

$$\zeta(t) = 0 \text{ if } t < 0; \; \zeta(t) = t \text{ if } t \geq 0. \tag{4.45}$$

Any of these fault representations may be considered by the fault mode observers as used in the NL-GLR framework. The main drawback of using the NL-GLR method is that fault mode observers need to be set up for every fault that needs to be identified accurately. Even though the method can be expanded to handle multiple faults (Deshpande *et al.* 2009), the number of fault mode observers required can become very large for a complex process. Dealing with a quick succession of multiple faults (the one causing the next) is therefore not a trivial task.

When identifying multiple faults the methodology of section 4.3.2.3 stays largely the same, but a fault mode observer needs to be defined for each postulated multiple fault combination. In equation 4.39, $\hat{b}_{f_j}$ becomes a vector containing the magnitude estimates for the multiple faults included in the specific fault mode observer (i.e. those postulated to occur together). An additional fault mode observer is therefore required for each multiple fault combination, which complicates the solution, and makes accurate isolability more difficult.

Multiple faults should however be distinguished from subsequent faults. Subsequent faults are said to occur if there is a sufficient time window between the onset of the faults, to the effect that the first can be isolated before the second occurs. The NL-GLR method, in the form presented here, handles subsequent faults directly.

If the plant nonlinearities are not too severe, the NL-GLR method may be simplified through linearisation of the process model along a nominal trajectory as described by Deshpande *et al.* (2009). Fault detection through the application of (4.38) is rather fast, and because fault identification is not expected to happen too frequently, the trade-off between accuracy in the presence of severe nonlinearity and fast execution has to be evaluated. In this work the full NL-GLR method is applied because the plant dynamics are not too fast, and it is therefore sufficient to achieve the fault identification in a reasonable amount of time.

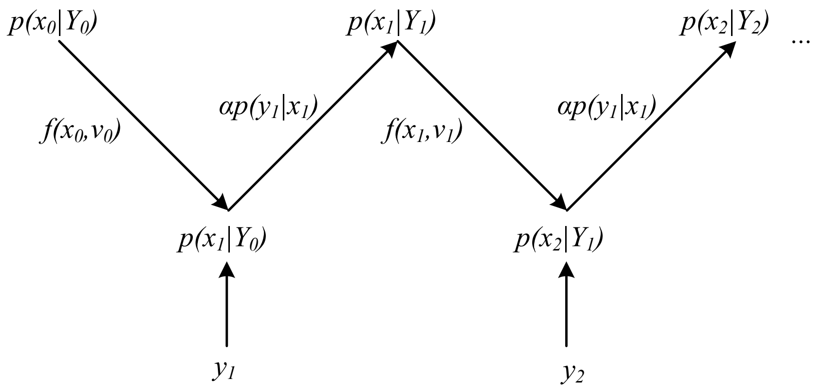

Figure 4.4. Graphical depiction of the recursive Bayesian estimation algorithm.

4.3.4 State estimation

In the case where process states are not readily available, probabilistic inference as discussed in Van der Merwe (2004); Ristic, Arulampalam and Gordon (2004) may be used to estimate them. Probabilistic inference is the problem of estimating the process variables, such as the states or parameters, of a system from the observations of the system. The inputs applied to the system are known along with the measured outputs. These known quantities are used in conjunction with the known process model of the system to calculate the states of the system.

The system presented in equations (4.32) and (4.33) are again applicable. The state estimation objective then is to calculate x_k at time k using the outputs up to that time $y_{1:k}$. The optimal solution to the probabilistic inference problem is the recursive Bayesian estimation algorithm, shown in Figure 4.4. In Bayesian terms the problem is to recursively construct the probability density function $p\left(x_k|y_{1:k}\right)$, which is the distribution of the states at time k given all the measurements up to time k. The recursive nature of the estimation problem implies that the probability density function (PDF) has to be known to a certain extent at some time in the past. How the PDFs are constructed recursively is specific to the estimation algorithm used. Some of the common approaches to recursive Bayesian estimation are discussed next.

4.3.4.1 The Kalman filter and its variations

The ubiquitous Kalman filter (Kalman 1960a) is the optimal solution to the recursive Bayesian estimation problem if the underlying system is linear and all probability densities are Gaussian. A Gaussian probability density function is fully characterised by its mean and standard deviation. It can further be shown that if $p\left(x_{k-1}|y_{1:k-1}\right)$ is Gaussian, $p\left(x_k|y_{1:k}\right)$ is also Gaussian for linear systems with Gaussian noise (Arulampalam *et al.* 2002). The recursive estimation problem in this case only involves the propagation of the mean and standard deviation of the PDF. Because the system is linear for this implementation it can be represented as

$$x_{k+1} = F_k x_k + B_k u_k + v_k \tag{4.46}$$

$$y_k = H_k x_k + n_k, \tag{4.47}$$

where F_k, B_k and H_k are matrices describing the state transition and output equations respectively. The state and output noise (v_k and n_k) are assumed to be zero mean Gaussian, with covariances Q and R respectively.

Given that the distribution at the previous time step ($p(x_{k-1}|Y_{k-1})$) is characterised by the mean $x_{k-1|k-1}$[1] and covariance $P_{k-1|k-1}$, the predicted mean and covariance are calculated as:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \tag{4.48}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k. \tag{4.49}$$

Once the current measurement becomes available the innovation (measurement residual) is calculated as

$$\tilde{y}_k = y_k - H_k \hat{x}_{k|k-1}, \tag{4.50}$$

and the innovation covariance is calculated as

$$S_k = H_k P_{k|k-1} H_k^T + R_k. \tag{4.51}$$

The optimal Kalman gain is calculated from

$$K_k = P_{k|k-1} H_k^T S_k^{-1}, \tag{4.52}$$

[1] The notation $x_{k|k}$ describes the value of x_k given all the measurements up to time k

and then the updated state estimate (mean) and updated estimate covariance are calculated as

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \tilde{y}_k \tag{4.53}$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1}. \tag{4.54}$$

For nonlinear systems the most widely implemented alternative is the EKF (Jazwinski 1970). The formulation here is basically the same as for the regular Kalman filter except that the system equations used are the linearised versions around the current operating point. The EKF is widely used for its relative ease of implementation and similarity to the well-known Kalman filter. Here the mean and standard deviation of the PDF are also propagated as the full characterisation of the PDF. The EKF should however be applied with caution as the linearisation step may lead to suboptimal performance, and sometimes even divergence of the filter (Van der Merwe 2004).

Another extension to the regular Kalman filter is the unscented Kalman filter (UKF) (Julier and Uhlmann 2004), which makes use of the unscented transform to calculate the transformed mean and covariance of a distribution which has undergone a nonlinear transformation. The difference between the UKF and the EKF is that the former uses the nonlinear system equations. The PDF is however represented through deterministically chosen sample points (known as the Sigma points) that completely capture the true mean and standard deviation. These sample points are then propagated through the nonlinear system equations. The statistics of the propagated sample points represent the true mean and standard deviation accurately to the 2^{nd} order for any nonlinearity.

Many more variations of the Kalman filter exist, such as the central difference Kalman filter (CDKF), the *square-root* UKF, and the *square-root* CDKF. Van der Merwe (2004) provides a more complete discussion of these variations.

4.3.4.2 Direct numerical integration

Direct numerical integration methods, also known as grid-based methods, make use of an N-dimensional grid that tiles the state-space, and the Bayesian recursion integrals are then approximated with large sums over the grid. Figure 4.5 shows how this may be done on a 2-dimensional grid. The function evaluations are done at the set locations indicated on the x and y axes by the red dots (the possible values of the state variables). The vertical axis represents the probability density function, the

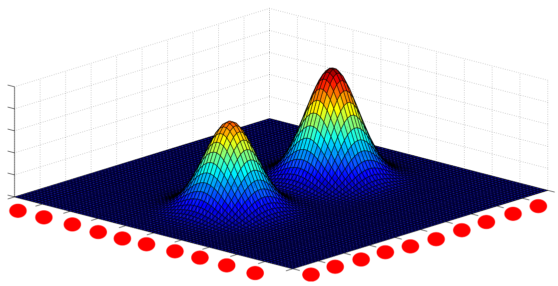

Figure 4.5. Graphical depiction of grid-based estimation, adapted from Van der Merwe (2004), with permission.

value of which will be known at the evaluation locations. Because the grid is fixed it should be selected to cover a large N-dimensional span of the state-space. These methods are therefore computationally very intensive and as the dimensionality becomes even moderately high, the computational effort becomes impractically large (Van der Merwe 2004).

4.3.4.3 Sequential Monte Carlo methods

Sequential Monte Carlo (SMC) methods (Doucet, De Freitas and Gordon 2001) also approximate the Bayesian integrals with finite sums, but unlike direct numerical integration methods the integration is done over an adaptive stochastic grid, which makes these methods practically implementable. Figure 4.6 shows how this approach differs from the grid-based approach. In this instance the grid is concentrated in the areas of increased likelihood. This means that fewer sampling points are needed to get comparable accuracy.

These methods do not make any explicit assumptions about the form of the distributions, and are therefore usable in possibly nonlinear and non-Gaussian systems.

Particle filtering is a technique of practically implementing a recursive Bayesian filter by Monte Carlo simulations. The required PDF is represented by a set of random samples and associated weights. The location of the sample represents the location where the PDF is evaluated, and the weight indicates the value of the PDF at this location. This approach is illustrated in Figure 4.7. The sizes of the particles in the figure represent the values of the PDF at those locations, and consequently the weights of those particles.

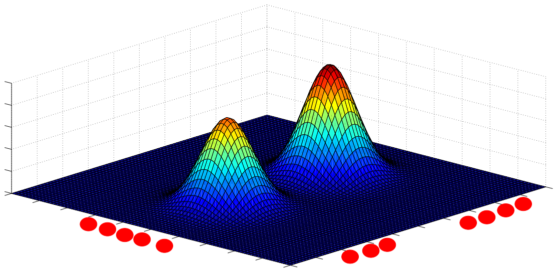

Figure 4.6. Graphical depiction of SMC-based estimation, adapted from Van der Merwe (2004), with permission.

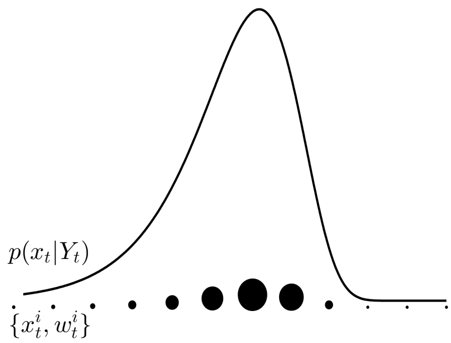

Figure 4.7. Distribution representation with particles.

Using this technique the PDF is approximated as

$$p(x_k|Y_k) \approx \sum_{i=1}^{N_s} w_k^i \delta(x_k - x_t^k) \tag{4.55}$$

where N_s is the number of particles and $\{x_k^i, w_k^i\}_{i=1}^{N_s}$ is the set of particles and associated weights. As the number of particles becomes large (i.e. as $N_s \to \infty$) this method of representing the PDF becomes equivalent to the functional description of the PDF.

The weights are defined to be (Ristic *et al.* 2004):

$$w_k^i \propto w_{k-1}^i \frac{p(y_k|x_k^i)p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{k-1}^i, y_k)}, \tag{4.56}$$

where $q(x_k^i|x_{k-1}^i, y_k)$ is a proposal distribution called an importance density. Ideally the importance density should be the true posterior distribution, $p(x_k|Y_k)$, but as this is not known in general, a proposal distribution is used. One popular suboptimal choice, that is used in this work, is the transitional prior

$$q(x_k^i|x_{k-1}^i, y_k) = p(x_k|x_{k-1}). \tag{4.57}$$

A complete treaties of the particle filter and some of its variations can be seen in Arulampalam *et al.* (2002); Van der Merwe (2004). There are many variations, but the one used in this work (which is a common implementation (Arulampalam *et al.* 2002)) is the sampling importance resampling (SIR) particle filter. The algorithm for the SIR particle filter, given the choice of using the transitional prior as the importance density and an assumption of Gaussian noise, is listed in Algorithm 4.1.

Algorithm 4.1 SIR particle filter

1. **Initialise:** For $k = 0$, draw N_s states (x_0) from the prior PDF $p(x_0)$.
2. **Propagate particles:** For each $k > 0$ sample $\tilde{x}_k \sim p(x_k|x_{k-1})$ using the state transition function (4.32) and the state noise distribution.
3. **Calculate weights:** The weight of each particle is given by: $w_k = p\left(y_k|g(\hat{x}_k, v_k)\right)$, which can be evaluated based on the output function (4.33) and the shape of the output distribution.
4. **Normalise weights:** Normalise the weights as
$$\tilde{w}_k^i = \frac{w_k^i}{\sum_{j=1}^{Ns} w_k^j}.$$
5. **Resample:** Multiply particles with high importance weights and suppress particles with low importance weights to overcome the problem of degeneracy (Arulampalam *et al.* 2002).
6. **PDF:** The required PDF is then given by
$$p(x_k|Y_k) \approx \frac{1}{N_s}\sum_{i=1}^{N_s} \delta(x_k - x_k^i).$$
7. **State estimates:** Once the PDF $p(x_k|Y_k)$ is known, the state estimate is calculated as a point estimate from the distribution. In this work the mean is used, which simply becomes (in the particle representation after resampling):
$$\hat{x}_k = \frac{1}{N_s}\sum_{i=1}^{N_s} x_k^i.$$

The resampling step listed in the SIR particle filter algorithm is necessary to overcome the problem of degeneracy present in the normal sequential importance sampling algorithm (Doucet *et al.* 2001). The problem is that the variance of the importance weights in equation (4.56) can only increase over time. After a couple of iteration steps all but one particle will have negligible weights. Much time is then spent computing weights that do not practically contribute to the accuracy of the particle filter. If the effective number of particles, given by

$$\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N_s} (w_k^i)^2}, \tag{4.58}$$

becomes significantly smaller that the actual number of particles, then degeneracy is becoming a problem. Degeneracy can be eliminated through the use of the resampling step, where particles with low importance weights are eliminated, and particles with high importance weights are multiplied. In this work the systematic resampling algorithm of Kitagawa (1996) is used, which uses the cumulative sum of weights (CSW),

$$CSW_i = \sum_{j=1}^{i} w_k^j, \tag{4.59}$$

and draws samples from $u \in [0,1]$ to redistribute the particle locations. The resampling algorithm pseudo-code is given in Algorithm 4.2, and is illustrated in Figure 4.8; the particles are respectively represented as x_k^i before resampling and x_k^{i*} after resampling.

Algorithm 4.2 Systematic resampling

$[\{x_k^{j*}, w_k^j\}_{j=1}^N] = \text{RESAMPLE}[\{x_k^i, w_k^i\}_{j=1}^N]$

1. Initialise the CSW: $c_1 = w_k^1$
2. FOR $i = 2 : N$
   - Construct CSW: $c_i = c_{i-1} + w_k^i$

   END FOR
3. Begin at bottom of the CSW: $i = 1$
4. Draw a starting point: $u_1 \sim \mathcal{U}[0, \frac{1}{N}]$
5. FOR $j = 1 : N$
   - Move along the CSW: $u_j = u_1 + \frac{1}{N}(j-1)$
   - Find the smallest value of i such that $u_j \leqslant c_i$
   - Assign sample: $x_k^{j*} = x_k^i$
   - Assign weight: $w_k^j = \frac{1}{N}$

   END FOR

One iteration of the SIR particle filter algorithm, including resampling, is illustrated in Figure 4.9.

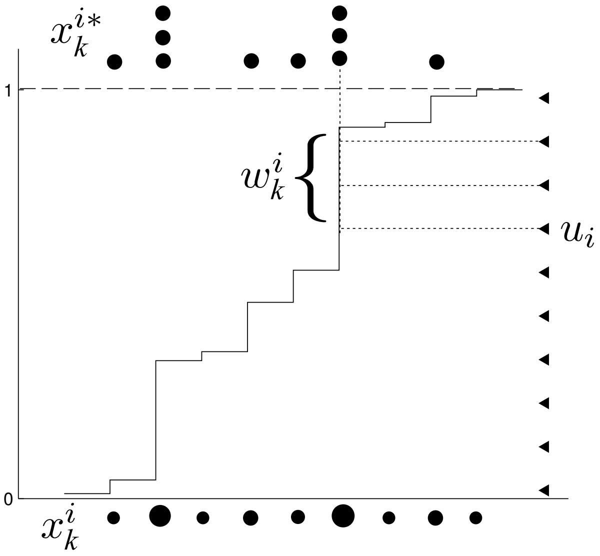

Figure 4.8. Resampling procedure used in the SIR particle filter implementation, adapted from Van der Merwe (2004), with permission.

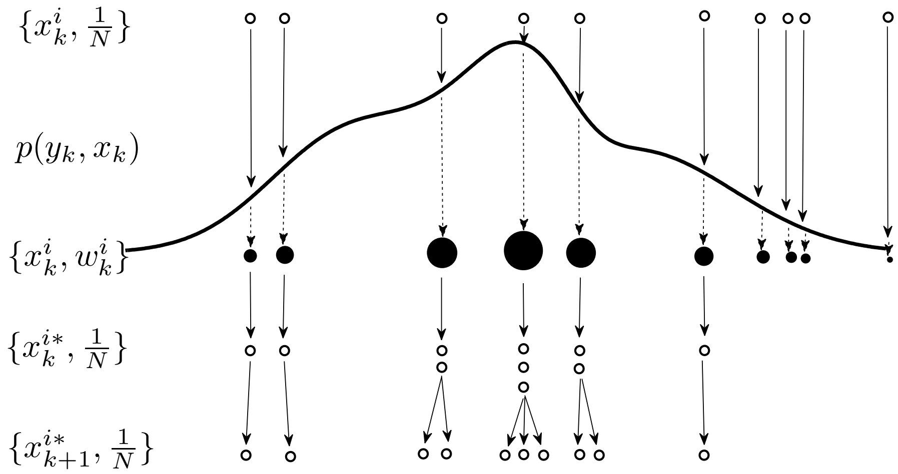

Figure 4.9. One iteration of the SIR particle filter, adapted from Van der Merwe (2004), with permission.

An interesting comparative study of nonlinear filters is presented in Psiaki (2013). This study includes most of the filters discussed in this section and highlights some of the strengths and weaknesses of each. With so many options for implementing probabilistic inference the question arises as to which method should be used. For linear systems with Gaussian noise the choice is simple because the Kalman filter is the optimal solution. For nonlinear systems the choice becomes more complex. A formal approach to performance assessment and filter selection for nonlinear filters is presented in Tulsyan, Huang, Gopaluni and Forbes (2013). In this work the particle filter was selected because of its accuracy for nonlinear systems. The particle filter is known to be computationally expensive when compared for example to the EKF or UKF. The process used in this work does however have relatively slow dynamics, which allows sufficient time to complete the particle filter calculations.

4.3.5 Fault-tolerant nonlinear model predictive control with particle filters

The way in which MPC is formulated leads to a natural representation of faults within the system. Actuator failures are easily represented as control constraints, and faults that change the process dynamics can be accommodated by modifying the internal MPC model. For sensor failures the information provided by that sensor has to be discarded, or at least adapted in the case of constant bias.

If one control input becomes constrained, the optimisation algorithm that determines the control moves will automatically compensate by using alternative control inputs to regulate the outputs according to the input move weights.

All of the elements described in this section are then combined to form the FT-NMPC as illustrated in Figure 4.10. The number of fault mode observers required depends on the number of faults that are postulated to occur. The fault detection algorithm of (4.38) runs continually. When a fault is detected the fault identification algorithm runs by making use of the fault mode observers. Once fault identification is complete, the updated controller constraints and parameters are supplied to the NMPC, which adapts to the identified fault.

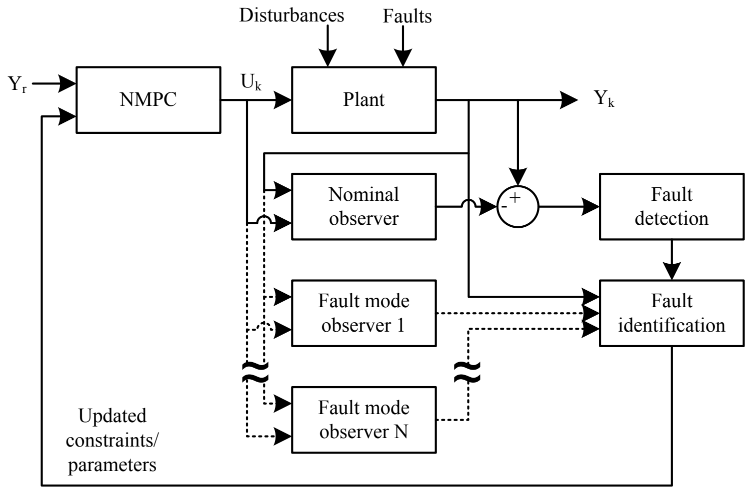

Figure 4.10. FT-NMPC layout

4.4 PLANT REGULATABILITY ANALYSIS

In the event that a fault has been detected, it becomes an important consideration whether the plant (or processing unit) will still be able to continue operating. If for example an actuator has failed, it is important to know if the plant will not in any case have to be shut down owing to the unavailability of that actuator. The first part of this section will describe the approaches that are available for completing such an analysis, and the second part will describe the method used in this work.

4.4.1 Controllability analysis

The term controllability was already defined long ago by Ziegler and Nichols (1943) as being the ability of a process to achieve and maintain a desired equilibrium value. Rosenbrock (1970) later introduced the term "functional controllability," which is applicable if there exists an input vector u for $t > 0$, which generates any suitable output vector, y for $t > 0$, from the initial condition $x(0) = 0$. State controllability was introduced by Kalman (1960b), and is defined as the ability to bring the plant from any initial state, $x(0) = x_0$, to any final state, x_f, in any final time, t_f, with a suitable input vector. The term controllability, without any qualifier, usually refers to state controllability, which is generally quite limited and has little practical value (Skogestad and Postlethwaite 2005). This is because the control action required to drive the plant to the final state may be extremely large and can therefore fall very far outside of the practical actuator limits, or it can take very long for the plant to reach the final state.

Morari (1983) introduced the concept of "dynamic resilience," as the quality of regulation that can be achieved through feedback. The method of Garcia and Morari (1982) is to use the IMC framework, where the ideal controller is the inverse of the plant, to determine the best achievable control performance. A good practical approach to controllability analysis is the input-output controllability test presented in Skogestad and Postlethwaite (2005). Input-output controllability describes the amenability of a plant model to be controlled, i.e. it is possible to find a controller that will keep the outputs within specified bounds in the presence of unknown, but bounded, disturbances and model uncertainty. Input-output controllability is widely used in systems theory (Yuan *et al.* 2011), largely for the powerful results that may be obtained with a relatively straightforward method.

A number of the available techniques for analysing controllability of linear processes can handle right-half-plane zeros and time delays. These can limit process controllability significantly. Yuan *et al.* (2011) provides a good overview of which methods are applicable when right-half-plane zeros or time delays are present.

Many of the methods listed above are based on frequency domain analysis, and are therefore not directly applicable to nonlinear systems. The simplest approach for a nonlinear system is to linearise the system around the operating point, and to apply any of the linear methods to the linearised system. This generally gives good results, even for strongly nonlinear systems, if the operating region does not vary too much (Yuan *et al.* 2011). In fault conditions the plant may be pushed to quite a different operating region and the linearised system analysis may fail.

Methods that handle nonlinear systems directly are categorised by Yuan *et al.* (2011) as being either analytical or optimisation based. The analytical methods generally focus on functional controllability. One of the main limitations to achieving acceptable control performance is the presence of non-minimum phase characteristics in the system, as is introduced by right-half-plane zeros. For nonlinear systems the concept of poles and zeros does not exist. The zero dynamics can however be mimicked by a reduced inverse, which is a minimal order realisation of the system inverse. The analysis of the zero dynamics will therefore reveal if the system has a stable inverse, and indicate the achievable performance (Trickett 1994).

Quantifying state controllability for nonlinear systems can be achieved by making use of repeated Lie derivatives, as presented by Haynes and Hermes (1970); Hermes (1974). The analysis can however become quite involved as the system size increases, and the result still only shows state controllability. This analysis also does not handle control constraints or time delays in the system directly. Owing to the lack of a powerful nonlinear equivalent to the input-output controllability test, optimisation-based methods can be used to analyse plants in the presence of uncertainty (with respect to the model or the disturbances).

The optimisation-based approach of Perkins and Walsh (1996) formulates the controllability analysis in the fashion of a min-max optimisation problem (Bemporad *et al.* 2003), the objective of which is to determine the best control input for the worst possible combination of disturbances and model uncertainty. This approach ensures controllability for all possible combinations of uncertainty, even though the probability of all the worst case disturbances appearing simultaneously is very slim. For this reason the approach gives notoriously conservative answers (Kerrigan and Maciejowski 2004).

On an industrial plant, where many sources of uncertainty exist, the applicability of the optimisation-based approach of Perkins and Walsh (1996) is limited. A more practical approach is to determine the stochastic robustness of the system as presented by Ray and Stengel (1993), where Monte Carlo samples of the uncertainty are drawn before the system is analysed. The method is applied to a linear system in the presence of uncertainty.

Monte Carlo simulation was also used by Wang and Stengel (2002) for robust control of a nonlinear system. The application of this approach to nonlinear controllability analysis in the presence of parametric uncertainty therefore seems warranted. Depending on the simulation configuration these methods can usually handle system time delays directly. The formulation of this approach is presented in the following section.

4.4.2 Adaptive hypothesis test for system regulatability

If a probabilistic sense of controllability is acceptable in contrast to a guarantee for all combinations of uncertainty in the system, the solution is usually easier to calculate and less conservative (Calafiore and Campi 2006). This analysis can be done via simulation, and the objective of such a simulation is to find a set of permissible inputs that will be able to regulate the plant outputs within the output limits in the presence of unknown disturbances and/or plant parameters. Input constraints are therefore handled directly, unlike in many of the methods listed above. In order to distinguish this approach from a well-defined formal controllability analysis, the term regulatability analysis will be used here. The term was defined in Definition 4.1.

In this section an adaptive hypothesis test is proposed to evaluate the regulatability of a system represented by equations (4.32) and (4.33).

It is assumed that this plant is nominally regulatable. This means that the system conforms to Definition 4.1 in the absence of faults. In the presence of at least one fault however the regulatability condition may not hold any longer. The objective is then to evaluate whether there exists a plant input vector for which the outputs (and states) remain within their respective limits. The future disturbance vector is however not known, and a representative disturbance vector (d^*) is selected such that $d_i^* \in D$. The set, D, depends on the plant in question and is defined according to the physical properties of the disturbances. An evaluation is then carried out to find $u \in U$ to keep $y \in Y$. If such a u exists, then the plant is regulatable for d_i^*.

Another $d_i^* \in D$ can then be selected and the search for a u to regulate the plant is repeated. The outcome of the search with each independent disturbance vector becomes the result of a binomial test. Choosing successive disturbance vectors in a Monte Carlo manner, and evaluating the regulatability of the faulty system provides the ability to statistically test whether the system is regulatable using the constructed binomial distribution.

Up to now the only uncertainty referenced in the plant is because of disturbances. Uncertainty in plant parameters, i.e. model-plant mismatch, may be included in the analysis by augmenting the disturbance vector with the uncertain plant parameters as $[d^*, \theta^*]^T$. The uncertain plant parameters are then included without any loss of generality.

An hypothesis test may be set up for the sequence of binomial samples to complete the regulatability analysis. The first consideration is the amount of samples required to complete the hypothesis test. For a one-sided test on a binomial proportion the sample size required is (Montgomery and

Runger 2006):

$$n = \left[\frac{z_\alpha \sqrt{p_0(1-p_0)} + z_\beta \sqrt{p(1-p)}}{p - p_0} \right]^2 \tag{4.60}$$

where p_0 is the null hypothesis probability value, p is the test statistic value, and z_α and z_β are respectively the critical values associated with the allowed probabilities of making type I and type II rejection errors. A type I rejection error is made when the null hypothesis is rejected, when it is in fact true. A type II rejection error is made when the null hypothesis is not rejected, and it is in fact false.

Montgomery and Runger (2006) explains that the probability of making a type I rejection error is only dependent on the critical value that is chosen. This means that the type I error probability can be set close to a desired value. Since the probability of incorrectly rejecting the null hypothesis can therefore be directly controlled, rejection of the null hypothesis is said to be a strong conclusion (Montgomery and Runger 2006:297). The probability of making a type II rejection error is not constant, but depends on the true value of the parameter in question and the sample size. Because of this dependence the decision to not reject the null hypothesis is regarded as a weak conclusion. The null hypothesis is therefore formulated such that it is likely to be rejected (and hence a strong conclusion regarding the regulatability of the system is likely to be made).

It can be seen from equation (4.60) that the required sample size becomes large when the test statistic value is close to the null hypothesis value. Equation (4.60) can be rearranged to indicate how far the null hypothesis can be away from the test statistic, given the number of evaluations, and to still be able to reject the null hypothesis as

$$\varepsilon = \frac{z_\alpha \sqrt{p_0(1-p_0)} + z_\beta \sqrt{p(1-p)}}{\sqrt{n}}, \tag{4.61}$$

where $\varepsilon = p - p_0$ represents the threshold. The critical values, z_α and z_β, are constants given the allowed rejection error probabilities. For example if one accepts a 5% probability of making a type I or type II rejection error, then the values for both z_α and z_β are 1.96. Given that $p \in [0,1]$ the maximum value of $p \cdot (1-p)$ is 0.25. The same is true for $p_0 \cdot (1-p_0)$. A high limit for the distinguishable

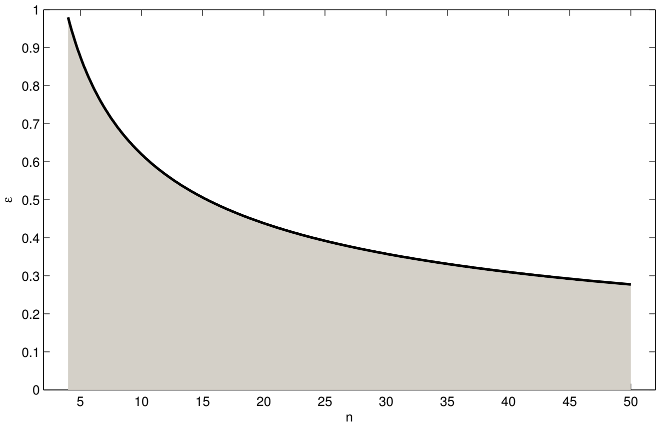

Figure 4.11. High limit for the distinguishable threshold as a function of the number of evaluations required.

threshold value given the number of evaluations done can then be computed as:

$$p(1-p);\ p_0(1-p_0) \leq 0.25 \tag{4.62}$$

$$z_\alpha\sqrt{p(1-p)} + z_\beta\sqrt{p_0(1-p_0)} \leq 0.5z_\alpha + 0.5z_\beta \tag{4.63}$$

$$\varepsilon \leq \frac{0.5z_\alpha + 0.5z_\beta}{\sqrt{n}} \tag{4.64}$$

which is shown in Figure 4.11 as a function of the number of evaluations. It is clear from the figure that if the required threshold is large the number of evaluations required is small. This would be the case when most of the evaluations fail, or when most of the evaluations succeed. When the required threshold is small, the number of evaluations required becomes large, as $n \to \infty$, $\varepsilon \to 0$. This also makes sense intuitively.

This threshold will be used in the regulatability analysis listed as Algorithm 4.3, with the following flow:

- Choose the allowed type I and type II rejection errors;
- Do a set number of initial evaluations;
- Define the null hypothesis;
- Define the alternative hypothesis;

- Define the test statistic;
- Determine whether the null hypothesis can be rejected; and
- If the null hypothesis is not rejected, do another evaluation, up to the evaluation limit.

Algorithm 4.3 Regulatability analysis through adaptive hypothesis testing

1. Choose z_α and z_β
2. FOR $i = 1 : N_0$
    - Choose disturbance vector $d^* \in D$
    - Evaluate if $\exists\ u \in U$, s.t. $y \in Y$
    - Increase n_{fail}, if the evaluation fails

    END FOR
3. Set $p_0 = \frac{n_{fail}}{N}$
4. Set $H_0 : p = p_0$
5. Set $H_1 : p > p_0$
6. Set $p = 1 - p_0$
7. IF $(p - p_0) > \varepsilon$
    - Reject H_0
    - STOP evaluation

    ELSE IF $(i > N_{max})$
    - Do not reject H_0
    - STOP evaluation

    ELSE
    - Choose $d^* \in D$
    - Evaluate if $\exists\ u \in U$, s.t. $y \in Y$
    - Increase n_{fail}, if the evaluation fails
    - Increase N
    - GO TO step 3

The adaptive nature of the hypothesis test is encapsulated by the way in which the null hypothesis, the alternative hypothesis, and the test statistic values are defined (steps 4, 5, and 6 in Algorithm 4.3). This means the test is to determine whether the test statistic value is larger (or smaller) than the null hypothesis value by a statistically significant margin. Which is to say the test is to determine whether the probability of regulatability is significantly larger than the probability of not being able to regulate the plant. There is no specific requirement for what this value should be.

An evaluation limit is included to ensure that the evaluation does not proceed indefinitely when the probability of being able to regulate the plant is indistinguishably close to the probability of not being able to regulate the plant.

The evaluation to find if $\exists\, u \in U,$ s.t. $y \in Y$ listed in Algorithm 4.3 is completed by searching for a set of inputs that will keep the plant within limits. This can be done in a similar manner to the minimisation of an objective function in an MPC formulation:

$$\min_{u \in U} V(u, x_k) \tag{4.65}$$

with the objective function given by

$$V(\cdot) = \sum_{i=1}^{N_{ss}} \left[\|y_{r,i} - y_i\|^2_{Q_r} + \|s_i\|^2_{Q_s} + Q_l y_i \right] + \|T_{ss} - t_F\|^2 + \|y_f - y_{f/2}\|^2_{Q_b}. \tag{4.66}$$

The objective function is purposefully defined similar to that used in the MPC control algorithm. $\|\cdot\|^2_Q$ is again used to represent the Q-weighted 2-norm. Q_r is the weighting matrix for setpoint tracking, y_r is the setpoint vector, s_i is a slack variable vector used to represent output limit violations, and Q_l contains the optimisation weights if optimisation is included in the MPC formulation. N_{ss} is the prediction horizon, chosen to be long enough for the plant to reach steady state. Additional to the terms in the standard MPC objective function, T_{ss} is the time to steady state (equal to N_{ss} multiplied by the sampling period) and t_F is the time to failure (if the plant cannot be regulated - see Figure 4.12). This time to failure is defined as the time at which the process begins to violate critical operating limits. If the plant outputs are regulatable, t_F is set equal to T_{ss} such that the term $\|T_{ss} - t_F\|^2$ reduces to zero. If the plant outputs are not regulatable this term will contribute a larger value to the objective function the sooner the plant fails (i.e. the smaller the value of t_F). Furthermore, y_f is the steady-state output vector given by

$$y_f = \lim_{t_f \to \infty} \int_{t_0}^{t_f} g(x, u, d^*)\, dt, \tag{4.67}$$

$y_{f/2}$ is a vector containing the outputs when they near steady state, and Q_b is a weighting matrix included to penalise unbalanced ramps in the steady state analysis.

For the practical calculability of y_f, a sufficiently large t_f may be selected over which the integral in (4.67) is evaluated. Figure 4.12 illustrates two possible outcomes of this evaluation. The dotted line is the absolute low limit of a particular output variable, e.g. the safe operating region limit above which

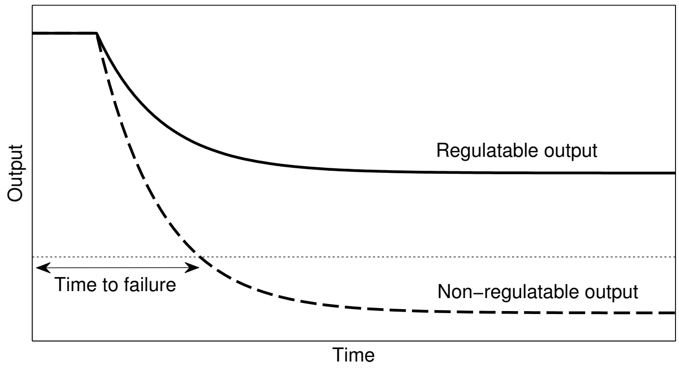

Figure 4.12. Possible outcomes for one iteration of the regulatability analysis. The dotted line is the low limit; the solid and dashed lines respectively show regulatable and non-regulatable output curves over time.

the output must remain. The solid line shows an instance where the output can be regulated to stay above the low limit. The dashed line shows an instance where the output cannot be regulated to remain above the low limit. In an instance where the output cannot be regulated, the mean time to failure can also be noted for all iterations of the search.

The initial states used to calculate the plant output predictions in equation (4.66) are the state estimates at the time of identification of the fault. The optimization problem of (4.65) and (4.66) is then solved. If it is possible to find an input vector that will maintain the plant within the critical operating limits, the regulatability condition is satisfied.

Penalisation of MV moves is purposefully omitted from equation (4.66) because it is essentially a steady state analysis and the regulatability of the plant should not be sacrificed for input move suppression.

It should be clear that the analysis assumes that no further faults will occur up to the point where the plant reaches steady state. The analysis therefore excludes fault propagation, where one fault leads to another. The fault identification algorithm does however handle subsequent faults (see Section 4.3.3). It could therefore happen that one fault enters the system, it is identified, the regulatability analysis is performed, and the system may be found to still be regulatable. This fault can then lead to a subsequent fault, which is again identified, and the regulatability analysis is repeated. The system may now be found to not be regulatable. The analysis does therefore not aim to include fault propagation, but it can handle fault propagation if fault mode observers are set up as required.

Once the regulatability of the system has been established, it is still required to analyse whether the system can be economically operated with the fault present.

4.5 ECONOMIC PERFORMANCE ANALYSIS

After it has been established that the system is regulatable, i.e. the plant can still be operated within limits, the question arises whether the plant should still be operated. In other words, should the plant continue to operate with the present fault(s) until the next planned opportunity for repair (the next planned shutdown), or should the plant be shut down as soon as possible, the fault(s) repaired, and the plant started up again.

For this evaluation a plant economic performance function is required. The plant economic performance function (see e.g. Wei and Craig (2009a)) is defined as the monetary value of operating the plant per unit time, and is symbolically represented as $\psi(u,y)$. The cumulative value of the economic performance function over a pre-defined length of time,

$$\Psi_i = \int_{t_0}^{t_f} \psi_i\,(u,y)\,dt, \tag{4.68}$$

is also of concern. In order to complete the economic operability analysis there are a number of monetary value functions required, as are associated with different plant modes. The time periods over which these are active may also be of concern. The economic values and time periods listed in Table 4.1 are required. These include values for start-up, shutdown, and nominal operation.

The decision is made to shut down the plant and repair the fault(s) if the cumulative monetary value of operating the plant (profit minus cost of operation) with the current fault(s) is smaller than the sum of the costs associated with shutting down and starting up the plant, plus the losses while the plant is down, plus the marginal cost of repairing the fault(s) right away, plus the cumulative nominal monetary value of operating the plant after the fault(s) are fixed up to the next planned shut-down. This evaluation can mathematically be expressed as

$$\int_{t_0}^{t_S} \psi_f\,dt < \Psi_{SD} + \Psi_O + \Psi_{SU} + \int_{t_0+t_{SD}+t_O+t_{SU}}^{t_S} \psi_n\,dt. \tag{4.69}$$

Table 4.1. Economic parameters required for economic operability evaluation.

Parameter	Description
Ψ_{SD}	Cost associated with shutting down the plant
t_{SD}	Time required to shut down the plant
Ψ_{SU}	Cost associated with starting up the plant
t_{SU}	Time required to start up the plant
Ψ_O	Cost associated with the plant being off-line
t_O	Time required to repair the current fault(s)
Ψ_R	Marginal extra cost to repair the fault(s) right away
ψ_n	Nominal monetary value for operation (per unit time)
ψ_f	Monetary value for operation with the current fault (per unit time)
t_S	Time until the next planned opportunity to repair the current fault(s)

If this is not the case, the plant is operated with the current fault(s) until the next planned repair opportunity. An example of such an hypothetical situation is illustrated in Figure 4.13. The plant operating with the fault is represented by the darker box. The lighter boxes represent shutting the plant down, repairing the fault(s), starting the plant up, and then operating with the nominal profitability up to the next planned shutdown. Intuitively one expects that the nominal monetary gain should be sufficiently higher than that of operating with the fault in order to justify a shutdown of the plant. Also, if t_S is very large, then the shut down and repair scenario will be favoured even if ψ_n is only slightly larger than ψ_f.

It is important to note here that Ψ_O is not the production loss, as is already accounted for by Ψ_n not being included while the plant is off-line. Ψ_O accounts for any additional costs associated with the plant being off-line such as penalties for non compliance with product delivery schedules.

This type of decision is intuitively made by plant managers when a fault has been identified. In this work however the decision making process is formalised such that the proper course of action may be taken according to the plant economic performance.

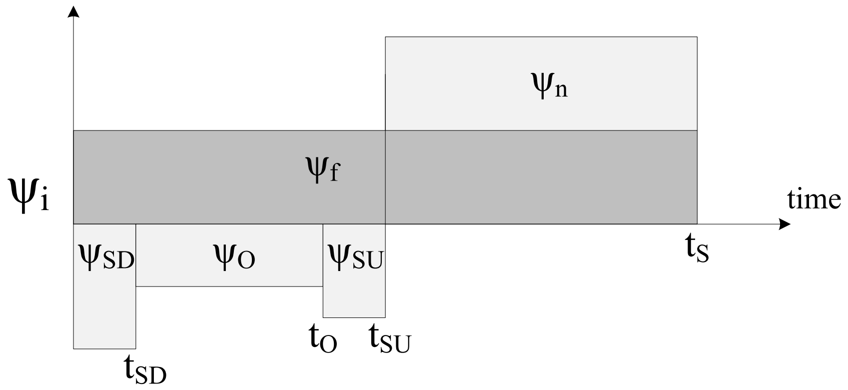

Figure 4.13. Comparison of shut-down, plant repair, start-up, and nominal operation against operating with fault(s) present.

4.6 CHAPTER CONCLUSION

Some of the key technologies required for lights-out process control were detailed in this chapter. The methods developed as part of this work were expressed more extensively.

On-line model evaluation, in the form of MPM detection and diagnosis is important to maintain MPC benefits. A closed-form expression was derived for the MPM if the plant and controller are sufficiently representable by transfer functions. For MPC, where the controller might not have a transfer function, a partial correlation analysis (Badwe *et al.* 2009) may be used to identify the model matrix elements that contain significant mismatch.

Fault-tolerant control is one of the major requirements for lights-out process control. FTC is quite easily incorporated into the MPC formulation. Model-based FDI is a natural choice for FTC with MPC because the model required by the controller can also be used for fault diagnosis. The nonlinear version of the GLR method is the quantitative fault diagnosis method of choice in this work.

With quantitative model-based fault diagnosis the observer design is the key to being successful. State estimation for linear systems with Gaussian noise is optimally performed with a Kalman filter. If the system is nonlinear the observer design becomes more complex. The EKF and UKF are common choices along with the particle filter as outlined in more detail in this chapter.

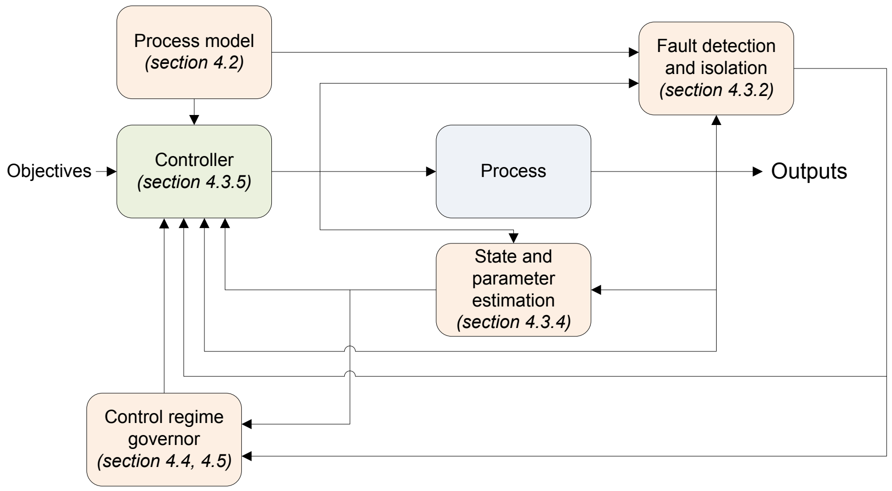

Figure 4.14. Framework for lights-out process control showing the sections of this chapter discussing the framework elements.

The effective combination of these elements leads to a fault-tolerant MPC that will try to control the plant optimally irrespective of the faults that may be present. For a certain class of faults however the plant may not be controllable any longer, and a controllability analysis is required.

A practically useful, constrained, nonlinear controllability analysis in the presence of parametric uncertainty is introduced in this chapter. This analysis is termed regulatability in order to not be confused with the many other formal controllability tests that have been proposed previously.

Even if the plant regulatability has been established, the economic operability has to be confirmed. An economic performance analysis was outlined where the objective is to determine whether it is more economical to shut the plant down and repair the fault, or to continue operating with the fault present.

A reduced version of the lights-out process control framework (Figure 2.3) is shown in Figure 4.14; the main sections of this chapter discussing the specific elements of the framework are indicated.

These methods are applied to a nonlinear ROM ore milling circuit simulation in the next chapter. Note that application examples for the closed-form MPM expression are presented in Addendum C, as it is not applicable to nonlinear models.

CHAPTER 5 SIMULATION STUDY OF A RUN-OF-MINE ORE MILLING CIRCUIT

5.1 CHAPTER INTRODUCTION

In this chapter a simulation study of a nonlinear run-of-mine ore milling circuit is presented to illustrate the use of some of the enabling technologies for lights-out process control (as presented in Chapter 4). A description of the nonlinear model is presented first, after which the controller design is shown. The specifics pertaining to the state estimation, regulatability analysis, and economic operability analysis are presented next. Lastly, the simulation results are shown and discussed.

5.2 PROCESS OVERVIEW

ROM ore milling is generally the first, and most expensive, unit operation in the metallurgical extraction process (Craig and MacLeod 1995), see Figure 3.1. The layout of a typical milling circuit (which is used in this chapter) is shown in Figure 5.1. Ore from the mine is added to the grinding mill along with steel balls and water. The addition of steel balls lets this process be classified as semi-autogenous grinding (SAG), where an additional grinding medium is added to grind down the feed ore (Wills 2006).

Ore is ground down into fine particles inside the mill, and exits as a slurry through an end-discharge grate. Note that large pieces of ore and steel balls cannot pass through the grate. The slurry is sent to a sump where further water is added. The slurry is then pumped to a cyclone for classification.

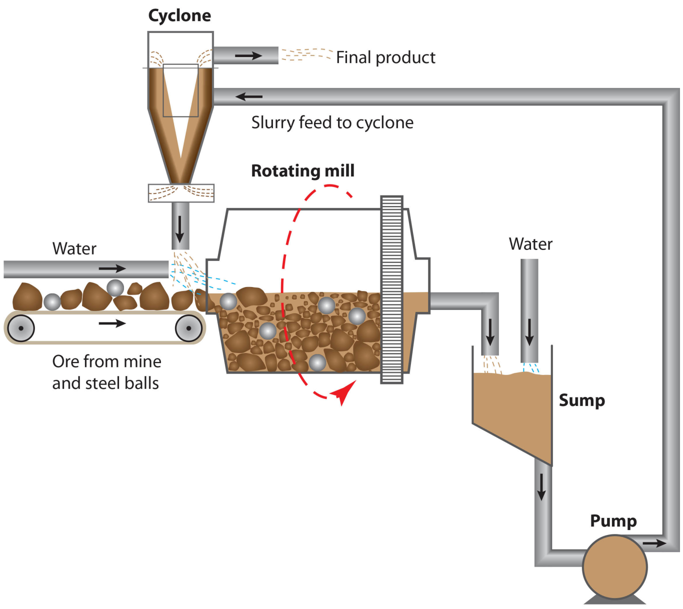

Figure 5.1. Grinding mill circuit layout.

Sufficiently ground down material leaves the top of the cyclone as the product of the milling circuit. Material that should be ground down further leaves the bottom of the cyclone and re-enters the mill.

The inputs into the milling circuit are the mill water feed (MIW), the mill feed ore (MFS), the mill steel balls feed (MFB), the sump water feed (SFW), and the cyclone feed flow-rate (CFF). The speed of turning of the mill (α_{speed}) is also sometimes included if the mill motor is fitted with a variable speed drive, but in this chapter a fixed value is assumed for α_{speed}. The milling circuit outputs are the load of material inside the mill (LOAD), the sump volume (SVOL), particle size estimate of the product (PSE), and the circuit throughput (THP). The mill motor power draw (P_{mill}) and the cyclone feed density (CFD) are other variables that can be specified as circuit outputs, but in this work they are not explicitly controlled.

5.2.1 Modelling of comminution circuits

The discussion that follows here is not intended to be an exhaustive discussion on modelling of comminution processes. It is meant to give the reader an overview of some other prominent models that are commonly used, and how these models compare to the one used in this work.

The most simple form of modelling that is commonly employed is empirical modelling. This is where models are derived from process data through system identification (Ljung 1999). This form of modelling is widely applied (see e.g. Craig and MacLeod (1996); Olivier *et al.* (2012a); Chen *et al.* (2007)) and easy to understand. These models are however not directly representative of the physics of the process, and are mostly linear. The latter is a rather large restriction for a nonlinear process such as comminution, and model quality can deteriorate quickly as the operating point changes.

A more accurate, and more complex, method of modelling is through the use of nonlinear phenomenological models. Here the approach is either to represent the phenomenon of breakage of feed into a product size distribution (population balance model), or to model the interactions of ore particles in the comminution machine on the basis of Newtonian mechanics (Le Roux *et al.* 2013). Owing to the nonlinear nature of comminution these types of models are more accurate and more representative of the true operation of the process.

One notable comminution circuit model was developed by J. A. Herbst and associates (as discussed in Rajamani and Herbst (1991); Herbst and Pate (1999)). This model is a verified dynamic population balance type model. Here the continuous particle size range is divided into a set of discrete intervals. For each discrete particle size interval a mass balance is compiled in the form:

$$accumulation = input - output + generation - consumption. \tag{5.1}$$

This type of description is common for population balance models. The true characterisation of the model is the breakage functions that are used and the number of size classifications. The breakage functions used in Rajamani and Herbst (1991) were verified experimentally for three mills.

Another milling circuit model of note is that presented by the Julius Kruttschnitt Mineral Research Centre, colloquially referred to as the JK model (see JKTech (1994)). This model is also a nonlinear population balance model but is a steady-state model, and is described by Morrison and Richardson (2002) as an industry-accepted tool for analysis and design of comminution circuits. A model of this type is indeed useful for steady-state simulation and calculating steady-state parameter values, but is unfortunately not as useful when implementing a model based controller for which a dynamic model is required. This is because the controller makes explicit use of the dynamics in the model when calculating the optimal control moves.

The development of the JK model into a dynamic population balance model is discussed by Valery and Morrell (1995). Another notable model is that presented in Apelt, Asprey and Thornhill (2002). This model is related to the JK model in that the rock and water charge state equations are the same. Different models are however presented for the ball charge and mill shell lining states. This model has 36 states of which 27 are used to represent the size classes of solids.

The question is posed in Le Roux *et al.* (2013); Le Roux and Craig (2013) as to whether so many size classifications are necessary to adequately represent a comminution circuit. The problem with models that use many states is twofold. Firstly, large parameter sets are difficult to fit accurately from real plant data. Secondly, the detailed models can have internal approximations that transmit and amplify any inaccuracies in an unknown way. A larger model matrix also makes the implementation of a model based predictive controller more complex. As such, it is preferable to have a model that is as small as possible while maintaining an acceptable level of accuracy.

5.2.2 Reduced-state nonlinear model

A reduced set model that uses only 3 size classes to represent ore is discussed and validated in Le Roux *et al.* (2013). The model parameters, as listed later in Table 5.2, were also derived and justified in that paper. This model was developed specifically for control purposes and is used in this work. This is a nonlinear dynamic model, and the reduced number of states makes the controller formulation more comprehensible and more feasible.

The model is in the form of a phenomenological population balance model with 5 states: rocks, solids, fines, water, and steel balls. Rocks are defined to be material too large to exit the mill through the discharge grate. Solids, which is material that is small enough to exit through the discharge grate, comprises out-of-specification coarse ore and in-specification fine ore. The milling equations shown later in this chapter express how the material transitions from one state to the next.

The ore feed composition can change significantly, and it is the change in feed material that is the most important disturbance for the milling circuit. This disturbance effect is also sufficiently incorporated into the milling circuit equations.

Table 5.1. Subscript nomenclature.

Subscript	Description
$X_{\square -}$	m – mill; s – sump; c – cyclone
$X_{-\square}$	w – water; s – solids; r – rocks; f – fines; b – balls
$V_{--\square}$	i – inflow; o – outflow; u – underflow

The nonlinear model is modular, in the sense that each component (or piece of equipment) is represented by a separate set of state transition and output equations (i.e. the models for the mill, sump, and cyclone are presented separately). The flow out of one component becomes the flow into the next component. As such, when representing the states of material in the pieces of processing equipment in the milling circuit, subscripts are used to identify the milling circuit component and the material state. When flows are presented the previously mentioned subscripts are also applicable, but it is also indicated whether this is an inflow, outflow, or underflow in the case of the cyclone. The subscript nomenclature is listed in Table 5.1.

5.2.2.1 Mill module

The mill is where the semi-autogenous grinding takes place with the aid of steel balls. The mill has five states, which are the hold-ups of the five material classifications used by the model. The mill state transitions are given by:

$$\begin{aligned}
\dot{X}_{mw} &= \mathrm{MIW} - V_{mwo} \\
\dot{X}_{ms} &= (1-\alpha_r)\frac{\mathrm{MFS}}{D_s} - V_{mso} + \mathrm{RC} \\
\dot{X}_{mf} &= \alpha_f\frac{\mathrm{MFS}}{D_s} - V_{mfo} + \mathrm{FP} \\
\dot{X}_{mr} &= \alpha_r\frac{\mathrm{MFS}}{D_s} - \mathrm{RC} \\
\dot{X}_{mb} &= \frac{\mathrm{MFB}}{D_b} - \mathrm{BC},
\end{aligned} \tag{5.2}$$

where the population balance nature of the equations (compared with equation (5.1)) is clear. The material outflow equations are:

$$\begin{aligned} V_{mwo} &= V_V \cdot \varphi \cdot X_{mw} \left(\frac{X_{mw}}{X_{mw} + X_{ms}} \right) \\ V_{mso} &= V_V \cdot \varphi \cdot X_{mw} \left(\frac{X_{ms}}{X_{mw} + X_{ms}} \right) \\ V_{mfo} &= V_V \cdot \varphi \cdot X_{mw} \left(\frac{X_{mf}}{X_{mr} + X_{ms}} \right). \end{aligned} \tag{5.3}$$

In (5.2), FP is the amount of fines produced, RC is the amount of rocks consumed, and BC is the amount of steel balls consumed. These variables are given by:

$$\mathrm{BC} = \frac{1}{D_b \phi_b} \cdot P_{mill} \cdot \varphi \cdot \left(\frac{X_{mb}}{X_{mb} + X_{mr} + X_{ms}} \right) \tag{5.4}$$

$$\mathrm{RC} = \frac{1}{D_s \phi_r} \cdot P_{mill} \cdot \varphi \cdot \left(\frac{X_{mr}}{X_{mr} + X_{ms}} \right) \tag{5.5}$$

$$\mathrm{FP} = \frac{P_{mill}}{D_s \phi_f \left[1 + \alpha_{\phi_f} \left(\frac{\mathrm{LOAD}}{v_{mill}} - v_{P_{max}} \right) \right]}, \tag{5.6}$$

where φ is the rheology factor of the slurry inside the mill. The rheology factor is an indication of the fluidity and density of the mill slurry, and this has an impact on the milling performance (Shi and Napier-Munn 2002). P_{mill} is the mill motor power draw. The rheology factor and mill power are respectively given by:

$$\varphi = \left(\frac{\max \left[0, \left(X_{mw} - \left(\frac{1}{\varepsilon_{ws}} - 1 \right) X_{ms} \right) \right]}{X_{mw}} \right)^{0.5} \tag{5.7}$$

$$P_{mill} = P_{max} \cdot \{ 1 - \delta_{P_v} Z_x^2 - \delta_{P_s} Z_r^2 \} \cdot \left(\alpha_{speed} \right)^{\alpha_P} \tag{5.8}$$

$$Z_x = \frac{\mathrm{LOAD}}{v_{P_{max}} \cdot v_{mill}} - 1 \tag{5.9}$$

$$Z_r = \frac{\varphi}{\varphi_{P_{max}}} - 1. \tag{5.10}$$

The rheology factor varies between zero for slurry that has a very low fluidity, e.g. thick mud, and one for high fluidity, such as for pure water.

The definitions and values of all the other parameters used in these equations are given in Table 5.2. Units are also shown for all parameters that are not dimensionless.

Table 5.2. Parameters and constants contained in the milling circuit equations.

Parameter	Value	Description
α_f	0.055	Fraction of fines in the ore
α_r	0.465	Fraction of rocks in the ore
ϕ_f	29.57	Power per ton of fines produced $[\mathrm{kW{\cdot}h}/\mathrm{t}]$
ϕ_r	6.03	Rock abrasion factor $[\mathrm{kW{\cdot}h}/\mathrm{t}]$
ϕ_b	90	Steel abrasion factor $[\mathrm{kW{\cdot}h}/\mathrm{t}]$
ε_{ws}	0.6	Maximum water-to-solids volumetric flow at zero slurry flow
V_V	84	Volumetric flow per “flowing volume” driving force $[\mathrm{h}^{-1}]$
P_{max}	1661	Maximum mill motor power $[\mathrm{kW}]$
δ_{P_v}	0.5	Power change parameter for volume of mill filled
δ_{P_s}	0.5	Power change parameter for fraction solids in the mill
$v_{P_{max}}$	0.34	Fraction of mill volume filled for maximum power
$\varphi_{P_{max}}$	0.57	Rheology factor for maximum mill power
α_{speed}	0.712	Fraction of critical mill speed
α_P	1.0	Fractional power reduction per fractional reduction from maximum mill speed
v_{mill}	59.1	Mill volume $[\mathrm{m}^3]$
α_{ϕ_f}	0.01	Fractional change in kW/fines produced per change in fractional filling of mill
ε_c	128.85	Coarse split parameter
α_{su}	0.87	Parameter related to solids in cyclone underflow
C_1	0.6	Constant
C_2	0.7	Constant
C_3	4	Constant
C_4	4	Constant

5.2.2.2 Sump module

The sump mainly acts as a buffer, and further water is added before the slurry is sent to the cyclone. The sump contents (water, fine ore, and coarse ore) are assumed to be fully mixed. The sump only has 3 states, which are the hold-ups of the sump contents. This is because no rocks or steel balls are discharged from the mill through the discharge grate. The sump state transition equations are given by

$$\begin{aligned} \dot{X}_{sw} &= V_{mwo} + \mathrm{SFW} - V_{swo} \\ \dot{X}_{ss} &= V_{mso} - V_{sso} \\ \dot{X}_{sf} &= V_{mfo} - V_{sfo}, \end{aligned} \tag{5.11}$$

and the outputs are:

$$\begin{aligned} V_{swo} &= \mathrm{CFF} \cdot \left(\frac{X_{sw}}{X_{ss} + X_{sw}} \right) \\ V_{sso} &= \mathrm{CFF} \cdot \left(\frac{X_{ss}}{X_{ss} + X_{sw}} \right) \\ V_{sfo} &= \mathrm{CFF} \cdot \left(\frac{X_{sf}}{X_{ss} + X_{sw}} \right). \end{aligned} \tag{5.12}$$

5.2.2.3 Cyclone module

The hydrocyclone classifies material based on weight, which relates to the particle size through the density. Smaller, in-specification, material is forced out of the top of the cyclone as overflow, and is the product of the milling circuit. Heavier, out-of-specification, material is forced out of the bottom of the cyclone as the underflow, and is sent back to the mill for further grinding.

The cyclone is described in the form of nonlinear static equations, along the lines of that presented in Nageswararao, Wiseman and Napier-Munn (2004), as:

$$V_{ccu} = (V_{sso} - V_{sfo}) \cdot \left(1 - C_1 \cdot e^{-\frac{\mathrm{CFF}}{\varepsilon_c}}\right) \left(1 - \left[\frac{F_i}{C_2}\right]^{C_3}\right) \cdot \left(1 - P_i^{C_4}\right) \tag{5.13}$$

$$V_{cwu} = V_{swo} \cdot \frac{V_{ccu} - F_u \cdot V_{ccu}}{F_u \cdot V_{swo} + F_u \cdot V_{sfo} - V_{sfo}} \tag{5.14}$$

$$V_{cfu} = V_{sfo} \cdot \frac{V_{ccu} - F_u \cdot V_{ccu}}{F_u \cdot V_{swo} + F_u \cdot V_{sfo} - V_{sfo}}, \tag{5.15}$$

where F_i and F_u are respectively the fractions of fines in the inflow and underflow. P_i is the fraction of fines in the feed solids. These variables are given by

$$F_u = 0.6 - (0.6 - F_i) \cdot e^{-\frac{V_{ccu}}{\alpha_{su}\varepsilon_c}} \tag{5.16}$$

$$F_i = \frac{V_{sso}}{V_{swo} + V_{sso}} \tag{5.17}$$

$$P_i = \frac{V_{sfo}}{V_{sso}}, \tag{5.18}$$

and $V_{cfo} = V_{sfo} - V_{cfu}$ and $V_{cco} = (V_{sso} - V_{sfo}) - V_{ccu}$. Nonlinear static equations are usable because the cyclone dynamics are much faster than those of the mill.

5.2.2.4 Circuit outputs

The milling circuit outputs are then given by:

$$\text{LOAD} = X_{mw} + X_{ms} + X_{mr} + X_{mb} \tag{5.19}$$

$$\text{SVOL} = X_{sw} + X_{ss} \tag{5.20}$$

$$\text{PSE} = \frac{V_{cfo}}{V_{cco} + V_{cfo}} \tag{5.21}$$

$$\text{THP} = V_{cco} + V_{cfo} \tag{5.22}$$

as well as P_{mill} given in equation (5.8).

5.3 CONTROLLER DESIGN

There are substantial nonlinearities present in the system equations (which become significant depending on how much the operating point changes). The rheology factor (φ) and mill power usage being two notable examples. The fact that the controller must be able to handle faults means that it must have the flexibility to control the process over the entire operating region. Later, when the results are presented, it will become clear by how much the operating point does change in the presence of faults. Operation over a wide span with this nonlinear model therefore justifies the use of NMPC over linear MPC.

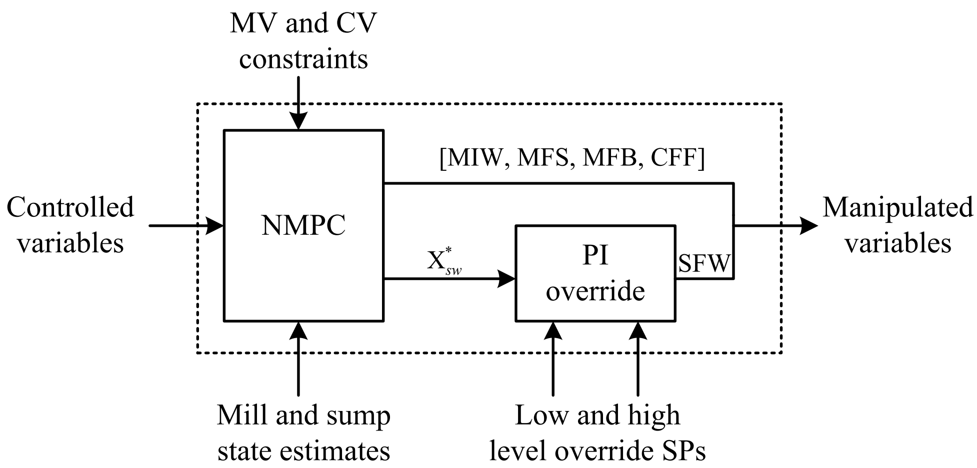

Figure 5.2. Interaction between NMPC and PI override controllers.

An NMPC is used to regulate the milling circuit along with an override PI controller to control the sump, which has faster dynamics. The interaction between the two controllers is shown in Figure 5.2. This layout is similar to the configuration used in Le Roux *et al.* (2016), although a dynamic inversion controller was used in that work instead of the PI override controller used here.

The NMPC receives the controlled variable measurements along with the CV and MV constraints, and the mill and sump state estimates. It then minimises the objective function of equation (4.35) using the parameters provided in Table 5.3. The manipulated variable values, that the NMPC provides, are:

$$\text{MV}_{NMPC} = [\text{MIW},\ \text{MFS},\ \text{MFB},\ \text{CFF},\ X^*_{sw}]\,, \tag{5.23}$$

where X^*_{sw} is the target hold-up of water in the sump. The NMPC CVs are:

$$\text{CV}_{NMPC} = [\text{LOAD},\ \text{PSE},\ \text{THP}]\,. \tag{5.24}$$

The controller is seemingly over-actuated because it has more MVs than CVs. The proper control of PSE does however require a certain ratio of water to solids into the mill. The amount of steel balls added to the mill also depend on the amount of feed ore and the feed ore properties. These additional constraints reduce the degrees of freedom of the NMPC. When controlling at a certain operating point and there are additional degrees of freedom, the MV move penalisation in the controller formulation will ensure a minimum move solution.

The PI override controller then determines the appropriate SFW to achieve the target X_{sw}^*, provided that the sump level will remain within limits. If the sump level cannot be maintained for the target X_{sw}^* the SFW value will be adjusted to maintain the level irrespective of the resulting X_{sw}.

The hold-up of water in the sump (X_{sw}) has an inherent effect on the cyclone feed density. The cyclone feed density in turn affects the split of material in the cyclone, and therefore affects the PSE. Even though the cyclone feed density is not specifically controlled, it is manipulated by adjusting X_{sw}, which therefore has an important effect on the product particle size.

The parameters used in the other control loop subsystems are shown in Table 5.4. Note that only LOAD and PSE have setpoints. The sump level (SVOL) does not need to be at any specific value, as long as the sump does not run dry or overflow. The circuit throughput (THP) should be maximised, hence it has an LP weight. The high and low limits for THP do not have practical meaning, they are chosen wide to allow the controller to maximise the throughput.

The velocity form of the PI controller (Seborg *et al.* 2003:p.201) is used here for the inherent anti reset wind-up it provides. The PI override controller layout is shown in Figure 5.3. The controller comprises the regular X_{sw} tracking control, as well as low and high level overrides to prevent the sump from running dry or overflowing. The setpoint of the low level override is set at 1, and that of the high level override at 19. A middle of three selector chooses the appropriate branch of the PI override to select when setting the SFW value. The output from each control block is given by the digital PI velocity form equation (Seborg *et al.* 2003):

$$\Delta p_k = p_k - p_{k-1} = K_c \left[(e_k - e_{k-1}) + \frac{\Delta t}{\tau_I} e_k \right] \tag{5.25}$$

where Δt is the sampling time, and K_c and τ_I are the tuning constants as listed in Table 5.5.

5.4 STATE ESTIMATION DETAILS

In order for the NMPC to be able to calculate the output predictions it needs the mill and sump states. Full state feedback is not assumed in this work, and two particle filters are used to provide the state estimates according to the method of Olivier *et al.* (2012b). No direct measurements of the mill output

Table 5.3. Values used for controller implementation.

Parameter	Symb	Value
	NMPC parameters	
MV high limits	$\overline{\text{U}}$	$[50,\ 200,\ 10,\ 450,\ 12]$
MV low limits	$\underline{\text{U}}$	$[0,\ 0,\ 0,\ 200,\ 4]$
Prediction horizon	N_p	18
Control horizon	N_c	3
Execution interval	t_S	1 minute
CV high limits	$\overline{\text{Y}}$	$[0.5,\ 0.85,\ 100]$
CV low limits	$\underline{\text{Y}}$	$[0.2,\ 0.5,\ 5]$
Setpoints	y_r	$[0.32,\ 0.67,\ -]$
Reference weight	Q_r	$\text{diag}([4,\ 1e4,\ -])$
LP weight	Q_l	$\text{diag}([0,\ 0,\ -2])$
MV move weight	R	$\text{diag}([0.375,\ 0.08,\ 12.5,\ 0.002,\ 200])$
Slack variable weight	S	$\text{diag}([4e5,\ 2e7,\ 4e3])$
	PI override parameters	
SFW high limit	$\overline{\text{U}}$	300
SFW low limit	$\underline{\text{U}}$	0
High SVOL override SP	-	19
Low SVOL override SP	-	1
Execution interval	t_S	10 seconds

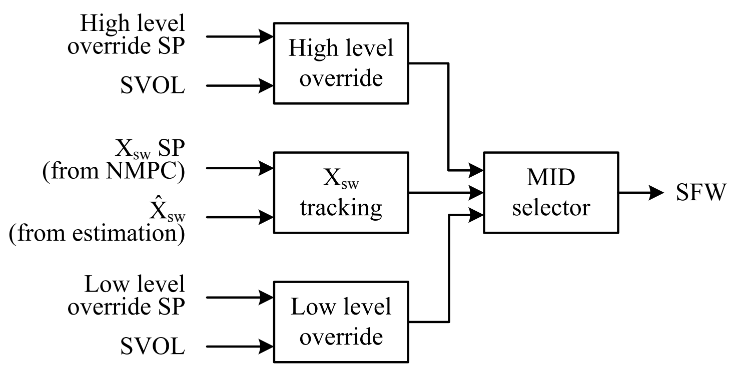

Figure 5.3. PI override controller layout.

Table 5.4. Values used for other elements in the implementation.

Parameter	Symbol	Value
FDI parameters		
Window length (samples)	N	30
Fault confirmation threshold	–	10
Mill particle filter parameters		
Number of particles	$\mathrm{N}_{\mathrm{s}}^{\mathrm{m}}$	1000
State noise	$\mathrm{Q}_{\mathrm{y}}^{\mathrm{m}}$	$0.01\ \mathbf{I}_5$
Output noise	$\mathrm{R}_{\mathrm{u}}^{\mathrm{m}}$	$0.01\ \mathbf{I}_5$
Sump particle filter parameters		
Number of particles	$\mathrm{N}_{\mathrm{s}}^{\mathrm{s}}$	200
State noise	$\mathrm{Q}_{\mathrm{y}}^{\mathrm{s}}$	$0.05\ \mathbf{I}_3$
Output noise	$\mathrm{R}_{\mathrm{u}}^{\mathrm{s}}$	$0.01\ \mathbf{I}_3$
Exponentially weighted moving average filter parameter		
Filtering coefficient	α	0.18

Table 5.5. PI override controller tuning.

Control branch	K_c	τ_I (hours)	SP
X_{sw}^* tracking	12	0.005	from NMPC
Low level override	15	0.1	1
High level override	15	0.1	19

components (V_{mwo}, V_{mso}, and V_{mfo}) are however generally possible on an industrial mill, as are required to complete the mill state estimation.

The sump and mill can be seen as two subsystems for which the states should be estimated separately. The sump states are in fact directly calculable, as was done in Le Roux *et al.* (2016). The state derivatives are however difficult to calculate accurately from the noisy process data, and as such a particle filter is rather deployed to calculate the sump states. The sump states are estimated first as they are readily observable by using the current MV and CV values.

Once the sump states are known the mill output component values are calculated through a component balance over the sump. This is accomplished by using equations (5.11) and (5.12). Because this calculation essentially contains the calculation of derivatives, the calculation error can become large in the presence of noise, which is the case here. The sump state estimates sent to the calculation are therefore further filtered with the use of a simple exponentially weighted moving average (EWMA) filter. The filter can be expressed as:

$$S_k = \alpha \cdot \hat{x}_k + (1-\alpha) \cdot S_{k-1}, \tag{5.26}$$

where $\hat{x}_k$ is the sump state vector to be filtered, α is the filtering coefficient, and S_k is the filter output at time k. The filtering coefficient is also listed in Table 5.4.

Now the mill outputs are available and the mill states are estimated by also making use of the mill inputs. The particle filtering method described in Section 4.3.4.3 is applied separately to estimate firstly the sump and then the mill states. The particle filter parameters are shown in Table 5.4.

5.5 REGULATABILITY ANALYSIS DETAILS

After any fault is detected the regulatability analysis of Section 4.4 is performed. The weighting matrices used in the analysis are the same as those used in the NMPC controller (see Table 5.3). The analysis does however encapsulate the entire milling circuit, i.e. the sump is included unlike in the NMPC. A slack variable weight for violations in the sump level output is therefore also required, and this value is set at 10^7. The time to steady state value used for the analysis is 5 hours. The CV limits used in the analysis are also the same as those for the NMPC in Table 5.3, but the absolute limits beyond which the circuit is considered to be non-operational are given by:

$$[\,\overline{\text{LOAD}},\ \overline{\text{PSE}},\ \overline{\text{THP}},\ \overline{\text{SVOL}}\,] = [0.70,\ 0.90,\ 100,\ 20] \tag{5.27}$$

$$[\,\underline{\text{LOAD}},\ \underline{\text{PSE}},\ \underline{\text{THP}},\ \underline{\text{SVOL}}\,] = [0.15,\ 0.30,\ 0,\ 0]. \tag{5.28}$$

The allowable probability of making a type I or type II rejection error is 5 %, for which $z_\alpha = z_\beta = 1.96$. The initial number of Monte Carlo samples drawn is 5. For these allowable rejection errors the null hypothesis will only be rejected if all 5 executions end up producing the same result. If this is not the case more Monte Carlo iterations are required, and the maximum number of samples taken is set at 20. The threshold of Figure 4.11 reduces below 0.5 for this number of samples. If the null hypothesis is not rejected at this point, a weak conclusion may be drawn regarding the regulatability of the plant, depending on the number of samples that have caused the plant to not be regulatable. Say for example that after 20 samples, 11 showed the plant to be regulatable and 9 showed it to not be regulatable. The difference is not large enough to reject any hypothesis with statistical significance. More samples show the plant to be regulatable than not, and it may be concluded that the plant can continue operating, but this conclusion is weak with regards to its statistical significance.

The disturbances considered in the regulatability analysis are changes in the values of α_f (the fraction of fines in the ore), α_r (the fraction of rocks in the ore), ϕ_f (the power needed per ton of fines produced), and ϕ_r (the rock abrasion factor). All of these parameters may change significantly during normal operation depending on the feedstock. The samples for the disturbance values (d_i) are drawn as

$$d_i \sim \mathcal{U}\left(d_n \pm 10\%\right), \tag{5.29}$$

where $d_n = [0.055, 0.465, 29.57, 6.03]^T$ are the nominal parameter values as shown in Table 5.2.

The number of control moves allowed when the regulatability analysis is performed is six. Move blocking is however used and the blocking vector is given by

$$U_B = [5\ 10\ 10\ 20\ 20\ 50]\,. \tag{5.30}$$

The initial blocking vector entry is the smallest and the entries then increase, which means that the initial control move changes are closer together. The controller is thus initially given the chance to make quicker moves to regulate the plant right after the fault has been detected. The controller is hereafter allowed to make some longer term moves, and finally to set the steady state MV values.

5.6 ECONOMIC PERFORMANCE ANALYSIS DETAILS

For the economic operability analysis an economic performance function that incorporates faults is required. The performance function for the mineral value, defined in Wei and Craig (2009a), is used here:

$$\begin{aligned} \psi\ [\$/\mathrm{h}] \quad &= \quad \mathrm{THP}\ [\mathrm{t/h}] \times \text{ head grade } [\mathrm{g/t}] \\ &\quad \times \text{ mineral price } [\$/\mathrm{g}] \ \times \text{ recovery } [\%] \end{aligned} \tag{5.31}$$

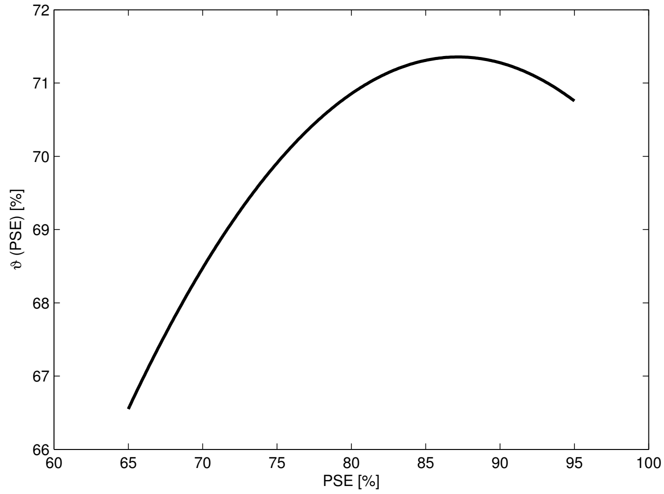

Figure 5.4. Recovery as a function of PSE, adapted from Wei (2010), with permission.

where the throughput (THP) is an output of the milling circuit, the head grade is given by Matthews and Craig (2013) to be 3 g/t, the mineral price used is \$ 32.00 per gram (which is the price of platinum at the time of writing), and the recovery is a parabolic function of the PSE, given in Wei and Craig (2009a), to be

$$\vartheta(\mathrm{PSE}) = -0.00978\ \mathrm{PSE}^2 + 1.705\ \mathrm{PSE} - 2.955. \tag{5.32}$$

This function is shown in Figure 5.4.

Note that the THP used in equation (5.31) has the units $[\mathrm{t/h}]$. The THP value obtained from the simulation (see equation (5.22)) is reported in $[\mathrm{m^3/h}]$. It is therefore important to use the cyclone feed density to convert the throughput, before using the value in the economic performance function. Also note that the cyclone feed density is not the same as the ore feed density.

Equation (5.31) can be used to obtain the nominal mineral value, as well as the mineral value when faults are present. If faults are present the PSE and THP values will be affected, and the cumulative economic performance, calculated using equation (4.68), will also be affected.

The costs associated with shutting down and starting up the plant largely depend on the plant layout. When this plant is shut down the feed to the mill is cut, but the mill keeps on running for a while to drain material from the mill. During this time maintaining the target PSE is nearly impossible. The downstream flotation unit can generally handle the off-specification PSE up to a point, but some

Table 5.6. Parameter values used in the economic operability evaluation.

Parameter	Value	Unit
Ψ_{SD}	1800	\$
Ψ_{SU}	2000	\$
Ψ_R	0	\$
t_{SD}	2	hours
t_{SU}	2	hours
t_O	3	hours
t_S	720	hours

material may go un-recovered. Similarly for start-up, some material may go un-recovered while the mill is getting up to speed and the cyclone is starting to take feed from the mill. Great care is taken to prevent losses in this process, but it is not possible to eliminate losses altogether.

The other values required for the evaluation, as defined in Table 4.1, are shown in Table 5.6. Note that the next planned shut-down is scheduled to be one month away, and it is assumed that spares of all actuators are available, implying that the marginal cost of fixing actuator faults right away is zero. It is also assumed that there is enough ore available to process, i.e. the milling circuit is the value chain bottleneck.

5.7 SIMULATION RESULTS

The results for nominal circuit operation, as well as for four separate fault scenarios are shown in this section to illustrate the performance of the FT-NMPC, as well as the regulatability and economic operability analyses. In the first simulation MIW gets stuck without the FDI running, and after some time the fault information is supplied to the controller. This is done to show the effect of a failure with and without the fault information available. In the second simulation MIW fails again, but this time the value goes to 0. The regulatability analysis shows that this failure is not as severe (if the fault information is available from the FDI) and the plant can continue operating. The economic operability of the plant is somewhat affected, but not to the extent where the plant needs to be shut down.

The third simulation shows a failure in CFF. The plant is still regulatable in this situation, but the economic operability is compromised.

The last simulation shows a failure in the ore feed to the plant (MFS) which is also successfully detected by the FDI algorithm. The outcome of the regulatability analysis however shows that the plant can likely not be controlled for this failure, and the estimated time to failure is noted.

The FT-NMPC performance for each simulation is shown first, followed by the regulatability analysis results, and thereafter by the economic operability analysis results. All simulations are propagated at a sampling period of 10 seconds, and the NMPC executes once per minute.

5.7.1 Nominal operation

The nominal simulation results are shown in Figure 5.5. The plant states and estimates are shown in Figure 5.6, for the mill and the sump. The nominal operation sets the baseline for the economic operability analysis, and it is a reference for comparison with the simulation results with faults that follow. It is clear from Figure 5.6 that the estimates provided by the particle filters are sufficiently accurate representations of the true states.

The nominal THP values for a variety of PSE targets is shown in Figure 5.7. This data was generated by operating the nominal plant at different PSE target values, and noting the THP achieved. The economic performance value for nominal performance, at a PSE of 0.6845 and THP of 20.5 m^3/h, is \$ 2005.26 per hour. The steady-state PSE and THP values seen here represent a typical throughput-quality trade-off found in many processes (Bauer and Craig 2008), as opposed to Le Roux *et al.* (2016) where a degree of independent control between these two parameters were sought. Independent control is however not possible if α_{speed} is not included as an MV.

The reason why α_{speed} is not included as an MV in this work is because the model is not designed for large deviations in operating point from the nominal α_{speed} value. For FTC the controller will necessarily move the MVs into a completely different region if it expects that is what is required. Moving α_{speed} far away from the nominal value may therefore seem like a good option when in fact the operability of the plant could be compromised. For example, if α_{speed} is increased too much the

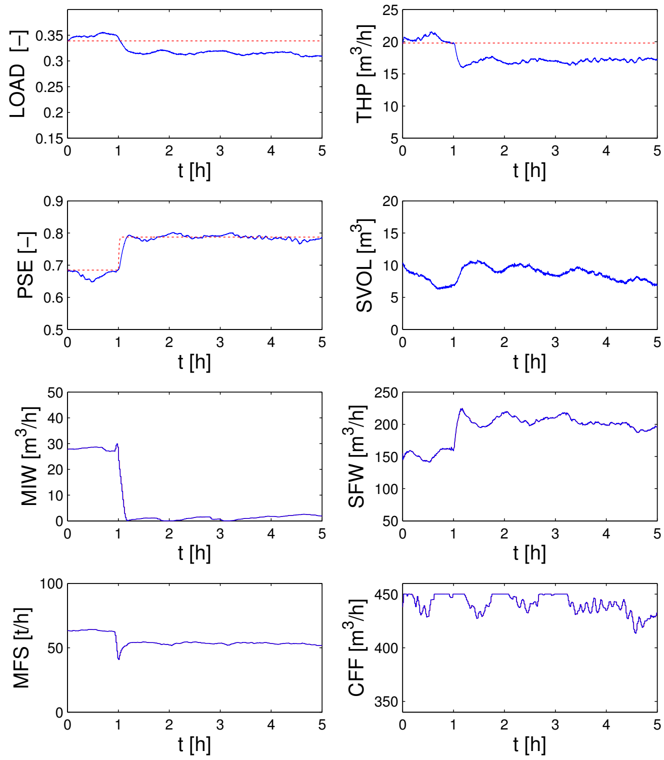

Figure 5.5. Outputs and inputs for nominal operation. The blue lines on the output plots show the measured values. On the LOAD and PSE plots the red lines indicate the setpoints. On the THP plot a red baseline is included with which the measured value may be compared. On the input plots the blue lines show the control actions requested by the controller, and the red lines show the actual actuator values (these may differ later when faults are introduced).

mill will start to approach centrifuging (Powell and McBride 2004), where the grinding medium stays connected to the mill shell for the whole rotation of the mill. In this state very little grinding takes place, which results in an increased LOAD, decreased THP, and worse control of PSE. At this point the mill is not operable any longer, but this operating effect is not sufficiently encapsulated in the model, for which reason α_{speed} is rather not used as an MV.

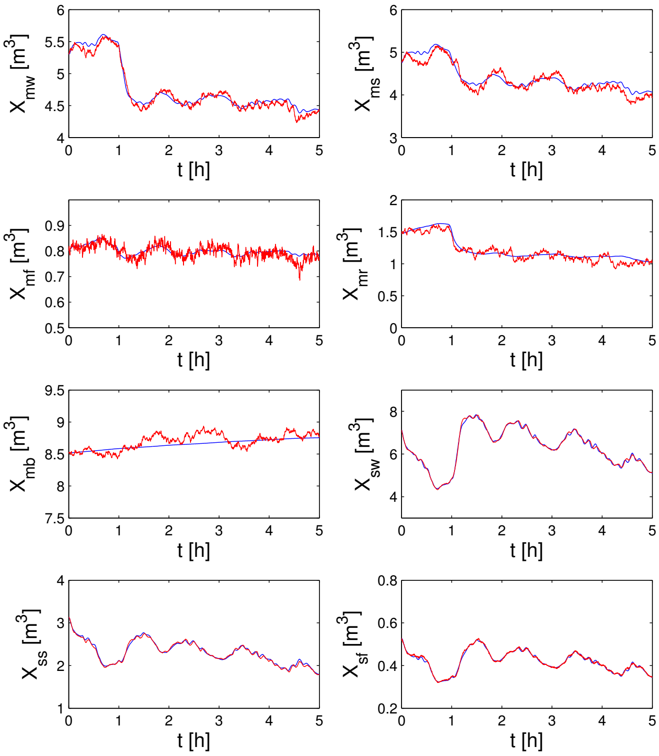

Figure 5.6. States and estimates for nominal operation. The actual state values are shown in blue, and the state estimates are shown in red.

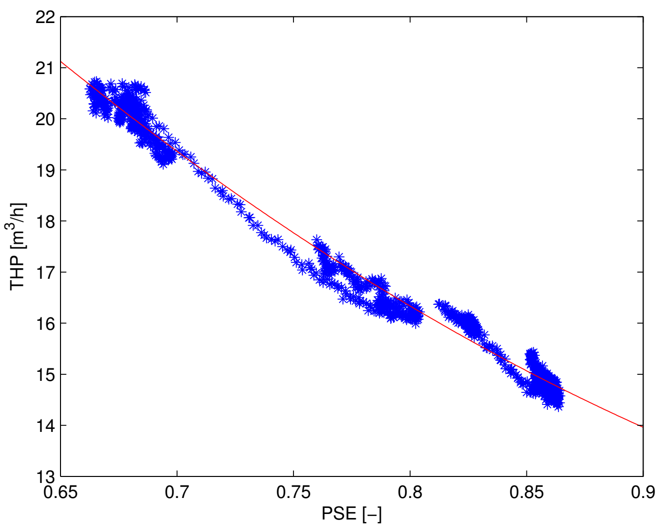

Figure 5.7. THP as a function of PSE. The measured values at different operating points are shown in blue, and a polynomial fit of these data is shown in red.

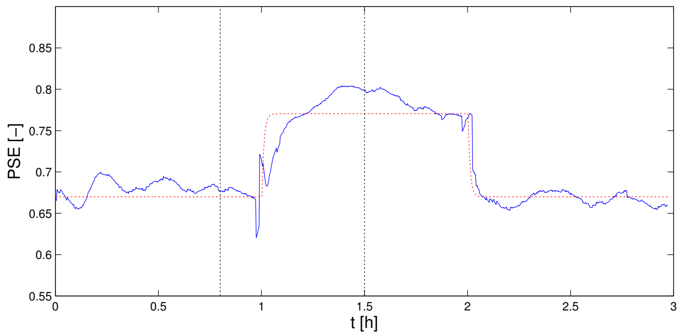

Figure 5.8. PSE tracking performance with MIW fault (unknown to NMPC between 0.8 h and 1.5 h, indicated by the vertical dashed lines). The setpoint is shown in red, and the measured value is shown in blue.

5.7.2 Mill water feed errors

Simulation scenario 1

The first simulation is run for a total of 3 hours. After 0.8 hours the valve supplying the mill feed water gets stuck such that the feed water remains constant at a value of 10 m^3/h for the rest of the simulation run. One hour into the simulation the PSE setpoint is increased by 15 % (such a large change will typically not be performed in practice, and is used here for illustration purposes only). Two hours into the simulation the PSE setpoint is returned to its original value. The setpoint changes illustrate the control performance in the presence of faults.

In Figure 5.8 the FDI is not active, and the fault information is artificially supplied to the NMPC after 1.5 hours. This is done to illustrate the control performance when the fault information is not available against when the fault information is available. It is visible from Figure 5.8 that the controller struggles to achieve acceptable reference tracking performance without the fault information (the first setpoint change), but when this information is available the performance is vastly improved. Without the fault information the controller incorrectly believes that the changes it is making in the MIW are reflected in the plant. With the fault information available however the controller knows that it cannot make use of MIW to achieve the required PSE, and it compensates by using the other manipulated variables.

The same scenario is repeated with the FDI active. The result for the PSE tracking is shown in

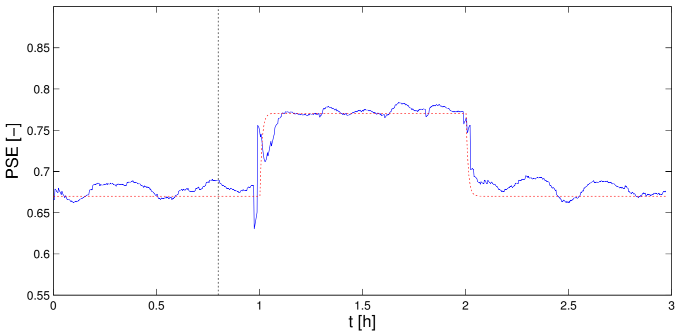

Figure 5.9. PSE tracking performance with MIW fault (the FDI is on in this case). The setpoint is shown in red, and the measured value is shown in blue. The time at which the fault is introduced is shown by the vertical dashed line.

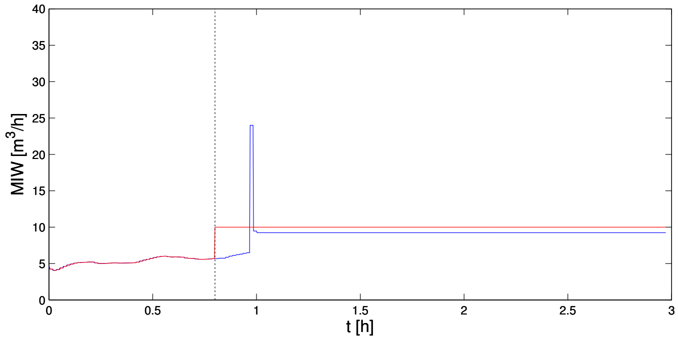

Figure 5.10. MIW actuator information for MIW = 10 m^3/h fault. The blue line is the requested value from the controller and the red line is the actual value seen by the plant. The time at which the fault is introduced is shown by the vertical dashed line.

Figure 5.9. The fault is correctly diagnosed shortly after the setpoint change in PSE is made. In this situation the PSE tracking is much better from the start.

The MIW actuator information is shown in Figure 5.10. The blue line shows the requested value from the controller. The red line shows the actual value that affects the plant. Shortly after the PSE setpoint change the MIW actuator error is detected. The diagnosed actuator value is 9.32 m^3/h, which is close to the actual fault value (10 m^3/h).

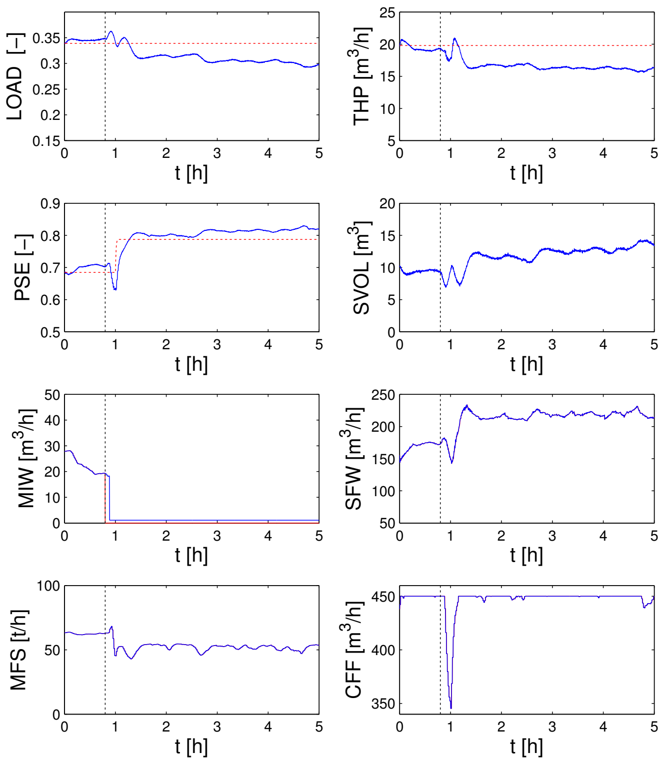

Figure 5.11. Simulation results with MIW = 0 m^3/h fault (FT-NMPC active). The blue lines show the measured values on the output plots. On the LOAD and PSE plots the red lines indicate the setpoints. On the THP plot a red baseline is included. On the input plots the blue lines show the control actions requested by the controller, and the red lines show the actual actuator values. The vertical dashed lines show the introduction of the fault.

Simulation scenario 2

For the second scenario the full FT-NMPC is used with no artificial fault information supplied to the controller. The simulation starts off with the same parameters as before, and there is also a step in the setpoint of PSE after one hour. There is no step back down to show how the FT-NMPC handles the higher PSE requirement. In this simulation the value of MIW goes to 0 m^3/h. The simulation results are shown in Figure 5.11. The fault is correctly detected as an MIW actuator error, shortly after the fault is introduced. The actual value of the faulty MIW is 0 m^3/h, and the detected magnitude is 1.09 m^3/h.

The regulatability analysis results are shown in Figure 5.12, where the shaded (blue) area shows the

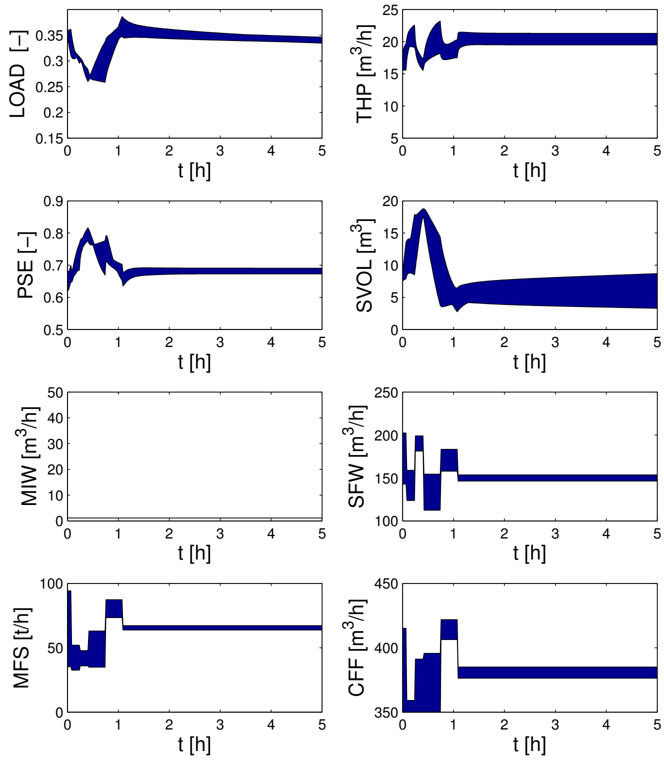

Figure 5.12. Regulatability analysis results for MIW = 0 m^3/h fault.

values within which the variables are predicted to remain given the current fault and disturbances. This means that values close together, where only a small shaded area is seen, indicate that the plant can be regulated tightly with the disturbances present. The results indicate that the plant is regulatable with this fault, and that operations can continue. The disturbance parameter values used in the regulatability analysis are shown in Table 5.7. This table also shows the parameter values used in the other simulation scenarios that follow. Note that from a regulatability analysis point of view the fault occurred at time equal to zero hours. This is because the analysis is performed straight after the fault has been detected.

At the point where the fault occurred, the predicted steady state values (see Figure 5.12) for PSE is 0.682 and for THP is 20.39 m^3/h. The fault economic performance value then equates to $\psi_f =$ \$ 1992.12 per hour. This value is not significantly lower than that of ψ_n (which is equal to \$ 2005.26 per hour). The economic performance comparison, done according to (4.69), shows that it is more economical to operate the plant with the faulty MIW actuator up to the next planned shutdown than it would be to shut the plant down in order to repair the fault.

The reason for the difference between the THP used in the economic performance evaluation and that seen as the eventual steady-state value in the actual results (Figure 5.11) is the change in PSE setpoint which has not yet occurred by the time the economic performance comparison takes place. This will also be noted in the results that follow.

5.7.3 Cyclone feed flow error

Simulation scenario 3

For the third simulation the scenario is similar to that of the second simulation, but this time the CFF value gets stuck at 360 m^3/h after 0.8 hours. The setpoint change remains the same. Shortly after the fault is introduced it is correctly detected as a CFF actuator error by the FDI algorithm, and the identified fault magnitude is 368 m^3/h. The simulation results with this error are shown in Figure 5.13. Even though the value of CFF has decreased significantly, the effect on the regulatability of the plant is minimal. This is indicated by the regulatability analysis results in Figure 5.14. The variability of all CVs (except for SVOL) is small, showing the ease of regulatability. The variability of SVOL is not of concern in this case because the steady-state value of the level does not matter, as long as it can be regulated at steady-state.

The economic performance analysis is carried out next with the steady state values obtained from the regulatability analysis. The predictions are for PSE at 0.6883 and THP at 18.81 m^3/h. The faulty economic performance value is $\psi_f = \$ 1843.49$ per hour. Using the values discussed in Section 5.6, the analysis shows that it would be more economical to shut the plant down, repair the CFF actuator and start the plant up again.

Intuitively it makes sense that the shutdown evaluation will favour operating the faulty plant if the next planned shutdown is in the near future. As the time until the next shutdown is extended, the evaluation will start to favour the option of rather repairing the fault. This is generally what is done intuitively in the process industry by plant managers, but the evaluation is usually not quantified according to the economic performance.

Table 5.7. Disturbance parameter fractional change values used in the regulatability analyses. The disturbance value is represented as $d_i = d_n(1+\Delta d)$.

Iteration	$\Delta\alpha_f$	$\Delta\alpha_r$	$\Delta\phi_f$	$\Delta\phi_r$
MIW error (see Section 5.7.2)				
1	−0.0881	−0.0268	−0.0465	−0.0296
2	0.0592	−0.0409	−0.0637	−0.0253
3	0.0313	−0.0218	−0.0793	−0.0530
4	−0.0107	0.0883	−0.0044	0.0119
5	0.0444	−0.0104	0.0817	0.0133
CFF error (see Section 5.7.3)				
1	−0.0857	−0.0416	−0.0175	−0.0495
2	0.0177	−0.0071	−0.0597	0.0250
3	0.0070	0.0692	−0.0301	−0.0562
4	−0.0906	−0.0884	0.0432	0.0179
5	0.0933	0.0605	0.0770	−0.0368
MFS error (see Section 5.7.4)				
1	0.0023	0.0790	−0.0398	0.0854
2	−0.0333	−0.0062	−0.0109	−0.0253
3	0.0682	0.0684	−0.0764	0.0448
4	−0.0924	−0.0463	−0.0118	−0.0387
5	−0.0060	0.0140	0.0562	−0.0943
6	0.0362	−0.0241	−0.0554	−0.0452
7	0.0696	−0.0102	−0.0991	−0.0713
8	0.0442	−0.0365	−0.0772	−0.0639
9	0.0812	−0.0746	−0.0443	0.0094

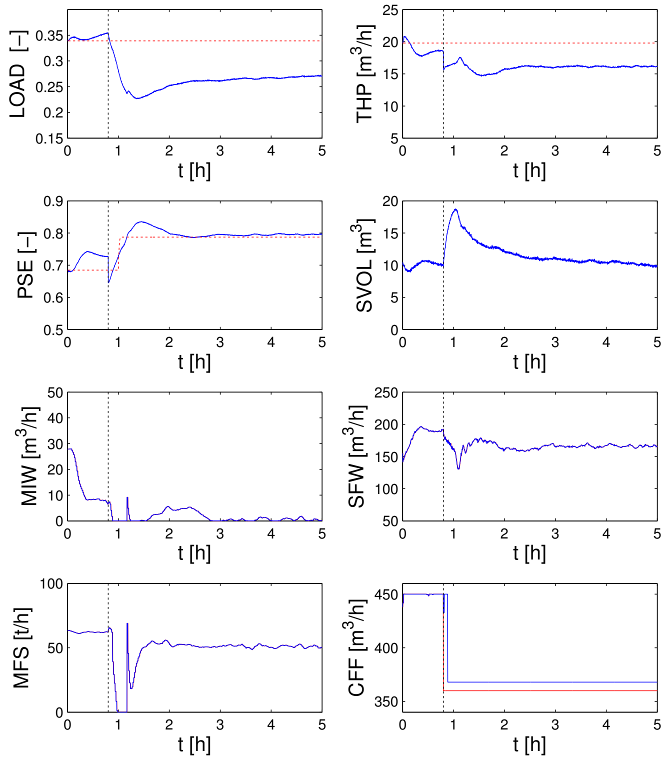

Figure 5.13. Simulation results with CFF = 360 m^3/h fault (FT-NMPC active). The blue lines show the measured values on the output plots. On the LOAD and PSE plots the red lines indicate the setpoints. On the THP plot a red baseline is included. On the input plots the blue lines show the control actions requested by the controller, and the red lines show the actual actuator values. The vertical dashed lines show the introduction of the fault.

5.7.4 Mill ore feed error

Simulation scenario 4

In the fourth simulation the value of MFS gets stuck at 33.25 t/h after 0.8 hours. This value was chosen specifically because it is close to the regulatability limit of the milling circuit. This means that it might not be possible to control the milling circuit for this input value. The regulatability analysis results are shown in Figure 5.15. It is visible from the results that for some disturbance samples the plant is regulatable, but for others it is not. In fact, after the initial five Monte Carlo simulations the null hypothesis was not yet rejected. Four more simulation samples were required, and of the nine evaluations only two passed.

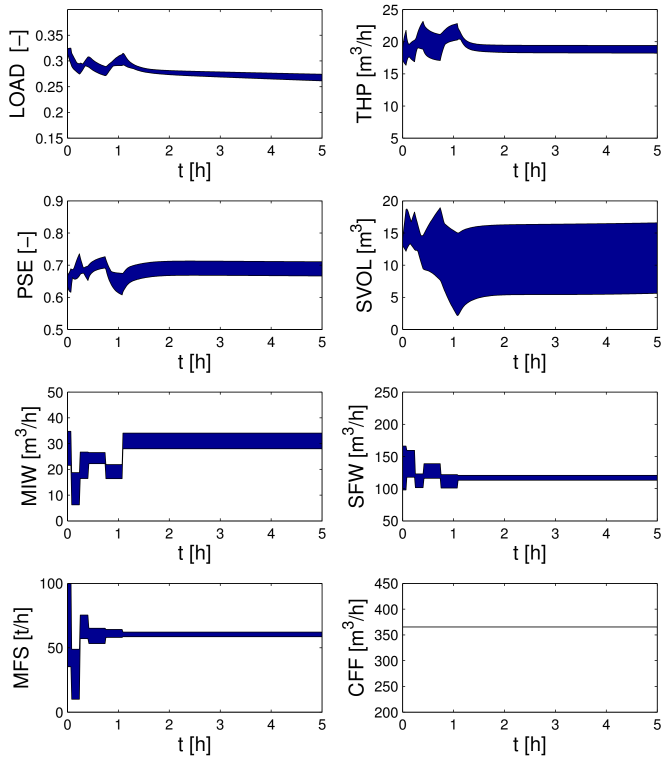

Figure 5.14. Regulatability analysis results for CFF = 360 m^3/h fault.

The null hypothesis is formulated according to step 3 in Algorithm 4.3, i.e. the null hypothesis is posed to the effect that the plant can continue operating (with a low probability of failure). Because of the observed population probability of failure, the null hypothesis is rejected. Note that nine samples were required in this case to decrease the threshold enough to reject the null hypothesis. The predicted time to failure is in the region of two hours.

The broad blue areas seen in Figure 5.15 indicate the large deviations that the disturbance values cause, and show that the plant is not very easy to regulate for this error. At this point the maintenance team may be informed that an MFS fault has occurred that is likely to cause a plant shutdown within two hours.

In order to illustrate whether the prediction of failure and the time to failure are correct, the simulation is allowed to run beyond the point where the regulatability analysis is performed. The simulation results for the MFS error are shown in Figure 5.16. It is seen that in fact the simulation fails just more than 2 hours after the regulatability analysis was performed. This is in line with the prediction that was made. It is clear that the controller struggles to keep the plant running, as the LOAD is falling

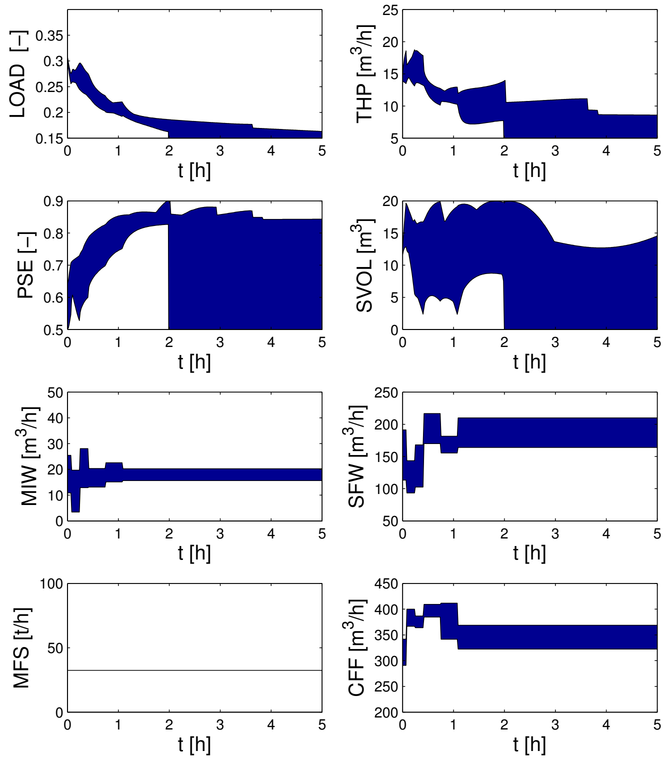

Figure 5.15. Regulatability analysis results for MFS = 33.25 t/h fault.

below the CV low limit and the PSE is above the CV high limit. These two violations are in direct contrast with each other and the controller does not have the necessary handles to maintain both. This is the case because the plant in question does not have a variable speed drive fitted to the mill motor, and therefore α_{speed} cannot be included as a control handle (the reason for this choice was justified earlier).

5.7.5 On the ease of solving the optimisation problem

The NMPC optimisation problem is solved in Matlab (version R2012b in this case) using the interior point algorithm (Byrd, Hribar and Nocedal 1999). The solution is found within the sampling time, meaning the controller can run in real time.

For the regulatability analysis the same interior point solver is used, but there are cases where the algorithm struggles to converge to the true solution. The root of the problem is illustrated in Figure 5.17. The input values are shown in red (the algorithm is trying to find the optimal values of these), the

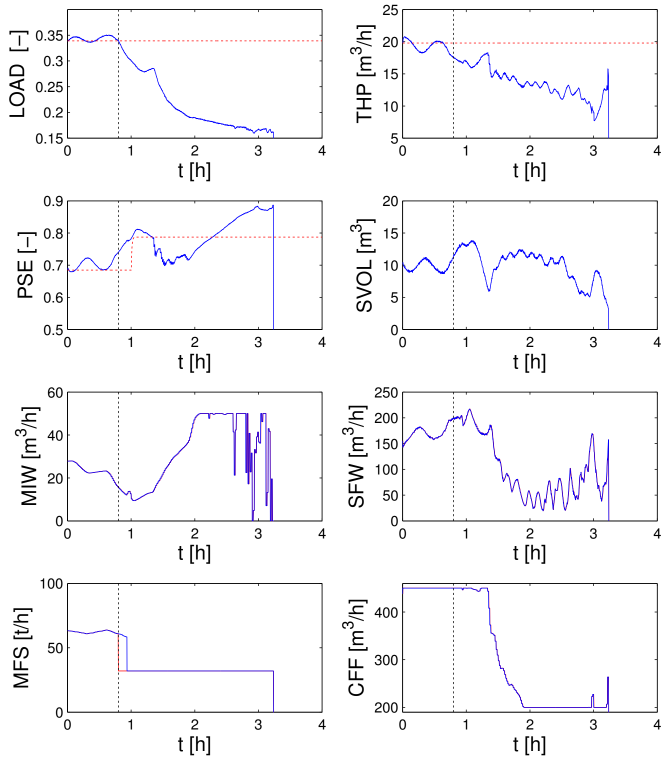

Figure 5.16. Simulation results with MFS = 33.25 t/h fault (FT-NMPC active). The blue lines show the measured values on the output plots. On the LOAD and PSE plots the red lines indicate the setpoints. On the THP plot a red baseline is included. On the input plots the blue lines show the control actions requested by the controller, and the red lines show the actual actuator values. The vertical dashed lines show the introduction of the fault.

output is in blue, and the CV low limit is the blue dotted line.

For the iteration shown, the plant output violates the low limit of zero. The simulation cannot progress beyond this point, which means that any change in the value of u_4 or u_5 will have no bearing on the objective function value. When moving any of these inputs and not noticing a corresponding change in the output, the optimisation algorithm in some instances terminates prematurely. Other gradient-based solvers also suffer from this effect, and in fact using derivative-free solvers like the genetic algorithm (Konak, Coit and Smith 2006), direct search (Kolda, Lewis and Torczon 2003), or simulated annealing (Ingber 1996), also does not solve the premature termination issue.

One way in which this problem can be overcome is through using alternative initial conditions for the optimisation algorithm. This is a technique that is sometimes used in global optimisation to overcome

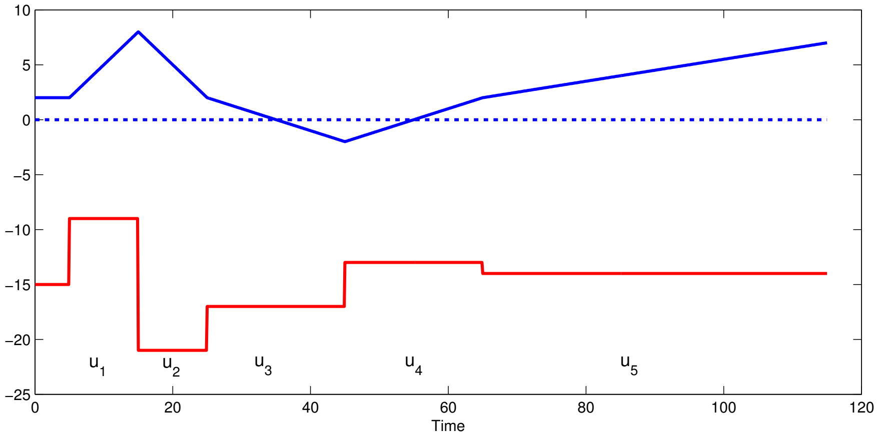

Figure 5.17. Possible optimisation problems in the presence of a non-regulatable plant failure. The input is shown in red, the output is shown in blue, and the CV low limit is shown as the dotted blue line.

the problem of getting stuck at local minima (Floudas 2013). In fact the input values near the time of failure are likely the ones that need to be re-seeded in order for the optimisation algorithm to continue. If however the plant really is not regulatable re-seeding should not continue indefinitely.

5.7.6 Possible areas of improvement of the method

When reviewing the desirable characteristics of the ideal fault diagnosis system (from Venkatasubramanian *et al.* (2003a) and as listed in Section 4.3.2) it is clear that the NL-GLR method is a reasonable approach, but it suffers some shortcomings. The main features of the method are quick detection, isolability, a degree of robustness, and adaptability. The gray-box, nonlinear milling circuit model used also has the advantage of limited modelling requirements, but those are more a feature of the model used than of the NL-GLR method. The method is also expandable such that it can handle multiple faults (Deshpande *et al.* 2009), even though this was not addressed directly in this work.

The method does however not, in the form implemented in this work, have the ability to identify novel faults. Any fault that is not within the presumed set, i.e. it does not have an associated estimator defined, will not be diagnosable. What would happen if an unknown fault enters the system, is that the fault with the closest matching effect on the outputs will be selected. One approach to overcome this problem is to evaluate the selected fault observer outputs against the actual plant outputs. Even if this set of outputs is the closest match, one may still evaluate if the match is good enough to select the fault as the actual fault. This evaluation could also provide a classification error estimate, which the method does not provide at present.

The calculations required for the estimator bank generally makes the GLR method computationally more expensive than some of its peers. Detection is quick, but diagnosis takes some more time. In this work, where the process dynamics are relatively slow, there is enough time to complete the required calculations. If the process response is much quicker this may also become limiting.

The premature termination of optimisation as mentioned in the previous section is also an area where the method can be improved.

When processing plants are shut down to fix a certain fault, other maintenance work can generally also be carried out for which a shutdown is required, but which is not critical enough to warrant a shutdown. The amount of additional maintenance work that can be completed while the plant is off-line will in general count in favour of shutting down the plant. This complexity is not currently handled by the evaluation to shut the plant down. The quantification of such additional maintenance work is however not trivial.

5.8 CHAPTER CONCLUSION

This chapter shows the implementation of a fault-tolerant nonlinear MPC to control a milling circuit simulation in the presence of faults. The NL-GLR method is used for FDI making use of particle filters. The state estimates used by the NMPC are also provided through particle filtering. The FDI is successful for a variety of faults simulated, and the FT-NMPC is able to compensate accordingly.

In the event that a fault is detected, a novel regulatability analysis based on Monte Carlo simulations and an adaptive hypothesis test is used to investigate whether the plant can still be operated with the fault(s) present. If the plant cannot be regulated with the fault present, the predicted time to failure is provided.

If the regulatability analysis is successful, an economic operability analysis is performed. This analysis shows whether it would be more economical to operate with the fault present up to the next planned shutdown date, or whether it would be more economical to shut the plant down, repair the fault, start up again, and then operate up to the next planned shutdown.

The simulation results show the promising nature of the analysis for a variety of faults. Such an analysis would be a valuable tool on processing plants, where decisions to shut plants down *ad hoc* in the presence of faults are rarely quantified according to the economic performance.

CHAPTER 6 CONCLUSION

The objective of this work is to explore the concept of lights-out process control in the minerals processing industry. Some of the key considerations are:

- How far along the road to lights-out process control the minerals processing industry is;
- What the requirements are for lights-out process control; and
- Whether these requirements can be successfully implemented on a minerals processing plant, with the vision of lights-out process control.

6.1 DEGREE OF AUTOMATION IN THE MINERALS PROCESSING INDUSTRY

In order to gauge the status of automation in the process industry a survey was done regarding the degree of automation in the minerals processing industry. The survey showed that automatic process control has had a significant impact on the industry, and process control is one of the main tools in overcoming the problems that the minerals processing industry faces today and in the future (Craig *et al.* 2011).

Operators are still intervening in the process to a fair amount. The main reasons for operator intervention are changes in operating conditions, process optimisation during normal operation, and handling of faults in process equipment or field instruments. All of these actions could be handled, presumably more optimally, by an appropriate advanced controller. In fact the amount of operator actions required indicates the scope for application of more advanced controllers in the industry.

Respondents to the survey also mostly believed that lights-out operation of minerals processing plants will be possible in the future, with most respondents indicating that it will be possible within the next 20 years.

6.2 ENABLING TECHNOLOGIES FOR LIGHTS-OUT PROCESS CONTROL

In order for lights-out process control to become a reality there are a few technologies that are required to be in place. Based on the survey results it seems that an appropriate optimising fault-tolerant controller that handles changes in operating point well is a must. The effective implementation of such a controller is challenging enough for nonlinear processes where the modelling effort is significant, but the maintenance and effective operation of such a controller is also not trivial.

MPC is the most successful APC technology currently employed in the process industry. The effective establishment and maintenance of an MPC controller is discussed with lights-out process control in mind (even though lights-out control is not only achieved through MPC). Additional to the control requirements listed previously, it is also required in the lights-out control framework that the MPC has a degree of autonomous controller maintenance. The control requirements for lights-out operation should also be considered from a plant-wide control perspective.

One of the keys to autonomous controller maintenance for linear MPC is automated, on-line model quality evaluation. The way in which model quality can be quantified is through MPM detection. A closed-form expression can be used for MPM when the plant and controller can be represented with transfer functions. Although many control applications fall within this scope, MPC might not (depending on the conditions listed in Section 4.2.2). A partial correlation analysis is proposed for MPM detection when MPC is used.

Additionally, to illustrate nonlinear FTC, a fault-tolerant nonlinear MPC controller was designed and implemented. The key requirements for this controller are effective fault detection and diagnosis, state estimation, and the correct formulation of the nonlinear optimisation problem. Even with such an FT-NMPC running, the plant operability in the presence of faults is still of concern. For certain faults operations can continue without much impact on performance. For other faults however the plant could have become inoperable. A Monte Carlo based regulatability analysis that handles nonlinear plants with input constraints is proposed in this work. This analysis can give a statistically significant indication of whether the plant is more likely to be operable than not, with the fault present.

Once the regulatability of the process has been established, the next step is to verify the economic operability of the process with the fault present. The result of this analysis will show whether it may be more economical to shut the plant down, repair the fault, and then start up again.

These technologies were applied to a nonlinear ROM ore milling circuit simulation. A variety of faults were selected to show the different evaluation outcomes. The FT-NMPC is effective in optimising process operations in the presence of faults, provided that the process remains controllable.

6.3 FUTURE WORK

The work presented here is focused on the minerals processing industry. Parallels were drawn to the entire process industry where applicable. The status of automation found through the survey and in literature for the minerals processing industry is expected to be in part representative of the process industry as a whole, but this will have to be verified. In future a similar survey may be conducted for the entire process industry. Care should however be taken to obtain sufficient representation from all areas within the process industry.

There are also certain areas where the current FT-NMPC implementation can be improved. In the previous chapter it was mentioned that the regulatability analysis sometimes terminates prematurely owing to the difficulty of solving the optimisation problem. A proper re-seeding algorithm is suggested to overcome this problem.

Regarding fault detection and diagnosis, the main areas where improvements can be made are to expand the current method to handle multiple faults as well as to handle novel faults. Deshpande *et al.* (2009) shows how multiple faults may be handled. For novel faults, it is proposed to correlate the plant outputs over the detection window to those provided by the closest matching particle filter. A certain level of correlation may then be required before the fault described by the closest matching particle filter is selected as the fault that has occurred. This means that novel faults may trigger the fault diagnosis algorithm, but they will not trigger the incorrect selection of a fault if the particle filter outputs do not match the plant outputs to an acceptable degree.

The evaluation of shutting down a plant based on the faulty economic performance is provided in a general framework here. Some plants do however have other intricacies that affect the decision of shutting a plant down. These can include statutory maintenance requirements, market commitments for product delivery, safety concerns, the risk of further failures following a fault, or effects on up- or downstream units that need to be considered. The economically driven decision to shut the plant down needs to incorporate these before application on such a plant.

The methods described in this work were applied to a ROM ore milling circuit simulator. Application to a larger value chain could also be explored to cast the methods completely into a plant-wide application scenario. Some other plant-wide considerations not covered in this work may arise.

The next step towards lights-out operation could also be to implement an FT-MPC in the lights-out control framework shown here on an industrial process or a pilot plant.

6.4 ON THE ROAD TO LIGHTS-OUT PROCESS CONTROL

The process industry is seemingly evolving towards lights-out operations. Production outputs are increasing with fewer operating personnel. The advances in digital technologies have also seemingly enabled the automation of more advanced tasks such that the replacement of humans may increase significantly (Frey and Osborne 2013). Autor (2015) warns against overestimating the impact this will have on unemployment, but the impact on the types of tasks that humans will perform in the future is still seemingly large.

The job of the process plant operator is expected to evolve dramatically as a large number of tasks they perform can be automated (or will be automatable in the near future). Operations personnel are expected to become fewer, and the number of operating units handled per operator is expected to increase. There are already a number of simpler processes where the operator only has to intervene by exception, and they do not even necessarily need to be on-site. An increase in this form of operation is expected in the medium term (over the next 20 years).

In the long term lights-out process control is expected to become a reality, along the survey results and indications of the literature cited in this work. Firstly simpler processes that can sufficiently be represented through linear models are expected to operate more in this fashion, and gradually more complex processes are expected to follow suit. The adaptation of technology in the process industry will also play a role in the timing of industrial application. Provision of safety and operability guarantees in the lights-out control framework are also required, and the availability of these will ease the transition into lights-out operation.

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ADDENDUM A MINERALS PROCESSING INDUSTRY SURVEY QUESTIONNAIRE

The questionnaire used to conduct the survey regarding the degree of automation in the minerals processing industry is provided here. This shows the reader the exact information supplied to the survey respondents.

The results and their analysis are provided in Chapter 3.

Degree of automation in the minerals processing industry - Respondent information

This survey has the aim of trying to determine the degree of process automation (automatic process control) in the minerals processing industry. By process automation (or automatic process control) we mean any automatic regulation with reduced or minimal human intervention. Basic process controls are designed and built with the process itself, to facilitate basic operation, control, and automation requirements. Advanced process controls are typically added subsequently to address particular performance or economic improvement opportunities. Advanced process controls are usually deployed optionally and in addition to basic process controls.

The survey is aimed at those who operate minerals processing plants, as well as vendors (in-house or external) who supply, install and service process automation and control equipment. If you are a vendor, please comment on the typical operation of the processes for which you supply process automation solutions.

1.1 Basic information:
(This information is optional, it is purely for verification purposes and will not be published or distributed in any way.)

Name:

Organization:

Department:

Email address:

Contact number:

* 1.2 What is your position?

- ○ Process Engineer
- ○ Metalurgist
- ○ Plant Superintendent
- ○ Plant Manager
- ○ Control/Instrumentation Engineer
- ○ Researcher
- ○ Systems Integrator
- ○ Sales Engineer
- ○ Other (please specify)

* 1.3 What is you geographical location?

- ○ Europe
- ○ North America
- ○ South America
- ○ Africa
- ○ Asia
- ○ Oceania

* 1.4 What commodity do you (or your clients) extract?
(Select all appropriate choices)

- ☐ Gold
- ☐ Copper
- ☐ Iron
- ☐ Platinum
- ☐ Silver
- ☐ Zinc
- ☐ Lead
- ☐ Phosphor
- ☐ Coal
- ☐ Other

(please specify)

* 2.1 How many operator actions are required during normal plant operation? (Disregard unnecessary actions such as acknowledging nuisance alarms)

- 5 - Operators are constantly busy
- 4 - At least one operator action per 10 minutes
- 3 - One operator action per 30 minutes
- 2 - One operator action per hour
- 1 - One operator action per shift

* 2.2 How important are these operator actions?

- 5 - Essential to safe and profitable operation
- 4 - Without these it would be difficult to keep the unit running
- 3 - Necessary but without them overrides would still keep the unit running
- 2 - Overrides and safety systems could also have kept the unit running profitably
- 1 - These actions have little impact on the profitability of the unit

* 2.3 What is the main reason for operator actions?

- Safety considerations
- Normal operational requirements
- Changes in operating conditions (external factors)
- Failures of instruments/equipment
- Poor control setup
- Other (please specify)

* 2.4 How many control loops are on your plant (or plants that you service)?

- Less than 20
- 20 - 100
- 100 - 1000
- More than 1000

2.5 How many advanced process controllers are on your plant (or plants that you service)?

- Less than 5
- 5 - 10
- 10 - 100
- More than 100
- Not sure

* 2.6 How often are control functions disabled and operated manually by the operator? (Only consider control functions that are set up correctly and do not need to be disabled permanently)

- 5 - At least once per hour
- 4 - About once every 4 hours
- 3 - About once per shift
- 2 - About once per day
- 1 - Less than once per day

* 2.7 What types of control technologies does your plant/unit use? (select all applicable options)

- PID control
- Model predictive control
- Expert system-based control
- Multivariable control
- Fuzzy logic
- Neural networks
- Linear programming
- Statistical process control
- Non-linear models/algorithms
- Constraint control

* 2.8 How many online measurements are made on your plant/unit?

- 5 - There is an abundance of measurements for control, optimization and planning funct
- 4 - More measurements are made than are required for basic control functions
- 3 - Just enough measurements are made for basic control functions
- 2 - Fewer measurements than are needed for basic control functions
- 1 - Just some measurements are made, other than that the unit is operated on operator

* 2.9 How many manual measurements are made on your plant/unit?

- 5 - Most of our important process variables are measured manually
- 4 - Many important process variables are measured manually
- 3 - Some process variables are measured manually
- 2 - Very few manual measurements are made
- 1 - We do not make use of manual measurements

* 2.10 How efficient would you rate the control setup on your plant/unit to be?

- 5 - We owe a big portion of turnover to our efficient controls
- 4 - Our control systems perform well
- 3 - The control setup helps us to keep the unit operational
- 2 - We struggle with efficient control
- 1 - Control functions are barely active

* 2.11 What do you think is the main factor that inhibits your control system from performing better?

- Lack of expertise in setting up and maintaining the control system
- Lack of expertise in operating the system
- Lack of understanding of the process dynamics
- Difficulty of the control problem
- Lack of instrumentation for online measurements
- Lack of actuators to implement control signals
- Focus is placed on other areas
- Other (please specify)

* 2.12 How are faults on instruments and actuators detected?

- Through specialized fault detection and isolation software
- Transmitters and actuators are used that provide some feedback regarding faults (e.g. c
- Faults are only detected by operators through their effects
- Faults often go undetected for extended periods of time
- Only during plant walks or routine inspections are faults detected

* 2.13 What functions do advanced controllers perform on your plant/unit? (Select all applicable options)

- None
- Regulatory control
- Optimization
- Planning functions
- Switching of control philosophies
- Not sure

* 2.14 What is the main benefit you gain from advanced process control?

- Reduction in variability of process variables
- Safety
- Environmental protection
- Not sure
- Other (please specify)

* 2.15 Does your control system give you the ability to specify objectives on the following control layers? (select yes or no for each option)

	Yes	No
Regulatory control (we can specify basic set-points such as levels and flows)	○	○
Optimization (we can specify optimization objectives such as the minimization of concentration)	○	○
Planning functions (we can specify for example the throughput of a unit)	○	○

* 2.16 Please record your level of agreement with the following statement: It will in future be possible to run our minerals processing plant(s) (or that of our clients) completely autonomously, i.e. with no human intervention.

○ 5 - Strongly agree
○ 4 - Agree
○ 3 - Neutral
○ 2 - Disagree
○ 1 - Strongly disagree

2.17 Briefly explain why you agree/disagree with the statement in 2.16.

2.18 If you agree with the statement in 2.16, by when do you think it will be possible to run your minerals processing plant(s) (or that of your clients) completely autonomously?

○ Already possible
○ Within the next 5 years
○ Within the next 10 years
○ Within the next 20 years
○ It will take more than 20 years

This concludes the survey. Thank you very much for taking the time to answer these questions.

ADDENDUM B PROVISIONS TO APPLY THE MODEL-PLANT MISMATCH EXPRESSION FOR LTI SYSTEMS TO MIMO PLANTS

It was stated in Section 4.2.1.1 that signals such as $r(s)$ are usually not square, which is a problem when trying to apply the MPM expression for LTI systems to MIMO plants. This is because a non-square matrix does not have an inverse in the traditional sense. Say for example the output $(y(s))$ is $n \times 1$, generated by applying an $n \times 1$ input signal $(u(s))$ to an $n \times n$ plant $(G(s))$ as

$$y = Gu, \tag{B.1}$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} g_{11} & \cdots & g_{1n} \\ \vdots & \ddots & \vdots \\ g_{n1} & \cdots & g_{nn} \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix}, \tag{B.2}$$

from which $y(s)$ is calculated to be

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} g_{11}u_1 + \cdots + g_{1n}u_n \\ \vdots \\ g_{n1}u_1 + \cdots + g_{nn}u_n \end{bmatrix}. \tag{B.3}$$

The MPM expression determines a transfer function from the "inverse" of the input signal as,

$$G = yu^{-1}. \tag{B.4}$$

In the SISO case this is not a problem as G, $y(s)$ and $u(s)$ are scalars. In the MIMO case however the expression cannot be applied directly as the non-square signal $u(s)$ does not have an inverse. If however the input signal is rewritten as the diagonal matrix

$$U = \begin{bmatrix} u_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & u_n \end{bmatrix}, \tag{B.5}$$

the output becomes

$$Y = \begin{bmatrix} g_{11}u_1 & \cdots & g_{1n}u_n \\ \vdots & \ddots & \vdots \\ g_{n1}u_1 & \cdots & g_{nn}u_n \end{bmatrix}. \tag{B.6}$$

Now U is square and does have a matrix inverse, provided it is nonsingular. Applying equation (B.4) now gives

$$G = YU^{-1}, \tag{B.7}$$

$$G = \begin{bmatrix} g_{11}u_1 & \cdots & g_{1n}u_n \\ \vdots & \ddots & \vdots \\ g_{n1}u_1 & \cdots & g_{nn}u_n \end{bmatrix} \begin{bmatrix} u_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & u_2 \end{bmatrix}^{-1}, \tag{B.8}$$

$$= \begin{bmatrix} g_{11} & \cdots & g_{1n} \\ \vdots & \ddots & \vdots \\ g_{n1} & \cdots & g_{nn} \end{bmatrix}, \tag{B.9}$$

which is equal to the original transfer function.

The input signal can easily be written in the form of a square matrix as in (B.5). The output is however not usually available as a square matrix. It is however apparent that the first entry of (B.6) is equal to the first output in (B.3) if $u_2 \cdots u_n = 0$. This means that a portion of the output signal generated without excitation in $u_2 \cdots u_n$ can be used to calculate the first entry of (B.6). The same argument holds for the calculation of the other entries of (B.6).

A similar situation holds true for measured disturbances. If disturbances are however unmeasured, care would need to be taken to use a portion of data that is disturbance free, as unmeasured disturbances are not explicitly handled by the expression.

ADDENDUM C APPLICATION OF THE MODEL-PLANT MISMATCH EXPRESSION

Making use of the application provisions listed in Addendum B, the MPM expression for LTI systems can be applied to general MIMO plants. This Addendum firstly shows the application of the expression to a simulated MIMO ball mill grinding circuit. Thereafter, an application to industrial plant data is shown.

C.1 APPLICATION EXAMPLE FOR A MULTIPLE-INPUT MULTIPLE-OUTPUT SYSTEM

The application of the MPM expression to a SISO system is straightforward, as presented in Olivier and Craig (2014). In order to illustrate the working of the MPM expression in the MIMO case, the algorithm is applied to a 2×2 ball mill grinding circuit for which MPM is introduced. Consider the ball mill grinding circuit of Figure C.1, which is described in Chen, Yang, Li and Li (2009).

The manipulated variables are the fresh ore feed rate (u_1 [t/h]) and the dilution water flow rate (u_2 [m^3/h]). The controlled variables are the product particle size (y_1 [% − 200 mesh]) and the circulating load (y_2 [t/h]). The nominal values and constraints for the manipulated and controlled variables are given in Table C.1. Care should be taken when using the method to not use data where the output or control variable values are saturated against the limits. This is because saturated data cannot be represented by a linear function, and are therefore not compatible with the MPM expression.

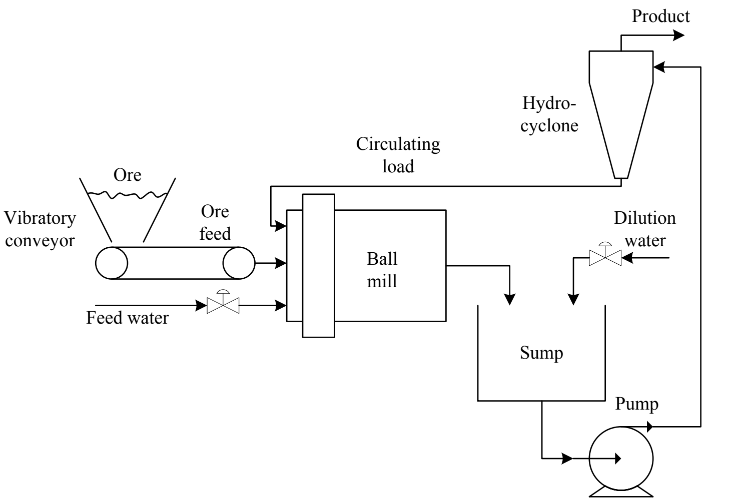

Figure C.1. Ball mill grinding example of Chen *et al.* (2009).

Table C.1. Nominal values and constraints for the 2x2 ball mill grinding circuit variables.

Variable	Description	Nominal	Min	Max	Unit
u_1	Fresh ore feed rate	65	60	70	t/h
u_2	Dilution water flow rate	45	40	50	m^3/h
y_1	Product particle size	70	68	72	%
y_2	Circulating load	150	140	170	t/h

The MIMO transfer function model of the milling circuit is given by

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} g_{11}(s) & g_{12}(s) \\ g_{21}(s) & g_{22}(s) \end{bmatrix} \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix}, \tag{C.1}$$

where

$$g_{11}(s) = \frac{-0.58}{2.5s+1}e^{-0.68s} \tag{C.2}$$

$$g_{12}(s) = \frac{4(1-0.9938e^{-0.47s})}{(2s+1)(6s+1)}e^{-0.2s} \tag{C.3}$$

$$g_{21}(s) = \frac{2.2}{6s+1}e^{-0.6s} \tag{C.4}$$

$$g_{22}(s) = \frac{2.83}{3.5s+1}e^{-0.13s}. \tag{C.5}$$

Milling circuits are often controlled by decentralised PI(D) controllers (Hodouin, 2011; Wei and

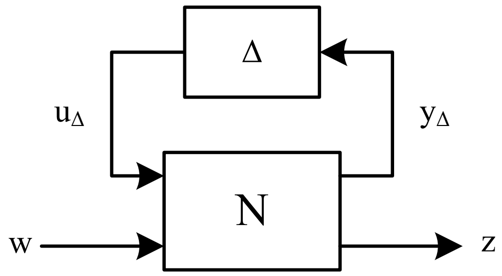

Figure C.2. General plant block diagram representation with uncertainty included.

Craig, 2009b) as was also implemented for this circuit by Chen *et al.* (2009). The diagonal PI controller is in the form

$$Q(s) = \begin{bmatrix} K_{c_1}\left(1+\frac{1}{\tau_{I_1}s}\right) & 0 \\ 0 & K_{c_2}\left(1+\frac{1}{\tau_{I_2}s}\right) \end{bmatrix}, \tag{C.6}$$

with $K_{c_1} = -2$, $\tau_{I_1} = 3.3$ min, $K_{c_2} = 0.42$, and $\tau_{I_2} = 5.2$ min. Next, this plant will be perturbed up to the point that robust performance is not achieved with the current controller. This gives a good indication of the point at which process re-identification may be necessary. The robust performance test is carried out as described by Skogestad and Postlethwaite (2005). The first step of this test is to represent the uncertainty in each channel in the model through an uncertainty weight of the form

$$w_I(s) = \frac{\tau s + r_0}{(\tau/r_\infty)s + 1} \tag{C.7}$$

where r_0 is the relative uncertainty at steady-state, $1/\tau$ is the approximate frequency where the uncertainty reaches 100%, and r_∞ is the magnitude of the weight at higher frequencies. The performance weight is specified as

$$w_P(s) = \frac{s/M + \omega_B}{s + \omega_B A} \tag{C.8}$$

where ω_B is the required bandwidth and A and M are respectively the upper bounds on the sensitivity function at low and high frequencies. Typically $A \approx 0$ and $M \geq 1$. Next, the generalised control configuration for representing uncertainty in the plant is derived (Skogestad and Postlethwaite, 2005:113) as is illustrated in Figure C.2, where w are the exogenous inputs and z the outputs. Nominal stability is achieved if N is internally stable. The tests for robust stability and robust performance make use of the structured singular value μ.

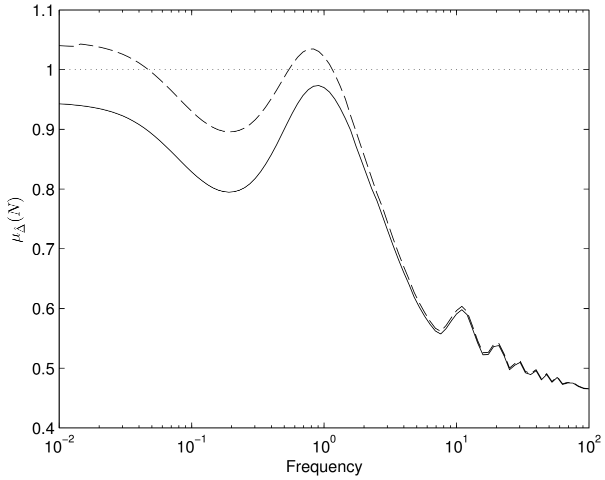

Figure C.3. Robust performance test results for 10% uncertainty. The result for the nominal plant is shown by the solid line, and for the perturbed plant by the dashed line.

$\mu(N)$ is defined as: Find the smallest structured Δ which makes the matrix $I - N\Delta$ singular, then $\mu(N) = 1/\bar{\sigma}(\Delta)$, where $\bar{\sigma}$ is the maximum singular value. For robust stability:

$$\mu_\Delta(N_{11}) < 1, \ \forall\omega \tag{C.9}$$

and N must be nominally stable. For robust performance:

$$\mu_{\hat{\Delta}}(N) < 1, \ \forall\omega, \ \hat{\Delta} = \begin{bmatrix} \Delta & 0 \\ 0 & \Delta_P \end{bmatrix} \tag{C.10}$$

and N is still required to be nominally stable. The test for robust performance is carried out for 10% gain uncertainty with

$$W_I = \frac{0.21s + 0.1}{0.1s + 1} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{C.11}$$

and

$$W_P = \frac{0.45s + 0.05}{s} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}. \tag{C.12}$$

The performance weight specifies integral action and a closed-loop bandwidth of 0.05. This test shows that the performance specification is achieved for 10% uncertainty (Figure C.3 shows the structured singular value, $\mu_{\hat{\Delta}}(N)$, for this test [solid line]).

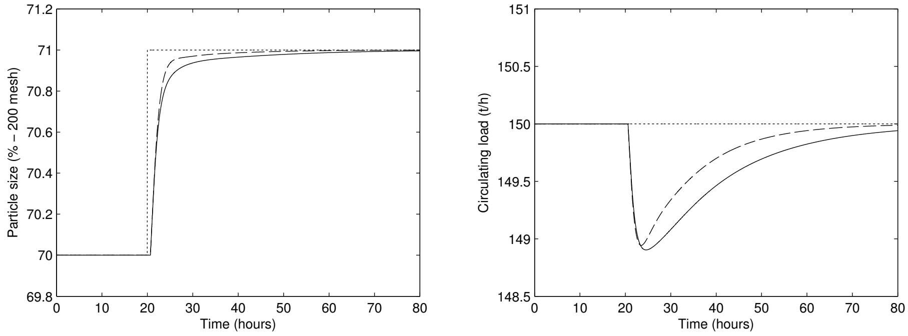

Figure C.4. Response of controlled variables for a step in the particle size showing the setpoint (dotted line), the nominal response (dashed line), and the perturbed response (solid line).

The plant is then perturbed to be

$$g_{11}(s) = \frac{-0.464}{2s+1}e^{-0.68s} \tag{C.13}$$

$$g_{12}(s) = \frac{4(1-1.1014e^{-0.47s})}{(2s+1)(6s+1)}e^{-0.2s} \tag{C.14}$$

$$g_{21}(s) = \frac{2.2}{6.6s+1}e^{-0.6s} \tag{C.15}$$

$$g_{22}(s) = \frac{2.547}{3.5s+1}e^{-0.13s}, \tag{C.16}$$

which is less severe than the mismatch introduced into the system by Chen *et al.* (2009), but more severe than allowed by the robust performance analysis weight. Robust performance is then not achieved, as illustrated in Figure C.3 (the structured singular value is shown by the dashed line for the perturbed plant). The uncertainty (and also the changed plant model) should now be calculated. The nominal and perturbed responses for a step in the particle size setpoint are shown in Figure C.4 and Figure C.5. The nominal and perturbed responses for a step in the circulating load setpoint are shown in Figure C.6 and Figure C.7.

Once the output signals have been generated the mismatch can be identified. The mismatch is calculated using (4.18) to be

$$\Delta_M = G - \hat{G} = \begin{pmatrix} \frac{0.0232\mathrm{e}^{-0.68s}}{s^2+0.9s+0.2} & \frac{-0.0066\mathrm{e}^{-0.67s}}{s^2+0.667s+0.0833} \\ \frac{-0.0333\mathrm{e}^{-0.6s}\,s}{s^2+0.3182s+0.0253} & \frac{-0.0809\mathrm{e}^{-0.13s}}{s+0.2857} \end{pmatrix}, \tag{C.17}$$

from which the actual transfer function is calculated to be exactly the same as the original transfer function as given in (C.2) - (C.5).

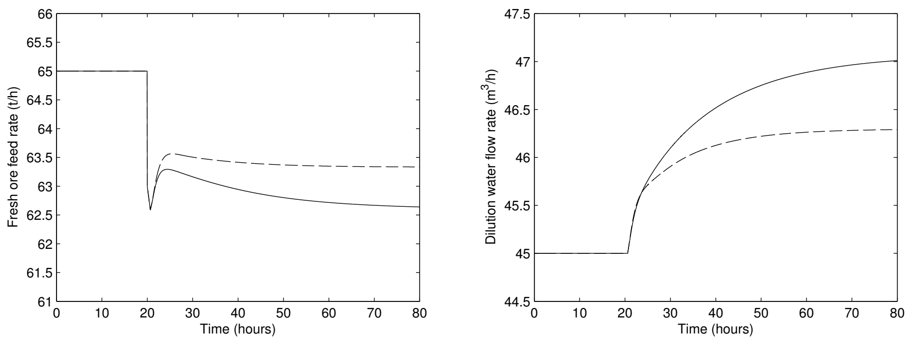

Figure C.5. Response of manipulated variables for a step in the particle size showing the nominal response (dashed line) and the perturbed response (solid line).

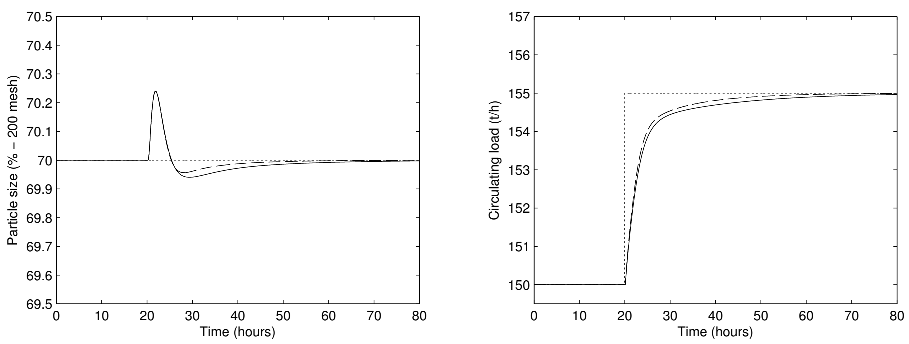

Figure C.6. Response of controlled variables for a step in the circulating load showing the setpoint (dotted line), the nominal response (dashed line), and the perturbed response (solid line).

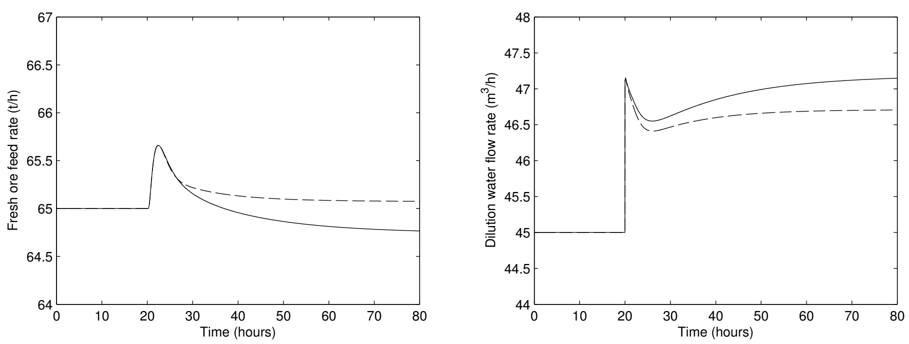

Figure C.7. Response of manipulated variables for a step in the circulating load showing the nominal response (dashed line) and the perturbed response (solid line).

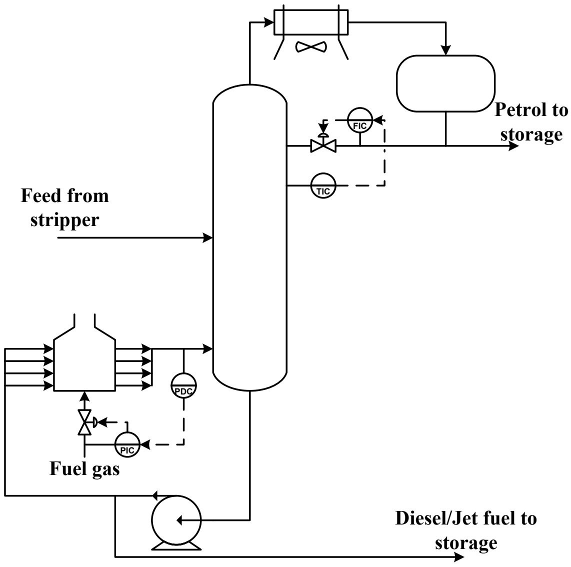

Figure C.8. Polymer splitter column.

C.2 INDUSTRIAL CASE STUDY

To show the application of the method to industrial data, a case study is presented in this section for a splitter column which is part of a Polymer Hydrotreating unit. The data presented was collected during a step testing campaign conducted in 2014.

The purpose of the Polymer Hydrotreater is to convert olefins to the corresponding paraffins to produce a slate of petrol and diesel or jet fuel. After the hydrotreating reaction has taken place, the material is sent to a stripper column (which mainly removes unwanted components) and finally into the splitter column. The splitter column (see Figure C.8[1] for a simplified process diagram) separates the lighter petrol cut from the heavier diesel or jet fuel cut. The unit can either produce diesel of jet fuel depending on the flashpoint[2] of the material in the bottoms of the splitter.

The main variables to be controlled in this splitter column are:

[1] TIC - temperature indicating controller; FIC - flow indicating controller; PDC - differential pressure controller; PIC - pressure indicating controller

[2] The flashpoint is the lowest temperature at which the material will vaporise to form an ignitable mixture in air.

Table C.2. Tuning parameters for splitter column controllers.

Loop	K_c	τ_I	τ_D
Top temp.	1	8	0.5
% Vaporisation	0.5	2	0

- The temperature near the top of the column (on the tray just below where the reflux is added); and
- The percentage vaporisation of fluid leaving the heater (this is a good indication of the temperature).

Together these variables largely define the operation of the column. The top temperature controller cascades to a reflux flow controller, and the percentage vaporisation controller cascades to a fuel gas pressure controller. Both control loops are in cascade configurations and the slave loops are sufficiently fast to ensure that the bandwidth of the slave loops are much larger than the bandwidth of the respective master control loops. The closed-loop transfer function of the inner loop is therefore approximately one ($T_{slave} \approx 1$) (Bequette, 2003). With this approximation the focus can shift to the master control loops.

A 5-hour excerpt of step test data is shown in Figure C.9 (where SP represents the setpoint). Note that the step test data have been standardised to start from zero for intellectual property reasons. This will however not have any effect on subsequent modelling as the constant bias is usually removed from all signals before system identification (Ljung, 1999).

The tuning parameters for the controllers are shown in Table C.2. All time constants shown are in minutes and the controllers have the form

$$Q = K_c\left(1 + \frac{1}{\tau_I s} + \frac{\tau_D s}{\alpha\tau_D s + 1}\right), \tag{C.18}$$

with $\alpha = 0.1$.

It is usually possible to sufficiently represent a binary distillation column with a linear model, if both products are of high purity and the reflux is large (Skogestad and Morari, 1988), which is the case in this example. The operating point also does not change significantly during the step testing campaign.

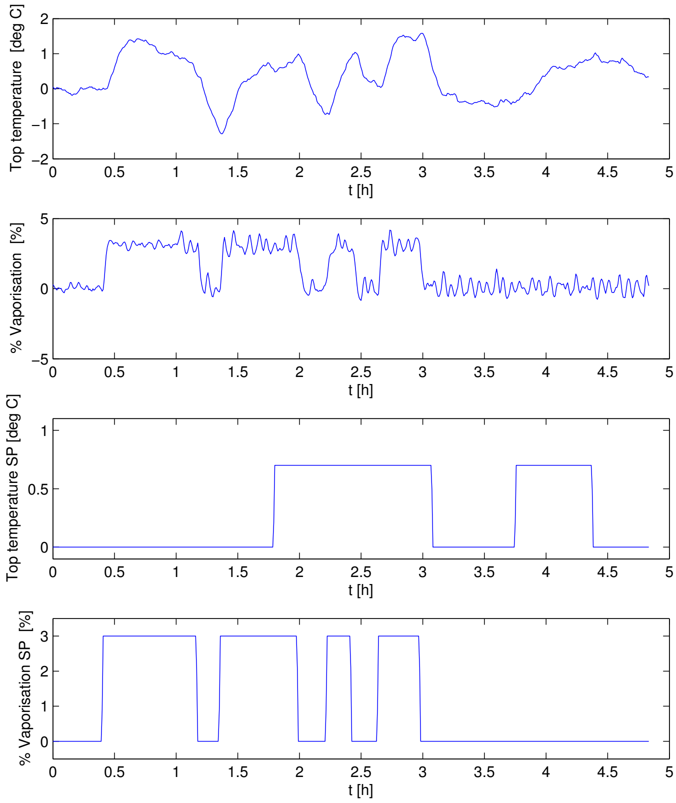

Figure C.9. Step test data for a period of 5 hours.

These reasons along with the fact that it is possible to obtain a representative linear model for the plant from the data[3], allows this process to be considered sufficiently linear.

In order to apply the MPM expression an initial model is needed ($\hat{G}$ in (4.19)). Hereafter the plant has to be perturbed, and operating data from the perturbed plant should be captured for use. As it is not possible for production reasons to perturb this industrial plant, the closed-loop operating data available are therefore assumed to be for the perturbed plant (G in (4.19)).

Model identification of the splitter column was done using third party vendor software. Selected step-test campaign data were used, and the resulting 2×2 transfer function matrix is shown in (C.19) (with time in minutes) as:

$$\begin{bmatrix} \text{Top temp.} \\ \%\ \text{Vapor.} \end{bmatrix} = \begin{bmatrix} \frac{-0.58}{10s+1} & \frac{4}{15s+1}e^{-3s} \\ 0 & \frac{3.8}{2.8s+1}e^{-0.5s} \end{bmatrix} \cdot \begin{bmatrix} \text{Reflux} \\ \text{Fuel gas} \end{bmatrix}. \tag{C.19}$$

[3]This will be shown later in this section, see Table C.5.

Table C.3. Summary of the referenced models

Model	TF	Description	How obtained
G	(C.19)	Perturbed plant model. Assumed unknown for the application of the MPM expression	SID using 3rd party software
$\hat{G}$	(C.20)	Assumed original model from which controller was designed	Adapted G based on plant changes
G^*	(C.27)	Calculated model	Obtained from (4.17) with plant data

Note again that this model is denoted as G because it is considered to be the perturbed plant. This model is assumed to be unknown and is simply shown here for the comparison that will be made once the MPM expression has been applied. A summary of the models referred to in this section is given in Table C.3.

Consider now the scenario where there was a plant shutdown during which changes were made to the original plant (represented by $\hat{G}$). Suppose that during the shut down the thermowell housing the element sensing the top temperature in the column was cleaned of a build-up of residue. This removes some lag when measuring the top temperature. Suppose also that the transmitter was re-calibrated for a smaller range. These two changes will cause the time constants of $G_{1,1}$ and $G_{1,2}$ to decrease by similar amounts when compared to $\hat{G}_{1,1}$ and $\hat{G}_{1,2}$, as well as causing the gains of both these transfer function elements to increase by similar amounts. Suppose that the changes are 20% in either case. This value is chosen large enough to have a significant impact on the output responses as can be seen in Figure C.10 and Figure C.11. This means the original model of the plant was:

$$\hat{G} = \begin{bmatrix} \frac{-0.464}{12s+1} & \frac{3.2}{18s+1}\mathrm{e}^{-3s} \\ 0 & \frac{3.8}{2.8s+1}\mathrm{e}^{-0.5s} \end{bmatrix}. \tag{C.20}$$

To reiterate, $\hat{G}$ is considered to have been the original model of the plant. The plant model is then assumed to have changed to G. The plant data available are assumed to be obtained from the closed-loop system where the plant is represented by G. These data will now be used to apply the MPM expression.

Q and $\hat{G}$ are known; r, u, and y are determined from the data. There are no measured disturbances that

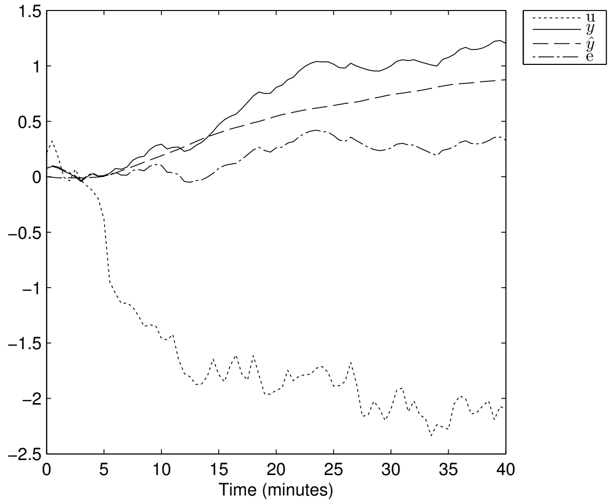

Figure C.10. Data for the top temperature showing the plant input (dotted line), plant output (solid line), model output (dashed line), and the error (dash-dot line).

greatly affect the process. A section of data is therefore selected for which no significant unmeasured disturbances seem to affect the plant so that (4.19) can be applied. Such an excerpt of data is shown in Figure C.10 for the top temperature when a setpoint change is made. Note that $\hat{y}$ is generated by propagating the measured u through the known system $\hat{G}$ as

$$\hat{y} = \hat{G}u. \tag{C.21}$$

A similar section of data is shown in Figure C.11 where a step change in the percent vaporisation is made.

The last signal needed for the application of the MPM expression is e in the Laplace domain. There are many ways in which this signal may be obtained, see for example Shardt and Huang (2011) for an overview of such methods. The method however used here is via a direct transfer function estimation method (described in Garnier, Mensler and Richard (2003)). The error model driven by the reference signal is defined as

$$er^{-1} = e_{M_r}(s) = \frac{B_0(s)}{A_0(s)} \tag{C.22}$$

with

$$y - \hat{y} = e_{M_r}r. \tag{C.23}$$

$B_0(s)$ and $A_0(s)$ are polynomials in s defined as (Garnier *et al.*, 2003):

$$B_0(s) = \sum_{i=0}^{m} b_i s^i \tag{C.24}$$

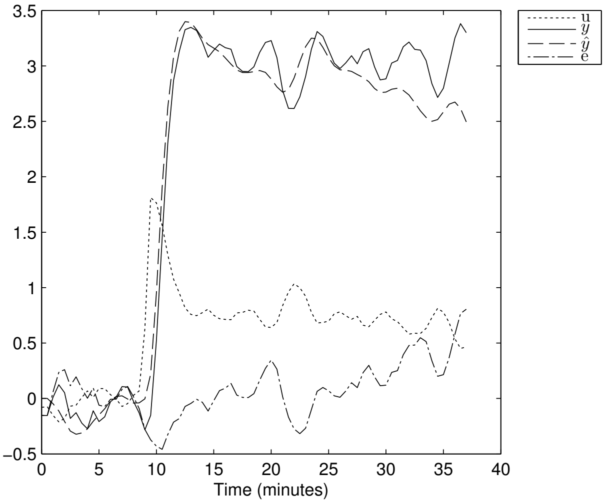

Figure C.11. Data for the heater outlet % vaporisation showing the plant input (dotted line), plant output (solid line), model output (dashed line), and the error (dash-dot line).

$$A_0(s) = \sum_{i=0}^{n-1} a_i s^i + s^n \tag{C.25}$$

and $n \geq m$, where n is the number of poles and m is the number of zeros of $e_{M_r}(s)$. The method makes use of the equation error to fit a continuous-time transfer function model to discrete-time data, and is included in the continuous time system identification toolbox in Matlab. The equation error is a linear algebraic function of the model parameters in the form (Young, 1981):

$$\varepsilon_{EE}(t) = A_0 y(t) - B_0 u(t). \tag{C.26}$$

This method supplies the signal in the Laplace domain, which means that all the signals needed to apply the MPM expression are now available. Once the MPM expression of (4.20) has been applied the calculated plant transfer function (denoted as G^*) is obtained to be

$$G^* = \begin{bmatrix} \frac{-0.677}{10.40s+1} & \frac{4.65}{15.87s+1}\mathrm{e}^{-3s} \\ 0 & \frac{3.81}{2.96s+1}\mathrm{e}^{-0.5s} \end{bmatrix}. \tag{C.27}$$

It can be seen that the calculated transfer function G^* is not significantly different from the identified model for the actual plant transfer function G in (C.19). The relative differences between the transfer function element parameters are shown in Table C.4. The main reason for the presence of any difference here is because of imperfect model identification.

Table C.4. Percentage difference between identified model G and calculated model G^*

Model	$G(1,1)$	$G(1,2)$	$G(2,2)$
Gain K	16.7 %	16.3 %	0.3 %
Time constant τ	4.0 %	5.8 %	5.7 %
Time delay θ	-	0 %	0 %

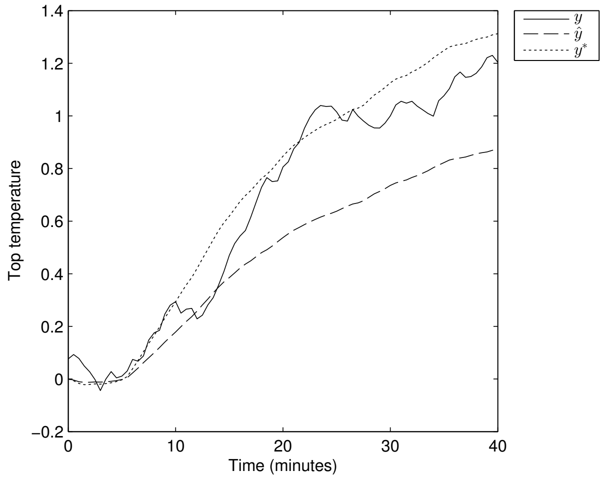

Figure C.12. Model comparison for $G_{1,1}$ showing the plant output (solid line), original model $\hat{G}$ output (dashed line), and the calculated model G^* output (dotted line).

Table C.5. NRMSE for the fit between models and plant output data

Model	$G(1,1)$	$G(1,2)$	$G(2,2)$
$\hat{G}$	44.14 %	51.48 %	87.15 %
G^*	75.01 %	76.53 %	87.63 %

The question remains whether the calculated transfer function is truly a better reflection of the plant than the model $\hat{G}$ derived previously. To illustrate this the model outputs of $\hat{G}$ and G^* are compared to the "actual" plant output in Figure C.12, Figure C.13, and Figure C.14 for the three non-trivial transfer function elements of G. To make the MPM detection worthwhile, the fit between the output related to $G^*_{1,1}$ and $G^*_{1,2}$ and the plant data should be much higher than for the output related to $\hat{G}_{1,1}$ and $\hat{G}_{1,2}$. This is indeed the case as can be seen from Table C.5 in which the normalised root mean square errors (NRMSE) for these comparisons are shown.

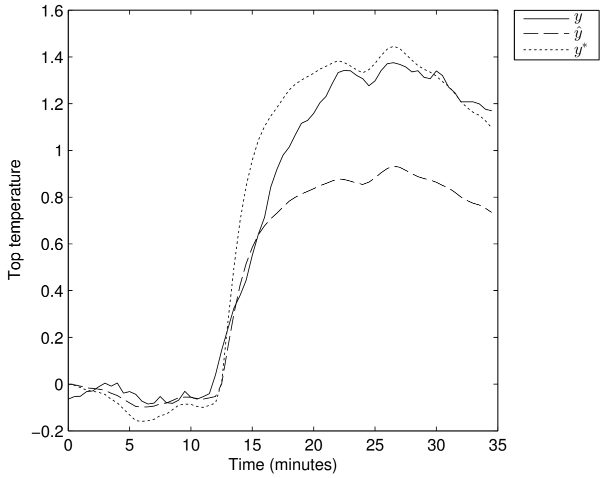

Figure C.13. Model comparison for $G_{1,2}$ showing the plant output (solid line), original model $\hat{G}$ output (dashed line), and the calculated model G^* output (dotted line).

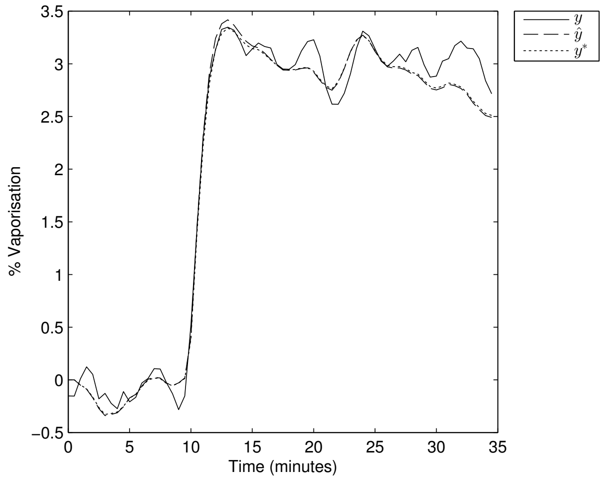

Figure C.14. Model comparison for $G_{2,2}$ showing the plant output (solid line), original model $\hat{G}$ output (dashed line), and the calculated model G^* output (dotted line).

"There are many problems, but I think there is a solution to all these problems; it's just one, and it's education."

– Malala Yousafzai