THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

IN

PRODUCT AND PRODUCTION DEVELOPMENT

CRUSHING PLANT DYNAMICS

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Crushing Plant Dynamics

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To Hanna

ABSTRACT

The performance of a crushing plant is an essential element in achieving efficient production of aggregates or metals. A crushing plant's operating performance depends on the design and configuration of each individual process unit, the configuration of the plant, the design of the control system, events occurring in the process and the physical properties of the incoming feed. The production process is a continuous process and as such it is also subjected to variations and changes in performance depending on the condition of the process. Crushing plants however, are traditionally simulated with steady-state simulation models which are not capable of predicting these conditions. A different technique is therefore necessary in order to estimate the actual behaviour of the plant with respect to time.

Crushing plants are affected by both gradual and discrete changes in the process over time which alters the performance of the entire system, making it dynamic. A dynamic simulation is defined in this thesis as continuous simulations with sets of differential equations with static equations to reproduce the dynamic performance of a system.

In this thesis multiple operational issues have been identified in order to achieve adequate process fidelity for simulation purposes. These operational issues have been addressed by introducing methods and models for representing different dynamic aspects of the process. These include: different types of bins to handle misaligned feeding, segregation and different flow behaviour, the use of system identification to measure actuator response to accurately estimate unit response, wear estimation for crushers, mechanistic models for crushers and screens for more accurate estimation of unit dynamics, segmented conveyors that can estimate material flow for conveyors with variable speed drives, parameter selection for optimum process performance, discrete events that occur within the process and different control strategies to capture the process dynamics.

Different applications for dynamic simulation have been explored and demonstrated in this thesis. These include: process evaluation, control development, process optimization, operational planning, maintenance scheduling and operator training. Each of these areas puts different constraints on the modelling of crushing plants and the level of fidelity, which is determined by the purpose of the simulation.

In conclusion, dynamic simulation of production processes has the ability to provide the user with in-depth understanding about the simulated process, details that are usually not available with static simulations. Multiple factors can affect the performance of a crushing plant, factors that need to be included in the simulation to be able to estimate the actual plant performance.

Keywords: Modelling, Dynamic Simulation, Crushing, Screening, Process Optimization, Control, Operator Training, Production Planning

PUBLICATIONS

This thesis contains the following papers.

Paper A: Asbjörnsson, G., Hulthén, E. and Evertsson, C. M., *Modelling and Dynamic Simulation of Gradual Performance Deterioration of a Crushing Circuit - Including Time Dependence and Wear*, Minerals Engineering (Journal), 2012, Volume 33, pp 13-19.

Paper B: Asbjörnsson, G., Hulthén, E. and Evertsson, C. M., *Modelling Dynamic Behaviour of Storage Bins for Material Handling in Dynamic Simulations*, Published in the proceedings of the XXVI International Mineral Processing Congress, New Delhi, India, 24-28 September 2012.

Paper C: Asbjörnsson, G., Hulthén, E. and Evertsson, C. M., *Modelling and Simulation of Dynamic Crushing Plant Behaviour with MATLAB/Simulink*, Minerals Engineering (Journal), 2013, Volume 43-44, pp 112-120.

Paper D: Hulthén, E., Asbjörnsson, G. and Evertsson, C. M., *Tuning of Real-Time Algorithm for Crushing Plants Using a Dynamic Crushing Plant Simulator*, Published in the proceedings of the 8th International Comminution Symposium, Cape Town, South Africa, 17-20 April 2012.

Paper E: Asbjörnsson, G., Hulthén, E. and Evertsson, C.M., *An On-line Training Simulator Built on Dynamic Simulations of Crushing Plants*, Published in the proceedings of the 15th IFAC symposium on Control, Optimization and Automation in Mining, Mineral and Metal Processing., San Diego, USA, 25-28 August 2013.

Paper F: Asbjörnsson, G., Muller, D., Hulthén, E. and Evertsson, C. M., *Implementation of Dynamic Simulation at Anglo Platinum*, Published in the proceedings of the 9th International Comminution Symposium, Cape Town, South Africa, 17-20 April 2014.

Paper G: Asbjörnsson, G., Hulthén, E. and Evertsson, C. M., *Development of an Operator Training for the Swedish Aggregates Industry*, Published in the proceedings of the 14th European Symposium on Comminution and Classification, Gothenburg, Sweden, 10-12 September 2015.

Paper H: Asbjörnsson, G., Bengtsson, M., Hulthén, E. and Evertsson, C. M., *Modelling of Discrete Downtime in Continuous Crushing Operation*, Presented at the 5th Computational Modelling, Falmouth, UK, 9-10 June 2015, Submitted to Minerals Engineering (Journal), July 2015.

Paper I: Asbjörnsson, G., Bengtsson, M., Hulthén, E. and Evertsson, C. M., *Model of Banana Screen for Robust Performance*, Presented at the 4th Physical Separation, Falmouth, UK, 11-12 June 2015, Accepted to Minerals Engineering (Journal), July 2015.

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Paper J: Hulthén, E., Asbjörnsson, G. and Evertsson, C.M., *A Training Simulator for Crushing Plant Operators*, Published in the proceedings of the XXVI International Mineral Processing Congress, New Delhi, India, 24-28 September 2012.

Paper K: Powell, M.S., Hilden, M.M., Evertsson, C.M., Asbjörnsson, G., Benzer, A.H., Mainza, A.N., Tavares, L.M., Davis, B., Plint, N. and Rule, C., *Optimisation Opportunities for HPGR Circuits*, Published in the proceedings of the 11th AusIMM Mill Operators' Conference 2012, Hobart, Tasmania, 29-31 October 2012.

Paper L: Asbjörnsson, G., Hulthén, E. and Evertsson, C.M., *Development of a Cognitive Supporting Training Environment*, Published in the proceedings of the XXVII International Mineral Processing Congress, Santiago, Chile, 20-24 October 2014.

Paper M: Bengtsson, M., Hulthén, E., Asbjörnsson, G. and Evertsson, C.M., *Advanced Material Modelling in Crushing Plants using Real-Time Algorithms*, Presented at the 5th Computational Modelling, Falmouth, UK, 9-10 June 2015.

CONTRIBUTIONS TO CO-AUTHORED PAPERS

In all of the Papers A-I, Asbjörnsson, Evertsson and Hulthén initiated the idea.

Papers A-E & G: Implementation was conducted by Asbjörnsson. Asbjörnsson wrote the paper with Evertsson and Hulthén as reviewers.

Paper D: Implementation of the finite-state machine was conducted by Hulthén. Asbjörnsson provided the simulator and performed the simulations. Hulthén and Asbjörnsson wrote the paper with Evertsson as a reviewer.

Paper F: Implementation was conducted by Asbjörnsson. Asbjörnsson wrote the paper, Muller provided the control algorithm and wrote the control chapter. Evertsson and Hulthén reviewed the paper.

Paper H: Implementation was conducted by Asbjörnsson. Asbjörnsson wrote the paper with Evertsson, Bengtsson, and Hulthén as reviewers.

Paper I: Modelling was conducted equally by Asbjörnsson and Bengtsson, Asbjörnsson performed the sampling and the simulations. Bengtsson wrote the paper with Asbjörnsson, Evertsson and Hulthén as reviewers.

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Gauti Asbjörnsson

Göteborg, October 2015

CONTENTS

NOTATIONS

f_i	Feed size distribution	[-]
p_i	Product size distribution	[-]
γ_i	Material properties	[-]
ρ	Material density	[kg/m^3]
m	Mass	[kg]
$\dot{m}$	Mass flow	[kg/s]
V	Volume	[m^3]
$\dot{V}$	Volumetric flow	[m^3/s]
v	Velocity	[m/s]
t	Time	[s]
α	Angle	[rad]
l_g	Geometric length	[m]
w_g	Geometric width	[m]
h_g	Geometric height	[m]
A	Area	[m^2]
F	Force	[N]
n	Number of sections	[-]
i	Specific section	[-]
u	Input	[-]
y	Output	[-]
x	State variable	[-]
$\dot{x}$	First order derivative of a state variable	[-]
$\hat{x}$	State variable estimation	[-]
w	Disturbance	[-]
f	Function	
h	Solver step length	[s]
b_i	Constants	[-]
a_i	Constants	[-]
c_i	Constants	[-]
RQ	Research question	
k	Probability parameter	[-]
λ	Probability parameter	[-]
LTI	Linear time-invariant	
G	Transfer function	[-]
Y	Laplace transform of the input	[-]
U	Laplace transform of the output	[-]
K	Steady-state process gain	[-]
s	Laplace operator	[-]
τ	Time constant	[s]
θ	Time delay	[s]

ξ	Damping coefficient	[-]
x_{max}	Top size of the particle size distribution	[mm]
x_{50}	50 % passing size on the particle size distribution	[mm]
b	Slope of the particle size distribution	[mm]
Q	Capacity	[kg/s]
E	Net specific energy	[kWh/t]
C	Energy material constant	[kWh/t]
bij	Breakage function	[-]
s	Selection function	[-]
$\mathbf{p}$	Particle size distribution vector in a crushing zone	[-]
$\boldsymbol{B}$	Breakage matrix	[-]
$\boldsymbol{S}$	Selection matrix	[-]
$\boldsymbol{I}$	Identity matrix	[-]
$\boldsymbol{M}$	Mode of breakage	[-]
q	Product quality	[-]
E_i	Screening efficiency	[-]
d_{50}	Cut point	[mm]
h_T	Theoretical opening area of the screen	[mm]
k_j	Passage rate	[1/s]
f_n	Frequency	[Hz]
CSS	Closed side settings	[mm]
ES	Eccentric speed	[rpm]
ET	Eccentric throw	[mm]
e	Error	[-]
PID	Proportional-integral-derivative controller	
K_P	Proportional gain	[-]
K_I	Integral gain	[-]
K_D	Derivative gain	[-]
APC	Advanced process control	
MPC	Model predictive control	
FSM	Finite state machine	
OPC	Object linking and embedding for process control	
SQL	Structured query language	
HMI	Human machine interface	
EA	Evolutionary algorithm	
GA	Genetic algorithm	
g_i	Inequality constraints	
h_i	Equality constraints	
FIFO	First in – first out	
LIFO	Last in – first out	
MIMO	Multiple input – multiple output	
DT	Downtime	[s]
TTF	Time to failure	[s]
WT	Waiting time	[s]
TBC	Time between calibrations	[s]
TTR	Time to repair	[s]
OEE	Overall equipment effectiveness	[-]

1 INTRODUCTION

The aim of this chapter is to:

- *Provide an overview of the process, the control and their operators.*
- *Introduce the simulation technique used in this thesis.*
- *Define the problems with plant simulations today.*

Rock material is one of the largest consumer products of our time. Constructions such as buildings, roads, bridges and railways are almost entirely built out of extracted rock material which has been processed into a usable product, such as aggregates and metals.

Rock occurrence, composition and structure will vary depending on its genesis and the evolutionary formations of the rock [1]. A rock is a collection of minerals that does not have a specific chemical composition. Minerals are however homogenous solids with a specific chemical composition of certain elements or compounds.

Aggregates are granular processed rock materials that has been formed either by nature through erosion or artificially through blasting and crushing. Aggregates have a versatile application spectrum when it comes to construction, traditional use includes: fundamental ingredients in concrete, in the foundation for drainage, around pipes and drains for better pressure distribution and much more [2]. Structural frames and rails are constructed from steel material which is a product of mining, a process in which the metals or minerals in the ore are extracted from the raw material and then used to create a product.

In Sweden, aggregates production is an industry with approximately 1400 active quarries spread throughout the country. In 2013 they produced 76.4 million tonnes of which 63.4 million tonnes were of crushed rock. Most quarries are however relatively small, with 74 % of the plants producing less than 10.000 tonnes annually [3]. Sweden is one of the major mining nations in Europe. In total, nearly 79.1 million tonnes of ore was mined in Sweden in 2013 from only 16 mines. Out of these 79.1 million tonnes, 37.4 million tonnes was from iron ore. The rest consisted of copper, zinc, lead, silver and other metals [4].

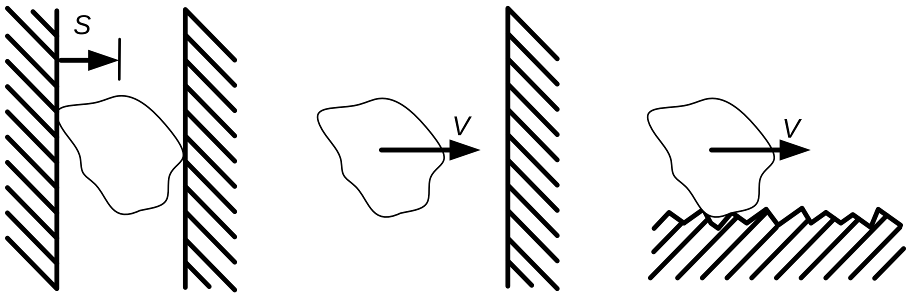
1.1 COMMINUTION AND CLASSIFICATION PRINCIPLES

Comminution is defined as the process of size reduction of particles [5]. In mining and aggregates production, the size reduction of rock material is achieved in different stages by blasting, crushing and grinding. Comminution of rock is categorised into three different crushing principles: compression, impact and attrition. These principles are described in detail by Evertsson [6] and Lee [7], who denote a more general name instead, form conditioned and energy conditioned crushing.

In form conditioned crushing, the size reduction is performed by a controlled compression of a particle or particles between two surfaces to a certain degree or displacement. Form conditioned crushing is the working principle in jaw crushers, gyratory crushers, cone crushers, high pressure grinding rolls and vertical roller mills (see Figure 1a). In the case of form conditioned crushing, the amount of size reduction is determined by the relative displacement of the surfaces while the force and energy required for the size reduction are functions of the displacement. This applies for both single particle and interparticle breakage.

In energy conditioned crushing, size reduction is determined by the amount of energy applied to the particles. Energy conditioned crushing is the working principle in vertical shaft impact crushers, impact mills and hammer mills (see Figure 1b). The more energy that is transferred to the particles, the harder the impact is between the particles and a solid steel wall or a bed of particles which subsequently determines the probability of particle breakage.

Attrition is breakage caused by shear failure [6] (Figure 1c), usually as a result of friction between particles, such as in interparticle breakage [7] and in the particle bed in tumbling mills. This friction is caused by the difference in relative motion between the particles which occurs in both form conditioned and energy conditioned crushing. This type of breakage usually generates more fines as small corners on the particle are chipped off in the process.



(a) *(b)* *(c)*

Figure 1. Schematic principles of form conditioned crushing (a), energy conditioned crushing (b) and attrition (c), as presented by Evertsson [6] and Bengtsson [8].

Classification is the process of separating material flows according to specific size, shape or properties. Different techniques can be used to separate the material into separate flows. Usually the technique used is determined by the particle size distribution of the feed. For a coarse material the most common method of separation is screening. The screening media can consist of vibrating steel wire mesh, steel bars, rubber modules or polyurethane modules. The material is transported over the deck due to the inclination and the oscillating motion of the deck. This enables the particles to move in the particle bed and pass through the deck if the particle is smaller than the size of the aperture, see Figure 2a. Particles larger than the aperture will however not pass through and are therefore transported over the deck [9].

For fractions smaller than 2 mm, vibrating screens often become insufficient due to pegging and blinding. In production of manufactured sand [10] and minerals processing [11] it is beneficial to use air-classifiers and hydrocyclones respectively to separate the material below 2 mm. The same principle applies in both units but with different media used; air or water. If the drag force on the particle, which is generated by the flow of the medium, is larger than the gravitational or the centrifugal force the particle will follow the flow. If, on the other hand, the gravitational or the centrifugal force is larger than the drag force, the particle will fall down, as illustrated in Figure 2b. The cut point can therefore be controlled by manipulating the velocity field of the medium [10].

In certain applications it is beneficial to separate particles with respect to their physical properties to increase the concentration of a specific mineral. In minerals processing this can be achieved with gravity separation, magnetic separation, electrostatic separation and flotation for example. In gravity separation the particles´ relative difference in density is utilized to separate the particles, similar to cyclones, Figure 2b. In electrostatic and magnetic separation the different levels of attraction to an electrical or a magnetic field are used to separate the valuable mineral from the waste gangue, Figure 2c. In flotation the hydrophobic material is separated from the hydrophilic material by adding reagents and air bubbles to the pulp. The air bubbles will adhere to the hydrophobic mineral surface and travel up to the froth, as illustrated in Figure 2d [5].

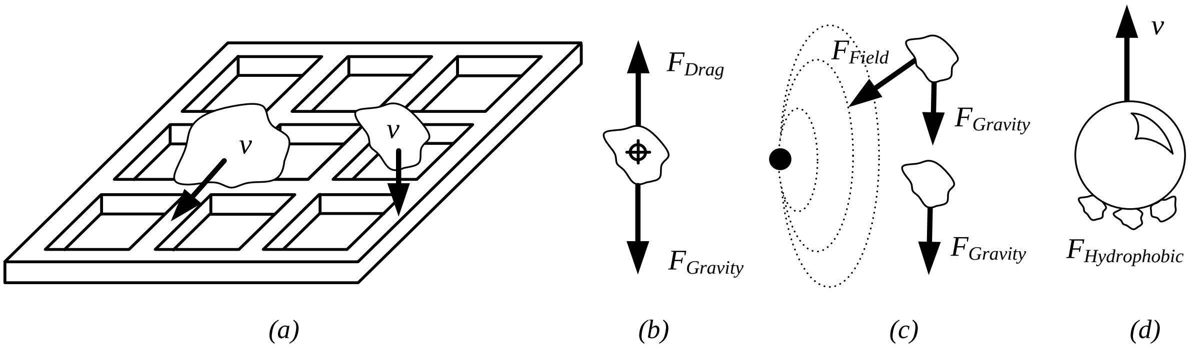


Figure 2. Four methods of separating the material with respect to certain particle size or grade. With a fixed aperture (a), with relative drag force (b), with an electrical or a magnetic field (c) and with hydrophobic properties (d).

1.2 CRUSHING PLANTS

A crushing plant is a configuration of different production units, such as crushers, screens, conveyors, bins, stockpiles and feeders. The number and configuration of units are dependent on the preferred product (Figure 4a) and process performance for which the plant and equipment are designed [12]. This can range from a single crusher with a couple of conveyors to multiple reduction stages in combination with a complex system of bins, screens and conveyors. Figure 3 shows a solution for a three stage crushing plant for an aggregates production application.

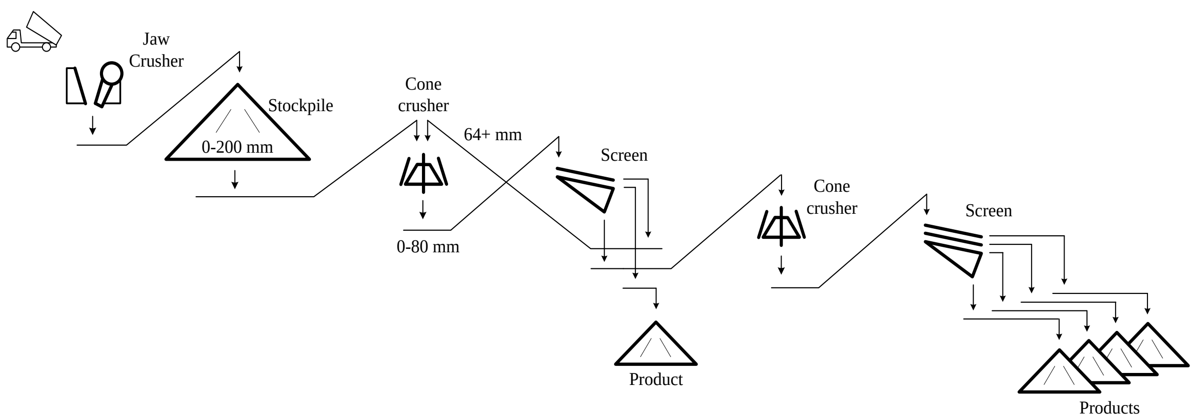


Figure 3. A crushing plant in an aggregates application.

In mining applications, the purpose is to generate fine particles as depicted in Figure 4b. The particles should be fine enough so that the valuable minerals in the ore can be liberated and concentrated [5]. Overgrinding should be avoided. After the dry crushing section, the fine material is fed to mills for further size reduction before being sent to concentration.

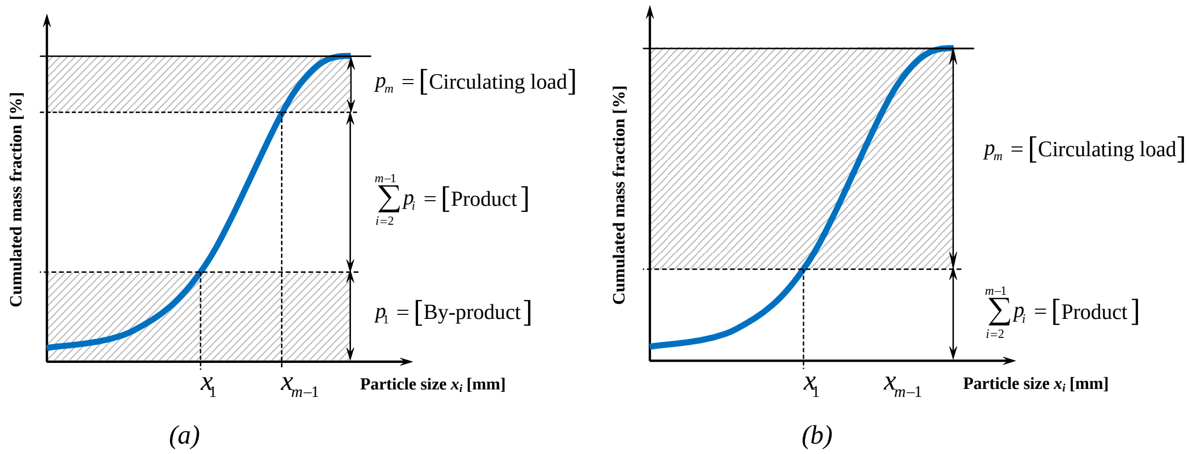


Figure 4. Schematic illustration of product, circulating load and by-product identified on a particle size distribution for aggregates (a) respectively mining application (b), as presented by Lee [7]. The cross-hatched area marks the undesired particle size fractions for both applications.

1.3 PLANT CONTROL

Any modern industrial process that involves mass production with continuous processes, such as mining and aggregates production, uses a high level of automation and process control to ensure safe operation while striving for high product quality and high production throughput. The larger and more complex the production system the higher the demand is on the level of automation. In crushing, the level of automation is relatively limited compared to other process industries, especially for aggregates production.

The control system design of a typical crushing plant consists of regulatory control on actuators, which operate under a supervisory controller, if included. How the controllers operate will depend on the control objectives, system dynamics, selection of control and manipulated variables and the configuration of the controllers [13]. Process units such as feeders are the most commonly controlled actuators in a crushing circuit. They are controlled by altering the frequency of the actuator with interlocks or with a controller which in turn changes the flow rate from the feeder to supply the subsequent part of the circuit with enough material. In Figure 5, a feedback controller with a supervisory controller for controlling either the Closed Side Settings (CSS) or the Eccentric Speed (ES) on a cone crusher is illustrated [12].

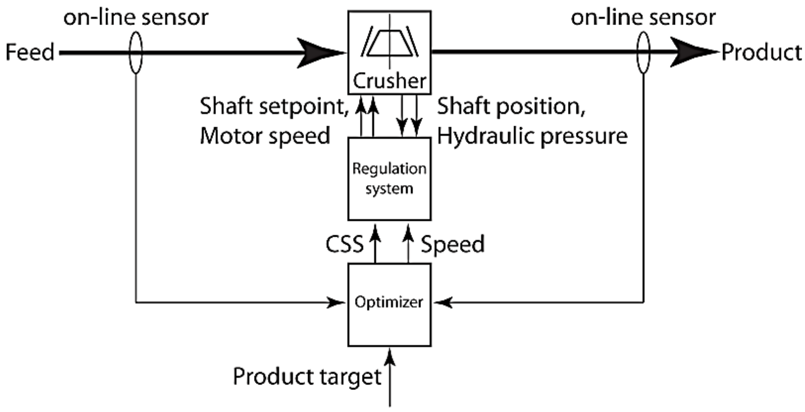


Figure 5. A closed loop process control for controlling the CSS and the ES of a cone crusher, as presented by Hulthén [12].

1.4 PLANT OPERATORS

Operators are responsible for keeping the production running. The level and the type of interaction an operator has with the process is determined by a number of factors such as: the level of automation integrated into the process, the size of the plant, the complexity of the process and the operational management [14]. In a larger plant, with a high number of personnel, an operator's tasks become more specific, such as maintenance, material hauling or process monitoring, whereas in a smaller plant, the operator can be involved in all of the previously mentioned tasks. Many decisions are made by the operators, decisions that rely on the operator's previous experience. Multiple operating decisions, which in many cases could be controlled by the supervisory control system, are left up to manual control. For instance, selecting the operating set points for a cone crusher, i.e. the CSS, is often done by operators, resulting in crusher performance being dependent on the operator's ability to select appropriate operating set points for particular conditions.

1.5 PLANT SIMULATION

Equipment manufacturers as well as plant designers use software packages for predicting plant performance. The most widely used type of simulation technique to date is steady-state simulations, meaning that the system is considered to be in mass balance and consequently all time-derivatives equal zero. By including time dependence and time derivatives it is possible to simulate dynamic behavior. This is referred to as dynamic simulation. Dynamic simulation calculates the performance of the system under different operating conditions as the system experiences changes in state variables over time. Eq. 1.1 illustrates how a system of first order differential equations and output variables y_i are linked to multiple input variables $(u_1(t),...,u_m(t))$ and internal state variables $(x_1(t),...,x_n(t))$ with respect to time t [15].

$$\begin{aligned} \frac{dx_i(t)}{dt} &= f(x_1(t),...,x_n(t),u_1(t),...,u_m(t)), \\ y_i(t) &= g(x_1(t),...,x_n(t),u_1(t),...,u_m(t)) \end{aligned} \tag{1.1}$$

Examples of steady-state simulation packages include: PlantDesigner (Sandvik), MODSIM (Mineral Technologies), Bruno (Metso Minerals), JKSimMet (JKMRC), IES (CRC ORE), Aggflow (BedRock Solution) & UsimPac (Caspeo) [16-19]. Examples of available software that can perform dynamic simulations include: SysCAD (Kenwalt), ProSim (Metso Minerals), Simulink (Mathworks), Aspen Dynamics (Aspentech) and Dymola (Dassault Systémes), With SysCAD and ProSim currently being the only feasible software with a built-in equipment library for comminution applications.

Plant simulations are usually used for evaluating plant performance, for improving a current design [18, 20] and for operator training. For process evaluation, the steady-state simulation technique is an industry standard with multiple available software that can perform the task. Steady-state simulations are easy to set up and can offer results within a few seconds. Dynamic simulation however, requires more configurations and more calculation time but in return it can give more detailed information about the plant performance under different conditions. Operator training is limited in minerals processing and the focus is mostly directed towards flotation operators. Outotec [21], Met Dynamics (SysCAD) and Rio Tinto Alcan (Honeywell UniSim) [22] offer the possibility of operator training in minerals processing based on dynamic simulations, Met Dynamic is the only one to offer it within comminution [23].

1.6 CHALLENGES WITH CRUSHING PLANT DYNAMICS

Every process is subjected to changes in performance and efficiency over time. Traditional plant simulations are performed with steady-state simulation and are limited to showing only the performance of the system in an ideal situation. However, actual plant performance usually tends to deviate away from the predicted plant performance. These dynamics are usually consequences of an altered state of the plant due to factors such as natural variations, unmatched, inappropriate or degrading equipment performance and stochastic events. These factors can cause considerable reductions in process performance if not attended to.

The applications of steady-state simulation are limited to evaluating plant performance and improving process configuration, while dynamic simulations have a wider application spectrum. Process simulations for aggregates production and mining are especially limited when it comes to the plant operation and control. With steady-state simulations, no considerations are taken with regards to control or operational perspective of the process. This can result in ineffective trial-and-error phases in the actual operation, where operators manually adjust equipment and control settings in order to achieve best possible performance of the system, disregarding or neglecting the change in the system over time.

Control development relies on process understanding. Simulations need to accurately represent the system dynamics under different conditions. Model structure, model validity and simulation purpose are therefore important. Empirical models allow the user to model an existing system while relying on data from the process. When simulating outside the validation space or a non-existing process, mechanistic or semi empirical models are more appropriate. Most process simulations in comminution are based on steady-state assumptions and empirical models.

Operators are responsible for keeping the process running. This involves the operators' capability to detect, analyse and evaluate the process performance and possible solutions. The lack of systematic training is probably the key bottleneck for enhancing the capacity of the human operator when it comes to control needs of the automation system [24]. Dynamic simulations are the foundation for mimicking plant behavior in an operator training system. In operator training the operators interact with simulated what-if process scenarios. These scenarios need to accurately represent the system dynamics in a virtual environment.

2 OBJECTIVES

The aim of this chapter is to:

- *Describe the purpose of the research project.*
- *Formulate the research questions.*

2.1 RESEARCH OUTLINE

Crushing plants, as a continuous process, are affected by gradual and discrete changes in the process that alter the performance of the entire system. The aim of this research is therefore to understand how crushing plants operate under different conditions over time and to develop methods for improving plant performance. Plant performance will include aspects of process throughput, process stability, production yield and product quality. In order to represent the time dependent effects that gradual and discrete changes have on the process, a dynamic simulation modelling platform needs to be developed. A dynamic simulation is defined in this thesis as continuous simulation with sets of differential equations together with static equations to reproduce the dynamic performance of a system.

The objectives of this research are thus to develop dynamic models and a simulation platform for the analysis of dynamic plant behaviour in crushing plants for the purpose of achieving process improvements. This thesis focuses on the plant operation and the performance of the crushing circuit for both aggregates plants and dry comminution processes in mining applications. The area of focus for a mineral processing plant is depicted in Figure 6.

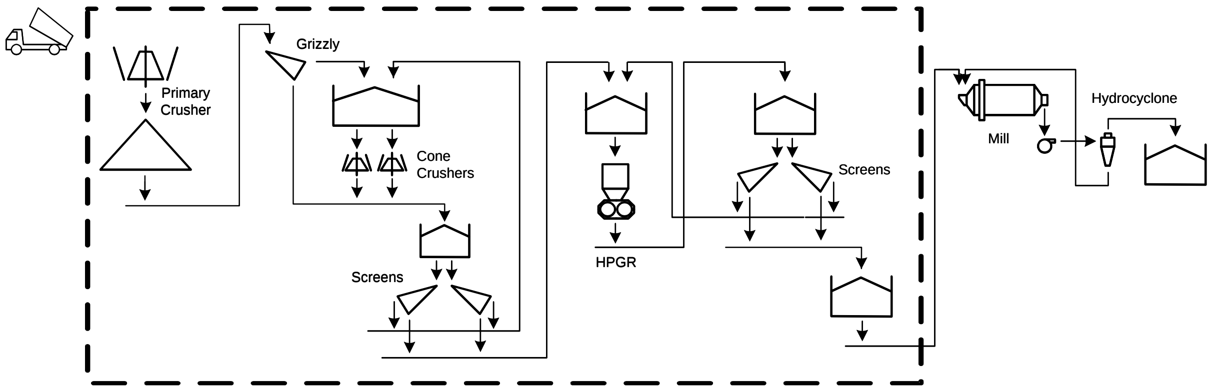


Figure 6. The focus of this research is the crushing and screening stages in aggregates and mining plants, depicted in the dashed box.

2.2 RESEARCH QUESTIONS

The scope of this thesis can be described by the following research questions:

RQ1. What methods and techniques can be used to satisfactory simulate dynamic crushing plant behaviour?

RQ2. What physical principles and phenomena can cause dynamic behaviour in crushing plants?

RQ3. What are the main applications for a dynamic simulation platform?

RQ4. What process related characteristics must be included in the process model to simulate the process performance and achieve useful information?

RQ5. How can suitable control strategies for crushing plants be developed with dynamic simulations?

RQ6. What aspects of using dynamic simulations for operator training should be utilized to improve operators' capability to maintain a safe and productive process?

These research questions will be addressed throughout this thesis and answered at the end of this thesis in Chapter 10 - Discussion & Conclusions. Figure 7 illustrates how the appended papers are relative to each research question and thesis chapters.

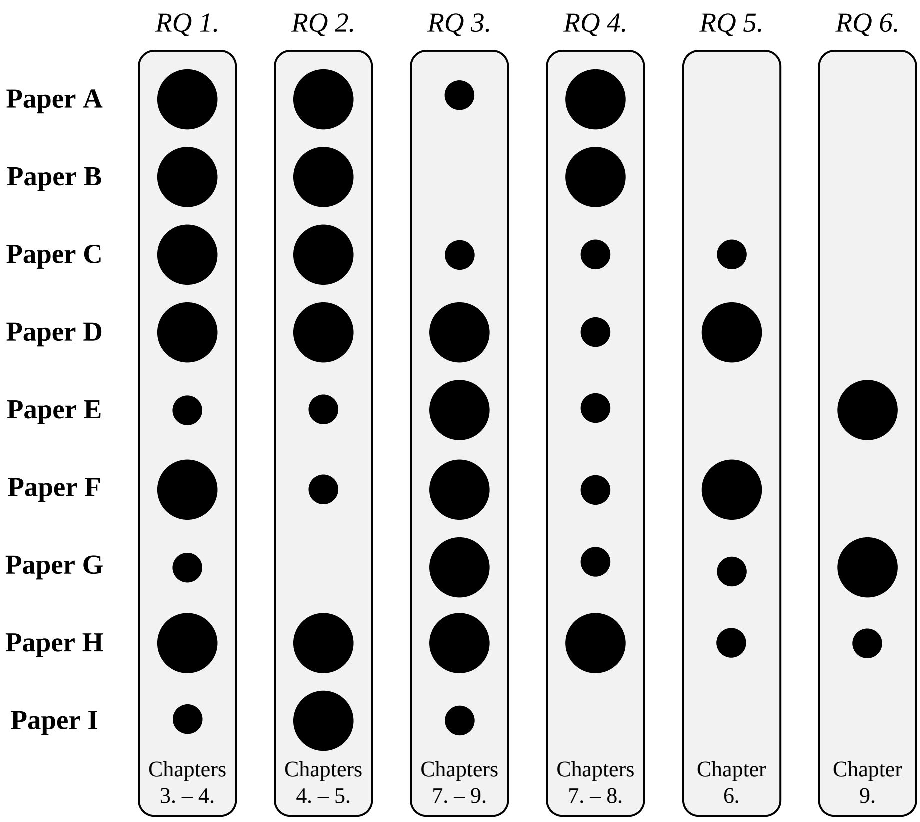


Figure 7. Illustration of how the appended papers are relative to each research question and thesis chapters. Larger sphere represents strong relation to the research question while a smaller sphere represents a weak relation.

3 RESEARCH APPROACH

The aim of this chapter is to:

- *Describe the research approach.*
- *Introduce the research methodology used in this thesis.*
- *Describe the numerical methods used for the dynamic simulations.*
- *Discuss the research evaluation.*

This research was carried out at the Chalmers Rock Processing Systems (CRPS), which is a part of the Machine Element Group at the Department of Product and Production Development at Chalmers University of Technology. The group has been active in research within the field of crushing and screening equipment [6-10, 25], and process performance of crushing circuits [12, 16] for two decades.

3.1 RESEARCH METHODOLOGY

The research approach which has been adopted at Chalmers Rock Processing Systems (CRPS) is characterised as a problem-based approach. The process of problem-based research has been described by Evertsson [6] and Lee [7] and is depicted in Figure 8. In problem-oriented research the choice of methods for solving the problem or question of interest is based on the nature of the problem itself. In other words the problem itself is in the focus rather than the method or tools required to solve it.

Svedensten [16] and Hulthén [12] adopted a different view to the problem-oriented research approach due to the nature of their respective problems. In their opinion, the importance of early implementation was essential for the validity of the results, making it an integrated part of the entire problem-oriented process. According to Crotty [26], each piece of research is unique and calls for a unique methodology. Therefore a general view of problem-based research is described here in detail in order to further show the holistic perspective of the approach.

This work, like other projects at CRPS, was initiated and objectives formulated with regards to an identified industrial problem or a research gap with an industrial relevance. The problem or question in hand is usually an entity in the system which for some reason causes undesirable changes in the process or can be improved to increase the performance of the process or an object.

The first step after the initial problem formulation is to identify the most significant aspect of the problem through both quantitative and qualitative methods such as literature studies, process observations, initial experiments, interviews, on-site data acquisition and data analysis.

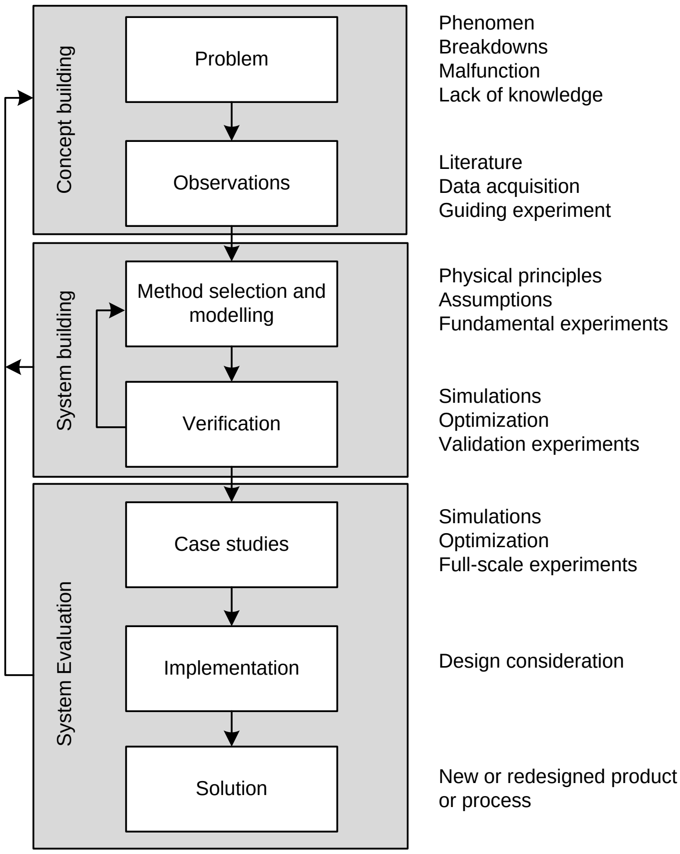


Figure 8. The applied problem-oriented research model slightly modified from Evertsson [6] to account for the system perspective of the research [27].

When the most significant aspect of the problem has been identified the task of method selection and modelling can start. As mentioned earlier, in problem-oriented research the choice of methods for solving the problem or question of interest is based on the nature of the problem itself. An in-depth knowledge of the problem is therefore essential before this phase can be appropriately carried out.

The models are run through a series of simulations and experiments to determine the fidelity of the results. This is an iterative process. If models or methods are not adequate enough the process is repeated with new sets of experiments or possibly new modelling or method selection which improves the representation of the studied object or process. If the models are adequate, larger case studies are performed to further evaluate the models and methods.

How the implementation is conducted is different depending on the characteristics of the problem. Generally the implementation is performed after the iteration process, often as an integrated part of the results from the research as depicted in Figure 8. However, as pointed out by Svedensten [16] and Hulthén [12], an early implementation, during the research phase, is quite important as it will add an additional dimension to the validation process and ensure that the research results are applicable in industry.

CRPS works in close collaboration with the Swedish aggregates and mining industries. By working closely with the industry, problem identification and research implementation becomes more qualitative as relevant challenges that are faced by the industry are studied.

3.2 SYSTEM RESEARCH APPROACH

The performed research is purposely carried out using a holistic system approach, combining different fields in several system levels. Each component in a system comprises of different entities described by sets of principles and attributes. The developed system includes complex aspects of different fields of engineering, technical solutions, human factors and management and their interaction over time [28].

Research using a system approach is by definition a multidisciplinary, iterative process, with a top-down approach to development, synthesis and operation of an actual system. A system fidelity is not determined by individual entities but by the configuration and the relationships between different entities [29, 30]. The performed research is therefore applied and explorative and aims to integrate available knowledge, models and technologies to produce a usable system.

The system approach adds additional iterative dimensions to the problem-based approach. Each study is aimed at specific entity or entities in the system, further defining the problem and increasing the fidelity of the system. The three phases of system development are illustrated in Figure 8 with grey blocks superimposed on the problem-oriented approach.

3.3 NUMERICAL METHODS

In order to approximate the continuous state variables different sets of numerical methods has been applied in this thesis with explicit finite difference approximations. The numerical methods approximate the integral of a system of the differential equation f over a specific time domain t (t_o to t_n), given an initial condition for the state variables x_i at time t_0, Eq. 3.1.

$$\frac{dx_i(t)}{dt} = f(x_1(t),...,x_n(t),u_1(t),...,u_m(t)), \quad t_0 \le t \le t_n, \quad x_i(t_0) \text{ given} \tag{3.1}$$

The numerical methods provide finite difference approximations for solving complex calculations of differential equations that cannot be solved analytically. In the Euler method the approximated solution is achieved by the current state variable and its first derivative, Eq. 3.2. The first derivative $f_i(\hat{x}_i(t_n),u_i(t_n))$ is multiplied by the step length h, i.e. the time between each estimation, which is added to the previously computed value for the state variable $\hat{x}_i(t_n)$ to obtain the new state value $\hat{x}_i(t_{n+1})$ over the mesh points that are distributed between t_0 and t_n according to the simulation step size h. This can be illustrated graphically by using Reimann's sums to estimate a definite integral as shown in Figure 9.

$$\hat{x}_i(t_{n+1}) = \hat{x}_i(t_n) + hf_i(\hat{x}_i(t_n),u_i(t_n)), \quad t_{n+1} = t_n + h \tag{3.2}$$

Improved representations of the Euler method are referred to as Runge-Kutta methods. All orders of the Runge-Kutta methods and their embedded versions address the problem of local truncation error that occurs in the numerical approximation. The local truncation error from the integration will depend on the nonlinearity of the input variable and the step length between each simulation step, i.e. the difference between the input function and the estimation in Figure 9. Decreased step size will result in decreased truncation error at the cost of more computational load [31].

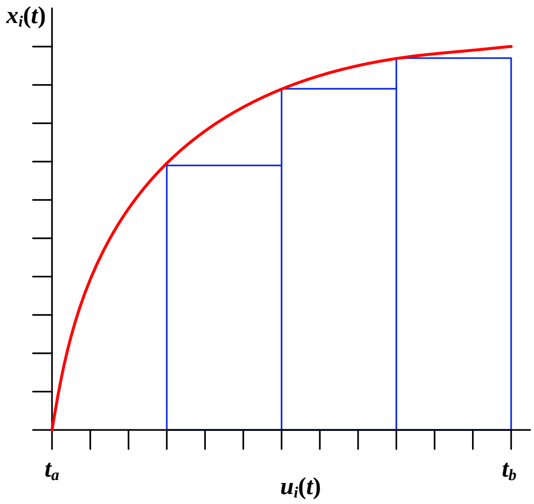


Figure 9. Graphical representation of the Euler method using left Reimann's sums for estimating a definite integral.

In the 2nd order Runge-Kutta method the average time derivative is computed with two points, instead of one as in the Euler method to get a linear approximation between the points. The general form for the 2nd order Runge-Kutta method is shown in Eq. 3.3 and Figure 10. The Heun method is one version of the 2nd order Runge-Kutta method. In the Heun method the value of b_2 is set to 0.5 which determines the value of b_1, c_1 and a_{21} [32].

$$\begin{aligned} \hat{x}_i(t_{n+1}) &= \hat{x}_i(t_n) + h(b_1 k_1 + b_2 k_2) \\ k_1 &= f_i(\hat{x}_i(t_n)\ ,\ u_i(t_n)) \\ k_2 &= f(\hat{x}_i(t_n) + a_{21} k_1 h\ ,\ u_i(t_n) + c_2 h) \end{aligned} \tag{3.3}$$

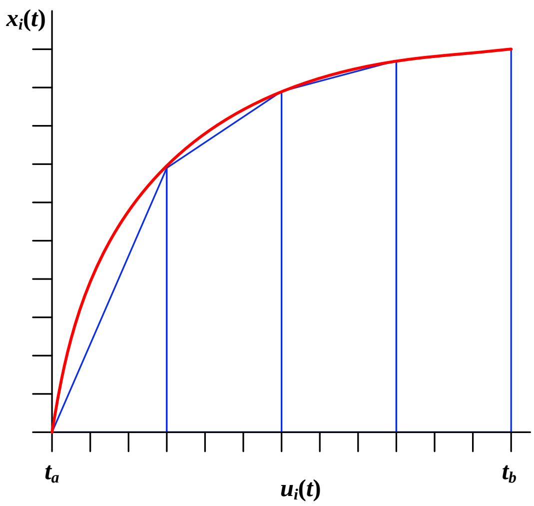


Figure 10. Graphical representation of the Heun method using trapezoidals for estimating a definite integral.

Increasing the order of the Runge-Kutta method increases the number of evaluations of the first derivative $f_i(\hat{x}_i(t_n), u_i(t_n))$ per step size and the order of the polynomial approximation for the state variable x_i. In the 2nd order Runge-Kutta method (previously shown) two points were used to estimate a linear estimation of the state variable x_i at t_{n+1}. For a s^{th} order Runge-Kutta, s points per step are used to create a polynomials approximation of the same order, Figure 11 illustrates this principle with the Simpson's rule. Eq.3.4 illustrates the general form of Runge-Kutta method of an order s. Parameters b_i, a_{ij} and c_i define the methods [33].

$$\hat{x}_i(t_{n+1}) = \hat{x}_i(t_n) + h\sum_{j=1}^{s} b_i k_i$$

$$k_1 = f_i(\hat{x}_i(t_n)\ ,\ u_i(t_n)) \tag{3.4}$$

$$k_i = f_i(\hat{x}_i(t_n) + \sum_{j=1}^{i-1} a_{ij} k_j\ ,\ u_i(t_n) + c_i h)$$

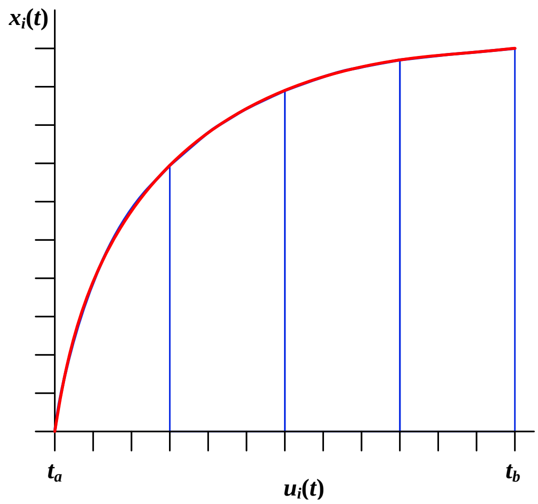


Figure 11. Graphical representation of the Runge-Kutta method by using Simpson's rule for estimating a definite integral.

Increasing the order of the solver will not only increase the accuracy of the numerical estimation, i.e. reduce the truncation error, but also increase the computational load since more points are evaluated during each step size.

Two dynamic simulation platforms have been used during this thesis. In Paper A the Kenwalt's software SysCAD was used to benchmark the leading commercial dynamic simulation platform for comminution, while in Papers B-I Mathwork's software Simulink was used. The 2nd order Runge-Kutta method was used in Paper A and H, while in Papers B-G and I the 3rd order Runge-Kutta method was used.

3.4 RESEARCH EVALUATION

The most recurring criteria for evaluating research is validity. Validity concerns the integrity of the conclusions that are generated from the conducted research [34]. Validation of the research is the process of determining the degree of fidelity of the system from the perspective of its intended purpose [35].

In Pedersen et al. [36] the research validation is described as structural validity and performance validity, from both theoretical and empirical perspective. Structural validity refers to the system's background information which is the foundation for the constructed system and the appropriateness of the selected examples to illustrate the problem. The performance validity states that the system produces satisfactory accuracy and that the results are useful and consistent within its domain of application.

Quist [37] describes his approach to theoretical structure validity by applying pragmatic congruence of a system where the modelled system is defined to have either weak or strong congruence to the observed system [38]. By comparing the estimated output with the observed value a quantitative evaluation of the theoretical structure validity in parameter selection and configuration is achieved.

Another important issue is the generalization of the system or external validation [34]. Can the knowledge and the results from this thesis be extrapolated from the particular context in which the research was performed?

These different aspects of research evaluation will be discussed in Chapter 10 – Discussion & Conclusions.

4 LITERATURE REVIEW

The aim of this chapter is to:

- *Provide an introduction to the modelling of comminution and classification circuits.*
- *Describe research that has focused on process simulation of crushing plants.*
- *Describe the recent research on control, optimization and operator training*
- *Describe the research on factors that influence plant performance.*

The research done on crushing plant simulation is diverse. The focus is mainly concentrated on single production units and steady-state simulations of process plants. Less focus is given to the interaction between different units, the operation of the plant and process controls. This seems to be the tradition in both the mining and the aggregates industry.

4.1 COMMINUTION

The essential parts of any crushing plant are the size reduction and size separation processes. The classical comminution theories, which were derived by Rittinger [39], Kick [40] and Bond [41] respectively, aim to describe the relation between comminution energy and size reduction for a given feed size. These three theories, are usually referred to as the first, second and third theory of comminution. These theories provided an estimation of product particle size from empirical testing for crushing and grinding. A significant drawback of these theories is however that they only rely on a single point on the particle size distribution curve as pointed out by Lindqvist [42], namely f_{80} and p_{80}. This is not enough to characterize the whole particle size distribution curve and can only provide a rough estimation of the breakage behaviour in comminution equipment. Walker et al. [43] and later Hukki [44] pointed out a more general form of the relation between comminution energy dE, size reduction dx and particle size x^n in Eq. 4.1. The energy is directly proportional to the size reduction but inversely proportional to particles size x depending on material energy constant C.

$$dE = -C\frac{dx}{x^n} \tag{4.1}$$

The most common mathematical model used today for expressing the comminution of particles is the population balance model, first introduced by Epstein, [45] Eq. 4.2.

$$f_i + \sum_{j=1}^{i-1} b_{ij} s_j m_j = p_i + s_i m_i \tag{4.2}$$

The population balance model is a mass balance equation which aims to describe the conservation of mass within a system and the transformation of material feed f_i to material product p_i. The transformation is based on the probability of particle selection s_i and particle breakage b_{ij} under a given system condition m_i [18].

The simplicity of the equation has made it popular when it comes to model size reduction in comminution equipment. Multiple researchers have applied the population balance model in different forms to express the probability of selection/breakage behaviour within specific units, such as: cone crushers [46], high pressure grinding rolls [47], ball mills [48], autogenous and semi autogenous mills [49].

Adjusting the population balance model to take into consideration the time derivative of mill content $m_i(t)$ was done by Valery, Eq. 4.3, [50]. Valery proposed dynamic models for mill ball charge, rock charge, water charge and mill liner weight as a function of feed rate, feed size, feed hardness, speed and water addition which in turn affects the power draw, grinding charge level, slurry level and product size distribution.

$$\frac{dm_i(t)}{dt} = f_i - p_i + \sum_{j=1}^{i-1} b_{ij} s_j m_j - s_i m_i \tag{4.3}$$

The applications of the population balance model are generally empirical and rely on extensive databases. There are however cases where a mechanistic modelling approach has been applied to estimate the generated collision energy within a constrained system [51].

In modelling of cone crushers there are two dominating modelling approaches: empirical modelling [46] and mechanistic modelling. A mechanistic model is a detailed analytical model based on the Newtonian mechanics [52] of the unit. A mechanistic model of a crusher has been proposed by Evertsson [6] and applied in Paper H. Empirical approximations were used in Papers A-G. These mechanistic models provide more accurate information since they take into consideration the crusher geometry and the repeated compressive crushing that occurs within the crushing chamber, see Eq. 4.4. The crusher model requires however, more detailed information about the crusher, such as geometry and form condition breakage behaviour. These models are however computational heavy and need a considerable amount of simulation time.

$$\mathbf{p}_i = \left[\left[\mathbf{B}_i^{\text{inter}}\mathbf{S}_i + (\mathbf{I} - \mathbf{S}_i)\right]\mathbf{M}_i^{\text{inter}} + \mathbf{B}_i^{\text{single}}\mathbf{M}_i^{\text{single}}\right]\mathbf{p}_{i-1} \tag{4.4}$$

Parameter $\mathbf{p}_i$ represents the product size distribution from crushing zone i and $\mathbf{p}_{i-1}$ corresponds to the product from the previous crushing zone (i-1) and the feed to zone i. Furthermore, $\mathbf{B}_i$ and $\mathbf{S}_i$ represent the breakage and selection matrix operators, respectively. $\mathbf{I}$ is an Identity matrix and the mode of breakage for each zone i is represented with the $\mathbf{M}_i$ matrix operator for both single particle and interparticle breakage.

Apart from the breakage behaviour, Evertsson also predicted crusher power draw [53], crushing pressure [53] and capacity [6]. The crusher capacity Q was formulated as an integral function with the bulk density of the material ρ in each compression zone, utility factor η, the velocity vector v of the particles during one revolution at the choke point in the crusher between the mantle radius R_i and the concave radius R_0 over the angle α, see Eq. 4.5.

$$Q_{\max} = \int_{0}^{\alpha_c} \int_{R_i(\alpha)}^{R_0} \rho(\alpha) v(\alpha) r dr d\alpha - \frac{1}{2}(\eta_{v,choke} \rho (R_0^2 - R_{i,\alpha_c}^2)) \int_{0}^{\alpha_c} v(\alpha) d\alpha \tag{4.5}$$

In Sbárbaro [54] the volume accumulation was described with the standard mass balance equation in Eq. 4.6. Parameters $\dot{m}_{in}$ and $\dot{m}_{out}$ represent the mass flow in and out of the system while $dm(t)/dt$ represent the rate of change of mass within the system. However, since the crusher hopper has a complex geometry the correlation between accumulated volume and level is nonlinear.

$$\frac{dm(t)}{dt} = \dot{m}_{in}(t) - \dot{m}_{out}(t) \tag{4.6}$$

4.2 CLASSIFICATION

Classification divides the mass flow according to specific size fractions, shape or properties. Classification is traditionally simulated with quite simple mathematical models. The most common approach is the phenomenological efficiency curve first introduced by Reid and Plitt [55, 56], see Eq. 4.7 and used in Papers A-H. The Reid-Plitt efficiency curve is based on the continuous probabilistic distribution proposed by Rosin-Rammler [57].

$$E_i = 1 - e^{\left(-\ln 2 (x_i)^{5.846}\right)} \tag{4.7}$$

The efficiency E_i is the weight fraction of a size range that is carried over to the oversize screening product x_i which is the relation between the cut point and the selected size fraction. The parameter m is the sharpness of the separation. Other forms of representing the efficiency of the separation are with the exponential sum expression derived by Whiten [46], in Eq. 4.8, and the polynomial function derived by Hatch and Mular [58]. Parameter α represents the sharpness of the cut and x_i is the relation between the cut point and the selected size fraction.

$$E_i = \left(\frac{e^{(\lambda x_i)} - 1}{e^{(\lambda x_i)} - e^{(\lambda)} - 2} \right) \tag{4.8}$$

Estimation of the cut point d_{50} can be achieved with the model proposed by Karra [59] with Eq. 4.9. The cut point is determined by a number of independent factors *A-G* (correspond to the operation and configuration of the screen), the theoretical open area h_T, the surface area of the screen A_{screen} and the theoretical amount of material $\dot{m}_{us}$ below the aperture in the feed.

$$d_{50} = \alpha h_T \left(\frac{\dot{m}_{us} / A_{screen}}{ABCDEFG} \right) \tag{4.9}$$

A more detailed analytical model based on the Newtonian mechanics [52] of vibrating screens has been proposed by Soldinger Staffhammar [9] and applied in Paper I. The mass flow is described by introducing layers in a segmented environment based on discrete step time Δt. The particles move through the bed ($\dot{m}_{i+1}$, $\dot{m}_i$, $\dot{m}_{up}$ *and* $\dot{m}_{down}$) by stratification due to the inclination and the oscillating motion of the deck, see Eq. 4.10. If a particle is within a given size fraction that is smaller than the aperture and it is in the contact layer, the probability of the particle to pass through the deck is determined by the mass flow of particles in the contact layer ($\dot{m}_{BP}$) and by a passage rate parameter k_j.

$$\dot{m}_{i+1,j,n_l} = \dot{m}_{i,j,n_l} + \dot{m}_{down,i,j,n_l-1} - \dot{m}_{up,i,j,n_l} - \dot{m}_{BP,i,j} k_j \Delta t \tag{4.10}$$

4.3 STEADY-STATE SIMULATION

Research on numerical crushing plant simulations has been conducted since the 1970´s, by researchers such as Lynch [60] and Whiten [46] (JKSimMet at JKMRC), King [19] (MODSIM at University of Utah) and Svedensten [16] (PlantDesigner at Chalmers University of Technology). These software, as well as Bruno (Metso Minerals), IES (CRC Ore) and Aggflow (BedRock Software LLC), are all steady-state simulations packages which are industrial standards for evaluating plant performance in both the aggregates and the mining industry.

According to Morrison and Richardson [20] there are three main application areas for steady-state process simulations:

- Data analysis
- Plant optimization
- Plant design

Data analysis of survey data with steady-state simulations is achieved by mass balancing and model fitting to obtain a best estimation with data redundancy from survey data [18]. This is necessary since equipment will exhibit different performance and load conditions during an operation and survey data only provides a snapshot of the process at a particular place and at a particular time.

Steady-state simulations have been used with great success for plant analyses and optimization [16, 61]. However, these simulators lack a certain perspective of the operation, namely, changes in the system over time and the performance at non-ideal operating conditions.

Steady-state process simulations are often used to evaluate and compare different circuit configurations and design [62]. Relying on steady-state simulation alone can however cause considerable operational issues. Steady-state simulations do not take into consideration material handling, regulatory or supervisory controllers and maintenance strategies which will have associated operating and maintenance issues throughout the circuit [63].

4.4 DYNAMIC SIMULATION

A commonly used platform for dynamic simulation is Simulink which is developed by Mathworks. However, other commercial software packages are available such as SysCAD and ProSim, as previously mentioned.

Whiten [64] was one of the first to discuss the necessary transition steps from steady-state models to dynamic models. The initial points only included: short constant residence time in production units, constant delay in conveyors and a variable delay time for material flow based on the last in – first out principle (LIFO). Additionally, it was enough to represent the particle size distribution with only five fractions.

The initial attempts to add dynamic perspective to steady-state simulation of crushing was done by Herbst and Oblad [65]. This was done by estimating discrete crushing zones in a cone crusher and with a static estimation of product size distribution as a function of mass flow, power, level in the crusher and feed size distribution. Disturbances were imposed on the circuit by altering feed rate, particle size distribution and ore hardness.

In the work by Sbárbaro [66], empirical models were used and modified to give the processing plant a dynamic response. This is done by including accumulation of mass, time delay and simple mixing models to enable model-based control system design. Sbárabro states that even though mechanistic models are able to provide a detail estimation of the factors affecting the unit, the empirical models are more feasible since they provide a reasonable compromise between representability and simplicity. However, no consideration was given to dynamic response of the actuators, gradual changes due to wear or discrete events.

Similar to Sbárbaro, Liu et al. [67], adds accumulation of mass, time delay and mixing models to empirical models. The focus is on a grinding circuit to visualize the possibilities of using dynamic simulation. The mill is assumed to have a constant residence time and three perfect mixers in series. The equipment used in this study only includes a mill and a hydrocyclone where even the model for the hydrocyclone does not include any dynamics, thus limiting the general purpose use of the model.

In Itävuo´s work [68] the base for the dynamic modelling is the mechanistic crusher model developed by Evertsson [6], with the addition of the effects from material properties studied by Ruuskanen [69]. Itävuo estimates the response of the actuators under different conditions to be able to estimate the actual response of the crusher when discrete changes are initiated such as changing the CSS. These simulations are computational heavy making the simulation time long and not suitable for all purposes, however these simulations are able to supply qualitative information about the process response and are therefore well suited to the development of a control system.

4.5 PROCESS CONTROL

Due to the nature of dynamic simulations the material stockpiles, bins and flows need to be controlled. In crushing plants, different types of regulatory and supervisory control loops are used to ensure safe operation while striving for high product quality and high production throughput.

Large majority of industrial controllers are regulatory Proportional-Integral-Derivative (PID) controllers and as high as 90-95 % of industrial controls are PID based [70, 71]. However, the derivative term is usually not included [71], resulting in a PI controller.

In recent years a large focus has been on different applications of feedback controllers in different crushing circuit configurations. These include: traditional PID approach [68, 70], ratio control [70, 72, 73], limiting controllers [54, 70], MIMO-PI controller [71], cascade controllers [71], mass balance method [71], linear quadratic regulators [74] and predictive PI controllers [70, 71]. All in order to improve the controllers' capability to reject disturbances and keep a stable process.

Supervisory controllers have been proposed to optimize the production in real time. On-line optimization has been done by Hulthén [12] by using a Finite State Machine (FSM) and an evolutionary operation approach as a supervisory controllers to identify optimum process parameters on-line. Atta has also demonstrated the possibility of using an Extremum seeking control to locate optimum configuration of the ES and CSS in a cone crusher [75].

4.6 OPTIMIZATION

An Evolutionary Algorithm (EA) has been used both for optimization of crushing circuits [16, 76] and crushing equipment [7, 77] successfully. The selection of Genetic Algorithm (GA) is best motivated by the algorithm capability to handle nonlinear complex problems and discrete variables [16, 78]. The drawback with the GA is the relatively long computational time compared to other optimization algorithms due to its stochastic approach and the risk of locating only local minimum.

Within the context of minerals processing research the term optimization is sometimes used instead of process improvements. In Napier-Munn et al. [18] an iterative manual method is described where the parameters are selected by inductive reasoning. Even if the method shows a potential for process improvements it is no guarantee that it is the process optimum. A systematic approach to process improvements through process surveys is to perform an experimental design. An experimental design provides an efficient way to improve the validation domain of the sample and obtain process improvements by studying the response surface from individual factors and their interactions [79].

4.7 OPERATOR TRAINING

The operators are an essential part of the process but are often overlooked [80]. Even though a major part of the process is controlled by automation the operators still interact with the process on different levels.

In Li et al. [24] the limitations regarding Human-Machine-Interfaces (HMI) are described using a simplified human supervisory model. The model consists of four different phases of human interaction with displays: detection, analysis, action and evaluation. In this study the authors identified several limitations when it comes to operator interaction with the process, one of them being the operator training. Li states that the lack of systematic training is probably the key bottleneck for enhancing the capacity of the human operator when it comes to control needs of the automation system.

Operator training allows the operator to interact with the simulated process in real time through a HMI. In the recent work of Toro et al. [81, 82] online applications were developed to allow the operators to log on, run predefined scenarios and score points with regards to the performance of the circuit. In both cases a limited part of the circuit was simulated.

4.8 FACTORS INFLUENCING PLANT PRODUCTION

Every production process experiences dynamic behavior as a result of internal and external disturbances. The process can be sensitive to wear, size segregation of the material, natural variations and more.

Wear on equipment and components in comminution circuits is extensive due to the physical nature of the crushing process and the abrasiveness of the rock material. It will have different effects on the process depending on the production unit and rock material. The study of wear in comminution is a reoccurring subject both due to the fact that it affects the production [12, 25, 83] and because of the environmental impact [84]. The wear in compressive crushers, such as gyratory and cone crushers, is typically categorized as only abrasive [25], this causes changes in the liner profiles and in turn affects the crusher´s performance. The amount of wear in a cone crusher depends on a number of factors such as material properties [65], particle size distribution [25] and moisture [85]. Bearman and Briggs stated that time dependency in a cone crusher is an important issue and dramatic reductions in performance can occur in a passive operating environment. An active environment includes matching the crusher control strategies, liners design and different operational strategies to the operating conditions and the product requirements [86].

Research on wear on screening media is not as comprehensive as the wear in crushers and mills but as pointed out by Svedensten [16], wear on screens does cause larger aperture on the deck and therefore alters the particle size distribution of the screened product. This is a large problem when considering quality of the aggregates production where production of a particular particle size is important because of quality requirements [87].

Segregation and inadequate material handling can reduce plant performance and product quality. In Powell et al. [88], several problems are identified that are considered to be a direct consequence of segregation and inadequate material handling in a dry crushing section in a mining application. If not attended to, these problems can cause reduced plant performance and could even cause premature equipment failure. Factors such as lower product quality, uneven wear, high stress amplitudes and premature equipment failure are considered as consequences of segregation and misalignment of crusher feed [89, 90].

Non-linear process behaviour is a part of the actual process. Hoppers and bins can have irregular geometries and even dead volumes which will affect how the mass flows and feeders' response will vary depending on their type and size. In Itävuo et al. [71] the non-linear and asymmetrical behaviour of a vibrating feeder was illustrated, Figure 12. Additional nonlinear performance will occur during overloading of screens [88] and from misaligned and non-choked conditions in crushers [89].

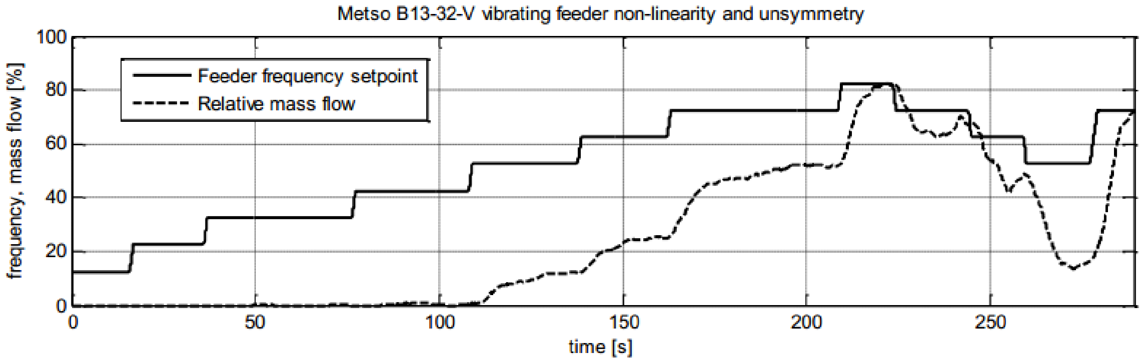


Figure 12. Non-linear response of a vibrating feeder [71].

One of the challenges in plant simulation is the estimation of natural variations. Variations occur everywhere, both in the production units and in the rock material itself [91]. Continuous monitoring, such as mass flow meters [12] and image analyses of particle size distribution [92] can provide helpful information about the process variations but certain information can still only by gathered by manual sampling from the process (material properties and often particle size distribution). This is not ideal as the samples are small compared to the amount of processed material and only reflect a momentary state at a certain part of the process.

Several factors that affect equipment performance with specific focus on cone crushers have been discussed from a holistic perspective by Evertsson [6] and from a time dependent perspective by Bearman and Briggs [86]. The effect of varying feed by, for example, feed grading, crushability, moisture content and more has been described in detail by Ruuskanen [69] but most of the data has been gathered when studying one factor at a time, therefore not taking into consideration the possible effects of interaction.

5 MODELLING OF CRUSHING PLANTS

The aim of this chapter is to:

- *Introduce the characteristics of dynamic modelling.*
- *Explain the modelling approach adopted in this thesis.*
- *Present the different elements needed for dynamic modelling of crushing plants.*

Modelling and simulation of industrial processes, such as crushing plants, provides an insight into the internals of the process which would be difficult to obtain otherwise. However, the modelling process is a complex task involving different systems that requires different modelling techniques depending on the characteristics of the problem.

In general, dynamic plant simulations include a number of different factors which affect the dynamic performance of the system. The process can be sensitive to startups, discrete events, wear, segregation, natural variations and other factors that commonly occur during operation. All depending on interaction between single production units, plant configuration, plant control loops and diverse events and disturbances that can influence the process, see Figure 13.

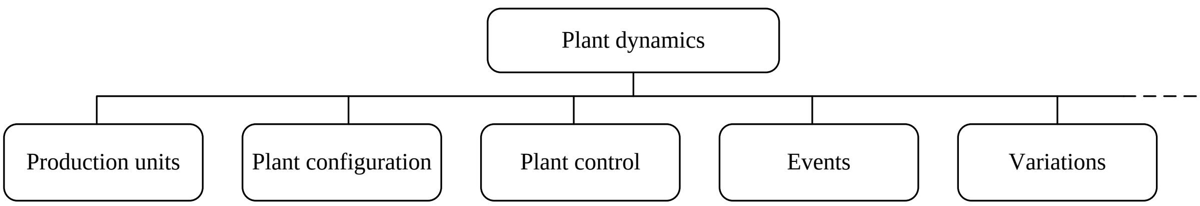


Figure 13. Plant dynamics can originate from different sources in the process operation.

Changes and variations occur everywhere in the process and can be either discrete or gradual. Figure 14 illustrates factors that can affect the total performance of the plant in one way or another, ranging from different settings of a single production unit to unavoidable consequences of the process such as wear and segregation. How these elements affect the process is dependent on multiple factors involving both the rock material itself and the utilized production units.

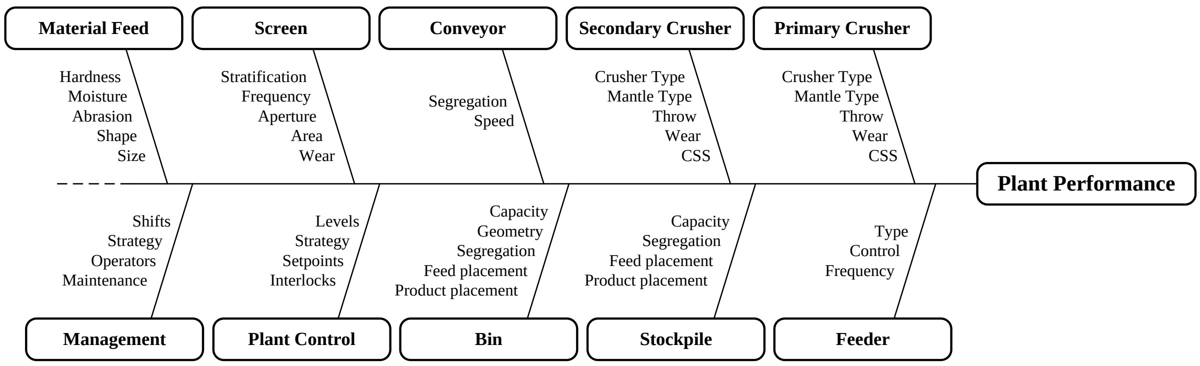


Figure 14. Cause-and-effect diagram over factors that can influence plant performance.

5.1 MODELLING APPROACH

A system approach was adopted for the modelling work in this thesis. With a system approach the modelling is done with a top down design perspective. In other words, the system is divided into smaller subsystems or models, denoted by the equipment level. Each subsystem can be further divided into smaller modules to represent the functional or fundamental level of a particular subsystem. Each subsystem is built as an individual model and can therefore be handled separately. Figure 15 illustrates the hierarchal structure of the modelled system.

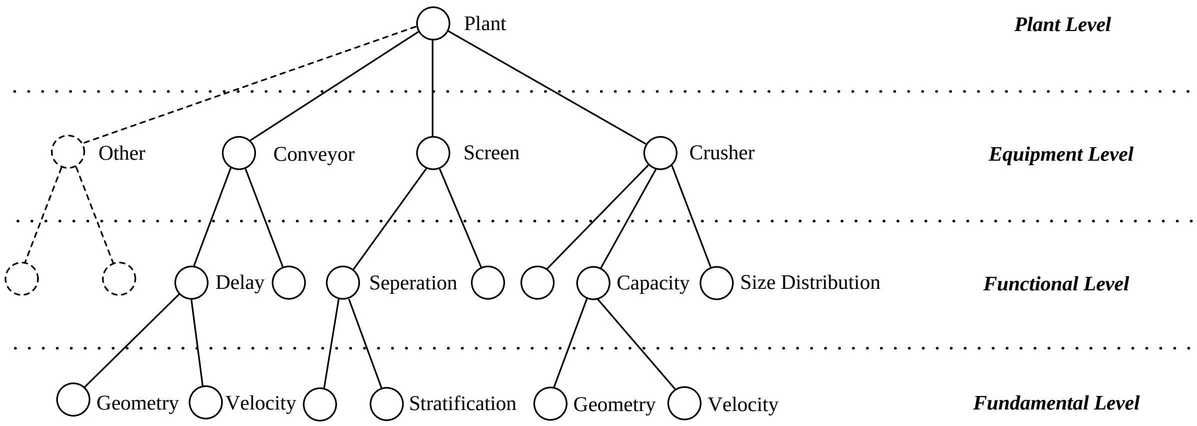


Figure 15. Illustration of the system hierarchy.

Since each single equipment model is an independent entity, the signal between the models needs to be standardized. The signal is transferred from one model to another and is transformed as it moves through each model. The signals contain information about the material which affects the performance of the system

The description of the material $u_{i,m}(t)$ includes information about the particle size distribution $f_i(t)$, the mass flow $\dot{m}(t)$ and properties of the material $\gamma(t)$ as illustrated in Eq. 5.1. Each model's output is bundled together into a vector which is sent as an input signal to the next model which in turn extracts the necessary information. Within each model a set of design parameters is defined as equipment specific input $u_{i,p}(t)$.

$$u_{i,m}(t) = \begin{bmatrix} f_i(t) \\ \dot{m}(t) \\ \gamma_i(t) \end{bmatrix} \tag{5.1}$$

Each module is expressed as a set of mathematical equations which is used to predict the performance of the system. The mathematical equations can be derived from fundamental principles of the physical behaviour of the system or empirically from experiments which aim to explain the correlation between different parameters. Simplifications and qualified assumptions are often needed in order to assure that the level of fidelity of the simulation matches the required computational time.

5.2 PLANT MODELLING

A crushing plant is a system of different production units and components connected together. The modelled system is built up by multiple subsystems connected together to form a plant model. A single crushing stage modelled in Simulink is illustrated in Figure 16. Each system consists of different time dependent production unit models that estimate the units´ size reduction, size separation, material transport or material storage depending on the unit. Each involved subsystem is arranged in an appropriate process structure and connected together. Once the process has been defined, the machine and operating parameters are configured according to user preference. Appropriate material properties are specified and operating conditions are defined. Finally, control loops for the circuit are created and discrete events are defined. These factors will determine the predicted performance of the system.

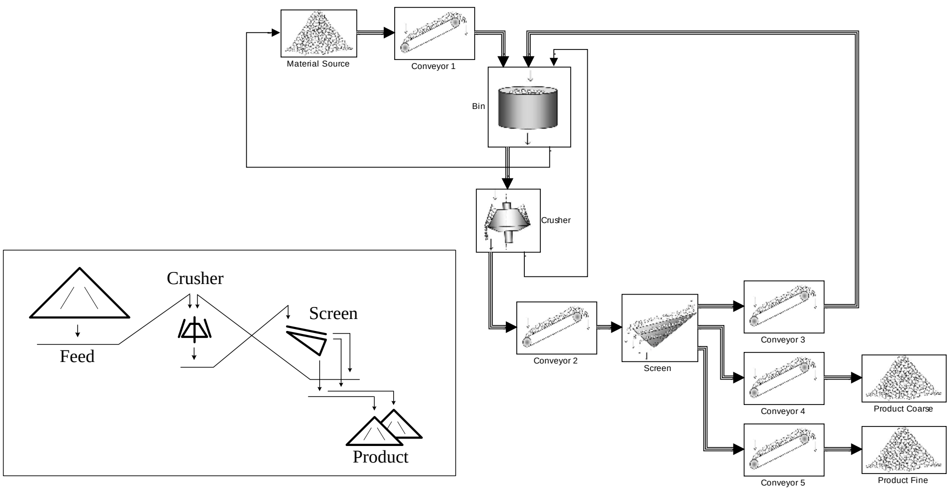


Figure 16. Flowsheet of a single crushing stage in Simulink with a simplified layout of the plant in the embedded picture. The broad signal lines between the production units represent the material signal presented in Eq. 5.1 while the thin signal lines are set points $y_{sp}(t)$ and process values $y_{i,p}(t)$.

The modelling work has been carried out with two different simulation platforms for comparison. The work was initiated with the simulation software SysCAD which is a commercial simulator with a built-in equipment library. The modelling work continued with Simulink in order to enable a more detailed level and flexibility of the models. Simulink is a commercial simulation software developed for simulating and analysing dynamic and discrete systems by Mathworks. It is widely used within many different types of industries as well as within academia for representing process behaviour and control systems. Simulink provides a graphical programming user interface with block-oriented modelling.

5.3 MODELLING SYSTEM DYNAMICS

The essential modelling principle in traditional steady-state simulation is that the system is at mass balance and with all derivatives equal to zero, Eq. 5.2. A general mass balance equation for a three stream connection point is illustrated in Eq. 5.3 where a_{SR} is the split ratio of the incoming mass flow, $\dot{m}_{in}$, to the two outgoing mass flows, $\dot{m}_{1,out}$ and $\dot{m}_{2,out}$.

$$\frac{dx_i(t)}{dt} = f(x_1(t),...,x_n(t),u_1(t),...,u_m(t)) = 0 \tag{5.2}$$

$$\left.\begin{aligned} \dot{m}_{1,out} &= (1-a_{SR})\dot{m}_{in} \\ \dot{m}_{2,out} &= a_{SR}\dot{m}_{in} \end{aligned}\right\} \Rightarrow \dot{m}_{in} = \dot{m}_{1,out} + \dot{m}_{2,out} \tag{5.3}$$

In a dynamic system, the system experiences different operating conditions when changes occur in the system. This results in the time-derivative not being equal to zero as defined in Eq. 5.2. These dynamics are usually consequences of an altered state of the plant over time due to factors such as natural variations, unmatched, inappropriate or degrading equipment performance and stochastic events.

In Figure 17 a general representation of a dynamic system is illustrated. The process model illustrated in Figure 17 represents a single unit which can be a crusher, a screen, a conveyor, etc. The input u includes information about the material characteristics ($u_{i,m}(t)$ in Eq. 5.1) and the design parameters $u_{i,p}(t)$. The material characteristics information fed into the model is the cumulated particle size distribution, mass flow and material properties as illustrated in Eq. 5.1. While the design parameters are the settings of the production unit involved, these can be fixed, such as Eccentric Throw (ET) in a crusher, or variables which can change over time, such as CSS. The disturbance, denoted with $w_i(t)$, illustrates the external changes in the process causing both gradual and discrete changes in the performance. The output $y_{i,m}(t)$ is the transformation of material through the model and $y_{i,p}(t)$ is equipment specific process value such as levels and power draw. The output signals are constructed in the same way as the input signals as they are often sent to a subsequential model. The internal state variable x and the differentiation of variable x describe the state of the system such as the accumulation of mass.

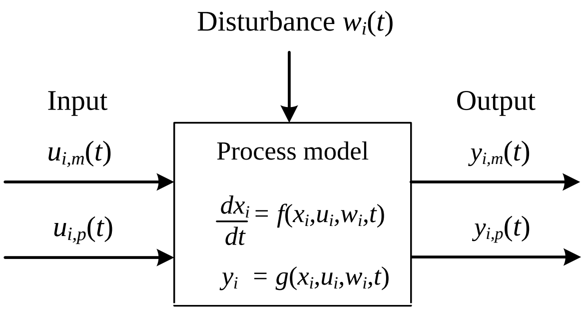


Figure 17. General representation of a dynamic system. The output $y_{i,m}$, $y_{i,p}$ and dx_i/dt are functions of inputs $u_{i,m}$ and $u_{i,m}$, the disturbance w_i and the internal state variable x_i, with respect to time t.

5.3.1 CONSERVATION OF MASS

One of the fundamental principles of simulating dynamic systems is the conservation of mass. In the mass balance equation previously presented, in Eq. 5.3, it was presumed that the total mass flow into the system was equal to the mass flow out of the system. In a dynamic simulation these constraints do not need to be fulfilled to have a system in mass balance. Instead the accumulated material in the system will change according to Eq. 5.4.

$$\frac{dm(t)}{dt} = \dot{m}_{i,in}(t) - \dot{m}_{j,out}(t) \tag{5.4}$$

The mass in the system $m(t)$ is therefore a result of the mass flow into the system $\dot{m}_{i,in}(t)$, minus the mass flow out of the system $\dot{m}_{j,out}(t)$. Mass cannot disappear nor be created, except in the source material block. The particle size distribution and the properties of the material $\gamma(t)$, in Eq. 5.5, such as shape, density and material strength are retained within the bulk material with a perfect mix model that is dependent on the accumulation of material and the mass flow into the system $\dot{m}_{i,in}(t)$ as illustrated in Eq. 5.6.

$$\gamma_i(t) = \begin{bmatrix} \gamma_1(t) \\ \gamma_2(t) \\ \vdots \\ \gamma_n(t) \end{bmatrix} \tag{5.5}$$

$$\frac{d\gamma_i(t)}{dt} = \frac{\dot{m}_{i,in}(t)}{m(t)}(\gamma_{i,in}(t) - \gamma_i(t)) \tag{5.6}$$

In Paper B a bin model was developed to estimate funnel flows in bins that are designed with a large flat bottom. This bin model was needed to increase the fidelity of the simulation due to process disturbance from uneven material flow and dead volumes. The developed model is depicted in two dimensions in Figure 18 where the bin is divided into several segments n in order to simulate the flow within the bin. A third dimension can be included with additional modelling and constraints to further increase the fidelity of the flow.

The model is defined by the number of segments n within the system and bed surface behaviour ($y_1(t)$, $y_2(t)$, ... $y_n(t)$). The feed i_f and product i_p placement are positioned in an appropriate section according to the reference. The basic measurements for the bin are entered: length l_g, width w_g and height h_g, in order to estimate the available space within the system. Looking into a single segment, the mass flow ($\dot{m}_{in}(t)$, $\dot{m}_{in,Left}(t)$, $\dot{m}_{in,Right}(t)$, $\dot{m}_{out}(t)$, $\dot{m}_{out,Left}(t)$ and $\dot{m}_{out,Right}(t)$) and bulk density ρ within that particular segment can be described by Eq. 5.7.

$$\frac{dy_i(t)}{dt} = \frac{n}{wl\rho}(\dot{m}_{in}(t) + \dot{m}_{in,Left}(t) + \dot{m}_{in,Right}(t) - \dot{m}_{out}(t) - \dot{m}_{out,Left}(t) - \dot{m}_{out,Right}(t)) \tag{5.7}$$

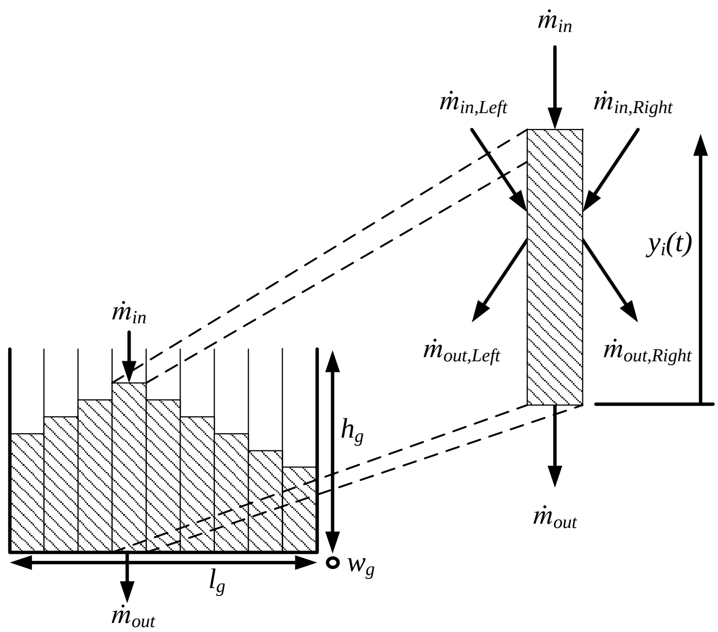


Figure 18. Principle idea with the segmented bin model.

During operation, as well as in simulations, the material focus is always on the total mass of the transported material. This is measured during operation with belt scales but this has to be changed into volumetric flow to be able to calculate the amount of space that a specific mass occupies. Volumetric flow rate $\dot{V}(t)$ is defined in Eq. 5.8, where $dV(t)$ equals the change in volume, $dm(t)$ equals the change in mass, dt is the time interval for the mass and ρ is the density of the bulk material.

$$\dot{V}(t) = \frac{dV(t)}{dt} = \frac{dm(t)}{\rho dt} \tag{5.8}$$

The flow of material within the bin will determine the material flow in the bin $\dot{m}_{in}(t)$, from the bins $\dot{m}_{out}(t)$ and surface level y. Since the material is segmented into n number of segments, the flow between segments is constrained by conditions that depend on the volume available in neighbouring segments i, the angle of repose α, the length of the bin l_g and the section placement of the feed inlet i_f and product outlet i_p respectively. In Eq. 5.9 the fundamental constraints of the flow are given and in Figure 19 a representation of flow during different conditions is illustrated.

$$\dot{m}_{in}(i) = \begin{cases} \dot{m}_{in}(t) & \text{if} \rightarrow y(i_p) - y(i) < \frac{l_g}{n}\tan(\alpha)\left|i_p - i\right| \\ \dot{m}_{in}(t) / \sum (y(i_p) - y(i) < \frac{l_g}{n}\tan(\alpha)\left|i_p - i\right|) & \text{if} \rightarrow y(i_p) - y(i) > \frac{l_g}{n}\tan(\alpha)\left|i_p - i\right| \end{cases} \tag{5.9}$$

$$\dot{m}_{out}(i) = \begin{cases} \dot{m}_{out}(t) & \text{if} \rightarrow y(i_f) - y(i) > \frac{l_g}{n}\tan(\alpha)\left|i_f - i\right| \\ \dot{m}_{out}(t) / \sum (y(i_f) - y(i) > \frac{l_g}{n}\tan(\alpha)\left|i_f - i\right|) & \text{if} \rightarrow y(i_f) - y(i) < \frac{l_g}{n}\tan(\alpha)\left|i_f - i\right| \end{cases}$$

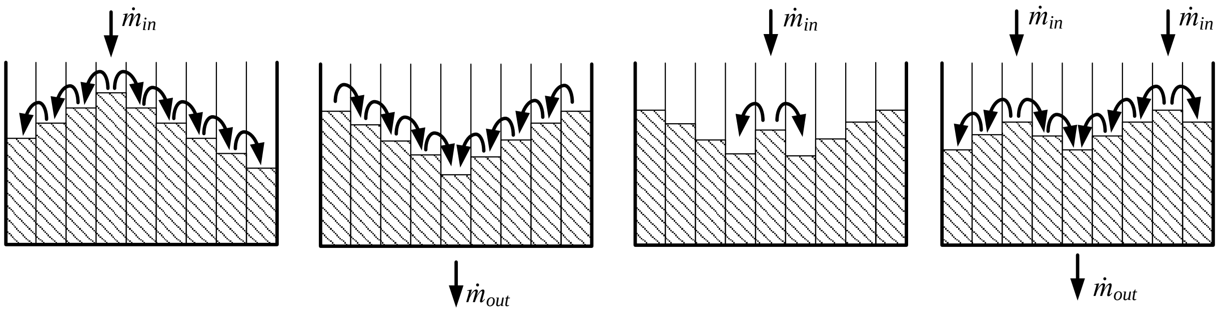


Figure 19. Representation of the flow under different conditions.

In Paper F a model for laminar material flow was presented. A perfect mixed model, as described by Eq. 5.6, perfectly blends the material and smoothens out all discrete changes in the particle size distribution and material properties. A first in-first out (FIFO) bin model was developed which was able to represent the laminar flow that can occur in bins with a high height-to-width ratio and steep bottom angle, see Figure 20 [93].

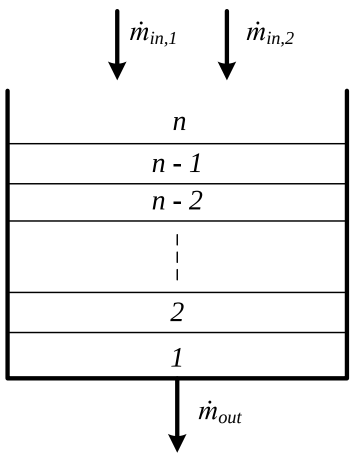


Figure 20. Principle idea with the FIFO bin model.

In a bin or a hopper with a complex geometry there will be a nonlinear relationship between measured level and occupied volume within the system. In Paper H a non-linear function was proposed to represent this relationship in a crusher hopper, see Figure 21.

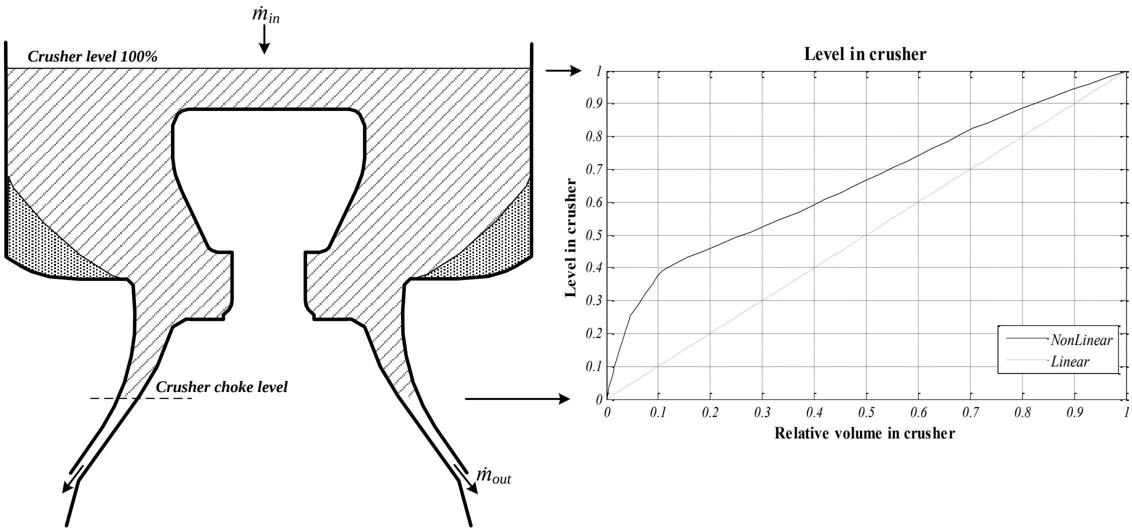


Figure 21. The relation between occupied volume and level in crusher. The available volume is marked with a cross-hatched area while the dead volume is marked with the shaded area.

5.3.2 DISCRETE EVENTS

During operation, plants should operate at or near full capacity. But due to different unit's reliability and maintenance strategy there are always disturbances in the process due to starts and stops of individual units which will affect the process. In a worst case scenario the disturbance may cause a considerable downtime (DT) for the entire plant. The reasons for stopping the process can be anything from scheduled maintenance, for keeping a certain product quality, to a total machine breakdown as depicted in the two scenarios in Figure 22.

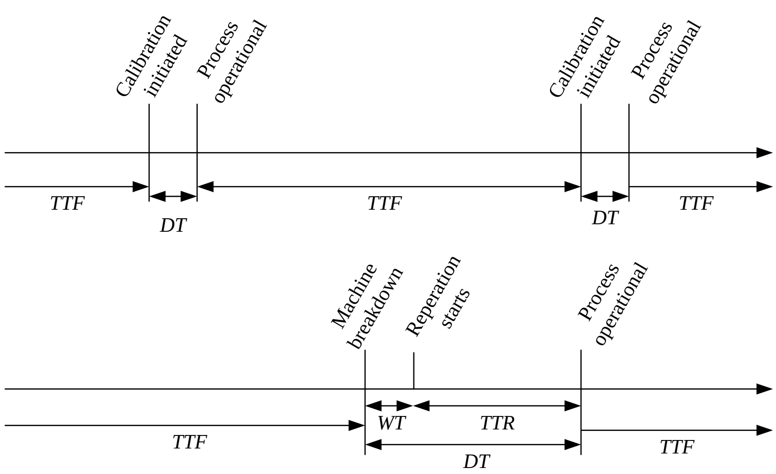


Figure 22. Two different scenarios for discrete events. The scenario above illustrates the calibration process as an event while the scenario below illustrates the consequence of machine breakdown.

The length of each downtime is determined by how well the plant is prepared to handle particular events and the severity of the breakdown. Events can be entered manually into the simulation as a single event or for deeper analyses a Discrete Event Simulation (DES) can be performed creating a hybrid simulation with discrete and continuous simulation running simultaneously. The DES model is used to represent batches and events which can in turn be used to automatically generate events that can disturb the process. The output from a DES would therefore be the time-to-failure (TTF), waiting time (WT) and time-to-repair (TTR), all being dependent on the probability of the event occurring and the severity of the problem [94].

DES models can be roughly classified into two categories, deterministic and probabilistic. With deterministic events the time and length of events are determined in advance which will give the same results every time, given that the initial conditions are the same. With probabilistic events however, the time and length of each event are not predetermined, instead the events occur depending on the selected probability distribution [15]. The principle of DES models for different events is illustrated in Figure 23 (Paper H). All discrete simulations were performed with SimEvent which is a toolbox of Simulink.

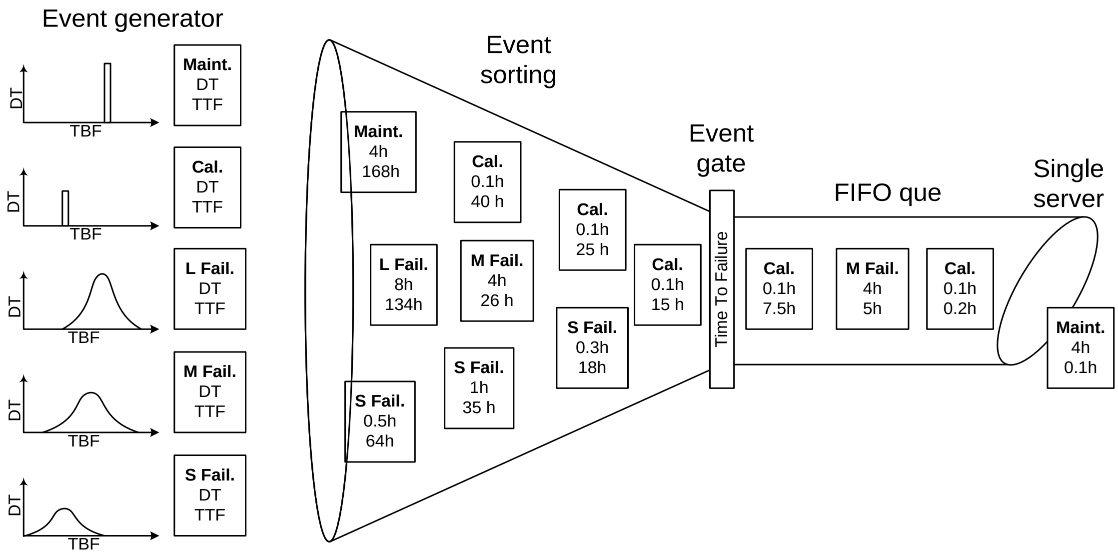


Figure 23. The principles of discrete event modelling for the process.

The definitions of different types of DT events are given in Table 1:

Table 1. Categorising the discrete events in the process.

Type	Probability	Description
External	Stochastic	Uncontrollable events outside the process
Upstream	Deterministic/Stochastic	Operational stop or stand by due to lack of feed
Downstream	Deterministic/Stochastic	Operational stops by due to downstream process full or down
In-stream	Deterministic/Stochastic	Delay or Standby due to lack of control
Failure	Stochastic	Break down that require unscheduled maintenance
Maintenance	Deterministic	Scheduled maintenance

Mechanical failures in the process were included as stochastic events with probability of failure as a function of maintenance. The failure probability is modelled as a Weibull distribution and an exponential distribution in SimEvents as shown in Eq. 5.10 and Eq. 5.11. The parameters k and λ describe the form of the distributions.

$$f(t,k,\lambda) = \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} e^{-(t/\lambda)^k} \tag{5.10}$$

$$f(t,\lambda) = \lambda e^{-\lambda t} \tag{5.11}$$

5.3.3 DYNAMIC SYSTEM RESPONSE

How a model responds to a change in a parameter during operation is crucial for the dynamic behaviour of the system. One way of simulating the step or impulse response of a system is with a differential equation or with a corresponding transfer function which can be derived analytically or empirically. Step responses from a first order system, a second order system and a pure time delay are illustrated in Figure 24 and given in Eq. 5.12-5.20.

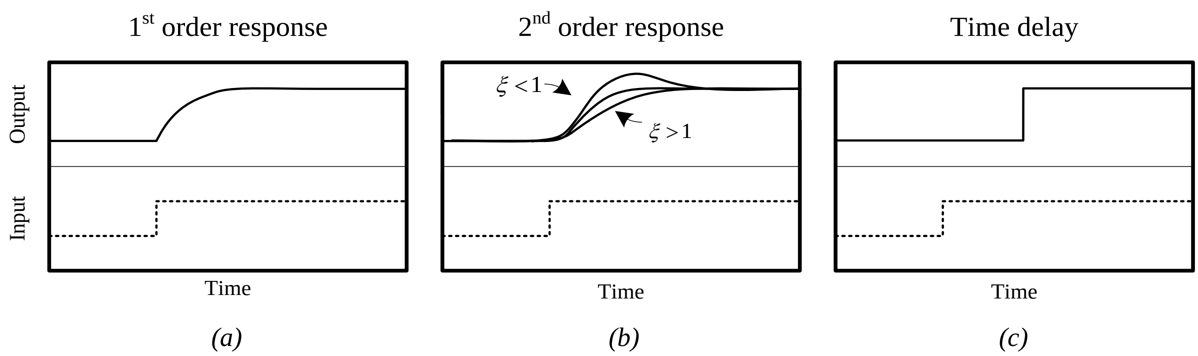


Figure 24. Step response for a first order system (a), a second order system (b) and a pure time delay (c). Modified from Marlin [95].

The response of a first order system (Figure 24a) is usually given by a simple first order differential equation in time domain or by the corresponding transfer function in frequency domain which is illustrated in Eq. 5.12 and Eq. 5.13. The parameter s is the Laplace operator. The time constant, which is denoted with a τ, is the time which the system takes to reach 63.2% of the final steady-state value which is equal to the steady-state process gain K and the difference in the forcing input $u(t)$.

$$\tau\frac{dy}{dt} + y(t) = Ku(t) \tag{5.12}$$

$$G(s) = \frac{Y(s)}{U(s)} = \frac{K}{\tau s + 1} \tag{5.13}$$

A second order system can be described with both a second order ordinary differential equation and with the corresponding transfer function in Eq. 5.14. A second order response can also be achieved by having two first order systems in a series. As with a first order system, a second order system is described with a time constant τ and the forcing function $Ku(t)$. However, an additional factor is included, the parameter ξ which is termed the damping coefficient. The damping coefficient determines if the step response which is depicted in Figure 24b, is overdamped ($\xi > 1$), underdamped ($\xi < 1$) or critically damped ($\xi = 1$). If the parameter ξ is too low the system will continue oscillating over a long time.

$$G(s) = \frac{Y(s)}{U(s)} = \frac{K}{\tau^2 s^2 + 2\xi\tau s + 1} \tag{5.14}$$

In Papers C-H a first order transfer function with delay (FOTD) was applied to the feeders installed throughout the circuit. However, in Paper F, system identification was used to get a more accurate estimation of the system response. Figure 25 illustrates the system boundaries for the system identification.

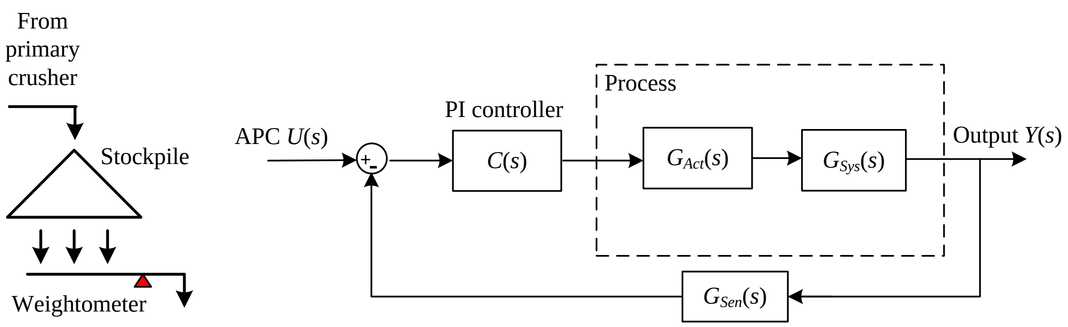


Figure 25. Illustration of the system used for system identification.

Six different linear time-invariant (LTI) models were estimated to be able to represent the system dynamics. These are LTI models with one, two or three poles, with and without zeros τ_z, critically damped with dead time θ and lag time τ_i, Eq. 5.15 - Eq. 5.20.

$$G_{P1D}(s) = \frac{Y(s)}{U(s)} = \frac{K}{1+\tau_1 s} e^{-\theta s} \tag{5.15}$$

$$G_{P2D}(s) = \frac{Y(s)}{U(s)} = \frac{K}{(1+\tau_1 s)(1+\tau_2 s)} e^{-\theta s} \tag{5.16}$$

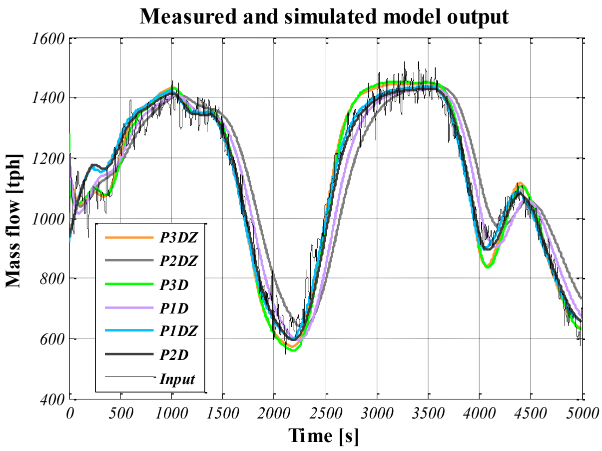
$$G_{P3D}(s) = \frac{Y(s)}{U(s)} = \frac{K}{(1+\tau_1 s)(1+\tau_2 s)(1+\tau_3 s)} e^{-\theta s} \tag{5.17}$$

$$G_{P1DZ}(s) = \frac{Y(s)}{U(s)} = \frac{K(1-\tau_z s)}{1+\tau_1 s} e^{-\theta s} \tag{5.18}$$

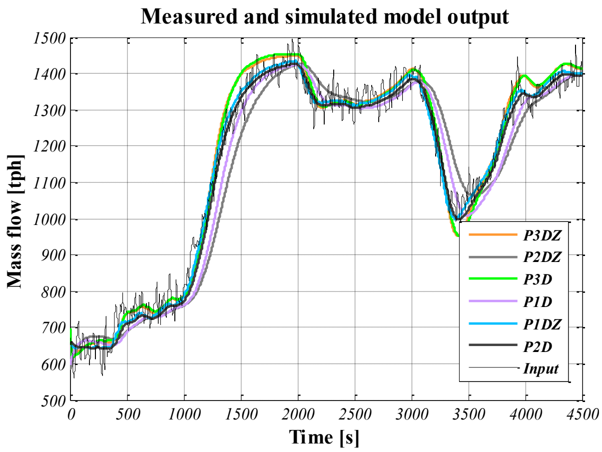
$$G_{P2DZ}(s) = \frac{Y(s)}{U(s)} = \frac{K(1-\tau_z s)}{(1+\tau_1 s)(1+\tau_2 s)} e^{-\theta s} \tag{5.19}$$

$$G_{P3DZ}(s) = \frac{Y(s)}{U(s)} = \frac{K(1-\tau_z s)}{(1+\tau_1 s)(1+\tau_2 s)(1+\tau_3 s)} e^{-\theta s} \tag{5.20}$$

A best fit was obtained with a LTI model with a single pole and a single zero. The fitted responses from the six models are illustrated in Figure 26 and the step response of each model is illustrated in Figure 27. The best fit response is marked with a blue thick line in Figure 27.



(a)



(b)

Figure 26. Measured and modelled response of the stockpile feeder for model fitting period (a) and validation period (b).

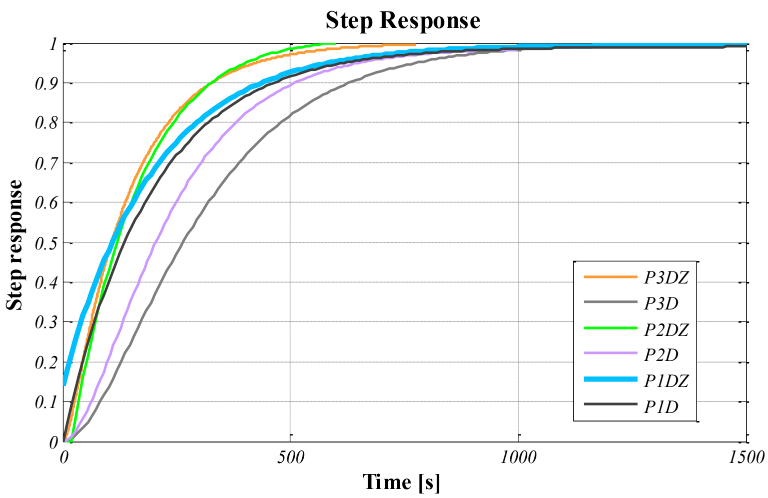


Figure 27. The step response of the different functions. The best fit was obtained with a first order transfer function with a zero (marked with a thick blue line).

The third part illustrated in Figure 24c is the dead time or transportation delay of the system. The dead time is the delayed step response of the system, the change in the input parameter u does therefore not affect the system output $y(t)$ until after the determined delay time θ has passed, as illustrated in Eq. 5.21 and Eq. 5.22.

$$y(t) = u(t-\theta) \tag{5.21}$$

$$G(s) = \frac{Y(s)}{U(s)} = e^{-\theta s} \tag{5.22}$$

Estimating the transport delay of a material is in some cases insufficient with a pure time delay. If a conveyor is equipped with a variable speed drive the material will have different dead time depending on the speed of the conveyor and the position of the material. In Paper E a state-space conveyor model capable of estimating the change in mass flow was presented, Eq. 5.22. This model keeps track of the material on the conveyor, allowing the user to manipulate the speed v of the conveyor and enable the stopping of the conveyor without deleting material. The level $\dot{x}_i$ in each segment is a function of conveyor speed v, conveyor length l_g, conveyor width w_g, the mass flow x_i between each segment, material density ρ and the number of sections n the conveyor is divided into.

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \vdots \\ \dot{x}_n \end{bmatrix} = \begin{bmatrix} -a & 0 & \cdots & 0 & 0 \\ a & -a & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & -a & 0 \\ 0 & 0 & \cdots & a & -a \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \cdot \frac{\dot{m}_{in} n}{\rho l_{\mathrm{g}} w_g}, \qquad a = \frac{vn}{l_{\mathrm{g}}} \tag{5.22}$$

The residence time of the material within different units is dependent on the material flow. The transport time for a particle travelling over a screening deck has been described by Soldinger Stafhammar [9]. In Papers E-H the Soldinger Stafhammar velocity model was used to estimate particles residence time on the screen. Where $l_{g,screen}$ is the length of the screen, f_n is the frequency of the deck, α is the slope and ET is the throw of the deck, Eq. 5.23.

$$t_{screen} = l_{g,screen} / ((0.064\alpha + 0.2)(380ET - 0.18)(0.095 f_n \alpha^{-0.5} + 0.018\alpha - 0.38)) \tag{5.23}$$

For a cone crusher the residence time $t_{crusher}$ is dependent on the occupied volume in the crusher hopper and the ES of the mantle. In Evertsson [6] a velocity profile in a vertical direction during a single nutation is derived. The residence time above the mantle is dependent on the mass flow out of the crusher while during crushing the residence time is dependent on the particles average velocity v, which is a function of ES, and the height of the mantle $l_{g,mantle}$, Eq. 5.24.

$$t_{crusher} = l_{g,mantle} / v + \frac{m(t)}{\dot{m}_{out}(t)} \tag{5.24}$$

5.3.4 WEAR

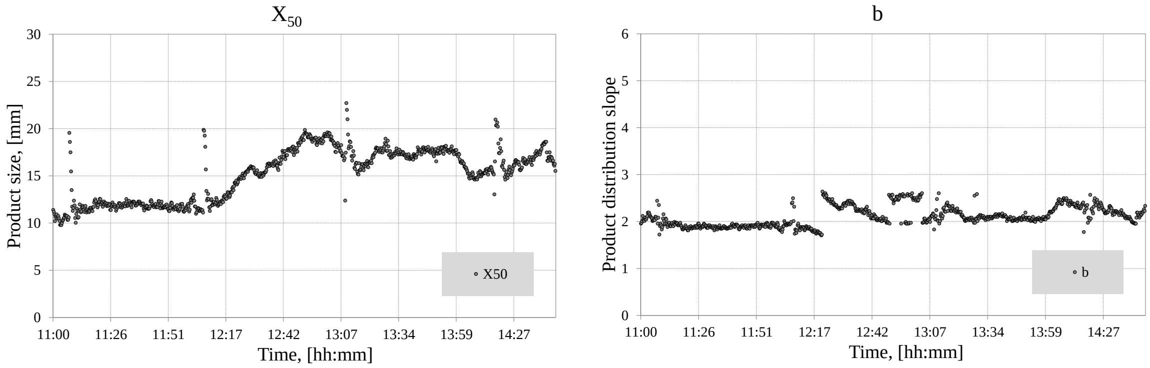
The crushing process is constantly affected by wear which causes gradual performance deterioration. How the wear affects the process is dependent on multiple factors. These include the characteristics of the equipment subjected to wear, the geometry of affected components and the properties of the rock material: mineral content, particle size distribution, moisture and more.

In Paper A, a specific focus was on the effect gradual wear has on a cone crusher and how it affects the product mass flow in the crushing circuit. The studied plant was an aggregates plant 80 km north of Gothenburg, which produces high-quality aggregates from granitic gneiss, ranging in size from 0-2 mm to 16-22 mm. All 10 conveyors in the tertiary phase of this plant were equipped with power meters that monitored and logged the electrical power draw. From these data, the mass flow could be calculated and changes in the particle size distribution estimated.

In Figure 28 and Figure 29 the calculated change in particle size distribution, due to wear, is expressed as the change in the size of the 50 % passing size x_{50} and the shape of the particle size distribution curve b as a result of a fitted Swebrec function [96] Eq. 5.25, to the logged production data. In Figure 30 the calculated change in the x_{50} parameter is displayed together with interpolated data between the measured CSS. Approximately one hour separated each measurement.

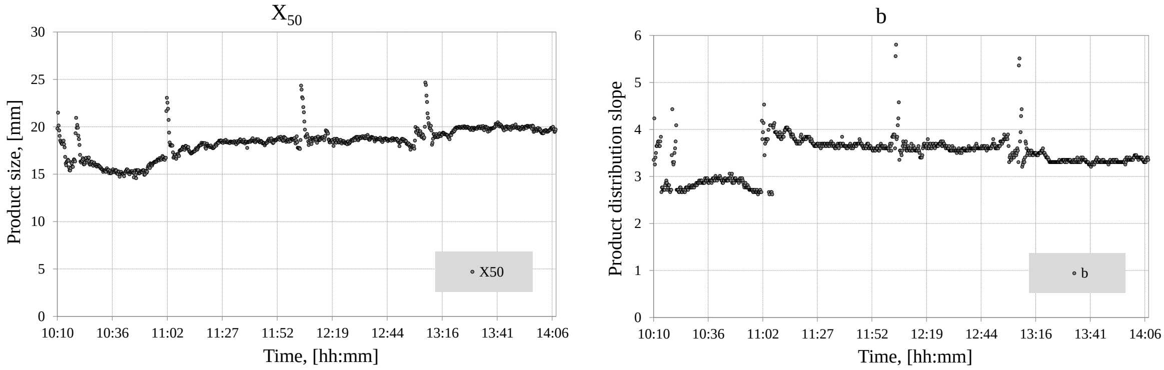
$$f(x) = \left(\frac{\ln\left(\frac{x_{\max}}{x}\right)}{\ln\left(\frac{x_{\max}}{x_{50}}\right)} \right)^{b} \tag{5.25}$$

Figure 31 shows the collected data, which is presented as a change at defined intervals, from the calibrations. Fitting a linear regression to the data points provides a simplified indication of the wear trend that occurred during the experiments. Looking at the wear rate in each single run, the rate varies between 0-3 mm/hour but when calculated together the wear rate becomes close to constant just below 1 mm/hour.



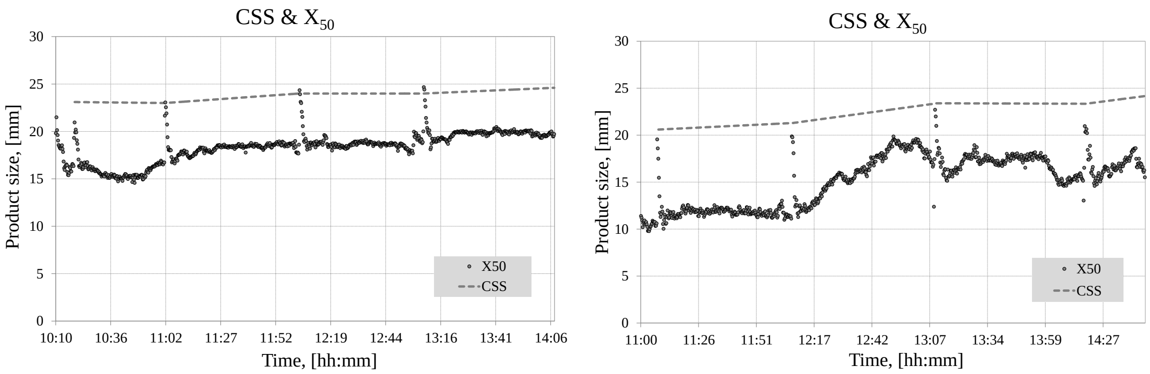
(a) *(b)*

Figure 28. Calculated change in the particle size distribution, x_{50} (a) and b (b), over time from the logged process readings of day 1.



(a) *(b)*

Figure 29. Calculated change in the particle size distribution, x_{50} (a) and b (b), over time from the logged process reading of day 2.



(a) *(b)*

Figure 30. The trend of CSS (dotted grey line - interpolated between tests) and x_{50}, (black dots – calculated from logged process readings) as a function of material flow through the crusher in two of the experiments, (a) and (b). The results are close to parallel. Spikes in the x_{50} curve indicate an interruption in the process due to calibrations or mechanical failure.

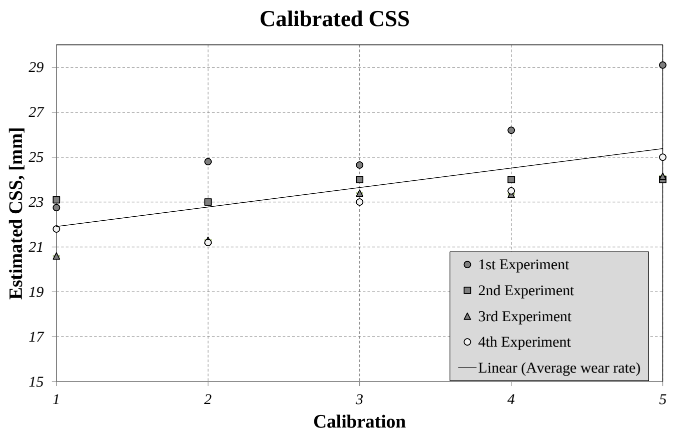


Figure 31. Linear regression of the wear trend (black line) generated from the results of the calibrations.

Eq. 5.20 was formulated to describe the changes in parameter x_{50}, given that the particle size distribution of the feed remains close to constant. Parameter a_1 is a function of the incoming particle size distribution and the condition of the crushing chamber which represents the ratio between the initial $CSS(t_0)$ and x_{50}. The parameter a_2 represents the wear rate depending on the amount of crushed material ($m_{crushed}(t)$) per hour.

$$x_{50} = a_1 CSS(t_0) + a_2 \int_{t_0}^{t} m_{crushed}(t)dt \tag{5.20}$$

5.3.5 VARIATIONS

One of the many factors that affect the plant performance is variation. Since the material is blasted from a solid bedrock the size distribution and mechanical properties of the rock is dependent on the type of explosives, the amount and location of the charge, the blast formation pattern and the geological formation of the bedrock [96]. In Papers A, C and H a varying particle size distribution of the feed was included. Figure 32 illustrates 25% increase and decrease around the reference feed size distribution to the circuit in Paper H.

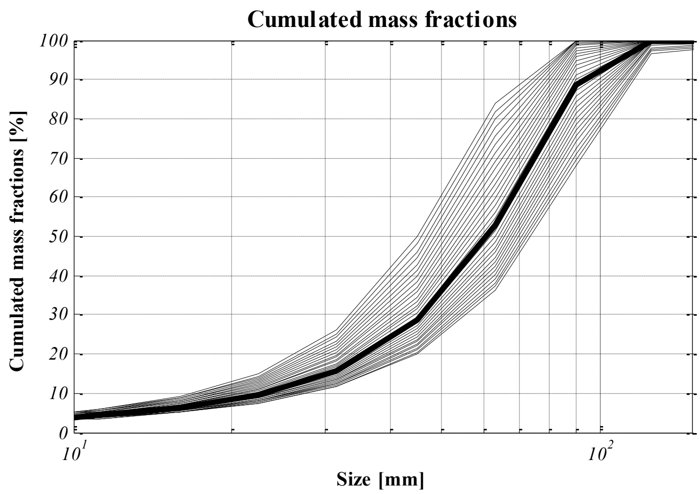


Figure 32. Systematic variation in the incoming feed from Paper H.

6 CRUSHING PLANT CONTROL

The aim of this chapter is to:

- *Introduce the different control strategies applied in this thesis.*

Due to the characteristics of dynamic simulation the material stockpiles, bins and flows need to be controlled as in reality. In crushing plants different types of control systems are commonly used to ensure safe and robust operation while striving for high product quality and high production throughput. In this thesis the controllers are defined as regulatory and supervisory controllers.

6.1 REGULATORY CONTROL

The most common form of regulatory control in comminution is the feedback control loop as illustrated in Figure 33.

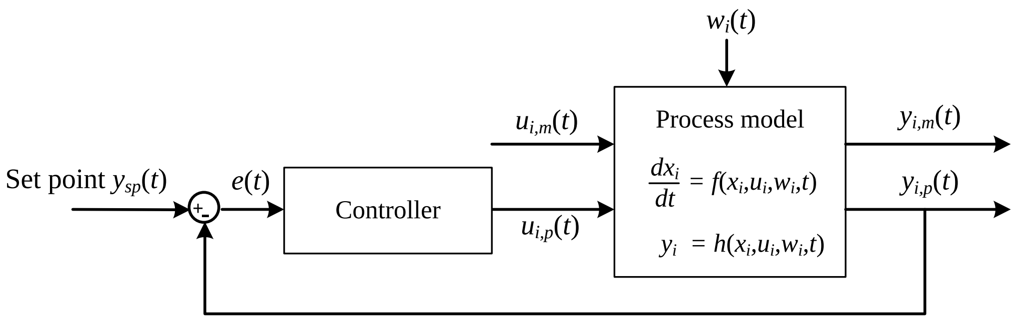


Figure 33. General representation of a feedback control loop. Modified from Marlin [95].

The feedback control loop works by manipulating variables $u_{i,p}(t)$ to change the measured control variable to a desired level in order to minimize the error $e(t)$ in Eq. 6.1, which is the difference between the process value $y_{i,p}(t)$ and the desired process value $y_{sp}(t)$.

$$e(t) = y_{sp}(t) - y_{i,p}(t) \qquad \lim_{t\to\infty} e(t) = 0; \tag{6.1}$$

The controller regulates the process to minimize the variations in the process output by compensating for the effect of disturbances in the process $w_i(t)$ or an altered reference value $y_{sp}(t)$. The most commonly used feedback controller is the PID controller, Eq. 6.2. The PID controller, as the name indicates, uses three mathematical functions to regulate the process and compensate for the error.

$$u_{i,p}(t) = K_P e(t) + K_I \int e(t)dt + K_D \frac{d}{dt} e(t) \tag{6.2}$$

A PI controller, such as illustrated in Figure 34, has been applied in Papers A-H for necessary control loops. The controller compares the set point $y_{sp}(t)$ and the actual process value $y_{i,p}(t)$ of the corresponding level and regulates the process accordingly. The level signal which is a function of the mass flow and the geometry of the production unit is sent from the monitored production unit model to the controller model as a scalar signal. How the controller reacts to changes in the process is dependent on the value of the parameters K_P, K_I and K_D, in Eq. 6.2. An increase from the estimated dead time will drive the system to an unstable operation.

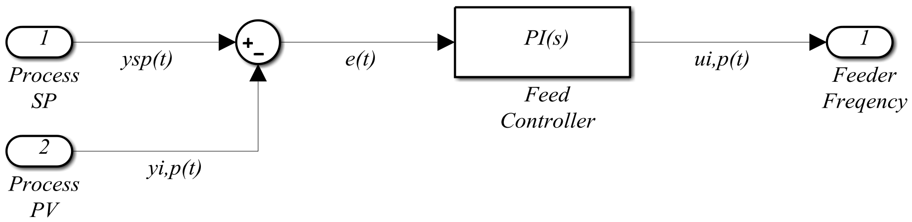


Figure 34. PI controller for the feeder frequency in Simulink.

In order to design a controller for the circuit a linear approximation can be done around the operational condition. Linear approximation has been used by Sbárbaro [54], Itävuo [71] and Airikka [70] in their controller tuning. The controller in this case aims to maintain a certain level in a bin above the crusher. A linear approximation for a part of the circuit from Paper H is shown in Figure 35.

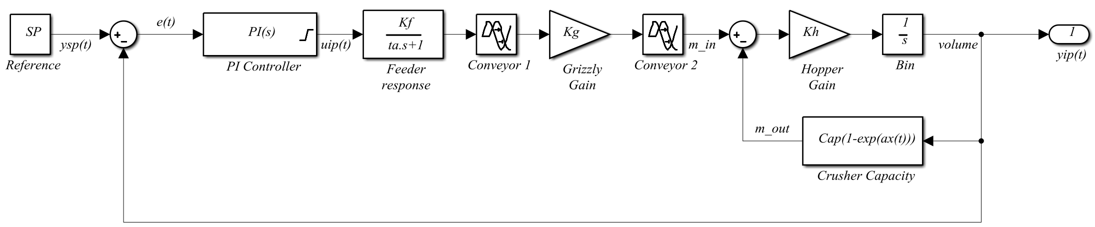


Figure 35. Linear approximation of the controlled part of a circuit.

The transient behaviour of the feeder is expressed with a LTI models. The *s* is the Laplace operator and the time constant, *T*, is the time which it takes the system to reach 63.2% of the final steady-state value which is equal to the steady-state process gain *Kf* and the difference in the forcing input $u_{i,p}(t)$. The split over the grizzly is represented with the gain *Kg* and conversion from mass flow to volumetric flow is given with the gain *Kh.*

Multiple controller tuning methods have been described by Åström [97]. In Papers A-G the controllers were tuned manually to give a reasonable response. The K_P and K_I parameters were automatically tuned in Paper H with a model-based approach in Simulink.

6.2 SUPERVISORY CONTROL

Supervisory controllers or Advanced Process Control (APC) aims to move the process output $y_{i,m}$ to an optimum process target by altering the regulatory controller´s set point y_{sp}, as illustrated in Figure 36. This can be used for example to optimize a production of a particular product in aggregates production by altering crusher ES.

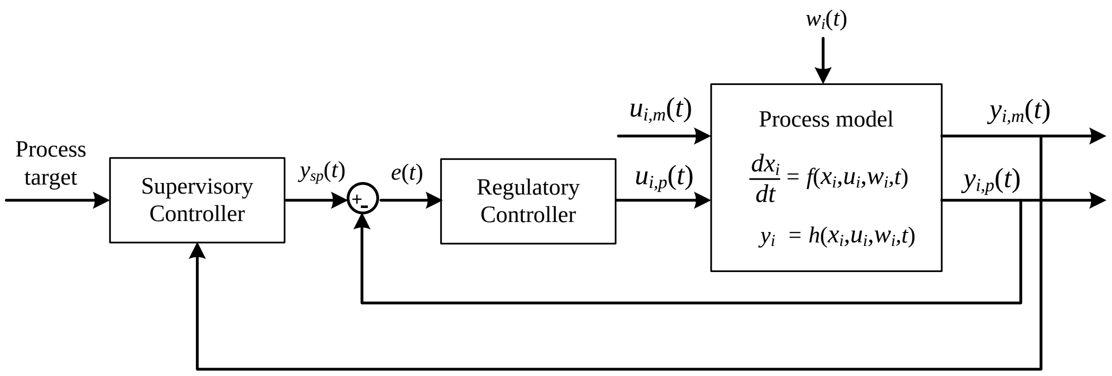


Figure 36. General feedback control loop with a supervisory controller for set point selection.

The development of an APC often entails the usage of dynamic models for predicting the behaviour of the system. This is to counteract the effect a change in the process has on the production before it occurs in the system. The models have to be sophisticated enough to be able to predict the performance of the system under different conditions.

In Paper D the purpose was to tune an existing control algorithm which has been developed by Hulthén [12]. The supervisory control algorithm was a Finite State Machine (FSM) which controls the ES of a crusher by making discrete step changes in speed (ΔES $^+$ and ΔES $^-$) with defined time intervals (LongTime) while observing the performance of the circuit. How the FSM works is illustrated in Figure 37.

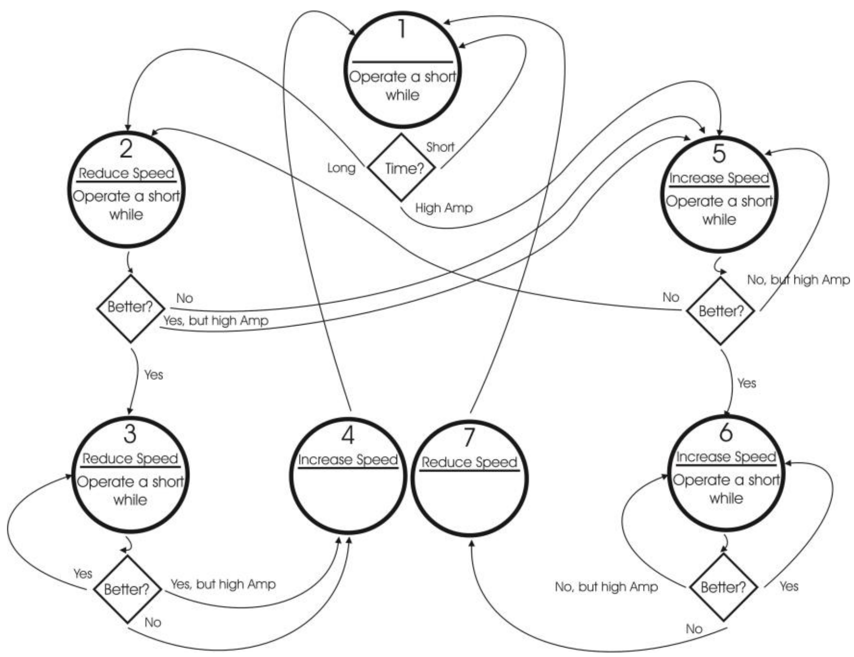


Figure 37. The FSM used for selecting appropriate ES [12].

In Paper F a supervisory control layer was implemented that includes model-based and model predictive control (MPC) capability for optimization purposes. The MPC calculates the various set point values for many of the regulatory controllers, and sets limits for some of the fuzzy logic rule-based controllers based on a economic objective function. The objective function was aimed to maximize the production of circuit product, while at the same time ensuring that the various constraints were not exceeded. An overview of the process layout and model predictive control paramenters is shown in Figure 38.

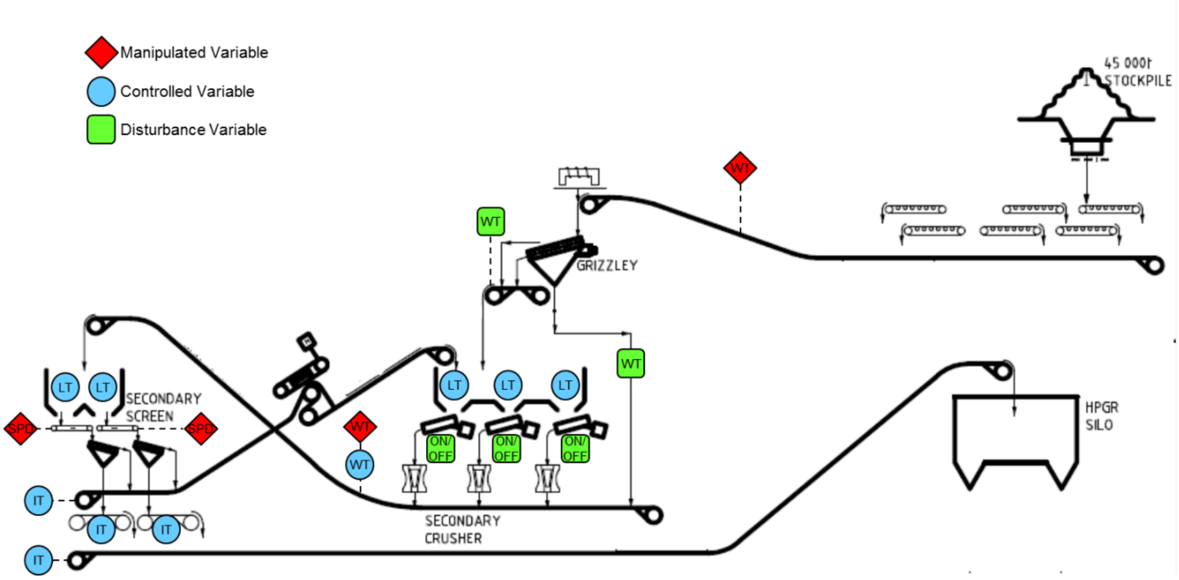


Figure 38. Process layout of the controlled process from Paper F. Picture provided by Duane Muller.

In order to drive maximum throughput, a "push-pull" control philosophy was implemented within the supervisory control layer. The "push" effect is achieved by introducing as much fresh feed into the circuit as the process states and limits allow by controlling the feed to the circuit. The "pull" effect is achieved by controlling the feeders below the screen bins, again subject to the process states and limits imposed by the equipment. This is achieved by using the belt scales on the crusher discharge conveyor as both a manipulated variable and a controlled variable. Using the discharge weight as an intermediate variable (both a manipulated variable and a controlled variable) enables accurate discharge weight control and as a result the disturbances affecting the screen bin level are minimized, and improved screen bin level control is achieved.

6.3 CONTROL IMPLEMENTATION

Incorporating the control system in a dynamic simulation makes it possible to test the control system in a controlled environment prior to commissioning of a plant. Unexpected consequences, such as instability and lack of robustness, can occur if the control system is implemented without a rigorous quality control of the code itself. In Paper D and F, two different methods of implementation of the supervisory controller were performed. In Paper D the FSM was included in the plant model with a function block, while in Paper F the control system was an offline version of an actual code at the plant and connected to the model from a third party software through an Object linking and embedding for Process Control (OPC) server.

7 PLANT PERFORMANCE

The aim of this chapter is to:

- *Demonstrate process improvements of crushing plants.*
- *Describe the performed user acceptance test.*
- *Describe process stability under different conditions.*

The traditional use of crushing plant simulators is to model, simulate and evaluate plant performance. In order to evaluate the performance of a particular plant a flowsheet of the plant is arranged so that it represents the layout of the plant. The plant can be an existing or non-existing plant, which usually affects the purpose of the simulation. The purpose can be to evaluate current configuration or assess different plant design alternatives.

Configuration of the equipment is done by selecting value for different production unit settings, such as CSS and screen apertures into appropriate unit models. Additionally the rock properties of the feed material are defined, such as particle size distribution, particle shape, material density and material strength. The steps above are applicable when dealing with steady-state simulation. However, when it comes to dynamic simulations additional aspects of the operation need to be considered such as material handling and control. After this has been done the simulation will determine the behaviour of the process over time and the performance of the system.

In the following sections the simulation results from Papers C, F and H are presented. The purpose of the simulations was to evaluate current design performance. This includes changed unit configuration in Paper A to achieve higher process saturation, user acceptance testing with experienced control engineers to validate process behaviour for model implementation in Paper F and to evaluate process performance under different feeding conditions in Paper H.

7.1 PROCESS IMPROVEMENTS

The general purpose of Paper C was to study how the plant operated under different operating conditions and find out what level of plant performance saturation could be achieved with implemented interlocks and PI controllers.

The modelled section consists of three cone crushers (a coarse crusher, intermediate crusher and a fine crusher) represented with empirical crusher performance models based on survey data. A single vibrating grizzly with sloth width from 80 mm, two double deck screens with top deck at 85x85 mm and bottom deck at 40x52 mm modelled with Reid-Plitt efficiency curve and two bins that are approximately 660 m^3 and 300 m^3, respectively. The incoming feed is a platinum group metal ore which has been crushed with a primary crusher down to approximately 0-250 mm, see Figure 40.

From a steady-state modelling perspective the plant would be modelled as depicted in Figure 39, with mass balance in point A and B and the performance determined by the crushers combined capacity. This will however give an unreliable result of the plant's actual performance, since dead time on conveyors and bin capacities affect how the process operates. The modelling approach in Figure 40 is therefore more suitable.

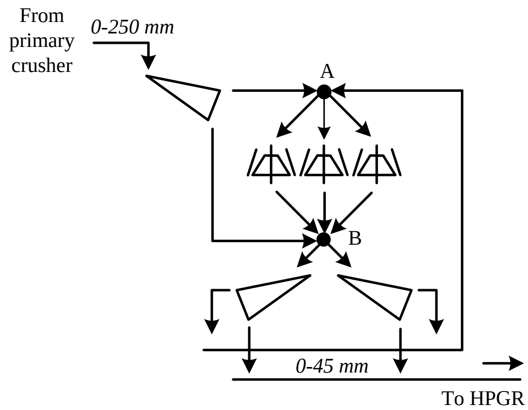


Figure 39. A steady-state view of the plant.

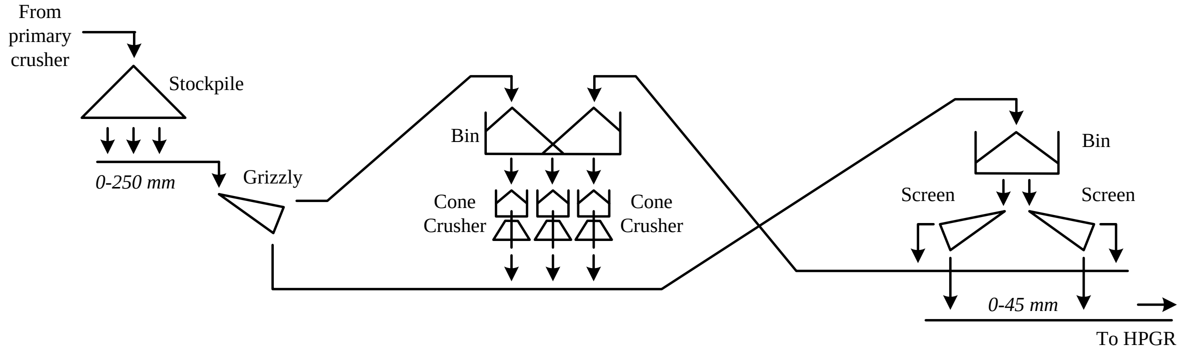


Figure 40. Flowsheet of the crushing section of the platinum processing plant as presented in Paper B.

Four different scenarios were simulated from different combinations of CSS and ET. The scenarios were configured according to the setup of the plant and from the measured process data, which was collected during two surveys. The first scenario involved simulating the process as it is usually configured and performed according to the surveys. In the second scenario the CSS of the coarse crusher was reduced from 55 mm to 40 mm. In the third scenario the ET of the fine crusher was increased from 38 mm to 44 mm. In the final scenario the changes from second and third scenario were implemented together.

7.1.1 PROCESS SIMULATION RESULTS

Variations in the particle size distribution and the mass flow were imposed and each scenario was simulated until it reached performance saturation. The simulation result from the 1250 tph target throughput in Scenario 1 is shown in Figure 41. Under these conditions the plant was stable and able to hold the target throughput of 1250 tph without any major fluctuations. However, in Figure 42, input feed rate was increased up to 1500 tph which caused the process to start fluctuating. Under these conditions the plant was not stable due to active triggers and the overall performance achieved became lower than the target feed rate.

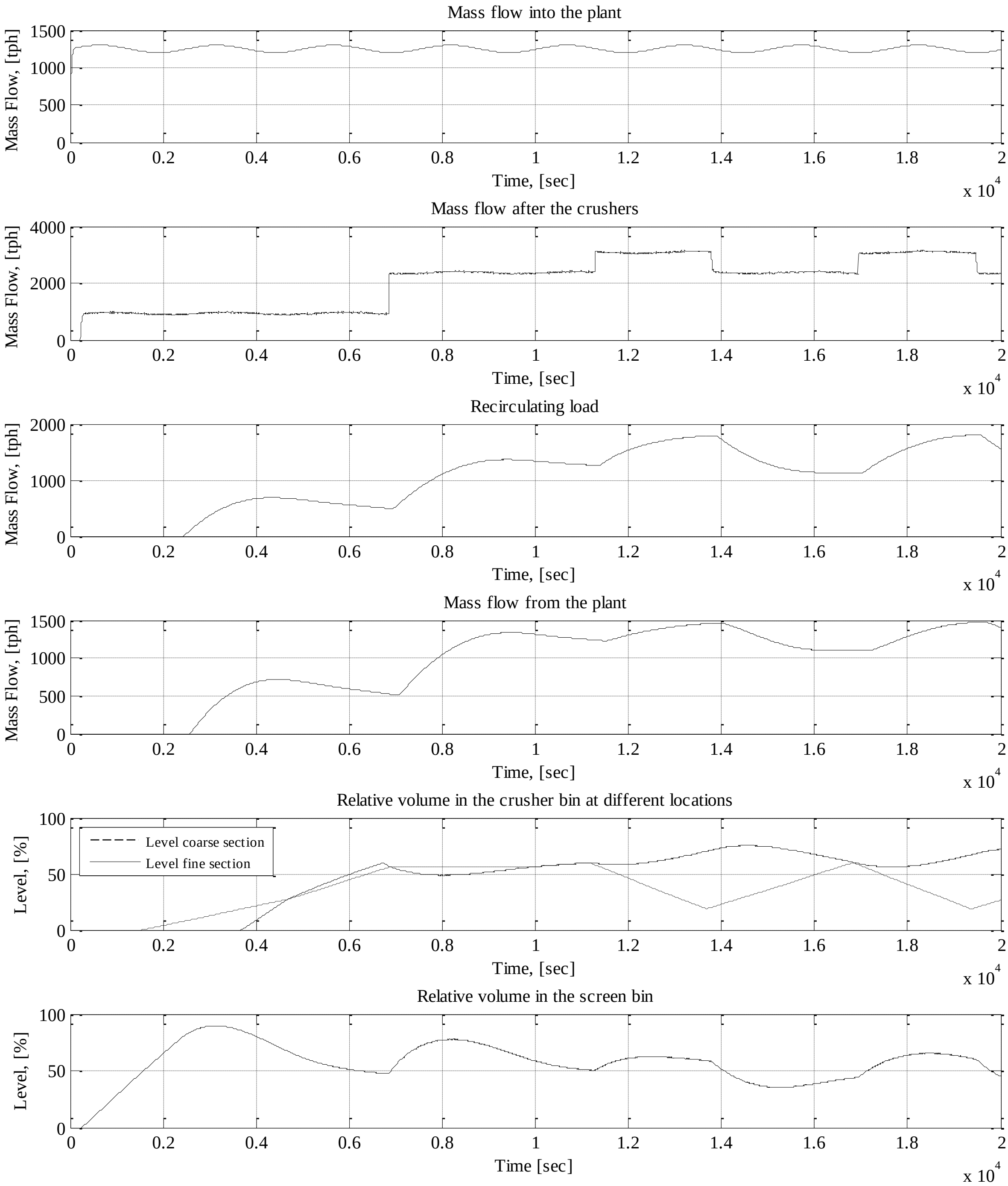


Figure 41. Simulation results from simulating 1250 tph in Scenario 1. The process is relatively stable with minor fluctuation.

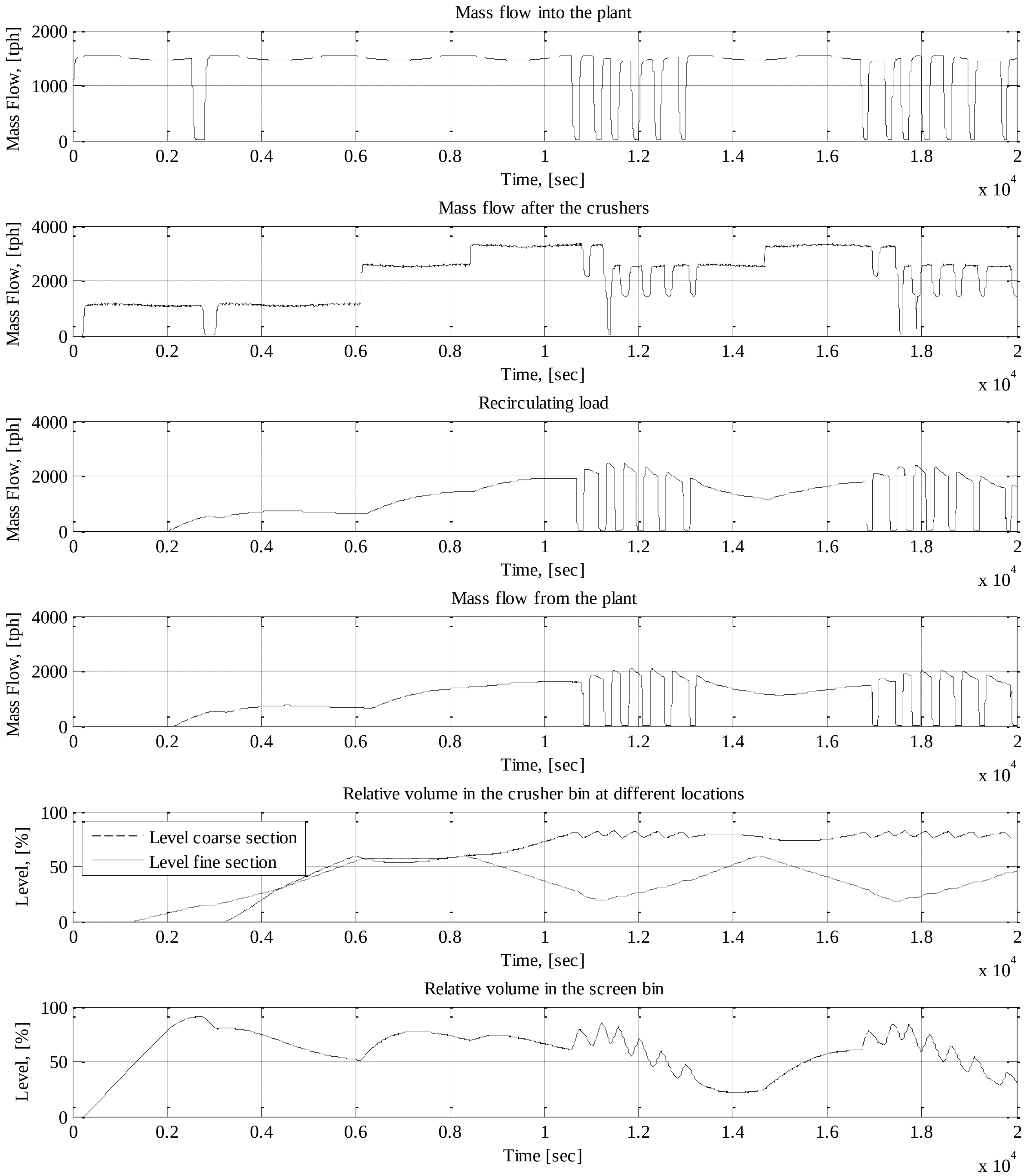


Figure 42. Simulation results from simulating 1500 tph in Scenario 1. The process starts experiencing major fluctuation after approximately 3 hours.

The results from the simulated scenarios in Figure 43 illustrate how the average performance of the plant reaches a maximum level at a certain feeder target feed rate. This is where the interlocks from the bins start interrupting the process due to overload. To respond to the overload the incoming feed into the circuit is shut off causing an unstable pattern in the process. Up to this point the plant experiences steady-state behaviour. The reference scenario (Scenario 1) was able to produce approximately 1275 tph in an uninterrupted operation. While, Scenario 2 and Scenario 3 were able to increase the overall capacity by 4.7 % resp. 8.2 %. The combined factors in Scenario 4 revealed a possible 13.3 % increase in plant capacity.

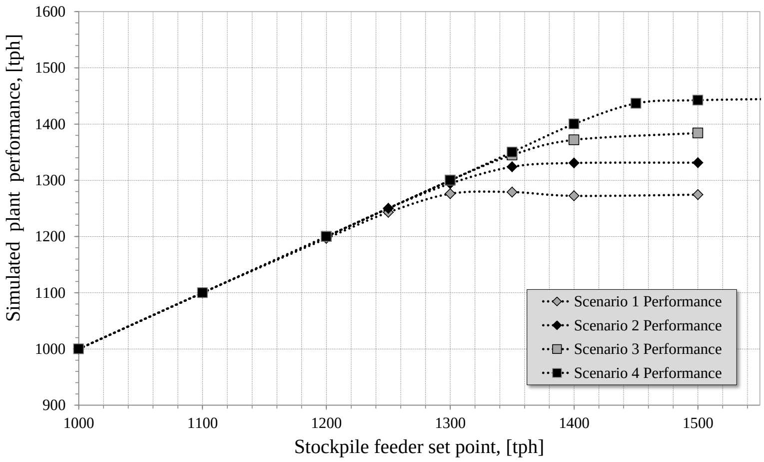


Figure 43. Average plant performance for different feed rates and plant configuration.

7.1.2 EMPIRICAL RESULTS

The empirical experiment of the scenarios gave a promising indication of the fidelity of the simulation, see Figure 44. By running Scenario 1 and Scenario 2 where the CSS of crusher 1 was reduced from 65 mm to 50 mm the overall plant performance increased by 4.9 %, from 1291 tph to 1354 tph compared to 4.7 % simulated. When reducing the capacity of crusher 1 by running the crusher at a smaller CSS the overall plant performance was increased. By running crusher 1 with a smaller CSS the rock material was crushed more in the initial pass and less material was recirculated to crusher 3.

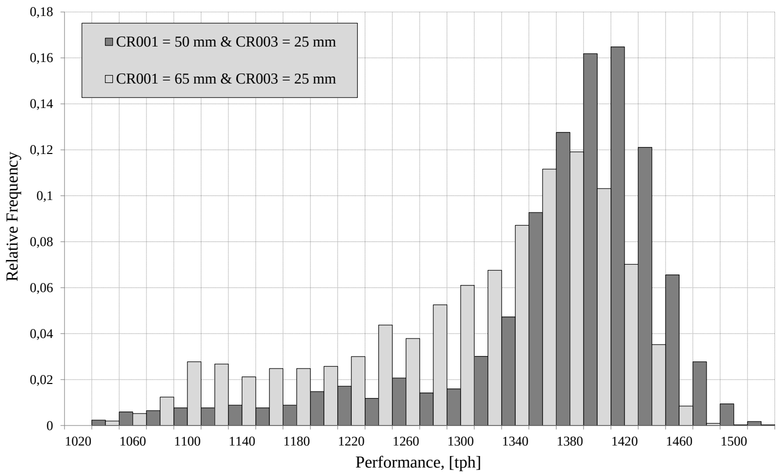


Figure 44. Plant performance for two different CSS of crusher 1 (CR001).

7.2 USER ACCEPTANCE TESTING

The aim of Paper F was to implement a dynamic simulation platform to support future debugging and tuning of an APC algorithm.

The objective of the study was to perform a visual verification of the start-up sequences of the plant and simulate different operating conditions with an offline version of the APC in a third party software. The implementation was a part of user acceptance testing of the simulation platform to verify that simulated system performance corresponds to the existing process performance in terms of process performance and fluctuation. The user acceptance testing was performed together with control engineers working with the existing process.

This builds on previous dynamic modelling work done in Paper C, Figure 40. The work was focused on system identification and the implementation of the APC algorithm in the dynamic plant model. The dynamic model of the plant was connected to the control system via OPC server and the response of the model validated against the behaviour of the plant. The system structure is illustrated in Figure 45.

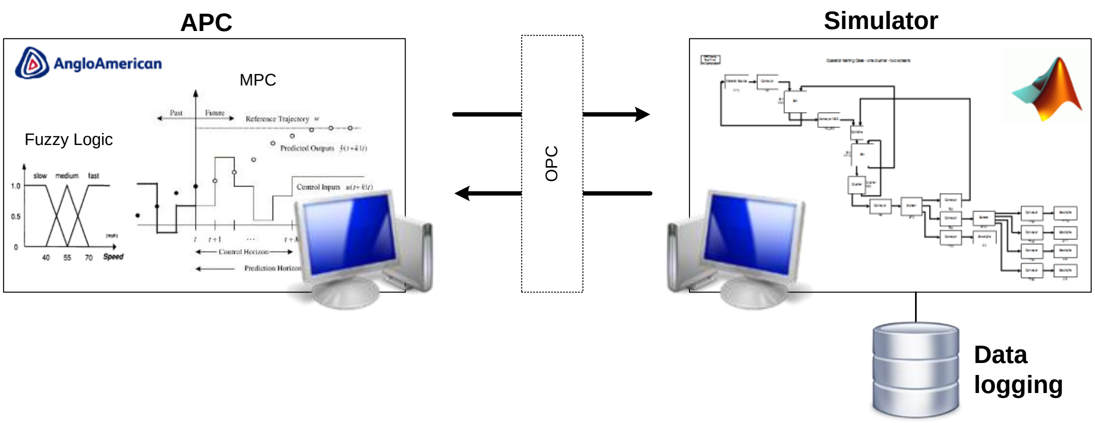


Figure 45. System structure for the implementation.

The step-time of the simulation was synchronized to the control system and ran at 10 times real-time for enabling observation while the simulations were running. An in-house developed HMI was used to observe the process during simulations.

7.2.1 SIMULATION RESULTS

The process simulation was run for 8 hours while under the simulation period no external disturbances were included. Between each simulation the simulation conditions were changed slightly to assess the response of each run, visual validations were performed with an experienced control engineer. Figure 46 illustrates the change in mass flow into the circuit (a), the mass flow on the conveyor after the crushers (b), the mass flow for the circulating load (c) and mass flow out from the circuit (d). For this period the plant average performance was at 1455 tph while the set point for the plant was at 1500 tph.

The modelled plant responded accurately to the implemented APC with some smaller process fluctuation according to visual comparison with the existing process. Running process simulation prior to commission of production processes is generally considered to increase reliability of the process and speed up the ramp-up time needed to reach predicted plant performance. An engineering support tool would also create a more efficient working procedure.

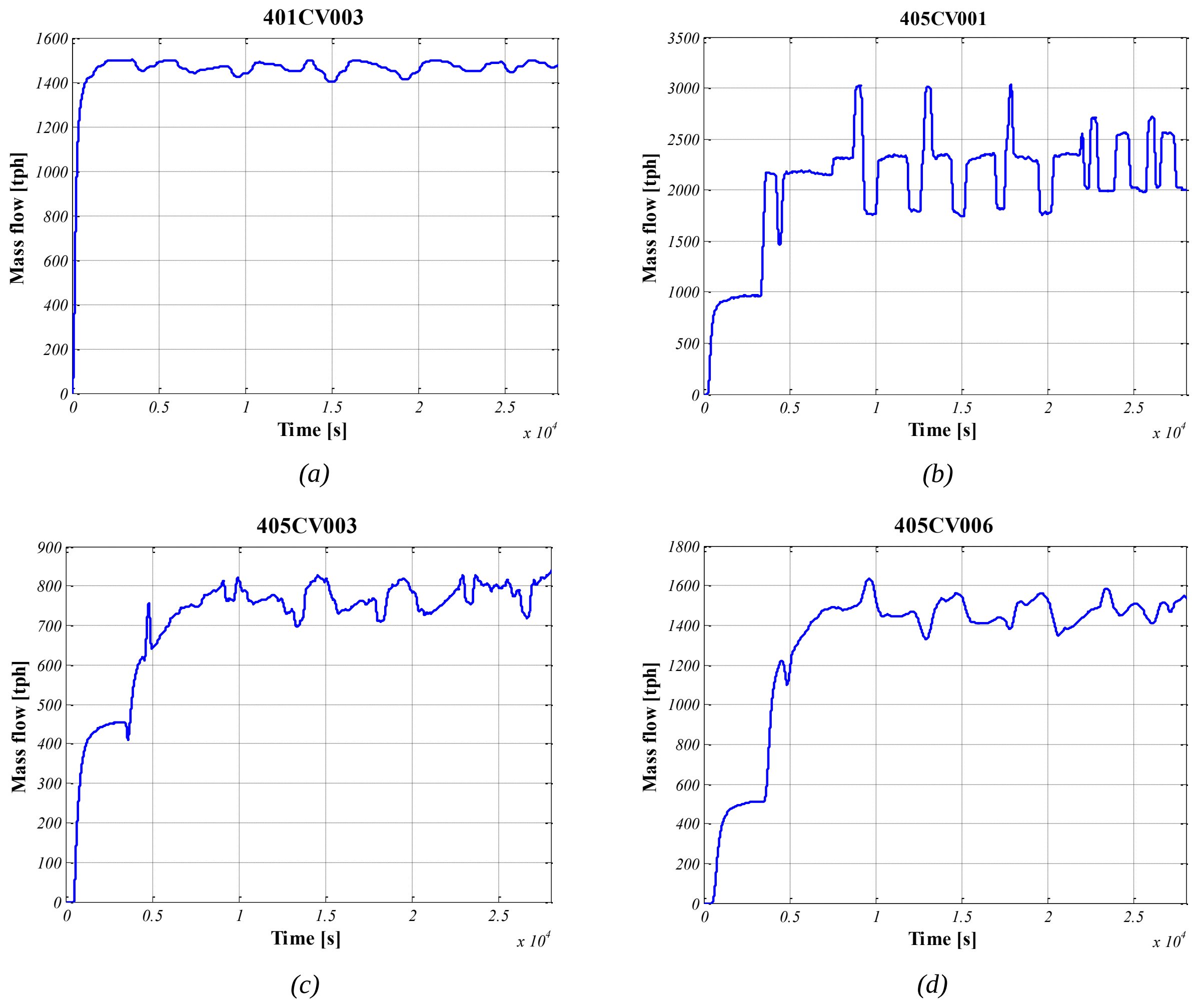


Figure 46. Data from the process simulation, mass flow into the circuit section (a), the mass flow on conveyor after the crushers (b), the mass flow for the circulating load on conveyor (c) and mass flow on conveyor out from the circuit (d).

7.3 SYSTEM STABILITY

A process is never under constant load and variations in the feed will change the performance of the process. In Papers A, C and H the particle size distribution from the feed was varied to evaluate the performance under different conditions. In Paper H the aim of varying the feed size distribution was to evaluate process robustness and ability to maintain a high process performance while operating at a constant CSS, as illustrated in Figure 32. The incoming feed was described by the Swebrec function, Eq. 5.25, with a constant slope factor *b* and linear incremental increase by the top size (x_{max}) and 50 % particle passing size (x_{50}).

7.3.1 SIMULATION RESULTS

The selected process unit parameters were applicable for around the original feed size distribution and below. The highest process performance was registered at 8 % increase in particle size distribution, Figure 47. However, at 10% larger feed size distribution the crusher 1 violated maximum pressure limit, resulting in an increased CSS for larger size distributions.

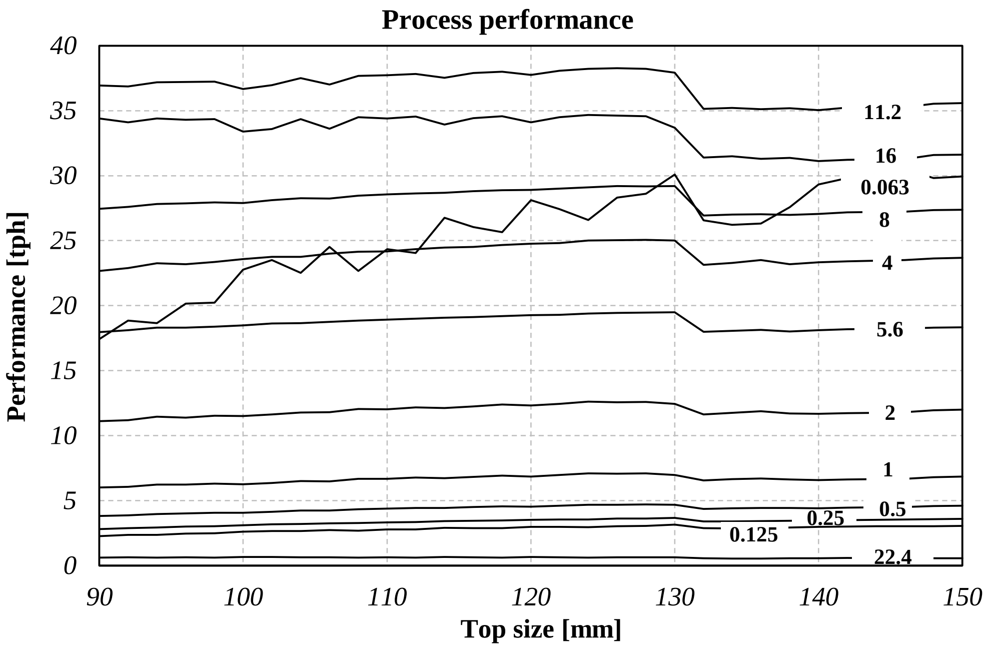


Figure 47. The process performance during different feed size distribution.

A crushing process is never under constant conditions for a long period. In order to assure high productive operation a robust process needs to be configured. This means the process is capable of handling change without losing too much efficiency. A process need to be able to handle variations in particles size distribution and in material properties without drastic effects. Controlling the process actively can have major benefits when it comes to increasing process robustness, availability and utilization.

8 PROCESS OPTIMIZATION

The aim of this chapter is to:

- *Describe the optimization of control algorithm.*
- *Describe the optimization of a crushing operation.*

Optimization implies the selection of best possible combination of design variables x to minimize the defined performance function $f(x)$ with regards to set inequality $g_i(x)$ and equality constraints $h_i(x)$. Formulated in a negative null form in Eq. 7.1 [98].

$$\begin{aligned} \underset{x \in P}{\text{minimize}} \quad & f(x) \\ \text{s.t.} \quad & g_i(x) \leq 0 \\ & h_i(x) = 0 \end{aligned} \tag{7.1}$$

There are multiple aspects of the process and production that can be improved in order to drive the process to an optimum performance. A well-tuned regulatory controller with an appropriate supervisory controller should drive the process to an optimum. The process however is time dependent, i.e. what is optimum at one point is not necessarily optimum later. The production should therefore be managed accordingly.

In the following sections the optimization results from Papers D and H are presented. The purpose of the simulations was to present methods for optimizing different aspects of the process. This includes optimizing the step changes in a real-time optimization algorithm to achieve higher production rate in Paper D and appropriate selection of unit configuration, calibration routine and maintenance approach in Paper H for optimum process performance

8.1 CONTROL OPTIMIZATION

In Paper D tuning of the FSM control parameters was performed to enable faster localisation of an optimum production of aggregates. The FSM is used for selecting appropriate ES for the crusher in order to achieve optimum performance. A GA was used to locate optimum control parameters within a given interval. As discussed in Section 6.2 the algorithm parameters are selected manually (ΔES^+, ΔES^- and LongTime). At the selected crushing plant, Figure 48, these parameters were set to:

- $\Delta ES^+ = 60$ rpm
- $\Delta ES^- = 60$ rpm
- LongTime = 480 sec

The modelled plant is a tertiary crushing stage in an aggregates quarry, which also has been studied in Paper A. This particular plant is equipped with a frequency converter which enables control of the ES of the crusher by altering the frequency of the motor. This crushing stage is designed with a Metso Nordberg HP4 cone crusher and two triple decked screens which produce products ranging from 0-2 mm up to 16-22 mm, the modelled plant is illustrated in Figure 48. Incorporated into the plant model is a frequency controller model, in which the algorithm for the FSM was implemented.

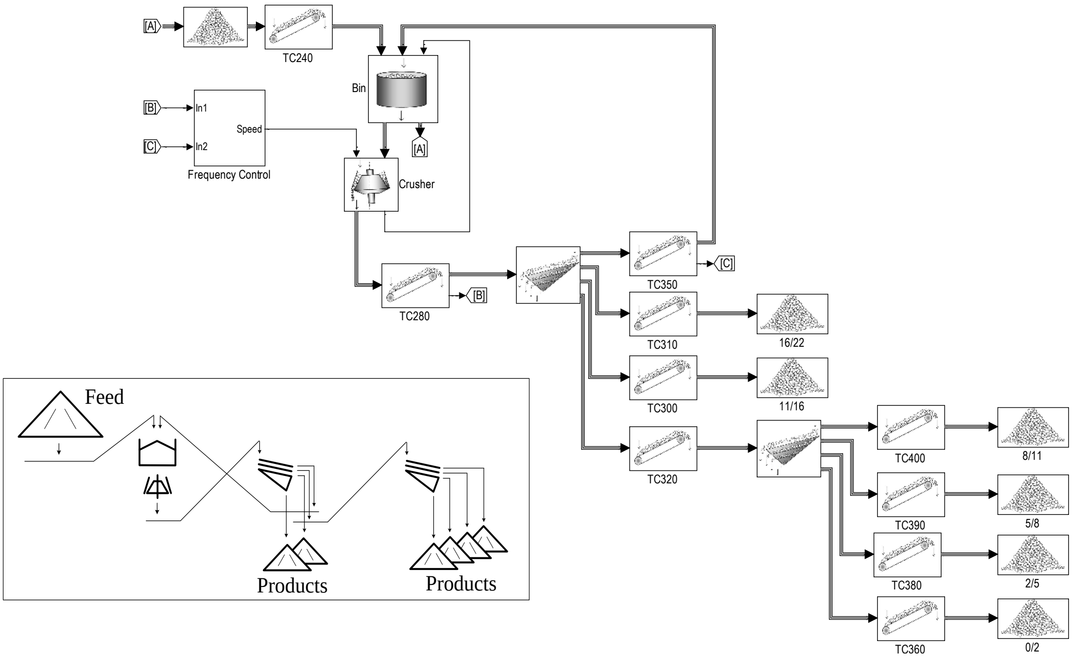


Figure 48. The modelled aggregates process and the frequency controller model in Simulink. A simplified layout of the plant is shown in the embedded picture.

8.1.1 CONTROL OPTIMIZATION RESULTS

Simulation results from running the process with the existing settings are illustrated in Figure 49 while the simulation with the optimized parameters is illustrated in Figure 50. The mass flow is shown in the upper graph and the speed set point is shown in the lower graph. The process was simulated for 12000 s which is approximately the time between each calibration and a disturbance was initiated at 6200 s to represent a short stop in the incoming feed rate. The optimum solution found is shown in Table 2.

Table 2. Optimum solution for the step changes in speed.

Variables	**ΔES $^+$**	**ΔES $^-$**	**LongTime**
Limits	20-100 rpm	20-100 rpm	300-1800 s
x^*	91 rpm	48 rpm	544 s

By optimizing the step change for the frequency converter a theoretical increase in production is possible. When comparing the current manually selected parameter against the optimized parameters, shown in Figure 49 and Figure 50, an increase of 0.5 % was estimated. It must be kept in mind that these 0.5 % add on to the manually tuned algorithm which gave about 5 % improvement to the process [12].

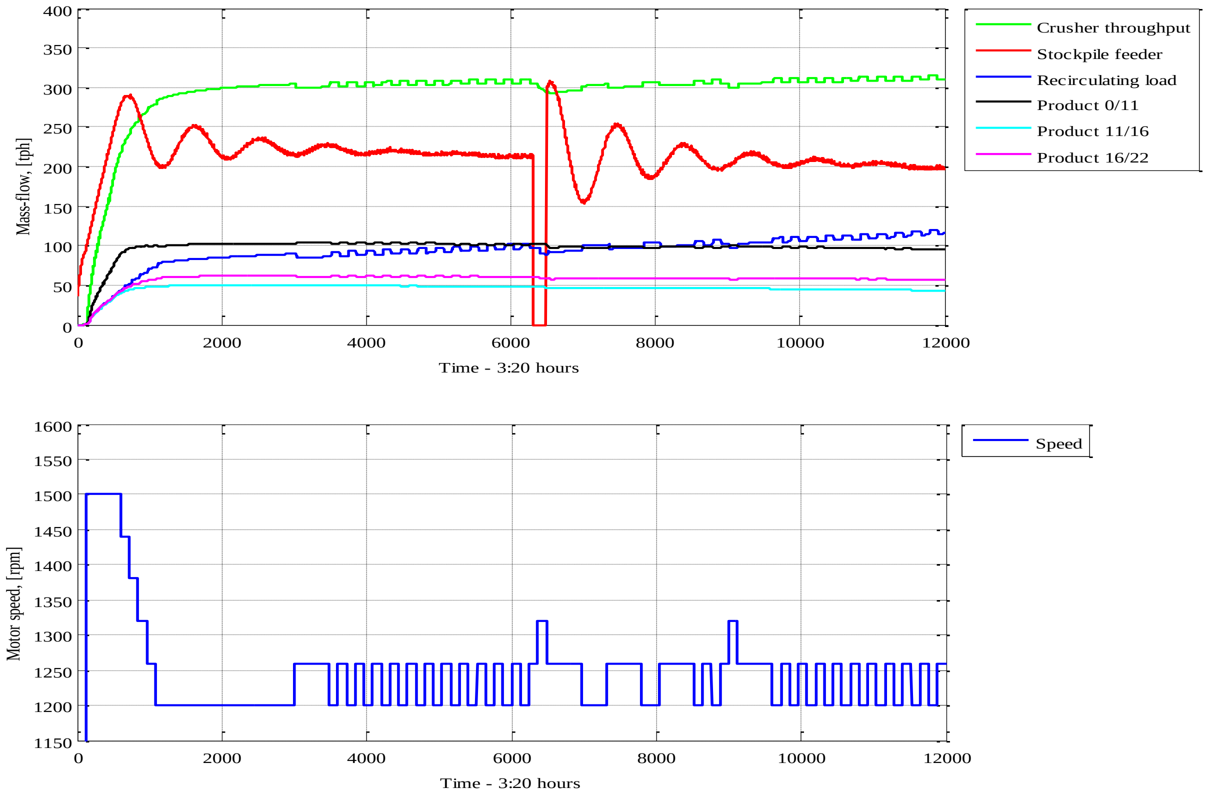


Figure 49. Simulation results with existing settings. The upper graph illustrates the mass flow on different conveyors while the lower one illustrates the change in ES set point during the simulation.

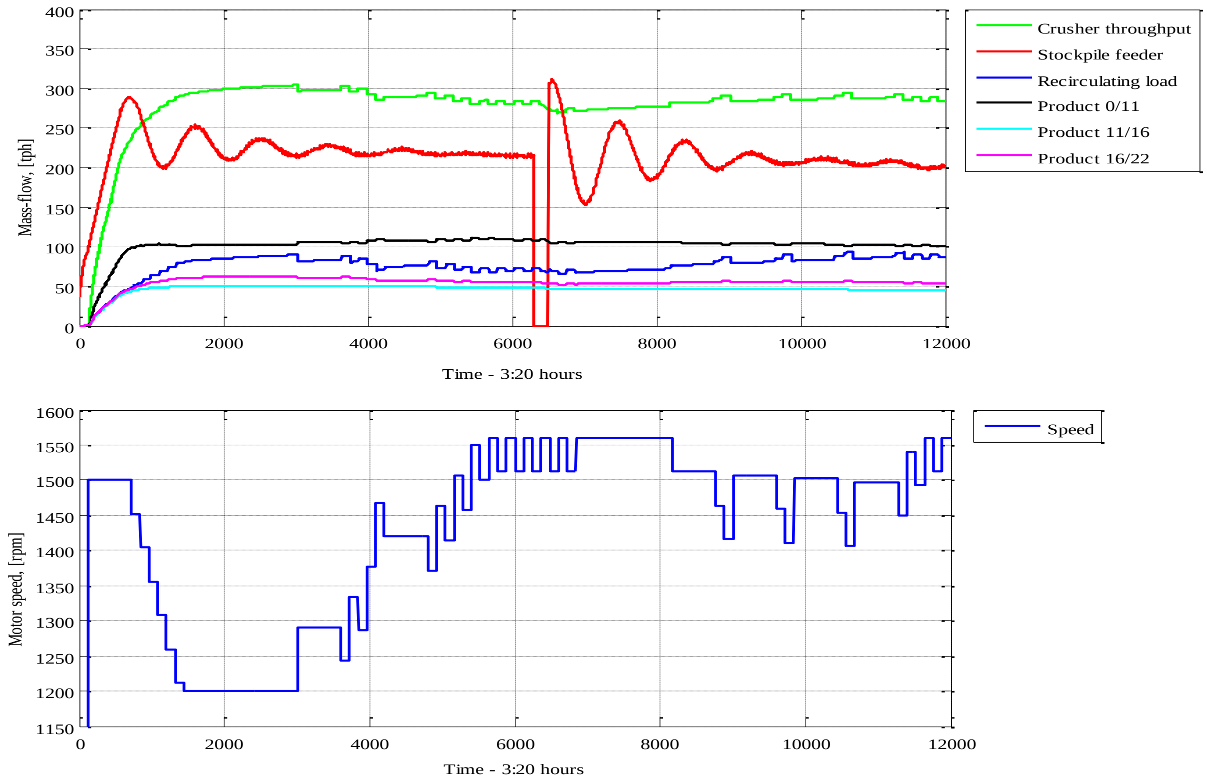


Figure 50. Simulation results after the optimization. The upper graph illustrates the mass flow on different conveyors while the lower one illustrates the change in ES set point during the simulation.

8.2 OPERATION OPTIMIZATION

The changes within the crushing process can be considered to be probabilistic or deterministic depending on the phenomenon. In the case of instant failure the event will have a certain probability of occurring and severity. Deterministic events are planned and scheduled such as breaks, shifts, and maintenance which aim to maintain a reliable and productive process. The characteristics of the consequences of an event will depend on the condition of the process, how the process is operating and how it is managed.

The aim of Paper H was to model, simulate and analyse these discrete phenomena that can cause the process to alter performance due to changing conditions over a long operating period. A novel method for combining discrete probability simulations with time dependent simulations for optimizing the process was presented.

The framework of this study is focused on integrated discrete event based and continuous time based models. This is achieved by running a probabilistic discrete event simulation to provide an input into a continuous time based crushing plant model that represents a conceptual closed-loop circuit configuration containing a feeder, bins, conveyors, crushers and a screen, as shown in Figure 51.

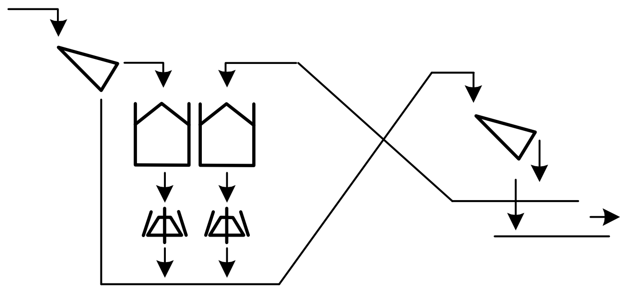


Figure 51. A closed loop secondary crushing circuit.

The DES represents the events in the process that can only change at a discrete point in time. Each event has specific attributes that determine duration of each event or activity. All DES models are considered to be mutually exclusive events. Events such as upstream, downstream and maintenance were given static deterministic behaviour, while mechanical failure will be stochastic and determined by the selected maintenance strategy.

The production simulation was given three different probabilities of mechanical failure: low, medium and high risk, see the illustration of the low and high risk in Figure 52. This will depend on how the operators maintain the process. For a preventive maintenance strategy large time and cost is spent on changing wear parts and adjusting the processes during predetermined service intervals with low risk of failure. During corrective maintenance however, less time is set up for service intervals and higher failure rate since the equipment is not changed until it breaks or is close to failing. An optimum solution is usually a combination of both strategies [99] since frequently changing wear parts prematurely and process stops due to unforeseen equipment failure are both detrimental for the process efficiency.

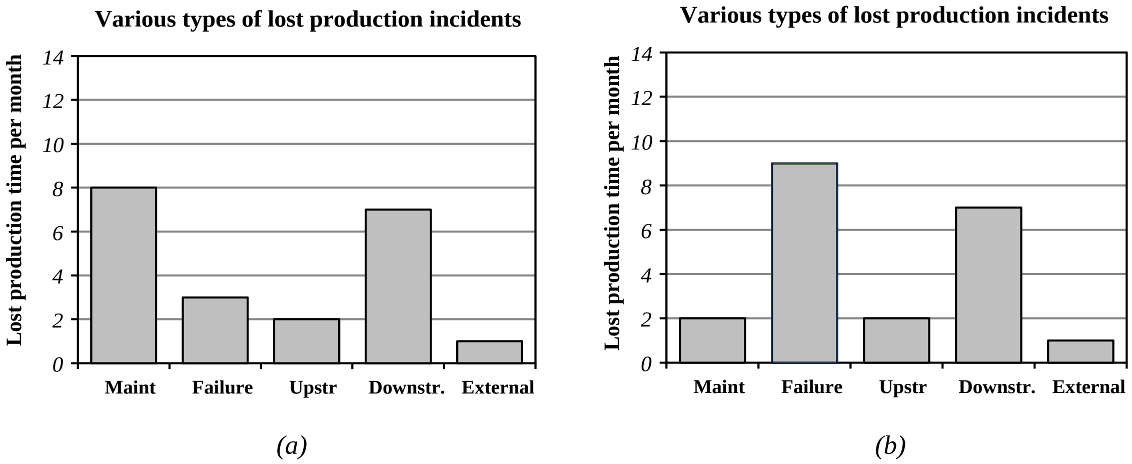


Figure 52. Illustration of the downtimes for preventive (a) and corrective maintenance (b).

Mechanical failures in the process are modelled as stochastic events with probability of failure as a function of maintenance. The three different failure modes were modelled as stochastic events depending on the severity of the failure. Short breakdowns that cause a DT of 30 min – 2 h were modelled with a Weibull distribution, Eq. 5.10. Medium long failures that take 2 – 4 h and long breakdown that take 4 – 12 h were modelled with an Exponential distribution, Eq. 5.11 and Figure 53. Each failure has a set WT of 15 min, which includes detection time and the time it takes to arrange needed maintenance.

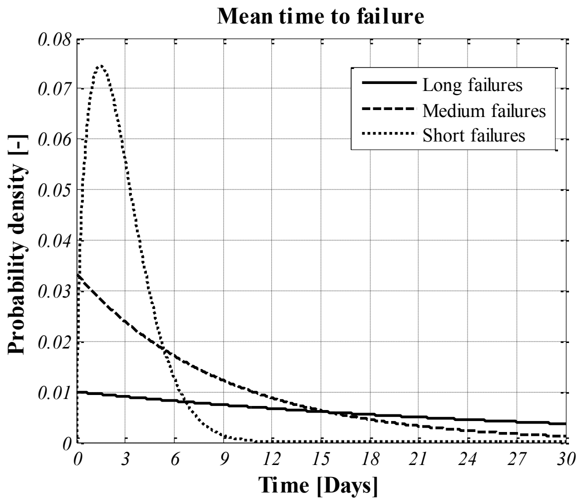


Figure 53. The different probability densities for failures.

The task was to optimize the production of sub 15 mm product ($\dot{m}_{Product}$*). Variable *x* is a vector of design variables while *p* is a vector of fixed parameters for the plant model, Eq. 7.2. Inequality constraints include: the smallest CSS, the grizzly aperture and the crushers pressure limit. The second screen aperture, crushers´ ET and ES are treated as equality constraint.

$$\max_{x \in P} \ \dot{m}_{product}(x) \tag{7.2}$$

8.2.1 OPERATIONAL OPTIMIZATION RESULTS

The average throughput from the circuit for 24 hours was 406.0 tph with standard deviation of 71.0 tph when no wear was estimated. The results from the first iteration are shown in Table 3. The second iteration included the wear rate in the crushing chamber which was set to constant. Each calibration was estimated to take 10 min and 50 hours of production was simulated. The average throughput from the circuit was 375.0 tph with standard deviation of 101.9 tph. The results from the second iteration are shown in Table 4.

Table 3. First optimization iteration – 8 hours base case scenario with no wear or events.

Variables	Primary screen	Crusher 1	Crusher 2
Limits	10-50 mm	20-40 mm	10-30 mm
x^*	Apert. – 20 mm	CSS – 28 mm	CSS – 19 mm

Table 4. Second optimization iteration - 50 hours with calibration.

Variables	Crusher 1	Crusher 2
Limits	2-50 h	2-50 h
x^*	Cal – 11054 s	Cal – 21656 s

Calibrating the crushers is essential in order to keep the process operating at the highest possible throughput. The difference in Overall Equipment Effectiveness (OEE) by calibrating the crusher with 10, 20 and 30 hours between calibrations (TBC) or at 20 hour intervals with continuous adjustment to keep a constant pressure is illustrated in Figure 54. The OEE for 10 hour TBC was calculated at 68.6 %, 66.9 % for the 20 hour TBC, 65.3 % for the 30 hour TBC and 71.4 % for the 20 hour TBC with pressure control. As illustrated in Table 4 the optimum calibration interval for Crusher 2 was around 6 h. Frequent calibrations will keep the crusher at a more stable load. Infrequent calibration will however increase the pressure distribution within the crusher chamber. Adjusting the crusher continuously can increase the performance of the crusher by 4.1-9.3 % instead of passively operating the crusher.

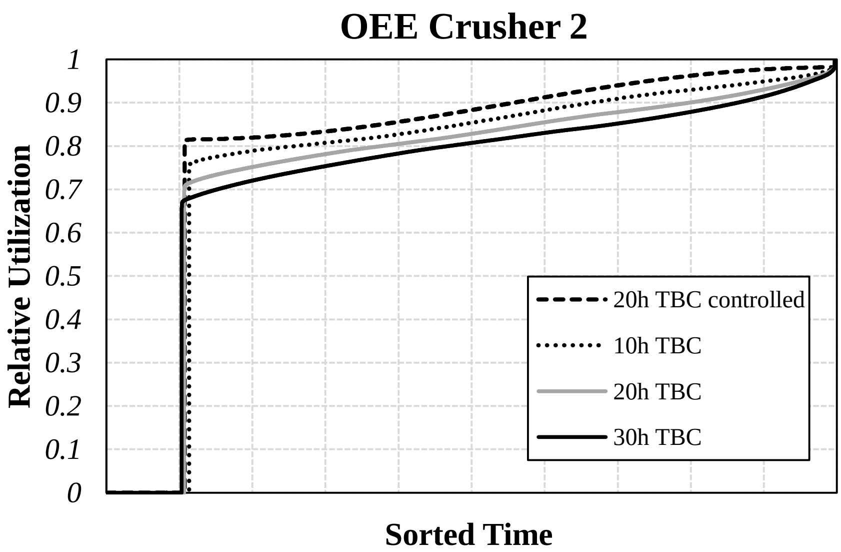


Figure 54. The difference in the crusher´s utilization if calibrated with 10, 20, 30 hour intervals or with 20 hour intervals while operating at a constant load.

9 OPERATOR TRAINING

The aim of this chapter is to:

- *Describe the approach to operator training with dynamic simulation.*
- *Introduce a performance evaluation of operator performance.*

Operators are responsible for managing the process in order to obtain a stable production of high quality products and high throughput. The operator's capability in making fast and effective decisions is therefore important. Operator training is often a manual process which is conducted by a verbal interaction between an experienced operator and an inexperienced operator. The operators' cognitive ability in detecting and analysing information from the process can therefore be limited for a novice operator. In Paper E and Paper G the aim was to develop a web based operator training environment with dynamic and discrete event simulation to support operators' cognitive capabilities.

9.1 SYSTEM STRUCTURE

The system structure utilized is a three-tiered distribution: Presentation layer, Application layer and Data management layer as illustrated in Figure 55. The presentation layer is a Thin-Client architecture where the operator or supervisor can access the HMI on a client's PC without an installation of an additional software. By using a standard web browser the operator and supervisor can access production reports, HMI graphics, historical trends and alarms in real-time from anywhere.

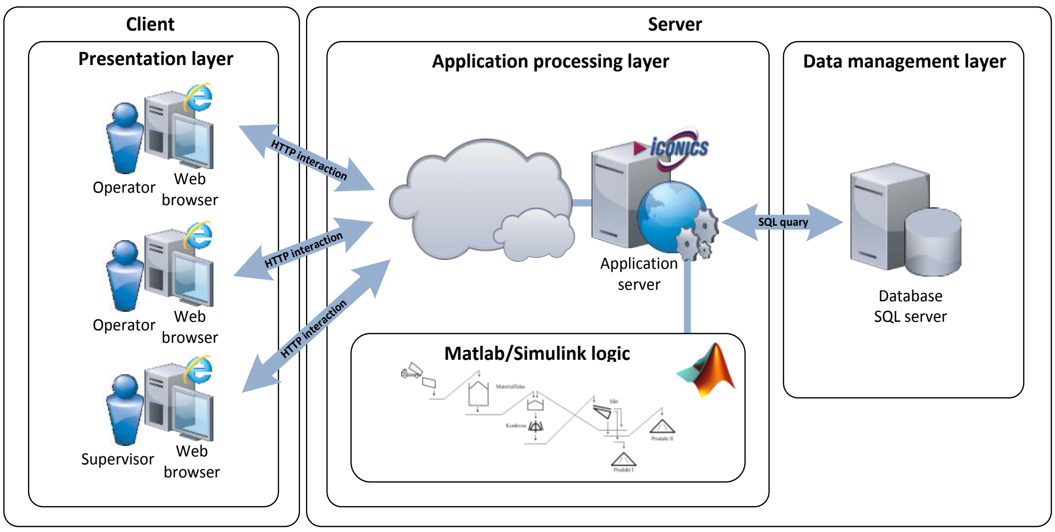
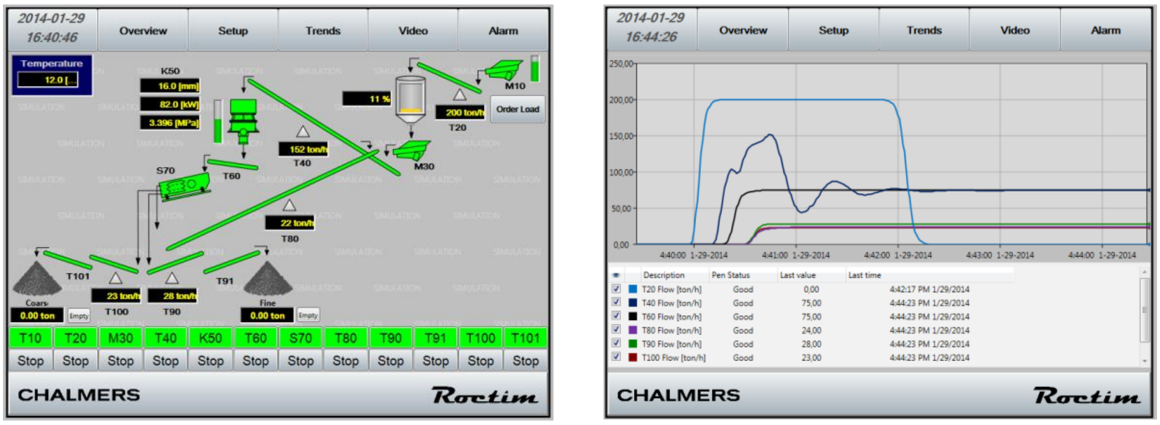


Figure 55. A schematic view over the three-tier application structure.

The process logic of the operator training is within the application process layer. Simulink runs continuous and discrete simulations and the output is dependent on the operator´s setup of the process and his interaction with it.

The data management layer allows for data storage of selected OPC tags with a SQL server. This enables information transfer of historical trends between the HMI and the Simulink model.

The HMIs were developed in ICONICS GENESIS 64 which is a Windows based application, see Figure 56. Three different process layouts were created in Paper G. The process layouts aimed to represent a mobile aggregates application, a stationary two stage aggregates application and a mining application.



(a) *(b)*

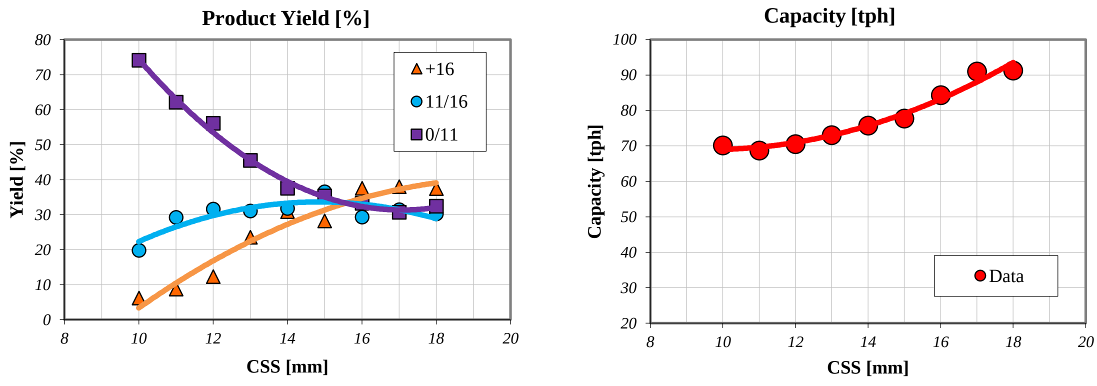
Figure 56. An overview interface developed to illustrate the status of the process (a) and process data display page (b) created for visualizing process data.

9.2 USABILITY STUDY

A usability study was performed to evaluate simulation performance, HMI arrangement and selected process tasks. The tasks were divided up into specific moments where the participants interacted with the process simulation to be able to evaluate the simulation and the HMI arrangement. The study was divided up into the following sections:

- Navigating the display
- Setting up the processes with regards to set quality requirements for:
  - Particle size distributions
  - Shape
- Manually operating the processes
- Automatic regulatory controllers
- Real-time Optimization
- Handling of disturbances
- Calibration routines
- Troubleshooting alarms

The participants started by selecting an appropriate setup for the process to produce 11/16 product according to Gc80/20 requirements [87], given a certain crusher performance, shown in Figure 57.



(a) (b)

Figure 57. Particles size distribution (a) and capacity (b) under different CSS. Data collected from a H36 cone crusher.

9.2.1 SIMULATION RESULTS

The participants were instructed to operate the process manually and maintain stable production for a specific time period by adjusting the feed rate into the circuit, example shown in Figure 58. T40 being the circuit feed rate and T60 is the crusher throughput. By operating the process with the automatic regulatory control the participants adjusted the set point for the PI controller, instead of trying to maintain constant level in the crusher manually. In Figure 59 a result from an imposed disturbance is shown which caused the mantle to move down and increase the CSS at time 3200 s and up again at time 3350 s. Fluctuation on T40 are caused by the PI controller and the change in T60 is due to changed CSS.

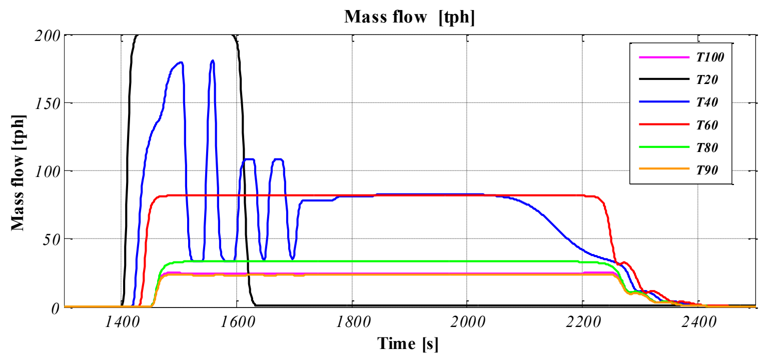


Figure 58. Mass flow manually stabilized by altering feeder frequency.

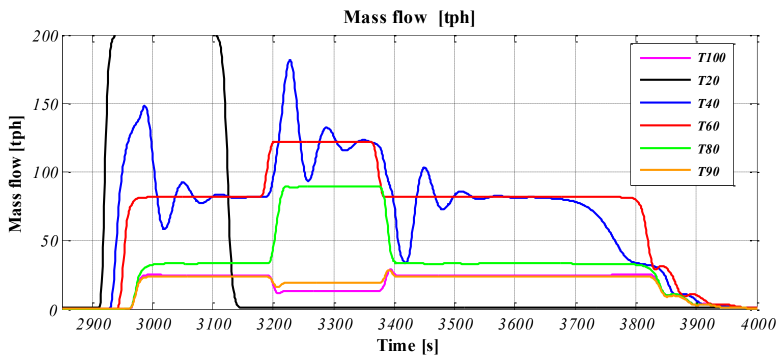


Figure 59. Operating the process with the PI controller active and adjusting CSS.

9.3 OPERATOR EVALUATION

Each group was allowed to vary the feed rate into the circuit, the CSS on the crusher and the apertures on the screens during manual operation of the process. The participants were instructed to find the best possible solution for their capabilities by reading the crusher´s performance map in Figure 57 and evaluating the process during operation. A performance function was formulated to evaluate the operators´ performance shown in Eq. 9.1.

$$Performance = \frac{m_p(1-\bar{q}_{shape})\sum_{t_1=0}^{t_2}(t_{psd})}{t_{total}} \tag{9.1}$$

The variable m_p is the total amount of material produced during the exercise while q_{shape} and t_{PSD} are product quality when it comes to the particle shape and the amount of over- and undersize. The development of the amount of undersize during the training period is illustrated in Figure 60. A penalty function was formulated to estimate the reduced performances of quality requirements where the set requirement was violated. With a performance function the operator performance during the training can be assessed and the improvement over time evaluated.

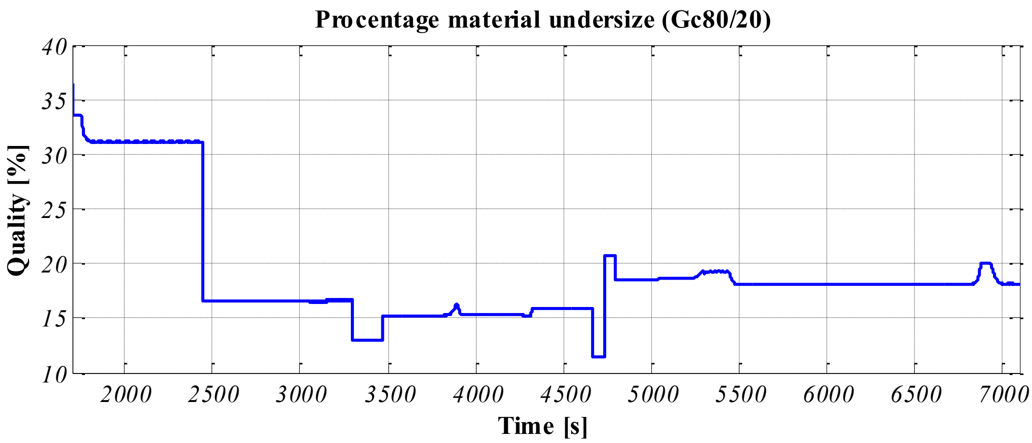


Figure 60. Percentage oversize in the product.

During the usability studies a number of different aspects appeared regarding the arrangement of the simulation based operator training. Aspects such as: direct feedback regarding the quality of the product which is important for the operator to evaluate their performance, understanding the importance of process optimization for process efficiency, increasing process awareness in a complex system and designing the process layout in the HMI in a way that minimizes mental load on operators. The information collected during the usability study gave valuable feedback regarding the development of a web based operator training environment and how to evaluate operators' development.

10 Discussion & Conclusions

The aim of this chapter is to:

- *Present the most important conclusions drawn in this thesis.*
- *Discuss the validity of the research.*
- *Answer the research questions stated in Chapter 2.*
- *Discuss the future work.*

The aim of this work was to understand how crushing plants perform under different conditions over time and to develop methods and tools for improving plant operation and production yield. During the development of the simulation platform different applications areas were tested for the implementation of the dynamic simulations.

10.1 General

Dynamic simulation of production processes has the ability to provide the user with in-depth understanding about the process behaviour and response. The details provided are usually not available with traditional steady-state simulations. However, the purpose of the simulation needs to be clear in order to obtain relevant information regarding the process.

As depicted in Figure 14 in Chapter 5 there are a number of factors that can affect plant performance. How some factors affect the process is clear, for example changing the aperture size on a screen will give a different cut point for the mass flow. However, other factors are more difficult to interpret and predict, such as feed material variations, unit failures and operator decisions.

Plant performance is not only affected by the selected production units and changes in the material properties but also by the configuration of the units and the applied control strategy. In a circuit with parallel flows the discrete operation of different units can cause the process to become unstable and in some cases lock itself during an overload. In Paper C it was demonstrated that a plant reaches performance saturation under a specific load. By simulating and evaluating process modification the plant performance could be increased. The empirical test revealed lower process variation and higher process throughput with an improved unit configuration.

One of the main sources of dynamics within the process is caused by material flow and material handling in bins. In Paper B, C and Paper F a large proportion of the reduced process performance originated from inadequate material handling. If not simulated properly multiple unexpected operational issues can occur such as process fluctuation and reduced unit performance.

Process performance will change during operation due to wear in production units (as illustrated in Paper A and H). If left unattended the performance will be reduced. To compensate for wear production units need to be maintained, calibrated and adjusted regularly. However, during each stop for correction the process performance is reduced and process variation is increased, since the process is not producing a product during that period. The choice between preventive and corrective maintenance is a balance of costs. Change of a wear part prematurely involves increased cost for the production since a part may have longer operational time left however, with more controlled DT. Waiting until the parts are worn out or broken can drastically reduce the productivity of the plant. Plant operators need to be attentive to the condition of the process and prepared for sudden failures.

Process optimization is an important issue for every process and organisation where the focus needs to be on maximizing the value for the customer while minimizing the used resources over time. In Paper D and Paper H a systematic approach to optimizing different aspects of the process was illustrated. Optimizing the process entails correct parametric configuration of the production units to maximize throughput, tuning and optimization of the control algorithm, the regulatory and supervisory controller, selecting appropriate operational approach, selecting appropriate maintenance strategy and operators' commitment and understanding of the process.

How the information and where the information is presented is essential for operators´ cognitive capability. The interface that the operator has towards the process should support the operator in detection, analysis, action and evaluation of the process, not increase the mental load. Too much information on a small display can have negative effects. By performing operator training, the operators' capability in reacting to changes in the process increases and becomes more effective. With an operator training simulator the operator is able to interact with the process without risking any potential damage to the actual equipment, thus providing the operator with valuable hands-on experience.

10.2 VALIDATION

Validity concerns the integrity of the conclusions that are generated from the conducted research [34]. Validation of the research is the process of determining the degree of fidelity of the system from the perspective of its intended purpose [35].

Structural validity refers to the system's background information which is the foundation for the constructed system and the appropriateness of the selected examples to illustrate the problem. With each study, in the appended papers, the aim has been to solve an existing and generic industrial problem regarding process operation, process optimization, process control and operator training. Every problem in the process discussed in this thesis has a generic form and can have either high or low influence on the process. The example processes and cases used in this thesis are aimed to emphasize these particular phenomena.

Theoretical structural validity has been achieved through the use of standardized and accepted models as the fundamental base for size reduction and separation. Each model is complemented with additional sub-models which enable an estimation of the transition from one state to another in a time dependant environment. These complementary sub models have been adapted from applied models from related fields within minerals processing, powder technology, control theory and chemical engineering to capture the process dynamics.

The performance validity states that the simulated system produces satisfactory accuracy and that the results are useful and consistent within its domain of application. Each study has been aimed to capture the dynamics that can cause the process to alter performance. In Paper C the estimated performance was compared to an empirical experiment for similar condition for performance validation. In Paper F a user acceptance test was used and the process adjusted until it gave an acceptable response. In Papers E and G a usability study was performed for operator training to provide feedback for further development. Papers A, B and H are focused on capturing a specific aspect that causes the process to change state. Papers E, G and H more conceptual than Papers A, C, D, and F that are aimed to mimic specific process plants.

Each paper was based on sampled data from specific plants or arbitrary processes with similar production units and configurations. Taking samples from a process however only provides a snapshot of the process at a particular place and at a particular time. According to Åström [97], a model is only valid at the time the experiment is performed. If the process dynamics change with time, it may not be valid at a later time. Empirical models are dependent on empirical data from a particular process and production unit to accurately represent the system. These models have a weak congruence since they need to be adjusted for every application. Mechanistic models are however based on the Newtonian mechanics within the unit and do often have a stronger congruence. In Papers A-F the models were empirical while in Paper H and I the simulation is based on the mechanistic models developed for cone crushers and screens.

10.3 ANSWERS TO RESEARCH QUESTIONS

The following answers are given to the research questions stated in this thesis:

RQ1. What methods and techniques can be used to satisfactory simulate dynamic crushing plant behaviour?

Traditional steady-state simulations are not adequate to represent time dependent behaviour properly. However, there have been a number of attempts to compensate for the lack of time perspective in steady-state simulation in order to represent the dynamics. In Svedensten et al. [16] the effect of wear and process variation on production was estimated by running steady-state simulation together with Monte Carlo simulation, which was used to estimate the performance distribution of the plant. In King et al. [100] the step changes in the process were evaluated by running multiple steady-state simulations in a sequence.

Dynamic simulation is defined in this thesis as continuous simulations with sets of differential equations together static equations to reproduce the dynamic performance of a system. The fundamental parts of dynamic systems are described in Chapter 5 - Modelling of Crushing Plants. Different modelling principles can be applied to estimate the different dynamics in a system, such as: first principle models, state-space models, transfer functions and differential equations. The material flow in a dynamic system is not constrained by the instantaneous mass balance in contrast to steady-state simulations for example. Instead it follows the principle of conservation of mass, which is described with a differential equation in Eq. 4.6.

When simulating long term conditions, the implementation of DESs is necessary in order to obtain reliable results. With a DES the simulation is not continuous any more. Instead the change in state is initiated at a specific time, making it discrete. With SimEvents a discrete event perspective can be added in the modelling environment making the plant simulation a hybrid one i.e. a combination of discrete and continuous simulation.

Different platforms exist that support the modelling of dynamic systems. During the work in this thesis two different platforms have been used and validated, SysCAD (Kenwalt) and Simulink (Mathworks). Both platforms are highly capable of simulating the dynamic behaviour that occurs in a crushing plant. Even though SysCAD is able to deliver a built-in equipment library Simulink provides more flexibility and better integration capabilities of the modelling environment in the development of a dynamic simulator.

RQ2. What physical principles and phenomena can cause dynamic behaviour in crushing plants?

Multiple factors affect the performance of a crushing plant, according to Figure 14. On a production unit level the internal dynamics within the fundamental level of each unit are essential for achieving high fidelity process simulations, Figure 15. Accurate representation of the unit and process level can be achieved with a bottom-up fundamental approach to the modelling when the models structure has been defined. Such has been the approach in the crushers in Paper H, screen in Paper I and material handling in Papers B, E and F.

The process is affected by gradual and discrete changes. The changes are usually caused by a change in operating conditions or unit condition. Wear on components happens gradually over a long time perspective while the unit response has a much shorter time constant. Changes in set points, calibrations, interlocks and failures are examples of factors that create discrete changes in the process. How the process responds to gradual and discrete changes is dependent on the configuration and the characteristics of the each individual production unit. Stochastic and systematic variations also contribute to the dynamic behaviour of the process and should not be neglected as observed in Paper A.

In dynamic simulations the transport and storage of material within time dependent equipment can cause process fluctuation if the design of the plant or the control system is not adequate to keep the process stable. When the material is transported with conveyors between different production units the process experiences a time delay and if the storage capacity is small in the subsequential production unit the control system needs to be able to take that into consideration and regulate the flow in order to keep the process stable. Studying the example in Chapter 7.1, the plant experiences a steady-state operation up to a certain target feed rate, after that the average plant throughput levels out due to process dynamics as illustrated in Figure 61.

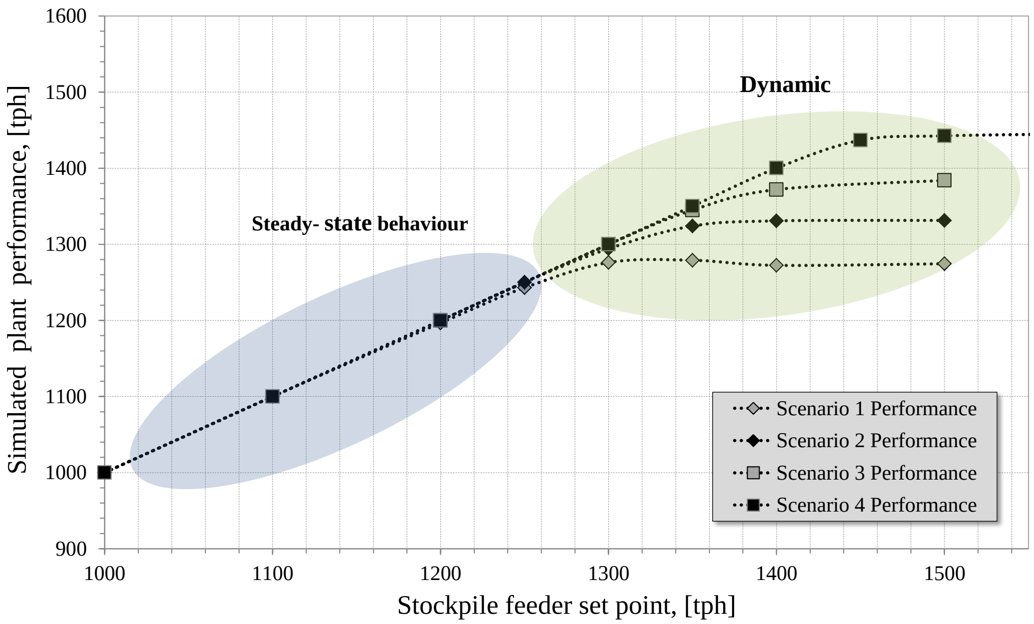


Figure 61. Plant's average production performance. In the blue area the plant operates in steady-state while in the green area the plant experiences fluctuation and limited throughput.

RQ3. What are the main applications for a dynamic simulation platform?

The main areas of application for dynamic simulation for industrial purposes that have been identified in this thesis are:

- Process simulation
- Evaluation of plant design
- Control development
- Process optimization
- Operational planning
- Maintenance planning
- Operator training

In all of these areas the use of dynamic simulation has shown to be essential. How the dynamic simulation is applied varies between each area and also within each area, depending on the general purpose of the simulation.

RQ4. What process related characteristics must be included in the process model to simulate the process performance and achieve useful information?

Which models are used and how the process model is configured is dependent on what the purpose of the simulation is, listed in the previous question. Some applications require higher level of fidelity while others require faster computational time in respect to each other. From a generic perspective the process needs to be able to accurately capture every possible source of dynamics in the process to supply relevant information for the selected purpose.

During operation the process will experience different performance over time. Each production unit may be subjected to substantial wear, changing the performance of the unit and possibly affecting the whole process. To maintain a highly efficient and productive process the process needs to be stopped for maintenance, calibrations and adjustments at regular intervals. The amount of wear is determined by how the units are operated and the material properties. The material properties are not constant but are usually within an interval depending on the source of the material and utilized pre-process. In order to minimize the effects from variation the control system regulates the flow which in turn maintains high throughput and safe operation. The operators are finally responsible for monitoring the process and evaluate if the process parameters need to be adjusted to increase production of a certain product or product quality depending on predefined product requirements, if not taken care of by a supervisory regulatory control system.

RQ5. How can suitable control strategies for crushing plants be developed with dynamic simulations?

The development of suitable control strategies is recommended according to the following path:

- Understand the process
- Identify control and manipulative variables
- Formulate the control objective
- Select appropriate candidates for control strategies
- Design the control algorithms
- Tune the algorithms
- Implement control algorithms in the process model
- Simulate and evaluate plant performance under different conditions
- Compare

Well defined production unit models support the understanding of the process and the identification of what variables can be considered to be control or manipulative variables and how they will affect the process.

The fundamental design and development of a control system starts by defining the control objective. This can be to control a certain level or mass flow within the process. An appropriately designed control system should provide a stable operation, an acceptable response to input commands, be insensitive to system parameter change, minimize steady-state error to input commands and reduce the effects of undesired disturbances [13].

Dynamic modelling is essential when it comes to developing, tuning and evaluation of control algorithms. Tuning can be achieved with a linear approximation of the process around the operational condition as illustrated in Paper H. While evaluating the process performance under different conditions, a complete process simulation with superimposed control algorithm is recommended. This can be achieved either by implementing the control algorithm in the model (Paper B and C) or through a third party software (Paper F).

RQ6. What aspects of using dynamic simulations for operator training should be utilized to improve operators' capability to maintain a safe and productive process?

For operator training, as illustrated in Paper E and Paper G, the operator needs to be able to interact with the process and make process changes in real-time. With a dynamic simulation running in real-time connected to an HMI this becomes possible, thus minimizing the need of interfering with or interrupting the actual production.

The operator needs to be able to select appropriate process parameters from a crusher performance mapping and be aware of the process conditions. The operator needs to understand how the crusher is operated, what are the operational limits of the crusher and its load history. The operator needs to recognize that the performance of the circuit often depends on how fast they can make the necessary decision and adjust the process accordingly.

How the information and where the information is presented is essential for operators cognitive capability. The interface that the operator has towards the process should support the operator in detection, analysis, action and evaluation of the process, not increase the mental load.

10.4 FUTURE WORK

The work presented in this thesis has been focused mainly on modelling and exploratory studies of different applications for implementation of dynamic simulation. With dynamic simulation new applications become possible compared to the use of steady-state simulations, applications such as operator training and control algorithm development. Each application is relatively time consuming to setup. A more easy-to-use graphical user interface and refined model structure would reduce the configuration time.

Cost is the largest drive of the process. Increasing the value of the product and striving to reduce the needed resources is necessary to secure business profit. An aggregates production each product has a different market value while cost of producing these products are directly related to energy consumption, source of energy, wear on components, process selection, human resources and product logistics. In order to optimize the efficiency of the process the cost needs to be clearly defined.

Environmental impact from quarries and mines is an important issue from a sustainable perspective. The material flow carries with it a footprint of consumed energy, hazardous chemicals and water. Estimating the environmental impact for each unit, such as water and oil use, as well energy and resource consumption is essential for estimating the accumulated environmental impact of the processed product.

The development and tuning of a control system is essential for ensuring safe and robust operation while striving for high product quality and high production throughput. There are multiple solutions available for regulatory and supervisory control systems, each with a number of advantages and disadvantages and applicability to certain process configuration. A detailed framework of available solutions for different objectives and configuration with the state of the art from academia and industrial applications would be valuable for future applications.

Operator training needs to be easily accessible and provide useful information for the participants. A site-specific process layout and operational specific aspects could provide the user with relevant information to use in daily operation. Such as how to configure the process with regards to market demand and available product to optimize process profit.

Many of the aspects that were illustrated in the Ishikawa-diagram in Figure 14 have been covered in this thesis. Segregation in bulk material is an operational issue that reduces overall unit performance and can increase localized wear in crushers and screens. Quantifying misaligned feed and segregation at different transfer points can provide a more accurate estimation of the process performance.

The efficiency of crushing and screening processes are essential for a sustainable operation and organisation. Understanding the process and process dynamics opens up for possibilities to improve the production in multiple aspects of the operation. The development of dynamic simulation and its related applications will continue as there is a need for engineering tools to be used both within academia and in the industry.

REFERENCES

1. Blatt, H., R. Tracy, and B. Owens, *Petrology : Igneous, Sedimentary and Metamorphic*. 3rd ed. 2010, New York: W. H. Freeman.

2. Hultkvist, L., *Berg för Byggande*. 2nd ed. 2007, Stockholm: The Swedish Aggregates Producers Association.

3. SGU, *Grus, sand och krossberg 2013*. 2013, Uppsala: Geological Survey of Sweden.

4. SGU, *Bergverksstatistik 2013*. 2013, Uppsala: Geological Survey of Sweden.

5. Wills, B. and T.J. Napier-Munn, *Wills' Mineral Processing Technology: an introduction to the practical aspects of ore treatment and mineral recovery*. 7th ed. 2011, London: Elsevier Ltd.

6. Evertsson, M., *Cone Crusher Performance*, in *Department of Machine and Vehicle Design*. 2000, PhD Thesis from Chalmers University of Technology: Gothenburg.

7. Lee, E., *Optimization of Compressive Crushing*, in *Department of Product and Production Development*. 2012, PhD Thesis from Chalmers University of Technology: Gothenburg.

8. Bengtsson, M., *Quality-Driven Production of Aggregates in Crushing Plants*, in *Department of Product and Production Development*. 2009, PhD Thesis from Chalmers University of Technology.

9. Stafhammar, M.S., *Screening of Crushed Rock Material*, in *Department of Machine and Vehicle Systems*. 2002, PhD Thesis from Chalmers University of Technology: Gothenburg.

10. Johansson, R., *Air Classification of Fine Aggregates*, in *Department of Product and Production Develpment*. 2015, PhD Thesis from Chalmers University of Technology: Gothenburg.

11. Narasimha, M.a., et al., *A semi-mechanistic model of hydrocyclones - Developed from industrial data and inputs from CFD*. International Journal of Mineral Processing, 2014. 133: p. 1-12.

12. Hulthén, E., *Real-Time Optimization of Cone Crushers*, in *Department of Product and Production Development*. 2010, PhD Thesis from Chalmers University of Technology: Gothenburg.

13. Dorf, R.C. and R.B. Bishop, *Modern Control Systems*. 9th ed. 2001, Upper Saddle River: Prentice Hall, cop.

14. Bainbridge, L., *Ironies of Automation.* Automatica, 1983. 19(6): p. 775-779.

15. Ljung, L. and T. Glad, *Modelling of Dynamic Systems*. 2002, Upper Saddle River: Pearson Prentice Hall.

16. Svedensten, P., *Crushing Plant Performance*, in *Department of Applied Mechanics*. 2005, PhD Thesis from Chalmers University of Technology: Gothenburg.

17. Herbst, J., et al., *Mineral Processing Plant/Circuit Simulators: An Overview*. Mineral Processing Plant Design, Practice, and Control Proceedings. Vol. 1. 2002, New York: Society for Mining, Metallurgy, and Exploration (SME).

18. Napier-Munn, T.J., et al., *Mineral Comminution Circuits - Their Operation and Optimisation*. 2005, Brisbane: Julius Kruttschnitt Mineral Research Centre.

19. King, R.P., *Modelling and Simulation of Mineral Processing Systems*. 1st ed. 2001, Oxford: Butterworth-Heinemann.

20. Morrison, R.D. and J.M. Rickardson, *JKSimMet: A Simulator for Analysis, Optimization and Design of Commintion Circuits*. Mineral Processing Plant Design, Practice, and Control Proceedings. Vol. 1. 2002, New York: Society for Mining, Metallurgy and Exploration (SME).

21. Outotec. *Outotec – Virtual Experience Training*. 2015.

22. Honeywell. *Rio Tinto Alcan Gove Improves Operator Training and Startup Time with UniSim.* 2015.

23. MetDynamics. *Opertor Training*. 2015.

24. Li, X., M.S. Powell, and T. Horberry, *Human Factor in Control Room Operations in Mineral Processing: Elevating Control From Reactive to Proactive.* Journal of Cognitive Engineering and Decision Making, 2012. 6: p. 88-111.

25. Lindqvist, M., *Wear in Cone Crusher Chambers*, in *Department of Applied Mechanics*. 2005, PhD thesis from Chalmers University of Technology: Gothenburg.

26. Crotty, M.J., *The Foundations of Social Research - Meaning and Perspective in the Research Process*. 1998, Australia: Allen & Unwin

27. Williamsson, K., *Research methods for students, academics and professionals*. 2nd ed. 2002, Wagga Wagga: Centre for Information Studies.

28. Kossiakoff, A., et al., *System Engineering Principles and Practice*. 2nd ed. Systems engineering and management. 2011, New Jersey: John Wiley & Sons, Inc.

29. Blanchard, B.S. and W.J. Fabrycky, *System Engineering and Analysis*. 4th ed. 2006, Upper Saddle River: Pearson Prentice Hall.

30. NASA, *NASA System Engineering Handbook*. 2007, Washington, USA: National Aeronautics and Space Administration.

31. Dormand, J.R. and P.J. Prince, *A family of embedded Runge-Kutta formulae.* Journal of Computational and Applied Mathematics, 1980. 6(1): p. 19-26.

32. Chapra, S.C. and R.P. Canale, *Numerical Methods for Engineers*. 6th ed. 2010, New York: McGraw-Hill.

33. Shampine, L.F., *Interpolation of Runge-Kutta Methods.* SIAM Journal on Numerical Analysis, 1985. 22(5): p. 1014-1027.

34. Bryman, A. and E. Bell, *Business research methods*. 2nd ed. 2007, Oxford: Oxford University Press.

35. Oberkamf, W.L., T.G. Trucano, and C. Hirch, *Verification, Validation and Predictive Capability in Computer Engineering and Physics.* Applied Mechanics Reviews, 2004. 57(5): p. 345-384.

36. Pedersen, K., et al. *Validating Design Methods & Research: The Validation Square*. in *ASME Design Engineering Technical Conferences 2000* 2000. Baltimore.

37. Quist, J., *Discrete Element Modelling and Simulation of Compressive Crushing*, in *Department of Product and Production Development*. 2015, Licentiate thesis from Chalmers University of Technology: Gothenburg.

38. Hofmann, M., *On the Complexity of Parameter Calibration in Simulation Models.* The Journal of Defense Modelling and Simulation, 2005. 2(4): p. 217-226.

39. Rittinger, R.P., *Lehrbuch der Aufbereitungskunde*. 1867, Berlin: Ernst and Korn.

40. Kick, F., *Das Gesetz der propertionalen Widerstande und seine anwendung felix*. 1885, Leipzig.

41. Bond, F.C., *The third theory of comminution.* Trans. AIME, 1952. 193: p. 484-494.

42. Lindqvist, M., *Energy considerations in compressive and impact crushing of rock.* Minerals Engineering, 2008. 21(9): p. 631-641.

43. Walker, W.H., et al., *Principles of Chemical Engineering*. 1937, New York: McGraw-Hill.

44. Hukki, R.T., *Proposal for a Solomonic Settlement Between the Theories of von Rittinger, Kick and Bond.* AIME Transaction, 1962. 223: p. 403-408.

45. Epstein, B., *The mathematical description of certain breakage mechanisms leading to the logarithmic-normal distribution.* J. Franklin inst., 1947. 244: p. 471-477.

46. Whiten, W.J., *The Simulation of Crushing Plants with Models Developed using Multiple Spline Regression*, in *10th International Symposium on the Application of Computer Methods in Mineral Industry*. 1972.

47. Dundar, H., A.H. Benzer, and N. Aydogan, *Application of population balance model to HPGR crushing.* Minerals Engineering, 2013. 50-51: p. 114-120.

48. Whiten, W.J., *Ball Mill Simulation Using Small Calculators*, in *AusIMM proc.* 1976. p. 47-53.

49. Valery, W. and S. Morrell, *The Development of a Dynamic Model for Autogenous and Semi-Autogenous Grinding.* Minerals Engineering, 1995. 8(11): p. 1285-1297.

50. Valery, W., *A model for dynamic and steady-state simulation of autogenous and semi-autogenous mills*, in *School of Engineering*. 1998, PhD thesis from University of Queensland: Brisbane.

51. Tavares, L.M. and R.M. Carvalho, *A Mechanistic Model of Batch Grinding in Ball Mills*, in *XXV International Mineral Processing Congress*. 2010: Brisbane.

52. Newton, I., *Philosophiæ Naturalis Principia Mathematica*. 1687.

53. Evertsson, M. and M. Lindqvist, *Pressure Distribution and Power Draw in Cone Crushers*, in *Minerals Engineering '02*. 2002: Perth.

54. Sbárbaro, D., *Control of Crushing Circuit with Variable Speed Drives*, in *16th IFAC World Congress*. 2005: Praque.

55. Plitt, L.R., *The Analysis of Solid-Solid Separations in classifiers.* CIM Bulletin, 1971.

56. Reid, K.J., *Derivation of an equation for classifier -reduced performance curves.* Can Metall Quart, 1971. 10: p. 253-254.

57. Rosin, P. and E. Rammler, *The Laws Governing the Fineness of Powdered Coal.* Journal of the Institute of Fuel, 1933. 7: p. 29-36.

58. Hatch, C.C. and A.L. Mular, *Simulation of the Brenda Mines Ltd secondary crushing plant.* AIME Transactions Volume 272, 1982.

59. Karra, V.K., *Development of a Model for Predicting the Screening Performance of a Vibrating Screen.* CIM Bulletin, 1979.

60. Lynch, A.J., *Mineral Crushing and Grinding Circuits: Their Simulation, Optimisation, Design and Control* Developments in Mineral Processing. Vol. 1. 1977: Elsevier Scientific Publishing Company.

61. Csöke, B., et al., *Optimization of stone-quarry technologies.* International Journal of Mineral Processing, 1996. 44-45: p. 447-459.

62. Powell, M.S., B. Foggiatto, and M.M. Hilden, *Practical simulation of FlexiCircuit processing options*, in *XXVII International Mineral Processing Congress*. 2014: Santiago.

63. Powell, M.S., et al., *Optimisation Opportunities for HPGR Circuits*, in *11th AusIMM Mill Operators' 2012*. 2012: Hobart.

64. Whiten, W.J., *Models and Control Techniques for Crushing Plants*, in *Control '84 Mineral/Metallurgical Processing* 1984, AIME.

65. Herbst, J. and A. Oblad, *Modern control theory applied to crushing. part 1: Development of a dynamic model for cone crusher and optimal estimation of crusher operating variables.*, in *Proceedings of IFAC symposium on Automation for Mineral Resource Development*. 1985: Queensland. p. 301-307.

66. Sbárbaro, D., *Advanced Control and Supervision of Mineral Processing Plants - Dynamic Simulation and Model-based Control System Desing for Comminution Circuits*. 2010, New York: Springer-Verlag London Limited.

67. Liu, Y. and S. Spencer, *Dynamic simulation of grinding circuits.* Minerals Engineering, 2004. 17(11-12): p. 1189-1198.

68. Itävuo, P., A. Jaatinen, and M. Vilkko, *Simulation and advanced control of transient behaviour in gyratory cone crushers*, in *8th Seminario Internacional de Procesamiento de Minerales*. 2011: Santiago.

69. Ruuskanen, J., *Influence of Rock Properties in Compressive Crusher Performance*. 2006, PhD thesis from Tampere University of Technology: Tampere.

70. Airikka, P., *Plant-wide process control design for crushing and screening processes*, in *Procemin 2013*. 2013: Santiago, Chile.

71. Itävuo, P., et al. *Tight feed-hopper level control in cone crushers*. in *XXVII International Mineral Processing Congress*. 2014. Santiago.

72. Atta, K.T., A. Johansson, and T. Gustafsson, *Control oriented modelling of flow and size distribution in cone crushers.* Minerals Engineering, 2014. 56: p. 81-90.

73. Itävuo, P., M. Vilkko, and A. Jaatinen, *Indirect Particle Size Distribution Control in Cone Crushers*, in *16th IFAC Symposium on Automation in Mining, Mineral, and Metal Processing*. 2013: San Diego.

74. Bolander, A. and S. Lindstedt, *Automation and Optimization of Primary Gyratory Crusher Performance for Increased Productivity*, in *Department of Product and Production Development*. 2015, MSc thesis from Chalmers University of Technology: Gothenburg.

75. Atta, K.T., A. Johansson, and T. Gustafsson, *On-Line Optimization of Cone Crushers using Extremum-Seeking Control*, in *IEEE Multi-conference on System and Control*. 2013: Hyderabad.

76. Huband, S., et al., *Maximising overall value in plant design.* Minerals Engineering, 2006. 19(15): p. 1470-1478.

77. While, L., et al., *A multi-objective evolutionary Algorithm approach for crusher optimisation and flowsheet design.* Minerals Engineering, 2004. 17(11-12): p. 1063-1074.

78. MathWorks. *MATLAB - Global Optimization Toolbox*. 2015.

79. Box, G.E., J.S. Hunter, and W.G. Hunter, *Statistics for Experimenters - Design, Innovation, and Discovery*. 2nd ed. 2005, Hoboken: John Wiley & Sons.

80. Li, X., et al., *The control room operator: The forgotten element in mineral process control.* Minerals Engineering, 2011. 24(8): p. 894-902.

81. Toro, R., J.M. Ortiz, and I. Yutronic, *An Operator Traininng Simulator System for MMM Cominution and Classification Circuits*, in *IFAC Workshop on Automation in the Mining, Mineral and Metal Industries*. 2012: Gifu.

82. Toro, R., J.M. Ortiz, and C. Zamora, *An Integrated Simulation-Based Solution for Operator Effectiveness*, in *16th IFAC Symposium in Automation in Mining, Mineral, and Metal Processing*. 2013: San Diego.

83. Andersen, J.S. and T.J. Napier-Munn, *The Influence of Liner Condition on Cone Crusher Performance.* Minerals Engineering, 1990. 3(1-2): p. 105-116.

84. Morrison, R.D. and P.W. Cleary, *Towards a virtual comminution machine.* Minerals Engineering, 2008. 21(11): p. 770-781.

85. Moshgbar, M., R. Parkin, and R.A. Bearman, *Application of fuzzy logic and neural network technologies in cone crusher control.* Minerals Engineering, 1995. 8(1–2): p. 41-50.

86. Bearman, R.A. and C.A. Briggs, *The active use of crushers to control product requirements.* Minerals Engineering, 1998. 11(9): p. 849-859.

87. Swedish Standards Institute, S.S., *SS-EN 13242+A1:2007*, in *Ballast för obundna och hydrauliskt bundna material till väg- och anläggningsbyggande*. 2007.

88. Powell, M.S., et al., *Transforming the Effectiveness of a HPGR Circuit at Anglo Platinum Mogalakwena*, in *SAG Conference*. 2011: Vancouver.

89. Quist, J., *Cone Crusher Modelling and Simulation*, in *Department of Product and Production Development*. 2012, MSc thesis from Chalmers University of Technology: Gothenburg.

90. Evertsson, M., et al. *Control Systems for Improvement of Cone Crusher Yield and Operation*. in *Comminution '14*. 2014. Cape Town.

91. Robinson, G.K., *Predicting variation in planned mineral processing plants.* Minerals Engineering, 2003. 16(3): p. 179-186.

92. Guyot, O., et al., *VisioRock, an integrated vision technology for advanced control of comminution circuits.* Minerals Engineering, 2004. 17(11–12): p. 1227-1235.

93. Engblom, N., et al., *Effects of process parameters and hopper angle on segregation of cohesive ternary powder mixtures in a small scale cylindrical silo.* Advanced Powder Technology, 2012. 23(5): p. 566-579.

94. Banks, J., et al., *Discrete-event system simulation*. 5th ed. 2010, Upper Saddle River: Pearson Prentice Hall.

95. Marlin, T.E., *Process Control - Designing Processes and Control Systems for Dynamic Performance*. 2nd ed. 2000, New York: McGraw-Hill Chemical Engineering.

96. Sanchidrián, J.A., et al., *Size Distribution Function for Rock Fragments.* International Journal of Rock Mechanics & Mining Science, 2014. 71: p. 381-394.

97. Åström, K.J. and T. Hägglund, *PID controllers: Theory, Design and Tuning*. 2nd ed. 1995, Research Triangle Park: Instrument Society of America.

98. Papalambros, P.Y. and D.J. Wilde, *Principles of Optimal Design: Modeling and Computation*. 2nd ed. 2000, Cambridge: Cambridge University Press.

99. Kenne, J.P. and L.J. Nkenungoue, *Simultaneous control of production, preventive and corrective maintenance rates of failure-prone manufacturing system.* Applied Numerical Mathematics, 2008. 58: p. 180-194.

100. King, H., et al., *Development of a dynamic simulator for modelling complex flows in mineral processing circuits*, in *Comminution '12*. 2013: Cape Town.