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ECONOMIC EVALUATION AND DESIGN OF AN ELECTRIC ARC FURNACE CONTROLLER BASED ON ECONOMIC OBJECTIVES

by

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Economic evaluation and design of an electric arc furnace controller based on economic objectives

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ABSTRACT

The economic benefits of Model Predictive Control (MPC) over conventional manual control on an Electric Arc Furnace (EAF) are determined by means of a simulation study. The structure used for the MPC controller is chosen such that the objective function, which is minimised by the controller, corresponds to the cost of a tap. Minimisation of the objective function thus constitutes minimising EAF operational cost. The major factors contributing to the cost of the tap are thus determined and their contributions relative to each other quantified. The procedure of translating functional control objectives into economic objectives is discussed, as is the relative cost contribution of the feed additions to the EAF.

An existing EAF model is expanded by modelling the slag foam depth. The foam depth is useful in ensuring efficient energy transfer to the melt. Great emphasis is placed on ensuring that the simulation study is representative of operational conditions typically experienced in industry. Only continuous measurements are therefore used for continuous feedback, and measurements taken at discrete time intervals are only fed back at the time intervals indicated by plant data. The full non-linear model is used to simulate the plant, even though a linearised model is implemented as the internal plant model for the MPC controller. Disturbances are chosen based on plant data and suggestions from industry.

The process of an experimental design for controller evaluation is discussed in detail. The selection of an appropriate experimental technique, possible threats to data integrity, tools for data analysis and capital budgeting tools form part of the complete experimental procedure. A framework is presented to ensure that useful data is generated and that valid conclusions are made concerning the data. This evaluation framework forms the basis of the experimental procedure used to compare the two control strategies (manual and MPC). The simulation study represents a test conducted over a period of one month, and randomisation is used to ensure that the test data is not correlated to the disturbances. Hypothesis testing is performed to ensure that the result is statistically significant.

Simulation results indicate large potential benefits attributable to MPC control. Improved utilisation of feed materials can potentially reduce the cost per ton of steel by 0.8 %. The major portion of the potential benefits is however due to the elimination of unscheduled delays, by ensuring that steel specifications are met at tapping, and that off-gas limits are not exceeded at any stage during the tap. These factors account for potential savings in excess of 7 % due to increased throughput.

Keywords: Electric Arc Furnace, Model Predictive Control, Economic evaluation, Experimental design, Hypothesis testing, Dynamic models.

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OPSOMMING

Die finansiële voordele van 'n Model Voorspellende Beheerder is in 'n simulasie-studie bepaal, deur dit te vergelyk met konvensionele hand-beheer op 'n elektriese boogoond. Die struktuur van die beheerder is sodanig gekies, dat die doelwit-funksie wat deur die beheerder geminimeer word ooreenkom met die koste van 'n tap. Minimering van die doelwit-funksie is dus ekwivalent daaraan om die bedryfskoste van die boogoond te minimeer. Die belangrikste faktore wat bydra tot die koste van 'n tap is daarom geïdentifiseer en die relatiewe bydraes tot die totale koste gekwantifiseer. Die omskrywing van funksionele doelwitte in terme van finansiële doelwitte is bespreek en die relatiewe kostes van die toevoer-materiale bepaal.

'n Bestaande boogoond model is uitgebrei deur die skuimslakdiepte te modelleer. Die skuimslakdiepte is van belang, aangesien effektiewe energie-oordrag na die bad hierdeur beïnvloed word. Klem is daarop gelê dat die simulasie-studie verteenwoordigend moet wees van omstandigdhede wat tipies in die industrie aangetref word. Slegs metings wat kontinu beskikbaar is word daarom kontinu teruggevoer. Metings wat slegs op diskrete tydstippe beskikbaar is word slegs teruggevoer op dié tydstippe aangedui in aanlegdata. Die volledige nie-lineêre model is gebruik om die aanleg te simuleer, al is 'n lineêre model gebruik as die interne aanleg-model vir die Model Voorspellende Beheerder. Steurings is gebaseer op aanlegdata en voorstelle deur aanleg personeel.

Eksperimentele ontwerp met die doel om beheerders te evalueer is in detail bespreek. Die keuse van 'n geskikte eksperimentele tegniek, potensiële bedreigings vir data integriteit, prosedures vir data analise en projek-evaluerings tegnieke maak deel uit van die eksperimentele prosedure.

'n Raamwerk is voorgestel waarbinne verseker kan word dat bruikbare data gegenereer sal word en dat geldige gevolgtrekkings gemaak kan word oor die data. Hierdie evalueringsraamwerk vorm die basis van die eksperimentele prosedure wat gebruik is om die twee beheerstrategieë te vergelyk (Model Voorspellende Beheer en hand-beheer). 'n Toets uitgevoer oor die bestek van een maand word deur die simulasiestudie voorgestel. Ewekansige tegnieke is gebruik om te verseker dat geen korrelasie tussen die data en die steurings bestaan nie. Hipotese toetsing is gebruik om te bepaal of die resultate statisties beduidend is.

Die simulasiestudie dui op groot potensiële finansiële voordele weens Model Voorspellende Beheer. Beter benutting van toevoer-materiale kan die koste per ton staal potensieel verminder met 0.8 %. Die grootste deel van die potensiële besparing is egter vanweë die eliminasie van ongeskeduleerde onderbrekings. Dit word bewerkstellig deur te verseker dat aan staal temperatuur en -samestelling spesifikasies voldoen word wanneer getap word en dat die afgas temperatuur nie gespesifiseerde limiete oorskry nie. Hierdie faktore kan potensieel lei tot addisionele besparings van groter as 7 % danksy verhoogte deurset.

Sleutelterme: Elektriese boogoond, Model Voorspellende Beheer, Ekonomiese evaluering, Eksperimentele ontwerp, Hipotese toetsing, Dinamiese modelle.

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Information regarding typical operational practices on Electric Arc Furnaces (EAFs) was obtained from Iscor and Corus steel, U.K. I which to thank Mr. Philip Schutte and his colleagues at Iscor in particular, for their willingness to discuss sensitive information and to answer endless questionnaires within a limited time span. I also which to thank Mr. Andrew Chown and his colleagues at Corus steel for their willingness to discuss their furnace practices at short notice. The information obtained during these two interviews provided useful insight into aspects typically not considered during purely theoretical analyses.

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CHAPTER 1: INTRODUCTION.

1.1. MOTIVATION.

A worldwide tendency of Basic Oxygen Furnaces (BOFs) being replaced by Electric Arc Furnaces (EAFs) is increasingly experienced in industry. In 1994 EAFs contributed approximately 31.6% to the worldwide steel production, and this figure is expected to rise to 40% by 2010 [1]. The major portion of EAF control is however commonly performed manually, and the efficiency is often highly dependent on operator experience. Large potential benefits exist in the efficient automation of the complete EAF steelmaking process, and in optimising EAF efficiency.

The potential economic benefits of implementing an advanced control strategy on an EAF are investigated in this dissertation by means of a simulation study. The harsh conditions in which EAFs are typically operated, and the accompanying lack of accurate measurements are a major drawback in implementing efficient feedback control schemes. Implementation of a model based control scheme e.g. Model Predictive Control (MPC) has the advantage that unmeasured variables can be estimated by an internal model. Some sub-systems of EAFs for which measurements are readily available or easily derived are commonly controlled, e.g. the positioning of electrodes. Static furnace models are also used extensively to calculate optimal feed additions to furnaces. None of these techniques however account for the high amplitudes of disturbances that typically act on the EAF, the optimisation of the complete EAF steelmaking process or the time dependence of some critical variables.

Steel producers are often required to aim at producing steel of a much higher quality than specified, in order to ensure that all specifications are met in the presence of disturbances. A controller capable of reducing product variations attributable to disturbances would thus increase profit, as expenses in improving steel quality beyond specifications will be reduced considerably. A simulation study incorporating typical disturbances and common EAF operating conditions would provide a useful guide in estimating the feasibility of implementing advanced control schemes on the increasing number of EAFs.

1.2. BACKGROUND.

A large portion of the work done on EAF control focussed on control of subsystems of the furnace, e.g. the electrical system. Position control of electrodes has been a research topic for quite some time. Reuter *et al.* [2] discussed the impedance-based electrode control of submerged arc furnaces. Akimoto *et al.* [3] discussed an optimisation strategy to utilise the available energy sources in the steel works optimally. Chirattananon and Gao [4] described the usage of an energy model of an EAF in determining optimal electrical inputs to the EAF. All of these strategies aim to reduce the energy usage of the EAF or the complete melt shop. The electrical power used by EAFs however accounts only for approximately 10.5% of the total cost of carbon steel production [5], and only a fraction of the total cost of EAF operation is thus influenced by these automatic control schemes.

Bekker, Craig and Pistorius [6] performed a functional evaluation on the control of an EAF off-gas system in a simulated environment. It was found that the off-gas system could potentially be used to improve furnace efficiency and to provide a safer workplace. The off-gas system also serves an important purpose in ensuring that environmental regulations are met. Although many advantages of improved off-gas control do not have large direct economic benefits, the indirect benefits are significant enough to justify inclusion of the off-gas system in the control of EAFs.

Another popular approach is the use of static furnace models to predict the optimal feed additions to the furnace. De Vos [7] developed a static furnace model to calculate the optimal flux additions to an EAF. All calculations are done prior to furnace operation and are not adjusted during a tap. Juuso and Uronen [8] presented a simulation study to optimise production alternatives for a ferroalloy process including an EAF. Deterministic steady state models are used to do predictions, but optimisation is done only at the design stage, and not real time.

For processes with non-linear performance functions or constraints, Bawden and MacLeod [9] showed that a decrease in product variations would increase profit. The performance function of an EAF would consist of the cost of the tap as a function of feed material consumption and of reaching control objectives. Since constraints exist on some of the control objectives and the EAF objective function is mostly non-linear (see Chapter 3), a reduction in product variations would most likely reduce EAF operating cost.

1.3. PROBLEM STATEMENT.

The problem statement consists of four parts:

- Identify the factors contributing to the cost of EAF steelmaking.
- Expand the existing EAF model to ensure that the cost of EAF steelmaking can be modelled accurately.
- Design a controller to minimise the cost of EAF steelmaking.
- Evaluate the efficiency of the control strategy under typical operating conditions.

1.4. CONTRIBUTION.

The EAF model presented by Bekker [6] was used as a basis for the simulation study. Viljoen [10] improved the Bekker model by improving the accuracy of the off-gas temperature model. An additional modelling effort was undertaken to model the slag foam depth inside the EAF, as described in Chapter 2. The slag foam depth is a useful variable in ensuring efficient energy transfer to the melt.

The design procedure of an MPC controller based on economic objectives is discussed in Chapter 5. Although the principle is not new, control objectives are usually based on functional specifications, or on setpoints that proved to be effective in previous control efforts. The transformation of functional control objectives into economic objectives are discussed in Chapter 4 and would ensure that steel of a required quality is produced in an economically optimal way. De Vos [7] reported significant savings using a static furnace model to optimise flux additions to the EAF. It is expected that savings can be increased further, by using a dynamic EAF model and an appropriate MPC controller (utilizing real time feedback and predictions) to reduce EAF operational cost.

Simulation studies are often performed as a preliminary step in controller evaluation, and the accuracy of the simulation model is often limited. The focus of the simulation study conducted in following chapters is to ensure that typical disturbances are modelled, that feedback is only used continuously if the variables are measured continuously, and that unrealistic requirements are not placed on the simulated controller.

The comparison of two controllers is often performed in an inappropriate way, leading to invalid conclusions or statistically insignificant results. A framework for experimental design is presented that ensures that useful data is generated, and the complete evaluation strategy is based on these principles. The complete simulation study thus presents a framework that will help to motivate automation of EAFs.

1.5. DISSERTATION APPROACH.

The logical flow of actions undertaken during the dissertation is depicted in Figure 1.1. A discussion of the actions shown in the figure follows.

The additional modelling effort comprises the slag foam depth model described in Chapter 2. The comprehensive EAF model thus consists of the Bekker model [6], the revised off-gas temperature model by Viljoen [10] and the slag foam depth model by Oosthuizen *et al.* [11].

The closed loop simulation is a preliminary step in ensuring that the MPC controller based on economic objectives meets all functional objectives. A detailed analysis of the economic implications is done in the economic evaluation section.

A comparison of the EAF under manual and MPC control in a noisy environment is done in Chapter 7 as an economic evaluation. Proper testing strategies are utilised to ensure that unbiased results are obtained and statistical significant data are generated. The overall profitability of the EAF is considered, as well as reaching the functional specifications.

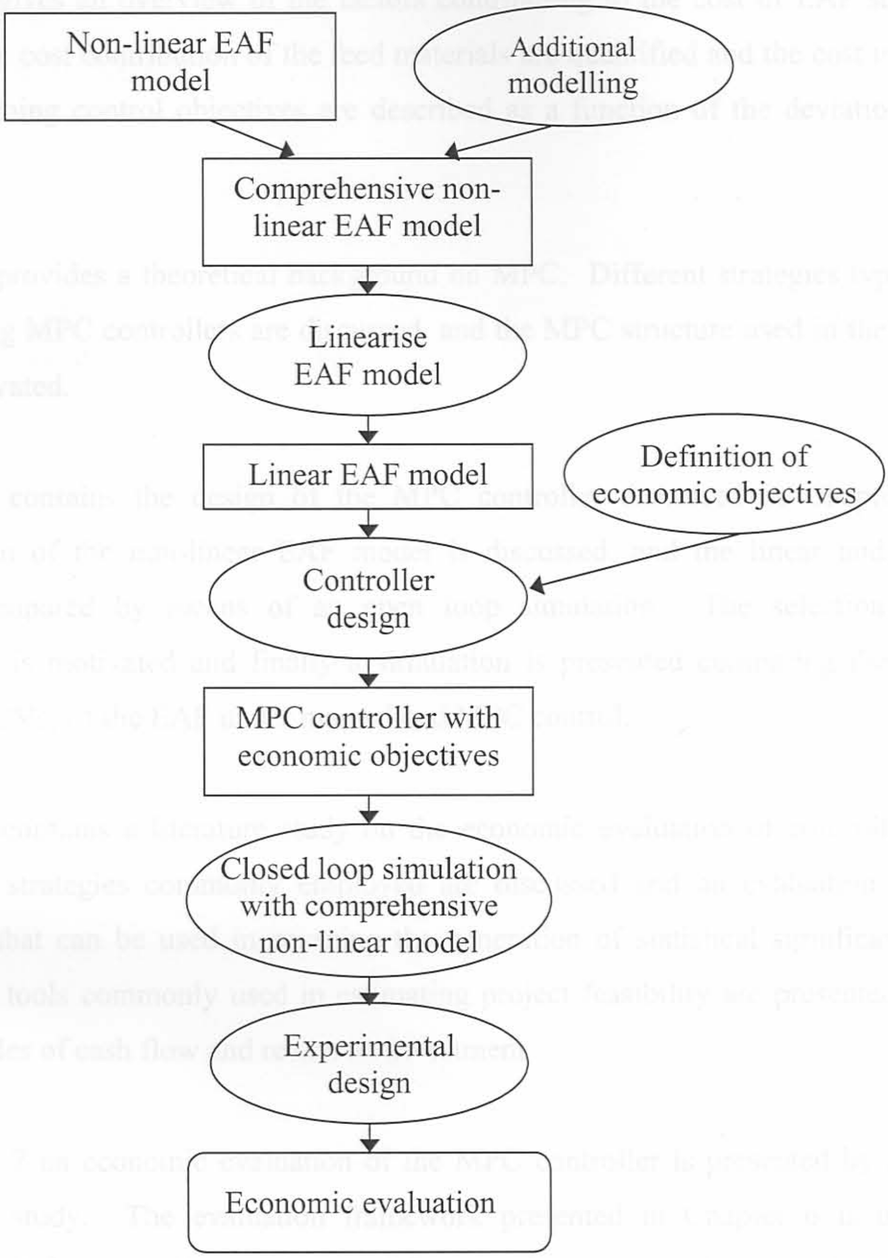

Figure 1.1. Logical flow of actions.

1.5. ORGANISATION.

In Chapter 2 a technical overview of the EAF process and simulation model is given. Control objectives typically used in industry are discussed, and the control objectives for the simulation study are motivated. The modelling of the slag foam depth is also described in this chapter.

Chapter 3 gives an overview of the factors contributing to the cost of EAF steelmaking. The relative cost contribution of the feed materials are quantified and the cost implications of not reaching control objectives are described as a function of the deviation from the setpoints.

Chapter 4 provides a theoretical background on MPC. Different strategies typically used in designing MPC controllers are discussed, and the MPC structure used in the simulation study motivated.

Chapter 5 contains the design of the MPC controller discussed in Chapter 4. The linearisation of the non-linear EAF model is discussed, and the linear and non-linear models compared by means of an open loop simulation. The selection of tuning parameters is motivated and finally a simulation is presented comparing the controlled variables (CVs) of the EAF under manual and MPC control.

Chapter 6 contains a literature study on the economic evaluation of controllers. Some evaluation strategies commonly employed are discussed and an evaluation framework presented that can be used in ensuring the generation of statistical significant data. A number of tools commonly used in estimating project feasibility are presented, based on the principles of cash flow and return on investment.

In Chapter 7 an economic evaluation of the MPC controller is presented by means of a simulation study. The evaluation framework presented in Chapter 6 is used in the experimental design and execution, and hypothesis testing is done to determine if the economic benefits predicted by the simulation study are statistically significant.

Chapter 9 contains a summary of the dissertation contents. Conclusions are made regarding the economic feasibility of advanced control of an EAF, and recommendations are made regarding further work.

CHAPTER 2: PROCESS OVERVIEW.

2.1. INTRODUCTION.

An overview of EAF steelmaking is presented as well as an overview of the model used for the simulation study. The control objectives are also motivated based on theoretical motives and practical considerations. Additional modelling required in describing the slag foam depth inside the EAF is described.

2.2. PROCESS DESCRIPTION.

One of the big advantages of EAF steelmaking is that practically all grades of steel can be produced in an EAF with a basic lining. These grades include the plain carbon steels, high manganese steels, high silicon steels, high aluminium steels, the entire range of stainless steels and high-speed steels and other alloy tool steels [12]. The process used for simulation purposes in this work produces plain carbon steels using an EAF.

A functional layout of an EAF with its off-gas system is shown in Figure 2.1.

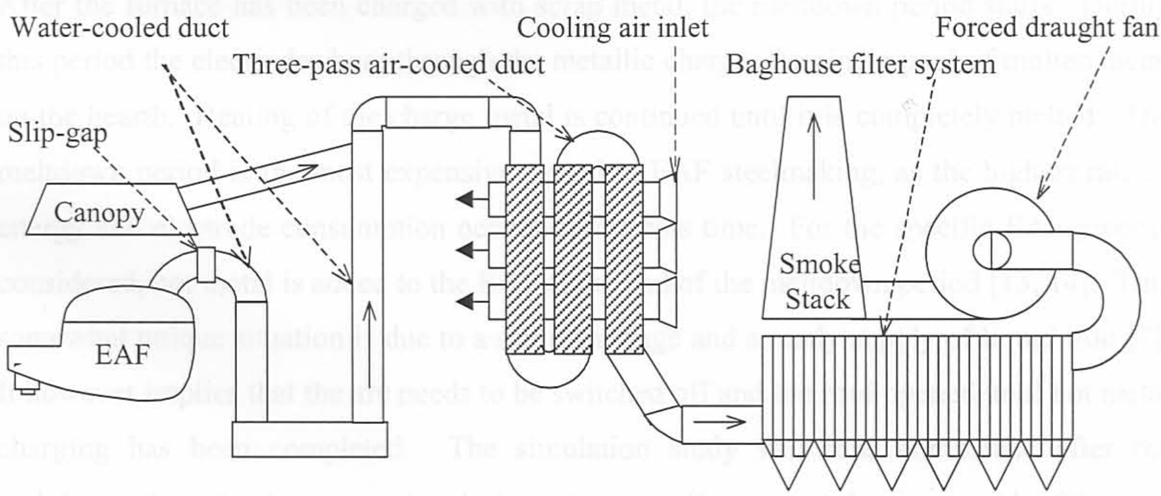

Figure 2.1. Functional layout of an EAF with an off-gas system.

The EAF off-gas system consists of an off-gas fan, a slip-gap and a bag-house. The off-gas fan provides a draught force to extract gases from the furnace. The slip gap serves the purpose of entraining air from the atmosphere for combustion of CO extracted from the furnace, and of cooling the off-gas. The combination of the slip-gap and off-gas fan provides a negative relative pressure inside the furnace. Before being emitted into the atmosphere, the off-gas needs to be filtered by the bag-house filter in order to satisfy environmental regulations.

EAFs produce steel by melting scrap and other sources of iron, using a three-phase electrical supply as the main energy-source. Graphite electrodes are used in a triangular arrangement to create the three-phase arc. The aim of the steelmaking process is to raise the steel temperature to a level suitable for further processing (secondary steelmaking) and to remove unwanted elements from the steel melt, especially silicon, carbon, sulphur, manganese and phosphorus [7].

The EAF steelmaking process can be divided into 4 phases: The meltdown period, the oxidising period, the composition and temperature adjustment period and the tapping period [12]. The 4 phases will now be discussed in more detail.

After the furnace has been charged with scrap metal, the meltdown period starts. During this period the electrodes bore through the metallic charge, forming a pool of molten metal on the hearth. Heating of the charge metal is continued until it is completely melted. The meltdown period is the most expensive period in EAF steelmaking, as the highest rate of energy and electrode consumption occurs during this time. For the specific EAF process considered, hot metal is added to the EAF at the end of the meltdown period [13, 14]. This somewhat unique situation is due to a scrap shortage and a ready supply of liquid iron [7]. It however implies that the arc needs to be switched off and the roof opened until hot metal charging has been completed. The simulation study will thus commence after the meltdown phase has been completed, as continuous off-gas control is impossible if the roof still needs to be opened.

During the oxidising period, phosphorus, silicon, manganese, carbon and iron are oxidised in the temperature range of 1300 - 1480°C. The reactions of silicon, phosphorus and manganese are exothermic and occur at a lower temperature, whereas the carbon reaction is less strongly exothermic and only occurs later in the tap. Practically all silicon in the metal is oxidised to SiO_2 early in the melt period, and enters the slag. It is thus essential to charge lime early in this stage to prevent damage to the refractories [5]. For the EAF under consideration, the main source of oxygen is oxygen gas injected through side lances. The direct injection of oxygen gas is extremely important in modern steelmaking practice, from the view of rapidly removing carbon from the bath. Excess carbon reacts with the oxygen to form carbon monoxide gas that bubbles out of the steel. This "carbon boil" stirs the bath, makes it more uniform in temperature and composition, whilst also removing some hydrogen and nitrogen from the steel [12]. The oxygen also provides an additional energy source.

To increase productivity, the oxidising period often overlaps with the composition and temperature adjustment period. During this period the temperature is adjusted to meet the tapping specification and the composition is adjusted if required. If a double slag process was used, the oxidising slag would be removed and a new slag formed during this period. Most carbon and low alloy steel grades made in EAFs are produced using a single slag process. If further refining of the steel is required to lower sulphur and oxygen contents, this is accomplished by means of ladle metallurgy treatment after the steel has been tapped from the EAF [12].

During the tapping period, the electrodes are raised, the tap hole opened and the furnace is tilted so that the steel is drained into a ladle. Steel is often refined further in the ladle after tapping to lower oxygen and sulphur content. Since the slag in the furnace contains iron oxide that inhibits the removal of sulphur and oxygen, various methods are employed to prevent the slag from mixing with the tapped steel. One method is to leave some steel in the furnace after tapping, to be used during the following tap. This is commonly referred to as the "wet heel" practice and prevents steel-slag mixing without wasting the excess steel.

In the basic EAF process, the function of the oxidising slag is to provide a reservoir for oxides of silicon, manganese, phosphorus, iron, etc. The slag also protects the bath from excessive oxidation, acts as a medium for the transfer of oxygen to the slag-metal interface, shields the arc from the atmosphere, protects the furnace refractories from the arc and provides an insulating blanket to minimise heat losses from the melt. Fluxes (burnt lime (CaO) and dolomitic lime (CaO, MgO)) are continuously added to the slag using conveyor belts, to adjust the basicity of the slag [5]. The slag basicity has a direct influence on the removal of silicon, phosphorus and manganese from the steel melt.

In some operations Direct Reduced Iron (DRI) is preferred to scrap, because it has a known and uniform composition and contains no residual elements such as chromium, copper, nickel and tin. Where scrap supplies are limited, DRI would form a significant part of the total iron charge. When DRI is melted, it furthermore forms a foamy slag, because it contains both carbon and iron oxide [12].

The "foamy slag" practice is used to protect the furnace refractories from the arc and thus allows more power to be applied to the arc, yielding higher efficiency. This practice involves a controlled carbon boil in the slag that results in the formation of a foamy slag layer of 300 mm or deeper. Carbon is often added to the slag at a controlled rate to react with the iron oxide in the slag, creating the carbon boil [12].

The off-gas system of an EAF serves the purpose of regulating the relative furnace pressure, limiting carbon monoxide (CO) emission and removing solid particles from the off-gas before being emitted into the atmosphere. A dangerous working environment results if CO present inside the furnace is emitted into the melt shop. This can be avoided by always maintaining a negative relative pressure between the furnace and its surroundings. It is typically attempted to keep the relative furnace pressure at approximately –5 Pa, as this value provides a good trade-off between energy-wastage and safety [13,14]. Environmental legislation also exists regarding CO emission and the dust composition of the emitted gases.

2.3. SIMULATION MODEL.

An EAF model presented by Bekker [13] and Bekker *et al.* [14] is used as a basis for all simulations. The off-gas temperature model was improved by Viljoen [10], and the revised off-gas temperature model used in the simulation study.

The EAF model consists of 17 mostly non-linear equations representing 17 state variables in the EAF. The first 14 states are tabulated in Table 2.1 and the other 3 states are used to model the second order mass flow with dead time in the off-gas duct.

Bekker [13] also derived additional output equations describing the off-gas mass-flow, the CO fraction in the off-gas and the percentage carbon in the steel melt. Additional to the revised off-gas temperature model by Viljoen [10], the modelling of the slag foam depth is discussed in Section 2.5.

Table 2.1. States of the EAF model.

State variable.	Description.
x1	Solid scrap mass.
x2	Liquid metal mass.
x3	Mass of carbon dissolved in the steel melt.
x4	Mass of silicon dissolved in the steel melt.
x5	Solid slag mass.
x6	Liquid slag mass.
x7	Mass of iron oxide in the slag.
x8	Mass of silicon oxide in the slag.
x9	Carbon monoxide gas in the furnace.
x10	Carbon dioxide gas in the furnace.
x11	Nitrogen gas in the furnace.
x12	Liquid metal temperature.
x13	Scrap and solid slag temperature.
x14	Relative furnace pressure.

Bekker [13] defined the relative furnace pressure, the off-gas temperature and the off-gas CO mass fraction as controlled variables. The manipulated variables used were the off-gas fan power and the slip-gap width. The other inputs were defined to be disturbances. Viljoen [10] added the liquid metal temperature, the carbon content and the liquid metal mass to Bekker's controlled variables and DRI addition rate and oxygen addition rate as manipulated variables.

The MPC controller designed in this dissertation will build on the work of Bekker and Viljoen by adding the graphite injection rate to the manipulated variables. The list of controlled variables will also be extended to include the depth of the foamy slag layer (see Figure 2.2). Emphasis will also be placed on unmodelled variations in feed compositions that occur under typical EAF operation. The choices of the manipulated and controlled variables will be discussed in more detail in Section 2.4.

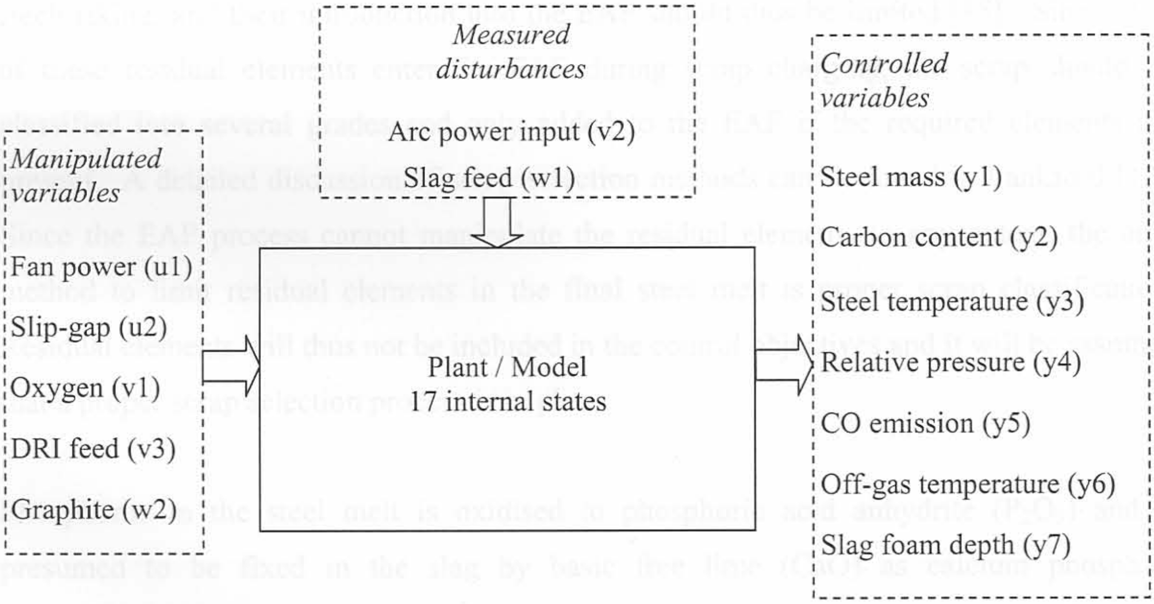

Figure 2.2. Schematic diagram of the EAF model.

2.4. CONTROL OBJECTIVES.

In order to define proper control objectives, steel specifications and commonly used control strategies were investigated. The choices of controlled variables indicated in Figure 2.2 will be discussed, based on the above-mentioned considerations.

For carbon steels, chemical composition limits are defined for carbon, manganese, phosphorus and sulphur. Limits also exist on residual elements including copper, nickel and tin. Residual elements cause the greatest problems during reheating and subsequent rolling operations, particularly tin and copper. These elements are enriched at the surface during reheating and form low melting point phases with iron. In many plain carbon steels, elements such as molybdenum, chromium and nickel have a deleterious effect on e.g. weldability [15]. The important feature about residuals such as copper, tin, nickel, molybdenum and to some extent chromium, is that they are not removed during EAF steelmaking, and their introduction into the EAF should thus be limited [15]. Since most of these residual elements enter the EAF during scrap charging, the scrap should be classified into several grades and only added to the EAF if the required elements are present. A detailed discussion of scrap selection methods can be found in Lankford [12]. Since the EAF process cannot manipulate the residual elements to any extent, the only method to limit residual elements in the final steel melt is proper scrap classification. Residual elements will thus not be included in the control objectives and it will be assumed that a proper scrap selection process is in place.

Phosphorus in the steel melt is oxidised to phosphoric acid anhydrite (P_2O_5) and is presumed to be fixed in the slag by basic free lime (CaO) as calcium phosphate ($4CaO \cdot P_2O_5$) [5]. Not only the basicity of the slag, but also the iron oxide content of the slag play a role in the removal of phosphate. The following conditions favour the removal of phosphorus from the steel melt:

- High slag basicity ($CaO/SiO_2 > 2.2$).
- High iron oxide (FeO) content in the slag.
- Relatively low temperature.
- A high slag volume of good fluidity.

The conditions favouring manganese removal are very similar to those favouring phosphorus removal. The following factors favour low residual manganese in metal:
- High slag volume.
- High iron oxide content in the slag.
- Relatively low temperatures.
- Semi-basic slag with a lime/silica ratio (CaO/SiO_2) < 2.2 [5].

Keeping the slag basicity as close as possible to 2.2 would thus favour both manganese and phosphorus removal. Since a high iron oxide content in the slag translates into a production loss, the iron oxide content cannot be raised excessively. The iron oxide content of the slag varies with the carbon in the steel at the end of the boil and typically ranges from 13% to 20% [12]. A slag FeO content of 15% thus favours manganese and phosphorus removal without resulting in excessive production losses.

The presence of the element sulphur in steel products has been a challenge both to operators and metallurgists ever since the early age of steel. The detrimental effect of sulphides in the steel results in inferior surface quality at the higher (>0.03%) sulphur end of the usual steel range. Sulphur removal from a steel bath under an oxidising slag is relatively limited, such that at best only half of the sulphur load introduced into the heat can be removed from the steel bath. Some sulphur is removed during the oxidation period (probably between 20% and 30%), but its removal is uncertain and not easily controlled [5]. The following conditions favour sulphur removal:

- High slag basicity.
- High temperature.
- Good slag fluidity.
- Intimate mixing of slag and metal.
- Low FeO content in the slag.
- Low dissolved oxygen content in the bath [5].

The first three conditions can easily be satisfied in a single oxidising slag furnace process. The last two conditions together with the first three can be obtained only in the final finishing period (reducing slag) of the double slag practice. If scrap with a low enough sulphur content cannot be obtained, the most efficient sulphur removing would occur during secondary ladle metallurgy.

Slag control is a very important factor in EAF steel production. The EAF permits the slag to be controlled to meet almost any desired characteristic, a fact that is the real basis of the flexibility of the EAF [12]. Sulphur, phosphorus and manganese in the melt are not modelled explicitly by Bekker [13]. Manipulation of the slag properties can however be used effectively to favour removal of the above-mentioned elements from the steel melt. The ratio between MgO and CaO is also of importance. Lankford [12] suggests that the CaO content of the slag should be at least 40%, although 50% is preferable for good sulphur removal. Taylor [5] suggests an MgO content of at least 12% in the slag to limit erosion of the refractories. To simplify the charging process a constant MgO/CaO ratio of between 0.3 and 0.4 should be used to obtain the required slag properties [5]. The following slag properties are suggested, based on the reasoning above:

- A slag basicity of 2.2.
- High FeO content in the slag (15%).
- Maintaining the MgO/CaO ratio constant at 0.35.

Although the above-mentioned slag properties can easily be derived from the existing model, an extensive modelling effort would be required to model the influence of improved slag control on the removal of inclusions in the melt (e.g. sulphur, phosphorus and manganese). Such an extensive modelling effort is outside the scope of this work.

Instead of manipulating variables related to the slag properties without confirmation that the strategy is efficient, it will be assumed that the existing slag additions satisfies the requirements defined above. De Vos [7] performed a thorough analysis on optimal slag additions to an EAF, and it is thus considered a reasonable assumption that slag additions are close to optimal. The slag addition rates as described in Bekker [13] will therefore be modelled as a measured disturbance, and no further effort would be made on manipulating slag properties more efficiently.

The most common method to reduce the carbon content of the steel bath is the injection of gaseous oxygen into the bath [12]. DRI has the further advantage that it contains both oxygen (FeO) and carbon. The residual oxygen inside the DRI is thus capable of oxidising the carbon without any oxygen additions. DRI however seldom contains the required balance between carbon content and residual oxygen, but by additional oxygen blowing carbon control is achieved fairly easily.

The two main disadvantages of EAF steelmaking are the inability of an EAF to produce low residual steels from high residual scrap (as discussed earlier) and the fact that the nitrogen content of EAF steel is about twice as high as steel made in Basic Oxygen Furnaces (BOFs) [12]. For certain grades of steel, particularly those produced for deep drawing applications, low nitrogen contents are desirable. The high nitrogen content of EAF steels occurs because of the breakdown of the N_2 molecule producing some atomic N in the vicinity of the arc. The local high temperatures close to the arc further increase the solubility of nitrogen in the steel bath. It was found experimentally that the nitrogen content in an EAF during the oxygen blow is very similar to that of other furnaces. After the oxygen blow, the nitrogen level tends to increase with time [5]. If low nitrogen levels are required, the following steps are suggested:

- The heat should be tapped as close to the completion of the oxygen blow as possible.
- The temperature profile should be at the required level for tapping at the end of the blow.
- Power should not be applied after completion of the blow.
- Avoid raising the temperature higher than required to limit nitrogen solubility.
- Add ferroalloys including manganese, chromium and vanadium as late in the heat as possible, as they increase nitrogen solubility.

Hydrogen is introduced in the EAF by rusted and damp charging materials and by additions of lime and fluorspar. The arc itself also dissociates water vapour in the atmosphere to molecular and atomic hydrogen. High quality low alloy steels are especially susceptible to "hair-line" crack formation caused by hydrogen. Hydrogen is removed in the ladle during secondary metallurgy and very little can be done during EAF operation to limit hydrogen absorption.

Temperature control can be obtained by matching the DRI-addition rate to the electrical power input. Operators typically adjust the DRI feed rate based on the bath temperature that is checked at 10 – 15 minute intervals. DRI feed rates typically vary between 28 and 33 kg/min/MW once the scrap is melted [5], but Dressel [16] reported feed rates varying between 5 and 35 kg/min/MW. Bath temperature should be maintained in the range between 1570 and 1630°C for good melting performance and good slag fluidity [5]. The tapping temperature may vary only within a very narrow range, and should equal approximately 1630°C [14].

The final steel mass will be determined by the EAF capacity and the requirements of the secondary metallurgical processes. A higher than required steel mass will necessitate additional heating to prevent the excess steel from solidifying, if the capacity of processes further downstream are exceeded. A too low mass will prevent continuous secondary processes, e.g. continuous casting to be operated efficiently. The continuous addition of DRI allows the control of the final steel mass, independent of the initial scrap charge.

The off-gas system limits the emission of dust by baghouse filtering, and regulates the emission of CO by adjusting the ratio between fan speed and slip gap width. It is assumed that the baghouse is functional and that visible emission and opacity regulations will thus be met. The exposure of workers to dust and other contaminants is governed by regulatory requirements. The threshold limit value for CO exposure as prescribed by the Occupational Safety and Health standards is 55mg/m^3 [5]. This translates into a CO emission fraction [mass/mass] of 9.14×10^{-5} at atmospheric pressure and an average temperature of 600K. CO emission should thus be limited to the greatest extent, since a 0.009% CO mass emission fraction is already considered a health hazard.

The off-gas exit temperature should also be controlled to prevent baghouse explosion. A non-functional baghouse necessitates a plant shutdown for repairs, which causes great production losses. The off-gas temperature is not measured directly before the bag-house, but at a point before the three-pass air-cooled duct (see Figure 2.1). The limiting temperature at this point is 773K (500°C), but Bekker [13] suggests controlling the temperature at approximately 100K lower to provide an adequate safety margin.

The negative relative pressure cause a loss of energy as a large amount of heat is extracted with the off-gas [13, 14]. A negative relative pressure is however essential in preventing hazardous gases inside the EAF from being emitted into the workshop. Process efficiency can be improved by reducing the magnitude of the relative pressure, thereby reducing energy wastage. A proper control system is however required to maintain safety standards when the relative pressure is operated closer to its limits. Although the theoretical optimal relative furnace pressure is 0 Pa, it is frequently suggested to control the relative furnace pressure at –5 Pa, as this is a good trade off between safety and efficiency [13, 14].

The foamy slag practice protects the furnace refractories from heat radiated from the arcs. Normal practice requires that the power to the arcs be decreased as soon as most of the slag has been melted and the furnace walls become exposed to the arc. However, this decrease in power slows down the heat. By using a foamy slag practice, a decrease in power is unnecessary and furnace productivity can be increased by the use of high power inputs [12]. Excessive foaming should also be avoided as the slag could foam out of the vessel [17]. A foamy slag layer of 300 mm or more is suggested to provide the required protection to the furnace walls [12].

The control objectives (excluding slag properties) are summarised in Table 2.2, based on the practices and motivation given before.

Table 2.2. Control objectives.

Control objective	**Motivation**
Regulate carbon content.	Meet steel specification.
Bath temperature 1570 - 1630°C.	Good melting performance and slag fluidity. Meet tapping requirements.
Steel tapping mass.	Secondary metallurgical demands.
CO emission < 0.009%.	Health and environmental standards.
Relative pressure slightly below 0 Pa.	Safety and energy efficiency.
Off-gas exit temperature < 773K.	Prevent bag-house explosion and accompanying economic implications.
Foamy slag-layer 300 mm or more thick.	Protect refractories and increase furnace productivity.

2.5. MODELLING OF SLAG FOAMING.

In order to control the slag foaming depth accurately, additional modelling of the slag foam characteristics was required. Jiang and Fruehan [17] defined the foam index of the slag (Σ) as

$$\Sigma = \frac{H_f}{V_g}, \tag{2.1}$$

where H_f represents the foam height (cm) and V_g is the superficial gas velocity (cm/s). In physical terms, the foam index is the average travelling time of the gas in the foam [s].

Conditions favouring slag foaming are slag basicities larger than 2.5 and an FeO content between 15% and 20% [17]. Jiang and Fruehan [17] presented experimental results showing the dependence of the foam index for a typical oxidising slag on the FeO content of the slag. Experiments were conducted for FeO contents up to 40% and a slag basicity of approximately 3. Linear regression yielded the relation given in Equation 2.2, with unit [s], which is valid for FeO contents between 20% and 40%.

$$\Sigma = 20172.58(\%FeO)^{-2.07} \tag{2.2}$$

Since the FeO mass in the slag and the liquid slag mass have already been modelled by Bekker [13], the foam index can easily be calculated for various slag compositions.

The superficial gas velocity (V_g) is determined by the amount of gas being produced by the steelmaking process and the physical dimensions of the EAF. Bekker [13] describes the various masses of CO, CO_2 and N_2 being formed by the steelmaking process in the calculation of the gas composition inside the EAF. Two sources of CO are modelled and one source of N_2. CO_2 is not formed by reactions in the steel or slag, but rather by combustion of CO in the gas phase. This occurs above the slag layer and can thus not be included in the calculation of the superficial gas velocity. The sources of CO and N_2 will be discussed in turn.

The rate of CO produced by injection of graphite into the slag is proportional to the rate of graphite injection. An assumption was made that all carbon introduced by the graphite injection reacts instantly with FeO to form CO and iron [13]. The rate of CO production is thus described by

$$G_1 = \frac{M_{CO}}{M_C} w_2, \tag{2.3}$$

for M_{CO} the molar mass of CO, M_C the molar mass of C and w_2 the graphite injection rate. The unit of G_1 is thus [kg/s].

The rate of CO produced by decarburisation due to reaction with FeO is given by

$$G_2 = \frac{M_{CO}}{M_C} k_{dC}(X_C - X_C^{eq}), \tag{2.4}$$

for k_{dC} the decarburisation rate constant, X_C the molar fraction of carbon in the steel and X_C^{eq} the equilibrium molar fraction of carbon in the steel [13].

Graphite is injected into the furnace using air as a carrier gas. For every 150 kg of graphite injected, 1 kg of N_2 is injected together with the carrier gas. The rate of N_2 production due to graphite injection is thus given by Equation 2.5.

$$G_3 = \frac{1}{150} w_2 \tag{2.5}$$

The molar quantity of gas produced can be calculated as

$$M = \frac{1}{M_{CO}}(G_1 + G_2) + \frac{1}{M_{N2}} G_3, \tag{2.6}$$

for M the number of moles gas produced.

The ideal gas law is now used to determine the volume of gas generated. Dividing the gas volume by the area of the slag layer yields the superficial gas velocity (V_g).

$$V_g = \frac{MRT}{PA} \tag{2.7}$$

R represents the universal gas constant, T the gas temperature that is assumed to be equal to the liquid steel temperature, P is atmospheric pressure and A the area of the slag inside the furnace.

The slag height (H_f) can now be calculated using Equation 2.1. Conversion of measurement units is required since the units of V_g is [m/s] whilst H_f has the units of [cm].

2.6. CONCLUSION.

An overview of EAF steelmaking was presented and the simulation model used was described briefly. A more detailed discussion of some aspects of steelmaking was presented, and some control objectives typically used in industry discussed, to justify the objectives chosen for the EAF under consideration. Modelling of the foamy slag layer was described to expand the available EAF model. Although the slag foam depth model was derived under steady state conditions, the exact slag depth is not critical and an approximation should suffice.

CHAPTER 3: THE COST OF EAF OPERATION.

3.1. INTRODUCTION.

A number of control objectives were defined in Chapter 2, based on metallurgical requirements of EAF steelmaking. In some cases, improved control of a certain variable might have no economic benefits to the process. As the driving force behind the majority of control projects is an increase in profit, the control of any variable should be justified on both functional and economic bases. In this chapter the choice of controlled variables will be justified from an economic perspective, and the relative cost contribution of each controlled variable calculated to show their relative economic importance. The cost of the feed materials and energy inputs to the furnace will also be quantified, and their cost contributions relative to the total production cost and the cost advantages of controlling certain variables quantified.

3.2. BACKGROUND.

In order to maximise profit of EAF operation, steel of the required quality needs to be produced in the shortest possible time, using the combination of feed materials resulting in the lowest cost. These three factors are to a certain extent conflicting, since throughput can for example be increased by using more expensive feed materials. An optimal point can however be found for which the cost of EAF operation is minimised.

The value of increased throughput will depend on the specific plant configuration. If the EAF is a bottleneck in the process, an increase in throughput will be a major cost consideration, whilst if the production capacity of the EAFs exceeds the demand of the casters or other downstream processes, throughput may not be critical [18]. For the process under consideration the EAF is a bottleneck [18], and any increase in throughput will increase the production of the plant in total.

Research has been done to determine the optimal feed additions to a furnace. De Vos [7] reported on the optimisation of flux additions to an EAF and reported reduction in production cost in excess of 3%. As in many other optimisation projects, a static furnace model was used, and the efficiency of the strategy during furnace operation could not be quantified accurately.

Very often the economic optimisation and the functional control objectives of a process are seen as separate objectives, and are handled by different systems [24]. By integrating the economic and functional control objectives, a controller can be designed that satisfies the functional control objectives and the economic goals set for the process simultaneously.

The first step in quantifying the cost of an EAF tap is to determine the factors contributing to EAF cost, as discussed in the next section.

3.3. COST COMPONENTS OF EAF OPERATION.

3.3.1. Operational cost considerations.

Taylor [5] identified the cost components, and their relative contribution to the total cost of producing steel with an EAF, as shown in Table 3.1. The analysis is however based on 1977 data, and the cost contribution of DRI is for example not included in the analysis. Discussions with a South African steel producer [18] resulted in a revised cost table, based on a 50:50 ratio of DRI and scrap charging (85 ton each). Ferroalloy additions are omitted from the revised cost estimate since these are typically added after the tap. The revised table is shown in Table 3.2.

Table 3.1. Operational costs as a fraction of total EAF operational cost (1977) [5].

Cost component	Percentage
Scrap.	58.2 %
Maintenance and other costs.	14.0 %
Electric power.	10.5 %
Electrodes.	6.2 %
Ferroalloys.	3.6 %
Labour.	1.9 %
Flux.	1.7 %
Refractories.	1.6 %
Investment.	1.6 %
Oxygen.	0.7 %

Table 3.2. Revised table: Operational costs as a fraction of total EAF operational cost (2000) [18].

Cost component	Percentage
Scrap.	29.7 %
DRI.	22.3 %
Electric power.	14.9 %
Maintenance and other costs.	14.0 %
Electrodes.	7.5 %
Refractories.	3.7 %
Flux.	3.6 %
Labour.	1.9 %
Investment.	1.6 %
Oxygen.	0.7 %
Graphite.	0.1 %

The percentages shown in Tables 3.1 and 3.2 describe the contribution to the total cost of an EAF tap for typical inputs. For control purposes, it is convenient to express the cost components in terms of the manipulated variables and the units typically used to describe their addition rates. Table 3.3 shows the quantities of the cost components typically consumed during a tap, and also the relative cost per unit, where the measurement unit is defined in column 5. Unmodelled components (electrode and refractory consumption) and indirect costs, not influenced significantly by the controller (maintenance, labour and investment) were omitted from Table 3.3.

Table 3.3. Table showing the per unit consumption during a typical tap.

Cost component	Percentage of total cost	Consumption	Per unit percentage	Unit
Scrap.	18.7 %	53.5 ton	0.35 %	/ton
Hot metal.	24.1 %	65 ton	0.37 %	/ton
DRI.	9.2 %	35 ton	0.26 %	/ton
Arc power.	14.32 %	70605 kWh	0.211 %	/MWh
Flux.	3.6 %	4.5 ton	0.8 %	/ton
Oxygen.	0.7 %	4220 Nm^3	0.129 %	/ton
Off-gas fan.	0.58 %	2760 kWh	0.21 %	/MWh
Graphite.	0.1 %	100 kg	1.0 %	/ton

The energy consumption of the off-gas fan was calculated using typical off-gas power inputs. The percentage for electric power indicated in Table 3.2, was subdivided into the power consumed by the arc and the power consumed by the off-gas fan, as indicated separately in Table 3.3.

In the model described by Bekker [13] hot metal is also charged to the EAF in addition to scrap and DRI. The scrap and DRI consumption required for a 50:50 charge ratio [18] was therefore reduced to account for the consumption of liquid metal, scrap and DRI as described by Bekker [13]. The percentage contribution of DRI and scrap to the cost of a tap was reduced proportional to the reduction in DRI and scrap consumption. The percentage contribution of the hot metal was chosen to keep the cost of the iron additions (scrap, DRI and hot metal) equal to that described in Table 3.2 (52 %). Although this assumption probably underestimates the cost of hot metal, the per-unit cost of hot metal as shown in Table 3.3 is already significantly higher than the cost of DRI and also higher than the cost of scrap. This explains why hot metal charging is being phased out [18].

The per-unit percentages are not affected by the configuration described by Bekker [13], as the consumption and percentages were reduced in the same proportions. As controller tuning is based on the per-unit percentages (see Chapter 5), the same controller tuning parameters could thus be used for the manipulated variables, whether hot metal is charged or not. Hot metal charging or the lack thereof would however influence the setpoints and control objectives significantly.

The data contained in Table 3.3 can be used by an operator or implemented in a controller, to ensure that the most economical options will be used to reach control objectives. The relative cost implication of reaching or not reaching certain control objectives will be discussed in the following section.

3.3.2. Cost implication of controlled variables.

The following controlled variables were defined:
- Percentage carbon in the steel melt.
- Steel temperature.
- Steel mass.
- CO emission.
- Relative furnace pressure.
- Off-gas temperature.
- Slag foam depth.

The cost implication of each one of these controlled variables will be discussed in turn.

3.3.2.1. Percentage carbon in the steel melt.

The carbon content of the steel melt has very little influence on the cost of the tap at any time during the tap. When the steel is tapped, however, the carbon content should meet the specifications the melt was intended for. The tolerances on carbon content vary for the different types of steel produced, but in general the allowable variations have a range of approximately 20 %. Since it is more likely that the carbon content would be too high than too low, it is often aimed at producing steel close to the lower end of the carbon specification. The 20 % range would thus not be divided symmetrically (+/- 10 %), but in a range of –5 % to +15 %. If the carbon specification is completely off target (more than +/- 50 % from specification), the melt might be scrapped, implying that the melt cost would more than double.

If the specification on carbon content is not met, some form of corrective action needs to be taken, unless the melt is scrapped. This corrective action includes switching on the arc for an additional time period, blowing more oxygen, or making some additions to the melt. The cost of these corrective actions is in general small compared to the cost of the melt. To blow oxygen for another 5 minutes would for example have a small impact on the total cost of a tap. Oxygen consumption contributes approximately 0.7 % to the total operational cost, and to blow oxygen at the maximum feed rate for an additional 5 minutes would thus increase the production cost with less than 0.1 %.

In many processes the EAF is a bottleneck in the process, which means that a caster or another downstream process is consistently waiting for steel from the EAF, or would have to slow down production if the steel melt from the EAF is delayed. Another matter of concern is that a delay of approximately 5 minutes exists between taking a steel sample and the availability of a result. If a corrective action adds 5 minutes to the melting time [18], 10 minutes would thus pass (time of corrective action added to the delay between sampling and the availability of a result) before the final composition is known and tapping may commence. If it is assumed that the typical production time of a tap is 100 minutes [13], the reasoning above shows that a production loss of 10 % would occur due to a too large deviation in carbon content. Although some losses are not accounted for using this approach (e.g. stopping and restarting the continuous caster) [18], the cost due to production losses account for the biggest part of cost due to variations in carbon content [18].

The cost of not meeting carbon specifications as a percentage of the cost of a tap, is shown in Figure 3.1 for a general case. The cost between 15 % and 50 % or –5 % and –50 % deviation from the desired carbon content is equal, since the cost of additions are negligible compared to the cost of lost production, as described above.

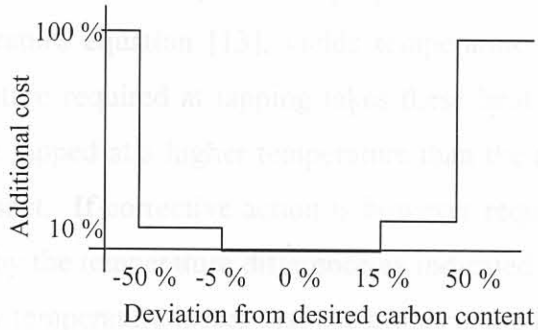

Figure 3.1. Additional cost due to deviation from the desired carbon content.

3.3.2.2. Steel temperature.

The steel temperature should be high enough to ensure proper tapping of the melt and also to contain sufficient heat as required by secondary metallurgical processes. A too high temperature may lead to unwanted reactions with the steel melt, more inclusions in the steel, and increasing EAF lining wear. Since none of the factors due to a too high temperature are modelled, the cost will be based on a too low temperature, and it will be assumed that a symmetrical cost distribution exists.

The tapping temperature may vary by approximately +/-10 K before corrective action is required [18]. Similar to the assumption for carbon content, the throughput would be a determining factor in the additional cost due to a too low temperature. If the temperature is too low, electrical energy (arc) or chemical energy (oxygen) will be added to increase the temperature, depending on the steel composition. The cost of the additions (oxygen or electrical energy) is once again small compared to the cost of lost production, but may become significant for large temperature differences. Temperature measurement delays typically vary between 3 and 5 minutes [18], and an average delay of 4 minutes will be used in this analysis, corresponding to a 4% increase in tapping time. The heat losses that occur during the time it takes to make a measurement are however significant, and need to be taken into account.

The heat losses can be calculated using the equation describing the temperature rate of change in the EAF model described by Bekker [13]. Substituting typical steel and slag masses into the temperature equation [13], yields temperature losses of approximately 0.26 K/s. The temperature required at tapping takes these heat losses into account, and steel would typically be tapped at a higher temperature than the actual requirement, since the delay is always present. If corrective action is however required, the steel would not only have to be heated by the temperature difference as indicated by the measurement, but additional to this also by temperature losses that occur during the measurement delay. Due to this fact and limitations on the maximum power input to the EAF, the tapping time would not only be increased by the measurement delay corresponding to 4 % of the tapping time, but also with another 4 % in recovering energy losses during the measurement delay. For steel temperatures more than 10 K lower than the specification, the additional time added to the tap is given by Equation 3.1, where ΔT is the difference between the measured and specified temperature.

$$\Delta\text{Time} = 8\ \% + 0.063\ \%(\Delta T\text{-}10) \tag{3.1}$$

Since it is assumed that throughput is the determining cost factor, any increase in tapping time corresponds to an increase in EAF operational cost. The additional cost of a tap due to not reaching the required tapping temperature is shown in Figure 3.2. It is assumed that the tapping temperature is never far below the required temperature, since this might cause the melt to solidify inside the EAF. The cost of a frozen melt will thus not be considered.

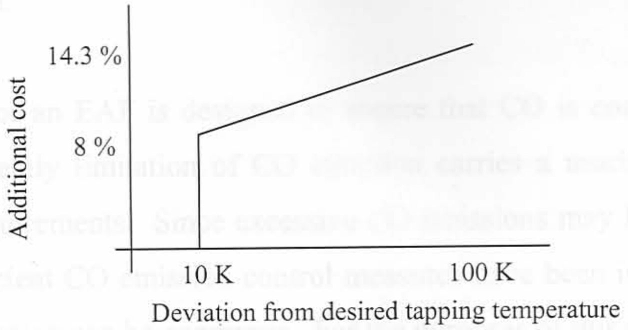

Figure 3.2. Additional cost due to deviation from the steel tapping temperature setpoint.

3.3.2.3. Steel mass.

The required steel mass is determined by the production capacity of the processes downstream from the EAF, or by the maximum capacity of the EAF, depending on where the bottleneck occurs. If it is assumed that the EAF is the bottleneck, any tap not utilising the maximum capacity of the EAF would translate into a production loss. A steel mass of 5 % below the required mass thus corresponds to a production loss of 5 %, equivalent to a cost increase of 5 %. Exceeding the capacity of the EAF might cause some problems that will not be considered. For the purpose of this analysis it will be assumed that exceeding the capacity of the EAF has no advantages, nor disadvantages. The total cost of a tap with a too high steel mass will however be higher due to increased feed and energy consumption. The additional cost due to variations in the steel mass from the desired mass is shown in Figure 3.3.

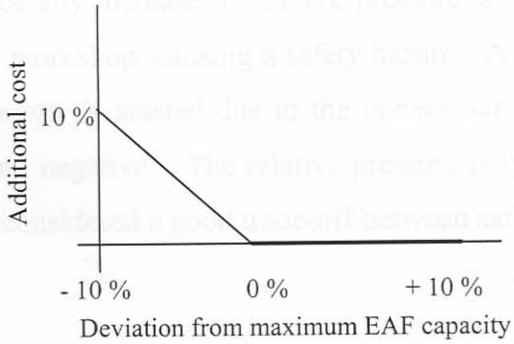

Figure 3.3. Additional cost due to deviation from specified steel mass.

3.3.2.4. CO emission.

The off-gas system of an EAF is designed to ensure that CO is combusted in sufficient quantities, but frequently limitation of CO emission carries a much lower priority than other operational requirements. Since excessive CO emissions may lead to a forced plant shutdown until sufficient CO emission control measures have been implemented, the cost of excessive CO emission can be enormous. For the purposes of this analysis, the cost of a forced plant shutdown will be approximated by the cost of 10 taps (1000 % additional cost). Although this is probably an underestimation, the cost is partly offset by the fact that CO emissions are typically averaged over a defined time period, and one peak CO emission of a short duration would thus not lead to legislative action against the plant. Different specifications exist for average CO emissions over different time periods, and the average CO emissions over a defined timeframe would thus have to be analysed.

The off gas system is designed to ensure adequate CO combustion with a large safety margin. It is thus unlikely that a plant would run the risk of a forced shutdown due to too high CO emissions. With regulations getting as low as 0.009 % CO (mass/mass) [5], it might be worth the effort of continuously monitoring and limiting CO emissions.

3.3.2.5. Relative furnace pressure.

The cost of not controlling relative furnace pressure efficiently, is easily underestimated by steel producers. Ideally the relative furnace pressure should be controlled at 0 Pa. This is however infeasible, since any increase in relative pressure would lead to the emission of dust and fumes into the workshop, causing a safety hazard. A too low relative pressure is also infeasible, since energy is wasted due to the unnecessary extraction of hot gases to keep the relative pressure negative. The relative pressure is typically controlled at –5 Pa [13] or lower, as this is considered a good trade-off between safety and efficiency.

Substitution of typical values into the EAF model [13], shows that the additional energy extracted with the hot gases is approximately 337 kW/Pa. Controlling the relative pressure at –5 Pa instead of the ideal 0 Pa, thus causes additional energy usage of approximately 1.7 MW, accounting for almost 4 % of the total EAF electrical input. Jones *et al.* [27] estimated that losses in the off-gas stream accounts for approximately 20 % of the energy input into an EAF. The value of 20 % is however an estimate of the total energy losses in the off-gas stream, including the energy required to keep the relative pressure at 0 Pa. The calculation of 4 % is based only on the additional cost contribution due to a relative pressure 5 Pa below the optimum value of 0 Pa. Significant savings in energy consumption are thus possible by improved relative pressure control, or in utilising the energy contained in the off-gas stream efficiently.

The cost of inefficient relative pressure control can be expressed as a fraction of the total cost of an EAF tap. As indicated in the preceding paragraph, a significant portion of the EAF electrical energy consumption can be attributed to inefficient relative pressure control. Electrical energy as a percentage of total EAF operational cost is approximately 14.9 %, and the cost of not regulating the pressure effectively can thus be calculated as 0.1255 %/Pa for negative relative pressure.

The analysis for positive relative pressure is much more complex, since the influence on the health of a number of workers needs to be taken into account. The duration of the positive relative pressure would thus be of importance in this analysis and the fume evacuation system in the workshop would also have to be considered [5]. This analysis of the cost of inefficient relative pressure regulation will focus only on negative relative pressure, and the cost impact of negative relative pressure is shown in Figure 3.4. It is assumed that a positive relative pressure of a short duration will not have a significant impact on the health of the workers, and that the relative pressure setpoint would be chosen adequately low to prevent frequent positive relative pressures. Improved regulation would thus enable specification of a higher relative pressure setpoint without compromising the health and safety of workers.

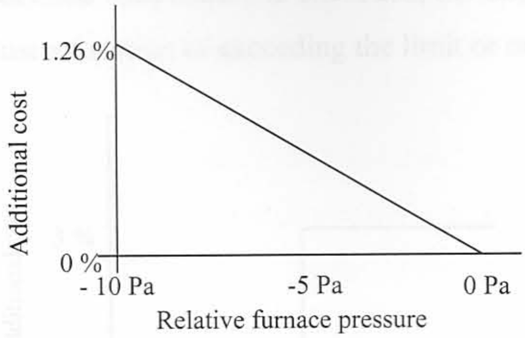

Figure 3.4. Additional cost due to deviation from 0 Pa relative furnace pressure.

3.3.2.6. Off-gas temperature.

Off-gas temperature needs to be limited to prevent the bag-house from exploding [13]. All possible steps are taken by steel producers to prevent bag house explosions, due to the severe impact of such an explosion. For the EAF under consideration, a trip switch ensures that the EAF operation is halted if a danger of bag-house explosion is detected, based on an off-gas temperature measurement. The time between the EAF being switched off and switched on again translates into a production loss, similar to the losses due to variations in carbon content and tapping temperature. For the purpose of this analysis it will be assumed that 3 minutes of production time is wasted [18] for each time the off-gas temperature exceeds a predefined limit of 773 K. The cooling losses during this period is approximately 0.2 % of the total cost of an EAF tap, that is once again insignificant compared to the cost of the lost production. Exceeding the specified off-gas temperature would thus lead to an increase in production cost of approximately 3 %, since the duration of a tap is approximately 100 minutes. The temperature-measurement of the off-gas is real time and no additional delay is associated with such a shutdown.

There is no advantage, nor disadvantage to a low off-gas temperature. Although variations in off-gas temperatures would be influenced by variations in the off-gas fan power consumption, this will be accounted for in a separate model. The cost as a function of exceeding a predefined temperature is shown in Figure 3.5. Since the EAF would be halted as soon as the predefined temperature is exceeded, the cost is not a function of the off-gas temperature, but just a function of exceeding the limit or not.

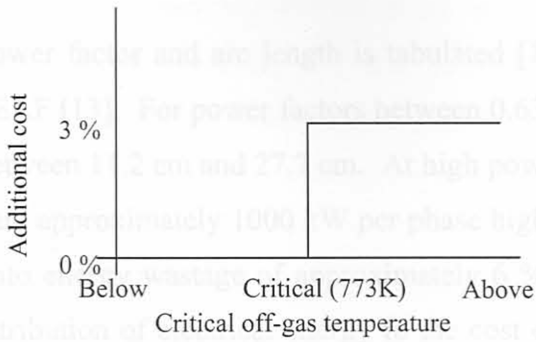

Figure 3.5. Additional cost due to exceeding the maximum off-gas temperature.

3.3.2.7. Slag foam depth.

Several advantages are attributed to foamy slags. These include decreased heat losses to the side-walls, improved heat transfer from the arcs to the steel (allowing higher power input), reduced power and voltage fluctuations, reduced audible noise, increased arc length without increased heat losses, and also reduced electrode and furnace lining consumption. Efficiencies of 60 – 90 % with foamy slags compared to 40 % with conventional slags have been reported [27]. The rate of energy loss in the EAF is also halved by using a foamy slag compared to a conventional slag [27]. The influence of the slag foam depth is however not quantified in any of the above-mentioned references, but just advantages of using a foamy slag layer.

The aim of foaming the slag layer is to ensure that the arc is covered in a slag layer, thus preventing radiation to the sidewalls and ensuring maximum energy transfer to the bath. Although some steel producers aim for a slag layer 3 times the depth of the arc length [18], a slag layer of at least the same depth as the arc length [17] seems to be a more reasonable aim. A slag foam depth much higher than the arc length has no advantages nor disadvantages, except for increased feed consumption in achieving the foam depth. It might however have operational disadvantages since a very large slag volume will have to be tapped into a vessel designed for a much smaller slag volume. A slag foam depth too low to cover the arc has a negative cost implication, since it will cause inefficient power transfer to the bath and increased heat losses.

The relation between power factor and arc length is tabulated [17] for a 60 MVA EAF, similar to the modelled EAF [13]. For power factors between 0.63 and 0.88, the arc length varies logarithmically between 11.2 cm and 27.7 cm. At high power factors the heat losses for a conventional slag are approximately 1000 kW per phase higher than for a foamy slag layer. This translates into energy wastage of approximately 6 %. Multiplication of this percentage with the contribution of electrical energy to the cost of EAF operation, yields an additional cost component of 0.9 %. For the purpose of this analysis it will be assumed that a linear relationship exists between heat losses and slag foam depth. For a slag foam depth of 0 cm the additional cost contribution would thus be 0.9 %, and for a slag foam depth of 30 cm or higher, the additional contribution would be zero. The additional cost as a function of slag foam depth is shown in Figure 3.6.

Heat losses due to inadequate slag foaming are not accounted for in Table 3.2 or 3.3, and are not modelled explicitly either. An analysis of the EAF under manual control however revealed that sufficient slag foaming was maintained throughout the tap. To ensure that a comparison of the EAF under manual and MPC control is done under similar conditions, the slag foam depth was included in the simulation study.

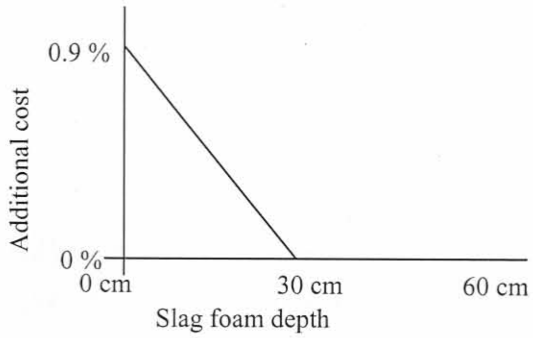

Figure 3.6. Additional cost attributable to slag foaming depth.

3.4. CONCLUSION.

The cost contributions of the feed materials relative to the total cost of an EAF tap were quantified. The relative costs of achieving the defined control objectives were also quantified using typical EAF operational practices as a framework. An addition of all the defined cost components for a specific EAF configuration, would give the total cost of a tap as a percentage, relative to the typical cost of a tap (100 %). The defined cost contribution can be used to determine the efficiency of new EAF operational practices, and also to design controllers minimising EAF cost.

CHAPTER 4: MODEL PREDICTIVE CONTROL.

4.1. INTRODUCTION.

Model Predictive Control (MPC) possesses many attributes which makes it a successful approach to industrial control design:

- Simplicity: The basic ideas of MPC do not require complex mathematics and are 'intuitive'.
- Richness: All of the basic MPC components can be tailored to the details of the problem in hand.
- Practicality: It is often the resolution of problems such as satisfying control- or output constraints, which determines the utility of a controller.
- Demonstrability: It works, as shown by many real applications in industry where MPC is routinely and profitably employed [20].

At present MPC is the most widely used multivariable control algorithm in the chemical process industry and in other areas [21]. While MPC is suitable for almost any kind of problem, it displays its main strength when applied to problems with:
- A large number of manipulated and controlled variables.
- Constraints imposed on both the manipulated and controlled variables.
- Changing control objectives and/or equipment (sensor/actuator) failure.
- Time delays.

The furnace model used for simulation purposes [13] consists of 17 states and 7 inputs (manipulated variables (MVs) and disturbances). Constraints exist on the controlled variables (CVs) of the EAF due to physical constraints and control objectives, and the MVs have limited ranges. MPC will therefore be used as the automatic control strategy to be compared to manual control as is currently used.

The remainder of this chapter will provide the theoretical background on MPC controller design and implementation.

4.2. BACKGROUND.

A conceptual diagram illustrating the principles of an MPC controller is shown in Figure 4.1 [20]. The heart of the controller is a model $M(\theta)$, parameterised by a set θ, which is used to predict the future behaviour of the plant. The prediction has two main components: The free response (f_r), being the expected behaviour of the output assuming zero future control actions, and the forced response (f_o), being the additional component of the output response due to the 'candidate' set of future controls (u). For a linear system, the total prediction can be calculated as $f_o + f_r$.

The reference sequence (r) is the target values the output should attain. The future system errors can then be calculated as $e = r - (f_o + f_r)$, where f_o, f_r and r are vectors of the appropriate dimensions.

An optimiser, having a user defined objective function J(e,u), is used to calculate the best set of future control actions by minimising the objective function, J(e,u). The optimisation is subject to constraints on the MVs and CVs.

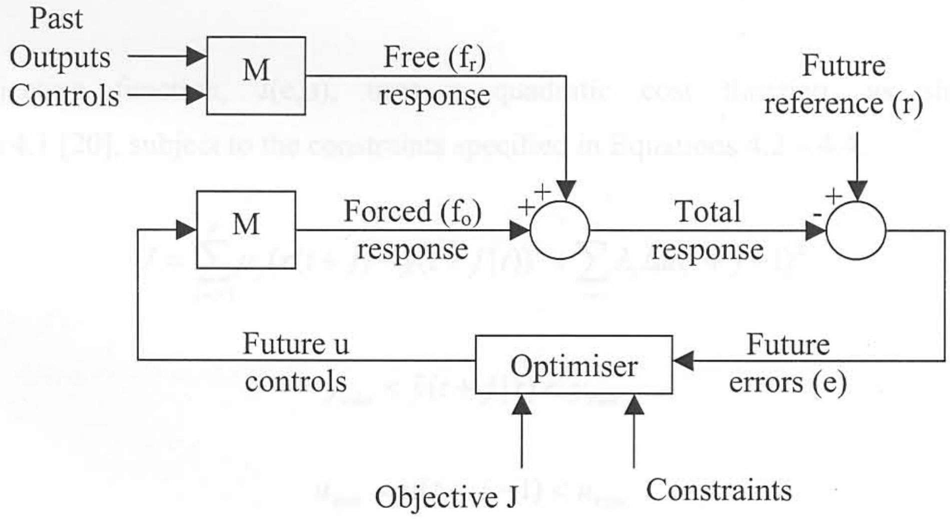

Figure 4.1. Basic Structure of MPC.

What makes MPC a closed loop control law is the use of the receding horizon approach. This implies that only the first of the set of control actions, u, is transmitted to the plant, after which the complete optimisation and prediction procedure is repeated, using the current plant output.

Another principle employed by MPC, is the use of horizons. The prediction horizon, P, specifies the number of future plant outputs to be calculated, using the model, M, the past control actions and the computed future control actions. The control horizon, C, specifies the number of future control actions to be calculated, in order to minimise the objective function, J(e,u), subject to the plant constraints. The future controls, u, will thus be a vector of dimension n × C, for n the number of manipulated variables. Only the first control actions (n × 1) will however be implemented, after which a new control sequence will be calculated.

The vectors f_r, f_o, and e will be vectors of dimension m × P, for m the number of plant outputs. The reference trajectory, r, has the dimension m × t, for t the total time for which the controller is implemented. For the calculation of e, a portion of r with dimension m × P is used to allow matrix manipulation.

The objective function, J(e,u), uses a quadratic cost function, as shown in Equation 4.1 [20], subject to the constraints specified in Equations 4.2 – 4.4.

$$J = \sum_{j=N1}^{P} \mu_j (r(t+j) - \hat{y}(t+j \mid t))^2 + \sum_{j=1}^{C} \lambda_j \Delta u(t+j-1)^2 \tag{4.1}$$

$$y_{\min} < \hat{y}(t+j \mid t) < y_{\max} \tag{4.2}$$

$$u_{\min} < u(t+j-1) < u_{\max} \tag{4.3}$$

$$\Delta u_{\min} < \Delta u(t+j-1) < \Delta u_{\max} \tag{4.4}$$

In Equation 4.1, $\hat{y}$ generally represents the future predictions of the system outputs, and $r - \hat{y}$ thus represents the predicted future errors, $\hat{e}$. Δu represents a differential control action. A differential value for u is preferred to an absolute value, as high frequency changes in u (Δu) tend to wear out actuators and might potentially cause instability. Constant high actuator values (u) however have no disadvantages to the actuators or stability, although it might influence plant operational cost (e.g. high feed rates) that need to be accounted for elsewhere.

μ_j and λ_j represents weights applied to the MVs and CVs. Weights applied to the outputs, μ_j, are used mainly to assign different priorities to different CVs. This is useful in ensuring that a CV that is much more critical than another enjoys the appropriate priority. For CVs with large differences in ranges, appropriate weights will ensure that relatively large deviations from variables with small nominal values enjoy a larger priority than relatively small deviations from variables with large nominal values.

Weights applied to variations in the MVs, λ_j, are used mainly for move suppression to prevent oscillatory behaviour. Increasing λ_j will prevent oscillation of the MVs, but large values of λ_j tend to slow down response times. Increasing λ_j thus trades system error minimisation against control signal variance [22].

In Equation 4.1, the differential manipulated variables are summed from 1 to C, the control horizon. The controlled variables are summed from N1 to P, the prediction horizon. For systems with dead time or inverse responses, the value of N1 is usually chosen large enough to prevent the inverse response, or unaffected response due to dead time, from being included in the cost function [22]. In the absence of dead time or inverse responses N1 = 1.

4.3. DESIGN STRATEGY.

The main tuning parameters are the control and prediction horizons (C and P) and the weights applied to the manipulated and controlled variables (μ and λ). Their functions will be discussed in turn.

The prediction horizon determines the number of predictions that are used in the optimisation calculations. Increasing the prediction horizon results in more conservative control action that has a stabilising effect, but it also increases the computational effort [23]. The predictions are furthermore just as good as the model used. A very large prediction horizon would thus be recommended only for a very good model and if feedback is limited.

The control horizon determines the number of future control actions that are calculated in the optimisation step to minimise the predicted errors. A large value for the control horizon, C, relative to the prediction horizon, P, tends to yield excessive control actions. A smaller value for C leads to a robust controller that is relatively insensitive to model errors [23]. Computational effort is also reduced by decreasing C.

A number of choices for the horizons have been suggested for the particular EAF model, all using a controller with a sampling interval of 1 s. Bekker [13] suggested using C = 2 and P = 6. This choice was based on defined criteria that had to be met and a trade-off between minimising computational effort and system error. Viljoen [10] continued on Bekker's research and controlled a different set of variables using additional manipulated variables. The control horizon was selected as C = 2 and the integral square error (ISE) between the setpoints and simulated plant outputs were determined for P between 5 and 8. It was found that P = 6 yielded the lowest ISE, as was also suggested by Bekker [13]. Oosthuizen [24] used a normalised ISE as criteria to determine the most suitable choices of C and P. A choice of C = 3 and P = 8 minimised the normalised ISE and was used effectively in simulations.

The choices of the three authors mentioned, all suggest that C should be relatively small compared to P (approximately 3 times smaller). Oosthuizen [24] also showed that no improvement is obtained by increasing P beyond 8, and that performance actually degrades due to modelling inaccuracies. Soeterboek suggested the following choices for N_1, C and P, for a system with dead time, d, a system order of n_A, a 5% settling time of t_s, a bandwidth of ω_b and a sampling time, $T_s = 2\pi/\omega_s$ [25]:

- $N_1 = d + 1$
- $C = n_A$
- $P = \text{integer}(t_s/T_s)$ for a well-damped system.
- $P = \text{integer}(2\omega_s/\omega_b)$ for a badly-damped system.

The computational effort is however not considered by Soeterboek, and might be an important consideration in the determination of C and P. The suggestions of Soeterboek [25] as well as the techniques described in [10, 13, 24] will be used to determine the most suitable horizons.

The other tuning parameters are the weights applied to the controlled and manipulated variables (μ and λ). A typical initial choice is $\mu = I$, the identity matrix of appropriate dimension and $\lambda = fI$, for f a tuning parameter, typically chosen as small as possible [25]. Variations in all the manipulated variables are penalised proportional to f. Increasing f thus causes less vigorous control [23]. The disadvantage of this approach is that all the manipulated variables and deviations of the controlled variables from the setpoints are penalised in equal proportions. This selection of μ and λ as discussed above would thus only be useful if the priorities of the controlled variables and the ranges of the manipulated variables are equal. Bekker [13] performed some trial and error tuning on μ and λ until the desired response was obtained. Oosthuizen [24] selected initial weights based on the ranges of the manipulated variables and the maximum errors of the controlled variables. Viljoen [10] introduced dynamic weighting that changes as the variable changes. In all three cases a lot of trial and error tuning had to be performed to get the required system response. None of these simulation studies [10, 13, 24] however took economic considerations (which complicates the weighting process further) into account.

Becerra *et al.* [26] presented three structures typically used to optimise plant performance economically, as illustrated in Figure 4.2.

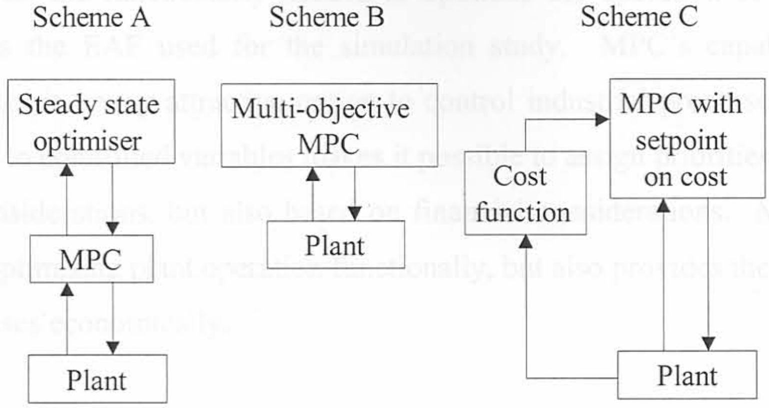

Figure 4.2. Implementation of MPC with economic objectives.

The scheme most commonly employed is Scheme A, where an upper level steady state optimiser provides setpoints for controlled variables and/or targets for manipulated variables to be used in the MPC algorithm. Scheme A has the disadvantage that plant operation is optimised only at steady state values, and no dynamic optimisation is possible. Schemes B and C addresses this problem to a certain extent, but have the disadvantage that some trade-offs need to be made between the functional and economic objectives.

This disadvantage can be avoided by implementing an MPC controller with only economic objectives. Instead of combining functional and economic objectives as suggested by Scheme B, the cost contributions of the MVs and CVs as discussed in Chapter 3 can be used to translate all functional objectives into economic objectives, prior to controller design. Minimisation of the MPC objective function would thus minimise plant operating cost, subject to the accuracy of the economic model.

The design and implementation of an economically and functionally efficient controller will be discussed in Chapter 5, using the structure of Scheme B and utilising the suggested tuning parameters as discussed in this chapter.

4.4. CONCLUSION.

MPC provides all the functionality needed to optimise the operation of a multivariable process such as the EAF used for the simulation study. MPC's capability to handle constraints makes it a very attractive option to control industrial processes. The weights that are applied to controlled variables makes it possible to assign priorities, not only based on physical considerations, but also based on financial considerations. MPC is thus not only useful in optimising plant operation functionally, but also provides the functionality to optimise processes economically.

CHAPTER 5: CONTROLLER DESIGN.

5.1. INTRODUCTION.

The design and analysis of a linear MPC controller that satisfies the control objectives defined in Chapter 3 will be discussed. The derivation of a linear plant model required for the design of an MPC controller is discussed in detail in Section 5.2. A comparison of the linear and non-linear models is made by means of open loop simulations. The outputs of the linear and non-linear models are thus compared for typical inputs to an EAF under manual control, as described by Bekker [13].

In Section 5.3 an analysis of the open loop system is done to determine the sampling interval to be used for the discrete system. The choices of the MPC tuning parameters and setpoints are discussed in Section 5.4, and a closed loop system analysis is performed in Section 5.5. Some details on the controller implementation are described in Section 5.6, and finally a comparison of the manual and MPC controlled EAFs is done by means of a simulation study.

5.2. PLANT LINEARISATION.

5.2.1. Model transformation.

The plant model [13] consists of 17 mostly non-linear equations that can be described in the following format:

$$\dot{x}_n(t) = f_n(\mathbf{x}(t), \mathbf{u}(t), \mathbf{d}(t)). \qquad (5.1)$$

f_n denotes a non-linear function describing the nth state's change with respect to time, $\mathbf{x}$(t) is the state vector, $\mathbf{u}$(t) is a vector of all the manipulated variables (MVs) and $\mathbf{d}$(t) is a vector of the disturbances. $\dot{x}_n$ is the derivative of the nth state with respect to time.

The linear model required for the controller design needs to be in state space format as described in Equations 5.2 and 5.3.

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{v}(t) \tag{5.2}$$

$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{D}\mathbf{v}(t) \tag{5.3}$$

The vector, **v**(t), is a combination of the vector of MVs ,**u**(t), and the disturbance vector, **d**(t). For the model considered, the following dimensions apply:

$\mathbf{x}(t) \in \Re^{17x1}$, $\mathbf{y}(t) \in \Re^{7x1}$, $\mathbf{v}(t) \in \Re^{7x1}$.

$\mathbf{A} \in \Re^{17x17}$, $\mathbf{B} \in \Re^{17x7}$, $\mathbf{C} \in \Re^{7x17}$, $\mathbf{D} \in \Re^{7x7}$.

The matrix elements for the linear system can be derived using Equations 5.4 – 5.7, using the principle of a Taylor series expansion [26]:

$$\mathbf{A}(n,m) = \frac{\partial f_n}{\partial x_m}, \tag{5.4}$$

$$\mathbf{B}(n,m) = \frac{\partial f_n}{\partial v_m}, \tag{5.5}$$

$$\mathbf{C}(n,m) = \frac{\partial y_n}{\partial x_m}, \tag{5.6}$$

$$\mathbf{D}(n,m) = \frac{\partial y_n}{\partial v_m} \tag{5.7}$$

in which y_n is the n^{th} output equation as a function of **x**(t) and **v**(t).

5.2.2. Linear model derivation.

A method commonly used in linearising non-linear plants, is to select an equilibrium point, and to linearise the plant at this point using Equations 5.4 – 5.7. This method was used in the first attempt to linearise the plant. Equilibrium or linearisation points were selected by calculating the average values of the states and the inputs (MVs and disturbances) based on plant data of the manually controlled EAF [13]. A simulation was done to compare the linear and non-linear models. A weighed integral square error (ISE) was also calculated for each state and output, by dividing the average error between the linear and non-linear simulations by the range (difference between minimum and maximum values) of the variable in the non-linear simulation. The sum of the weighed ISEs was used as a measure of the accuracy of the linear approximation of the non-linear EAF model.

Although the sum of the weighted ISE is capable of showing the average difference between the linear and non-linear models, it gives no indication of the accuracy of the approximation of each individual variable. An analysis of the individual weighted ISEs and an examination of graphs of the models indicated that some variables, particularly the off-gas temperature and composition, were inaccurately approximated by the linear model. Selecting different linearisation points also failed to solve this problem. Since the off-gas variables are CVs with large cost implications (see Chapter 3), a method was needed to improve the model accuracy. Instead of choosing linearisation points based on expected operating conditions, a gradient algorithm [28] was used to manipulate the matrix elements (of matrices **A**, **B**, **C** and **D**) individually in order to minimise the weighted ISE of the complete model. A block diagram of the gradient algorithm is shown in Figure 5.1.

The weighted ISE of the percentage carbon in the melt didn't show exceptionally large deviations, but the large range of the carbon content increased the complexity of the linearisation. The carbon content is reduced from approximately 3 % at the beginning of the melt to 0.072 % at tapping time [13]. Very small model deviations are thus required close to the tapping time, whilst relatively large variations are initially allowed. This problem was overcome by creating two separate linear models for the carbon content, to be used during different time periods of the simulation.

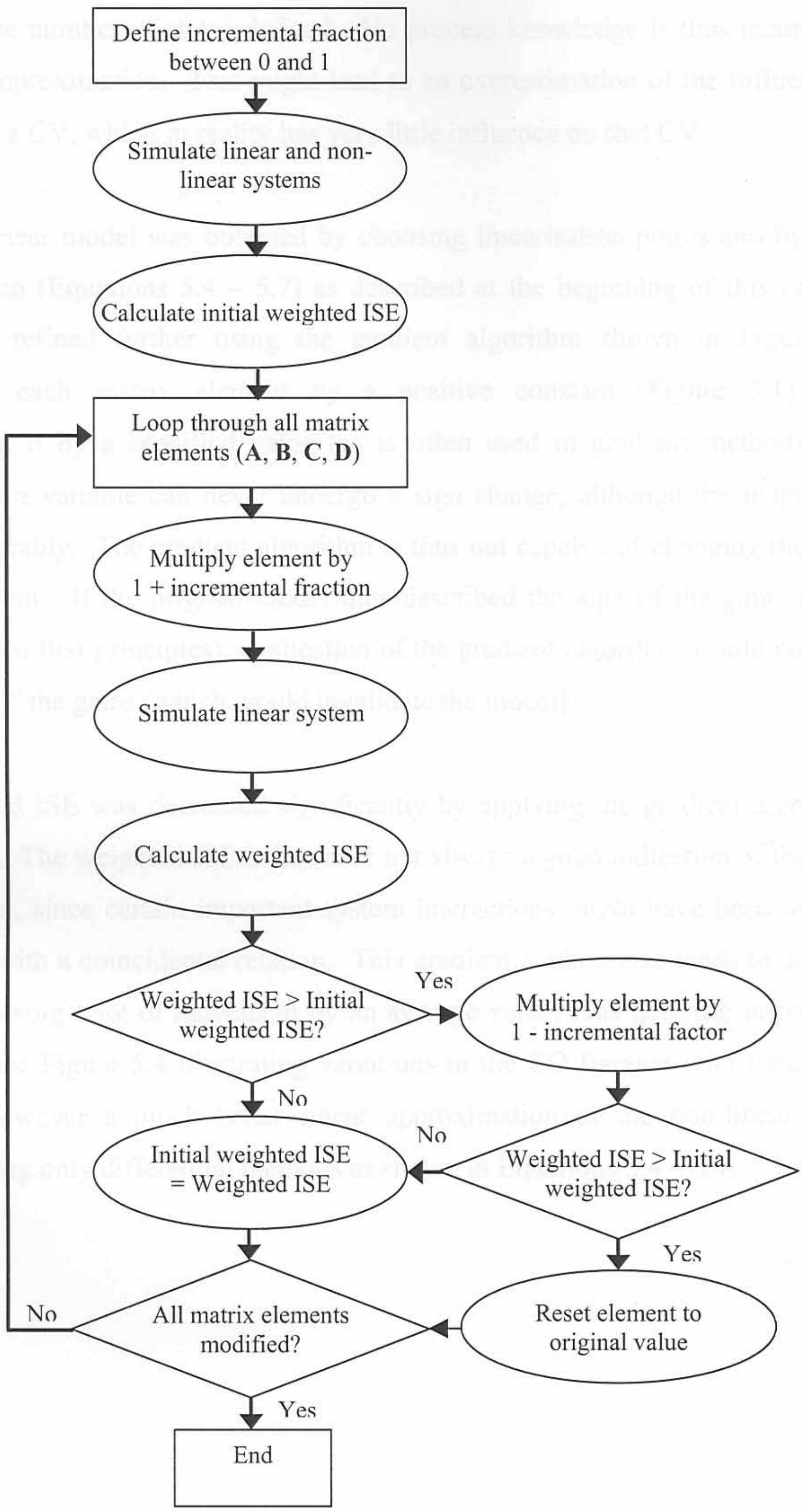

Figure 5.1. Block diagram of the gradient algorithm used to derive a linear model.

This gradient method has the disadvantage that a partial black-box approach is followed, with only the number of states defined. No process knowledge is thus incorporated into the model approximation. This might lead to an overestimation of the influence of some variables on a CV, which in reality has very little influence on that CV.

An initial linear model was obtained by choosing linearisation points and by performing differentiation (Equations 5.4 – 5.7) as described at the beginning of this section. This model was refined further using the gradient algorithm shown in Figure 5.1. By multiplying each matrix element by a positive constant (Figure 5.1) instead of incrementing it by a specified value (as is often used in gradient methods [28]), it is ensured that a variable can never undergo a sign change, although the magnitude might vary considerably. The gradient algorithm is thus not capable of changing the sign of any matrix element. If the original model thus described the sign of the gains correctly (as expected from first principles), application of the gradient algorithm would not change the sign of any of the gains (which would invalidate the model).

The weighted ISE was decreased significantly by applying the gradient algorithm to the two models. The weighted ISE is however not always a good indication of the correctness of the model, since certain important system interactions might have been overlooked or substituted with a coincidental relation. This gradient method also tends to approximate a variable showing a lot of movement by an average value, thus ignoring important system dynamics (see Figure 5.4 illustrating variations in the CO fraction with time). The final model is however a much better linear approximation of the non-linear model than obtained using only differential methods as shown in Equations 5.4 – 5.7.

5.2.3. Comparison of linear and non-linear plant models.

Simulations of the linear and non-linear plant models are shown in Figures 5.2 to 5.8 for the 7 CVs, using typical inputs as described by Bekker [13]. The relative furnace pressure, CO fraction and off-gas temperature are measured continuously. Some drift in these variables is therefore not much of a concern since feedback will ensure sufficient corrective action when frequent updates are used. It is however important that these variables should characterise system dynamics accurately, as they will be used for model predictions.

The linear models of relative pressure and off-gas temperature (Figures 5.2 and 5.3) characterise the system dynamics reasonably accurately, although a large drift is observed. Continuous feedback would however easily compensate for this, as is described above. The linear CO-fraction model (Figure 5.4) however contains very little dynamic information, and therefore a large safety margin and a short prediction horizon would be required to account for model inaccuracies. The linear CO-fraction model is in general a bad approximation of the non-linear model, but no linearisation attempt proved effective in improving the accuracy of the linear model. It was therefore decided to use the best obtainable model, but to keep the design specifications conservative to account for model inaccuracies.

The carbon content and liquid metal temperatures are only updated 5 times during the tap. It is thus essential that very little drift is present in these two variables, since the accuracy of any predictions between these updating intervals would depend on the accuracy of these models. Figures 5.5 and 5.6 indicate a good correlation between the linear and non-linear models. Using two models for the carbon content furthermore ensures that a good approximation is obtained for the full duration of the tap.

The steel mass is not measured during the tap, and a good model is thus essential. For the steel mass, linearization using differentiation was preferred over the gradient method, to prevent the possibility of ignoring important system interactions and including coincidental relations. Figure 5.7 indicates a good correlation between the linear and non-linear models with very little drift.

The linear and non-linear slag foam depth models seem to correlate well, although the influence of the FeO content in the slag is not modelled sufficiently, as can be seen between t = 35 minutes and t = 60 minutes in Figure 5.8. The FeO content in the slag increases from t = 0, reaches a maximum at t = 43 minutes and then decreases until the end of the tap [13]. Depending on the instrumentation, slag foam depth can be measured continuously or at discrete intervals. For these simulations it will be assumed that slag foam depth is updated at the same time intervals as the manual temperature and carbon content measurements, and model inaccuracies might thus necessitate a conservative design strategy.

The combined usage of Taylor approximations for non-linear functions and a gradient algorithm provided a linear model of sufficient accuracy to be used for the design of an MPC controller.

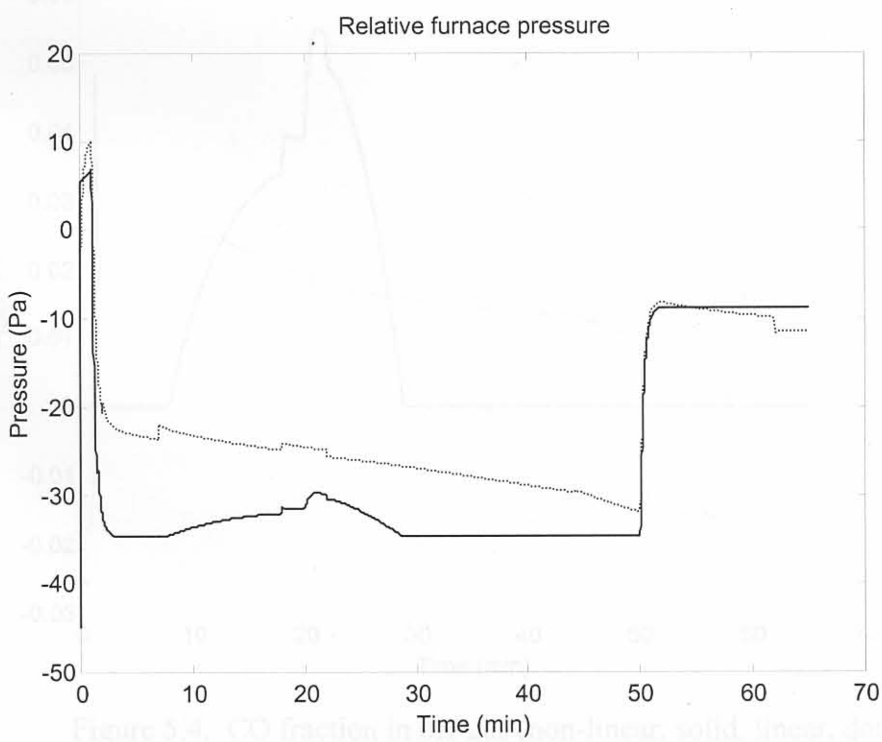

Figure 5.2. Relative pressure (non-linear, solid, linear, dotted).

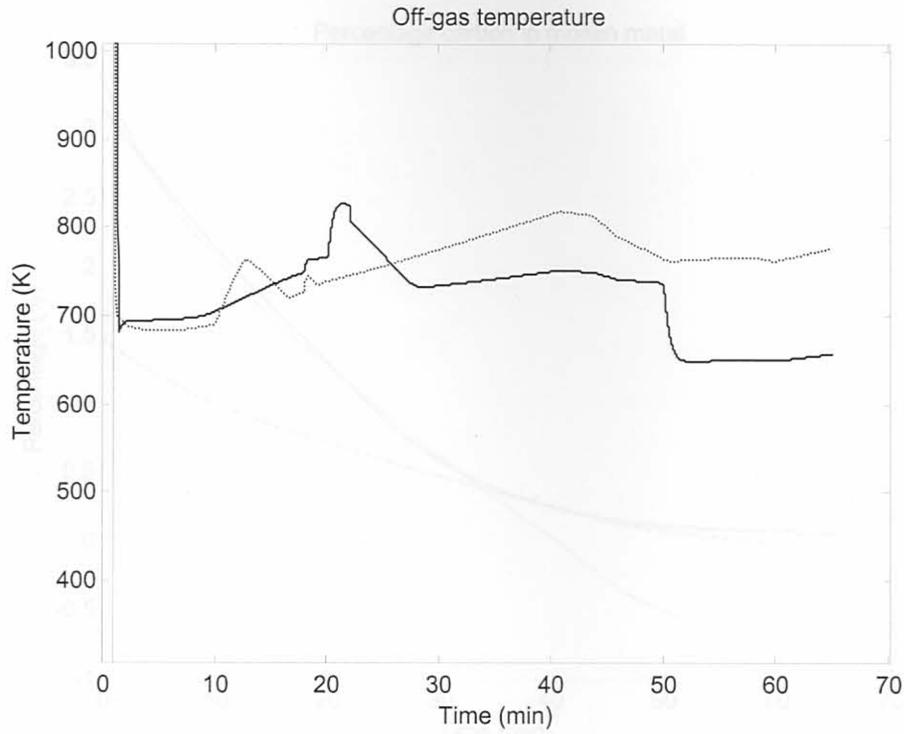

Figure 5.3. Off-gas temperature (non-linear, solid, linear, dotted).

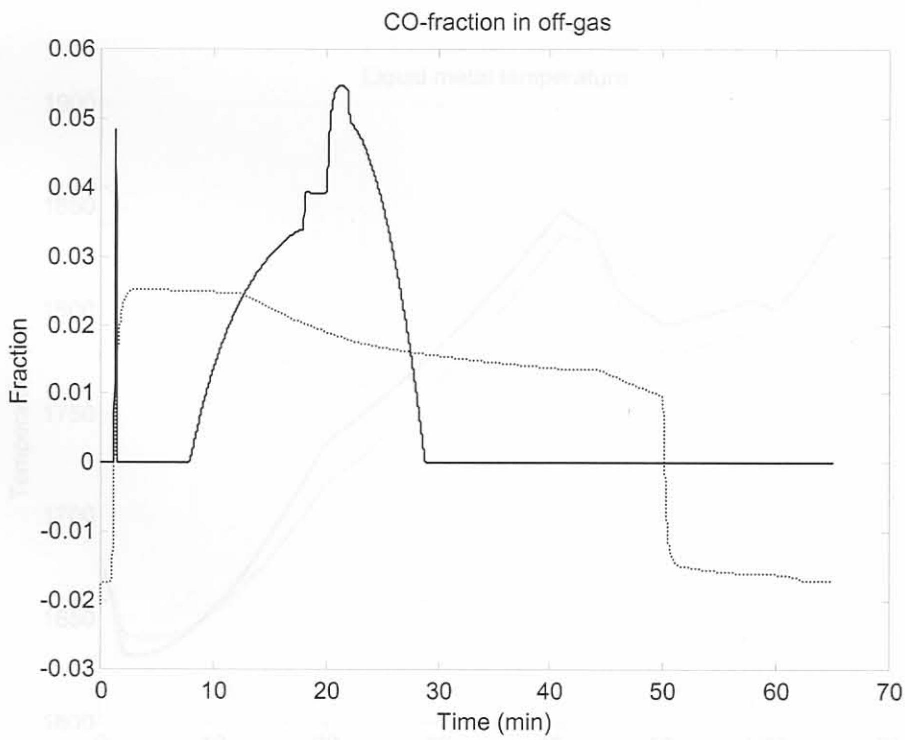

Figure 5.4. CO fraction in off-gas (non-linear, solid, linear, dotted).

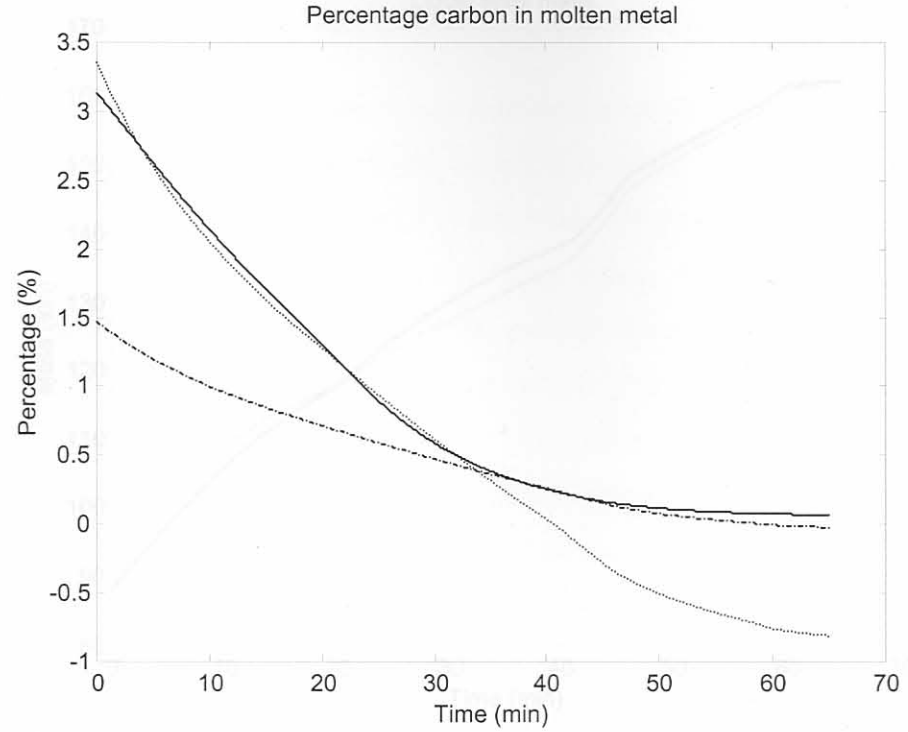

Figure 5.5. Percentage carbon in molten metal (non-linear, solid, linear model for first half, dotted, linear model for second half, dash-dotted).

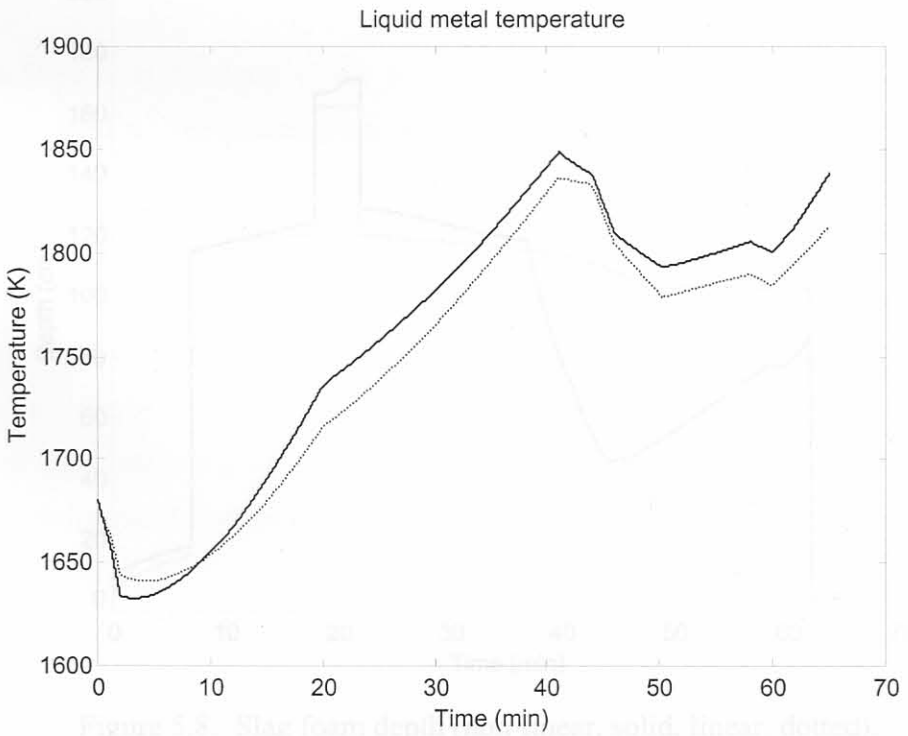

Figure 5.6. Liquid metal temperature (non-linear, solid, linear, dotted).

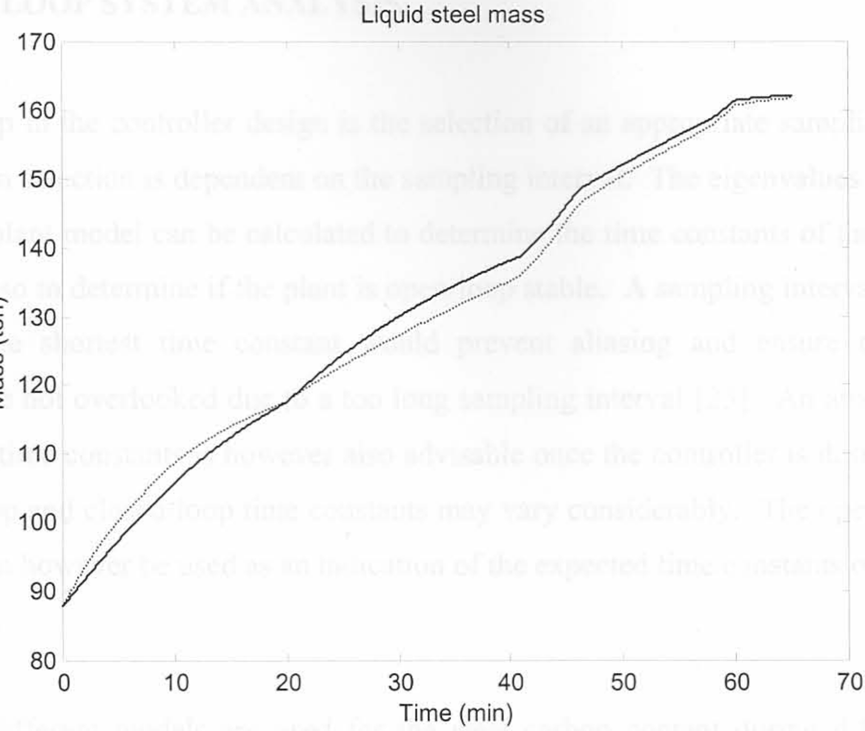

Figure 5.7. Liquid metal mass (non-linear, solid, linear, dotted).

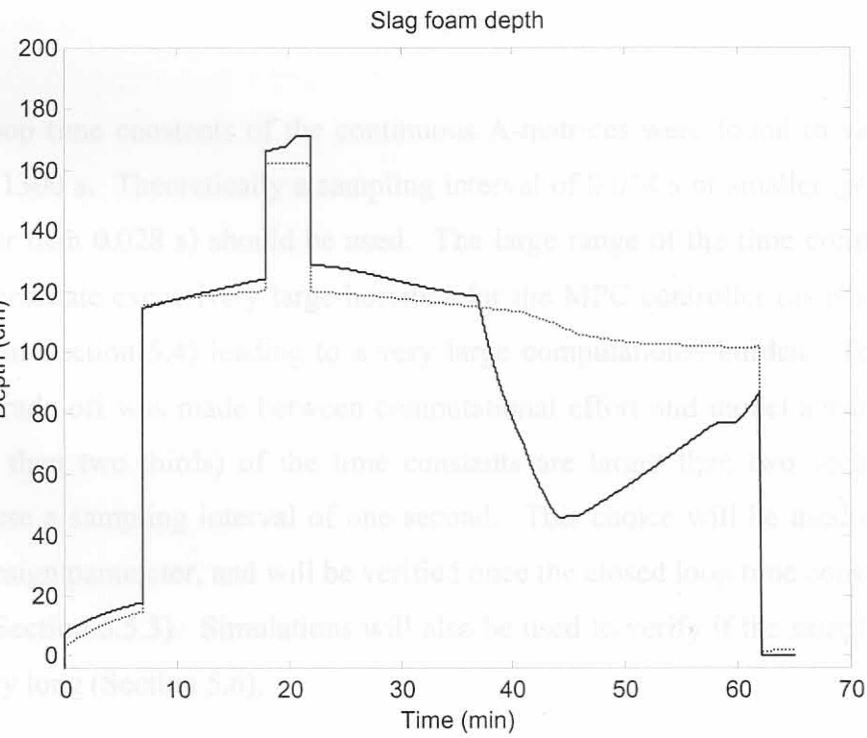

Figure 5.8. Slag foam depth (non-linear, solid, linear, dotted).

5.3. OPEN LOOP SYSTEM ANALYSIS.

The first step in the controller design is the selection of an appropriate sampling interval, since horizon selection is dependent on the sampling interval. The eigenvalues of the open loop linear plant model can be calculated to determine the time constants of the open loop plant, and also to determine if the plant is open-loop stable. A sampling interval of shorter than half the shortest time constant would prevent aliasing and ensure that system dynamics are not overlooked due to a too long sampling interval [23]. An analysis of the closed loop time constants is however also advisable once the controller is designed, since the open loop and closed-loop time constants may vary considerably. The open loop time constants can however be used as an indication of the expected time constants of the closed loop system.

Since two different models are used for the steel carbon content during different time frames, the eigenvalues had to be determined for both models. For both models all eigenvalues were found to be smaller than zero, indicating that the system is open loop stable.

The open loop time constants of the continuous A-matrices were found to vary between 0.028 s and 1300 s. Theoretically a sampling interval of 0.014 s or smaller (preferably 10 times smaller than 0.028 s) should be used. The large range of the time constants would however necessitate excessively large horizons for the MPC controller (as is discussed in more detail in Section 5.4) leading to a very large computational burden. To avoid this problem, a trade-off was made between computational effort and model accuracy. Since most (more than two thirds) of the time constants are larger than two seconds, it was decided to use a sampling interval of one second. This choice will be used as an initial controller design parameter, and will be verified once the closed loop time constants can be calculated (Section 5.5.3). Simulations will also be used to verify if the sampling interval is sufficiently long (Section 5.6).

5.4. DESIGN PROCEDURE.

The sampling interval chosen in Section 5.3 will be used in the design procedure. The remainder of the design procedure consists of a selection of control (M) and prediction (P) horizons, input- and output weights and also the definition of constraints for the MVs and CVs and the selection of setpoints [21]. These design parameters and final tuning adjustments will be discussed in the following sections.

5.4.1. Control and prediction horizons.

Authors seem to differ on initial choices of the prediction horizon, but agree that a large portion of the system response (more than 50 %) should be included in the prediction horizon [23]. The product of the sampling time and the prediction horizon should thus exceed 2.5 times the slowest time constant (τ) (assuming a settling time of 5τ). The accuracy of the model used for predictions should however also be considered, since smaller horizons tend to work better with an inaccurate model. Once again the wide range of the time constants and also the accuracy of the model (linear model used to control a non-linear plant) require that a trade-off be made. It was found that most of the time constants are below 20 seconds, suggesting a prediction horizon of 50. Some trial and error tuning showed that a prediction horizon of 25 provided adequate control. A shorter prediction horizon led to sustained oscillation due to a limited prediction interval in the presence of model uncertainty. Higher values of the prediction horizon frequently lead to an infeasible quadratic problem, since model inaccuracies drove the non-linear EAF model into an infeasible region (exceeding the maximum off-gas temperature), whilst the linear EAF model predicted that the EAF would remain inside the feasible region. This was mainly due to modelling inaccuracies in the off-gas temperature and the fact that a hard constraint was specified to prevent the off-gas temperature from exceeding the maximum specified temperature.

For inaccurate models a small control horizon is usually suggested [23]. Simulation studies indicated that M = 5 is a good choice, but M = 3 resulted in a controller much more robust to unmeasured disturbances. It was decided in favour of the more robust controller (M = 3), although control tended to become much more sluggish.

5.4.2. Constraints on manipulated variables.

Constraints were specified on the MVs to ensure that they are only manipulated within their typical operational ranges. These operational ranges were determined by examining plant data [13] and also through private communication [18]. The minimum and maximum ranges of the MVs are shown in Table 5.1. The minimum limit on the off-gas fan was specified to prevent model inaccuracies when the off-gas flow-rate approaches zero. From a process perspective, the specification of a lower safety limit on the off-gas fan is also feasible, as this would prevent the build-up of gasses inside the EAF due to insufficient off-gas flow-rates. No limit was placed on the rate of change of the MVs, but the selection of weights in Section 5.4.4 serves the purpose of suppressing excessive movement in the control actions.

Table 5.1. Constraints on MVs.

MV	Minimum	Maximum
Off-gas fan power.	0.1 MW	2 MW
Slip-gap width.	0 m	0.6 m
Oxygen injection rate.	0 kg/s	5 kg/s
DRI addition rate.	0 kg/s	35 kg/s
Graphite addition rate.	0 kg/s	1 kg/s

5.4.3. Constraints on controlled variables.

Constraints were placed on the CVs to prevent the model from exceeding physical limitations (e.g. a mass becoming negative). The maximum constraints were in general specified much larger than the maximum values obtainable by the CVs, and can thus be approximated as infinity (∞). These maximum constraints (approximated as ∞) are of little significance for the controller since they are never reached.

Two exceptions to the constraints mentioned above are the constraints placed on the off-gas temperature and slag foaming depth. The minimum limit of the off-gas temperature was set to 300 K due to physical temperature constraints. A maximum constraint of 760 K was specified to ensure that the off-gas would never exceed the maximum specification of 773 K (500°C), thereby including a small safety factor of 13 K. This upper limit was thus not based on physical constraints, but was chosen to satisfy the control objective on the off-gas temperature. This furthermore made the specification of an off-gas temperature setpoint and weight unnecessary, since no cost implication is associated with any off-gas temperature between 300K and 773 K.

Similar to the specification on the maximum off-gas temperature, a minimum limit was specified for the slag foaming depth. No benefit or disadvantage is associated with a slag foaming depth higher than 30 cm. Energy transfer to the melt only decreases if the slag foam depth is lower than 30 cm. Due to modelling inaccuracies, the slag foam depth of the non-linear model decreased below 30 cm although the linear model showed a sufficient depth. To prevent this from occurring in the absence of feedback, the minimum constraint on the slag foaming depth was increased to 50 cm, which yielded satisfactory results. No maximum constraint was specified for the slag foaming depth (∞), but the increasing cost of the feed materials prevents the slag foam depth from becoming excessive. In reality the height of the furnace or another opening in the furnace (e.g. slag door) would limit the maximum height of the slag layer.

For a system with more CVs than MVs, better control often results from specifying fixed setpoints only for variables where good regulation is required, whilst allowing other variables to float between certain limits. For the EAF under consideration much improved control was obtained, especially on the other off-gas variables, by relaxing the weights on the off-gas temperature and slag foaming depth, and specifying limits. A summary of the constraints on the CVs used in the controller is given in Table 5.2.

Table 5.2. Constraints on CVs.

CV	Minimum	Maximum
Relative furnace pressure.	$-\infty$	0 Pa
Off-gas temperature.	300 K	760 K
CO-fraction in off-gas.	0	1
% Carbon in steel.	0 %	100 %
Steel temperature.	300 K	∞
Steel mass.	0 kg	∞
Slag foam depth.	50 cm	∞

5.4.4. Weights.

The selection of proper weights is crucial for this controller since the economic impact of each CV is reflected by its weight. An inaccurate choice of weights will cause the objective function to differ from the real costs experienced on the plant, and would prevent the real cost of EAF operation from being minimised. The objective function as shown in Chapter 4 is in the form of Equation 5.8 [20], with weights on the CVs indicated by μ_j and weights on variations in the MVs indicated by λ_j. The weights on the MVs serve the purpose of suppressing oscillation and excessive movement of the MVs. These weights should be chosen as small as possible to minimise their contribution to the objective function [23], and are typically found by trial and error.

$$J = \sum_{j=N1}^{P} \mu_j (r(t+j) - \hat{y}(t+j\,|\,t))^2 + \sum_{j=1}^{C} \lambda_j \Delta u(t+j-1)^2 \tag{5.8}$$

Additional to the CVs defined previously, 5 other CVs were defined to represent the MVs. This was necessary since the objective function does not consider absolute values of the MVs (only variations), although the absolute values of the MVs determine their cost contribution to the tap. Only μ_j is thus used to specify the economic objectives whilst λ_j is used to increase stability.

In Chapter 3, the control objectives defined in Chapter 2 were translated into percentages of operating cost, as a function of deviation of the CVs from their setpoints. The relative cost contribution of the MVs were also tabulated in Chapter 3. To minimise the cost of the MVs, the setpoints for all the MVs were chosen equal to zero. Table 5.3 gives the per unit percentages for the MVs in the unit that feed rate is typically specified. These values, divided by the ranges of the MVs as specified in Table 5.1, were used as the μ_j values for the CVs corresponding to the MVs.

Table 5.3. The cost contribution of feed materials under typical operating conditions.

MV	Cost contribution	Per unit cost	Unit
Off-gas fan power.	0.58 %	0.725 %	/MW
Slip-gap width.	0 %	0 %	/m
Oxygen feed rate.	0.7 %	0.54 %	/kgs^{-1}
DRI feed rate.	9.18 %	1.1 %	/kgs^{-1}
Graphite feed rate.	0.1 %	2.895 %	/kgs^{-1}

The next step is to translate the economic implication of not reaching the setpoints on the CVs into similar per unit percentages. The costs defined in Chapter 3 need to be transformed into a form similar to the objective function given by Equation 5.8. This was done by linearising the economic implication over the ranges the CVs are expected to vary. A straight line was thus fitted between the minimum and maximum cost contributions of each CV for the expected range of each CV, and the gradient of the line calculated to represent the per-unit cost. An example follows:

Equation 5.9, which describes the percentage increase in the cost of a tap as a function of deviation from the tapping temperature setpoint (see Chapter 3), is an example of a non-linear cost function that needs to be linearised.

$$\begin{aligned} \Delta\%\text{Cost} &= 8\,\% + 0.063\,\% \cdot (\text{abs}(\Delta T) - 10) \ldots \text{for abs}(\Delta T) > 10 \\ \Delta\%\text{Cost} &= 0 \qquad\qquad\qquad\qquad\qquad\qquad \ldots \text{for abs}(\Delta T) < 10 \end{aligned} \tag{5.9}$$

Δ%Cost describes the percentage increase in operating cost if the tapping temperature differs more than 10 K from the setpoint. If the tapping temperature is within 10 K of the setpoint, no corrective action is required and $\Delta\%\text{Cost}_{min}$ = 0 %. If it is assumed that the maximum tapping temperature deviation from the setpoint would be approximately 50 K, $\Delta\%\text{Cost}_{max}$ = 10.52 %. The gradient of the increase in cost due to deviation from the tapping temperature setpoint is thus 10.52 % / 50 K = 0.2104 %/K, as shown in Table 5.4. A steel temperature 50 K below the setpoint at tapping would thus increase the cost of the tap by 10.52 %.

The expected maximum ranges of the CVs, the economic implication at the maximum deviation (calculated using the assumptions in Chapter 3) and the per-unit costs are shown in Table 5.4. The per-unit costs shown in Table 5.4, divided by their maximum ranges, were used for the μ_j values corresponding to the CVs.

Table 5.4. The economic implication of not reaching control objectives.

CV	Maximum range	Cost at max.	Per unit cost	Unit
Relative pressure.	5 Pa	0.628 %	0.1256 %	/Pa
Off-gas temperature.	100 K	3 %	0.03 %	/K
CO emission.	0.1 %	1000 %	10 000 %	/CO fraction
Carbon content.	0.001 %	10 %	10 000 %	/%C
Steel temperature.	50 K	10.52 %	0.2104 %	/K
Steel mass.	18 t	10 %	$5.55\text{x}10^{-4}$ %	/kg
Foamy slag depth.	30 cm	0.9 %	0.03 %	/cm

Although the objective function as given by Equation 5.8 is quadratic, most costs described in Chapter 3 are linear functions, whilst the non-linear costs are linearised as described above. The fact that a quadratic objective function, as given in Equation 5.8, is used to represent a linear cost function is no reason for concern as a transformation can easily be made. The ISE between a linear function of the format $y_1 = k_1x$ and a quadratic function of the format $y_2 = k_2x^2$ ($k_2 = \mu_j$, $x^2 = (r-y)^2$) over a defined range, x_{max}, is minimised by choosing $k_2 = 5/(4k_1x_{max})$. The derivation of this relation follows.

Assume that a linear function, y_1, is represented by Equation 5.10, and a quadratic function, y_2, is represented by Equation 5.11.

$$y_1 = k_1 x \tag{5.10}$$

$$y_2 = k_2 x^2 \tag{5.11}$$

The objective is to minimise $(y_1 - y_2)^2$ over the range x_{min} to x_{max}, by calculating an appropriate relation between k_1 and k_2. The ISE is given by Equation 5.12. As y_1 and y_2 are symmetrical, the calculation can be simplified by choosing $x_{min} = 0$, which yields Equation 5.13.

$$ISE = \int_{x_{min}}^{x_{max}} (y_1(x) - y_2(x))^2 \, dx \tag{5.12}$$

$$ISE = \frac{1}{3}k_1^2 x_{max}^3 - \frac{1}{2}k_1 k_2 x_{max}^4 + \frac{1}{5}k_2^2 x_{max}^5 \tag{5.13}$$

By differentiating the ISE with respect to k_2 and setting the derivative equal to zero, the values of k_1 and k_2 that would minimise the ISE can be calculated, as shown in Equation 5.14.

$$\frac{\mathrm{d}ISE}{\mathrm{d}k_2} = -\frac{1}{2}k_1 x_{max}^4 + \frac{2}{5}k_2 x_{max}^5 = 0 \tag{5.14}$$

The ratio between k_1 and k_2 that would minimise the ISE can now be calculated, as shown in Equation 5.15.

$$k_2 = \frac{5}{4} k_1 / x_{\max} \tag{5.15}$$

In many cases the quadratic representation (Equation 5.11) is a more accurate representation of the real cost implication than the linear approximation (Equation 5.10), since a small deviation in general has a very small cost implication whilst a large deviation in general has a much larger implication.

5.4.5. Setpoints.

Setpoints were chosen to correspond with values obtained from the manually controlled EAF. For the relative pressure, a setpoint of 0 Pa was specified, since this would minimise energy losses in the off-gas stream, without compromising the safety of workers. The relative pressure never approached the critical level of 0 Pa in the simulation study (Figure 5.12). The setpoints for the CO-fraction in the off-gas necessitated a much lower relative pressure to avoid the build-up of CO inside the EAF. Depending on the specific operating conditions on a plant, a lower relative pressure setpoint may be specified if it is found that the relative pressure frequently tends to become positive. The weight, μ_j, may also be modified to account for the cost implication of positive relative pressure, rather than for the cost of excessive energy wastage, as used in this simulation study.

The setpoint for the CO-fraction was set equal to zero, since this would minimise the possibility of legislative action due to excessive CO emission.

The carbon setpoint was specified as an exponential function starting at 3.14 % and ending at 0.072 %. The setpoint has a time constant of 975 seconds, implying that 4 time constants elapse during a tap. A comparison of the setpoints, the manually controlled variables and the MPC controlled variables are shown in Section 5.6.

The setpoint for the liquid metal temperature is based on the temperature profile of the manually controlled EAF. The setpoint is 1680 K during the first 10 minutes of the simulation. Between t = 10 minutes and t = 40 minutes, the temperature setpoint increases linearly to 1850 K. For the remainder of the simulation the setpoint remains at 1850 K, which is also the tapping temperature (see Figure 5.16).

The setpoint for the liquid steel mass is a linear function increasing from 87925 kg to 162110 kg. The initial steel mass is based on the liquid metal present inside the EAF when the automatic control can commence (after scrap has been melted partially and hot metal added [13]). The setpoint for the final steel mass at tapping time is identical to the final steel mass obtained under manual control.

The setpoints for the off-gas temperature and slag foam depth are not of much importance as the constraints specified on these two variables make setpoint following unnecessary. The weights, μ_j, on these two variables were also reduced by a factor of 1000 to prevent these variables from contributing significantly to the objective function (other than when reaching constraints). The weights were not reduced to zero since this tends to cause numerical instability in the minimisation function. Setpoints were therefore specified as 500 K and 50 cm respectively, although their influence on the objective function is negligible.

For the MVs modelled as CVs, setpoints were specified equal to zero. This was done to ensure that as little as possible of the feed materials or energy inputs are used during the steelmaking process, subject to other cost implications and constraints. The only exception is the slip-gap width, as a larger slip-gap opening has no direct cost implication, but indirectly influences the off-gas fan power required to maintain a certain relative pressure. A small weight, μ_j, however takes care of this and the setpoint was kept at zero.

5.4.6. Additional tuning.

Modification of the weights described in Section 5.4.4 should be avoided, as this would reduce the accuracy of the EAF cost model. The accuracy of the cost model described by the objective function in Equation 5.8, can however in some cases be increased. This is possible if the assumptions implicit to the derivation of the weights are invalidated in a certain operating region, or if limitations of the objective function reduces model accuracy.

One such case was already discussed in Section 5.4.3, where the weights of the slag foam depth and off-gas temperature were reduced by a factor of 1000, and limits specified within which these two variables are allowed to vary. The accuracy of the cost model was increased considerably by this step, as the quadratic objective function (Equation 5.8) is symmetrical, whilst the off-gas temperature only contributes to the cost if it exceeds a maximum value, and the slag foam depth only if it is lower than a minimum value.

Another modification to the weights suggested in Section 5.4.4 was made to the weights on the steel temperature and carbon content. The weights for these two CVs were calculated assuming typical specifications at tapping. At any other stage during the tap, the steel temperature and carbon content is however of little importance. Due to the large range of the carbon content, the weight should ideally vary inversely proportional to the carbon content, as was simulated by Viljoen [10]. A simpler approach was followed by specifying two different weights for the two different controllers used during the two time frames for which the different carbon models were defined in Section 5.2.3. The weight of the carbon content was thus reduced by a factor of 10 during the first half of the simulation, whilst the steel temperature weight was increased by a factor of 10. During the second half of the simulation, the original weights were used, as the assumptions used in deriving these weights are more accurately approximated closer to tapping time.

To avoid invalidating the cost model, further tuning was limited to choosing appropriate weights on variations in the MVs (λ_j) to ensure stability. Minor adjustments were made to the tapping temperature weight to improve setpoint following, but the objective function of final controller remains an accurate mapping of the cost model described in Chapter 3.

5.5. CLOSED LOOP SYSTEM ANALYSIS.

Analysis methods for non-linear systems are restricted to systems satisfying specific conditions, and very often simulations are the only method of analysing complex non-linear systems. The simulations shown in Section 5.6 indicate that the system is stable and that control objectives are met. A single simulation is however not sufficient in proving stability or good setpoint following, and a more rigorous analysis method is required.

For a linear system without constraints, numerous tools exist to characterise the system properties [23,27,29]. An approximation of the properties of a non-linear system, based on a linear approximation, is however only valid in the region where the two models are accurately matched. A comparison of the open-loop linear and non-linear models (Section 5.2.3) indicates that a good linear approximation of a non-linear system can be obtained. With the exception of the off-gas temperature and slag foaming depth, constraints on the CVs are either irrelevant or not reached under typical operational conditions (see Section 5.6) and the MVs also seldom reach their constraints. Instead of drawing conclusions on a single simulation study, it was decided to analyse the properties of the closed loop system more thoroughly by using the linear model without constraints.

A constant MPC gain matrix can be calculated for a linear unconstrained system, using the methods and functions described in [21]. Since two different linear models were used, two different MPC gain matrices would result, and the analysis would be based on both these models. The closed loop transfer function of the MPC controlled EAF can be determined from the MPC gain matrix and the linear system [21], which can be used for further analysis. The limitations of the approximation however need to be taken into account and will be discussed where applicable.

5.5.1. Stability.

The stability of the closed loop system can be analysed by calculating the eigenvalues of the closed loop **A**-matrix. Since a discrete implementation of the controller is used, the system would be stable if all the eigenvalues are within the unit circle [27]. For both models the absolute value of the maximum eigenvalue was smaller than 1, which implies that the system is stable. This conclusion may be invalidated if some non-linearity forces the system into an unstable region, but since the linear and non-linear models seem to correlate well, this is unlikely.

5.5.2. Frequency domain analysis.

The frequency domain analysis of the system was performed using singular value decomposition (SVD) [29]. Similar to Bode plots used for single-input single-output (SISO) systems, singular values give an indication of the system gain at specific frequencies for multiple-input multiple-output (MIMO) systems. For MIMO systems the gain would however not only depend on the frequency, but also on the direction of the input-vector. The SVD plot would thus consist of two lines indicating the minimum and maximum system gain at a specific frequency, for different input vector directions.

For the closed loop system, the inputs would correspond to the setpoints and the outputs to the system outputs. The direction of the setpoint-vector would thus vary as different setpoint combinations are specified. For good setpoint following, the SVD plot must have two properties: Firstly, the gain must be close to unity (or 0 dB) for the frequency band in which good setpoint-following is required. This would ensure an exact mapping from the setpoints to the outputs. The second requirement is that the minimum and maximum singular values must not differ significantly within this frequency band. Large variations between the minimum and maximum singular values would imply that the gain (and thus the mapping from the setpoints to the outputs) varies significantly as the direction of the setpoint vector changes, which is clearly undesirable.

The Matlab functions: mod2frsp.m and svdfrsp.m was used to generate the SVD plots. These two functions also allow specification of the inputs and outputs to be included in the analysis. Various combinations of CVs can thus be analysed to determine which combinations would yield good setpoint following and which not.

Figure 5.9 shows an SVD plot of all 7 CVs: Relative furnace pressure, CO fraction in off-gas, off-gas temperature, percentage carbon in steel melt, liquid metal temperature, liquid metal mass and slag foam depth. It can be seen that significant differences exist between the minimum and maximum singular values. Simulation studies confirmed that poor setpoint following is obtained when attempting to control all 7 CVs. This can be explained by noting that the EAF has 7 CVs and only 5 MVs. The controller thus attempts to satisfy all 7 control objectives by manipulating only 5 MVs. The deviations of the CVs from their setpoints are based on the relative weights in order to minimise the objective function. Good regulation is not achieved on any of the CVs, and control is in general very ineffective.

This problem was partly overcome by relaxing the weights on the off-gas temperature and slag foaming depth, as discussed in Section 5.4.6. This implies that 5 MVs can now be used to control 5 CVs, unless the off-gas temperature or slag foam depth are close to their constraints. A linear analysis excluding slag foam depth and off-gas temperature would also give a more accurate representation of the non-linear system, since the variables that reach their constraints would be omitted from the analysis. An SVD plot is shown in Figure 5.10, illustrating the frequency domain analysis of 5 of the CVs, excluding the off-gas temperature and slag foam depth. It can be seen that the difference between the minimum and maximum singular values decreased considerably, but the difference is still unacceptably large and the gain at low frequencies is far from 0 dB.

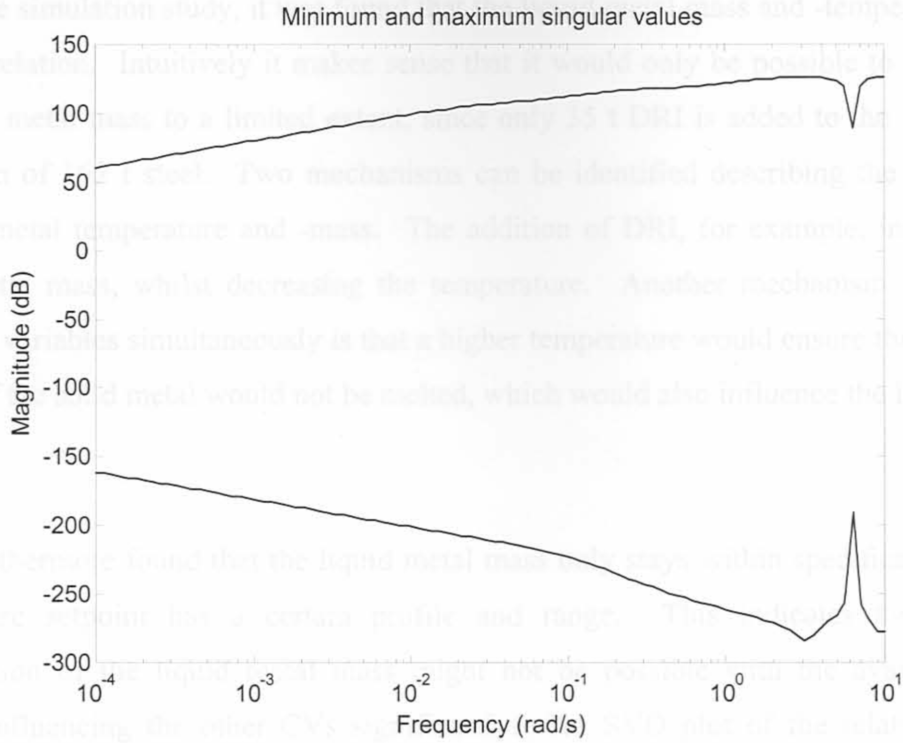

Figure 5.9. SVD plot for all seven CVs.

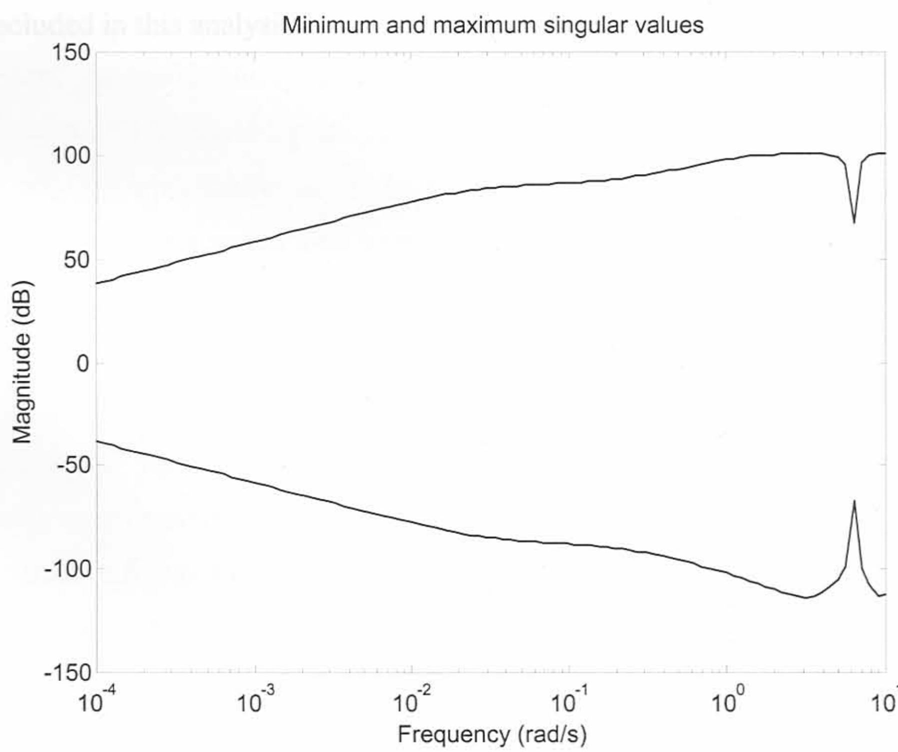

Figure 5.10. SVD plot for 5 CVs (excludes off-gas temperature and slag foam depth).

During the simulation study, it was found that the liquid metal mass and -temperature have some correlation. Intuitively it makes sense that it would only be possible to manipulate the liquid metal mass to a limited extent, since only 35 t DRI is added to the EAF in the production of 162 t steel. Two mechanisms can be identified describing the correlation between metal temperature and -mass. The addition of DRI, for example, increases the liquid metal mass, whilst decreasing the temperature. Another mechanism influencing these two variables simultaneously is that a higher temperature would ensure that a smaller portion of the solid metal would not be melted, which would also influence the liquid metal mass.

It was furthermore found that the liquid metal mass only stays within specifications if the temperature setpoint has a certain profile and range. This indicates that efficient manipulation of the liquid metal mass might not be possible with the available MVs without influencing the other CVs significantly. An SVD plot of the relative furnace pressure, CO fraction in off-gas, percentage carbon in steel and liquid metal temperature is shown in Figure 5.11. The slag foam depth, off-gas temperature and liquid metal mass are thus not included in this analysis.

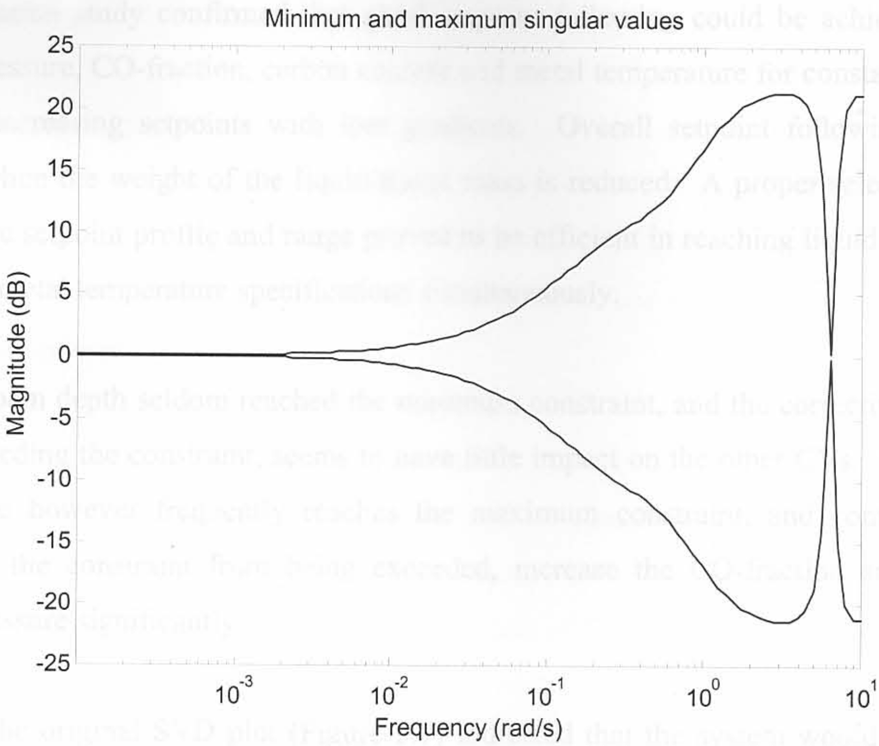

Figure 5.11. SVD plot for relative pressure, CO-fraction, percentage carbon in steel and steel temperature.

The minimum and maximum singular values are very close together for all frequencies below 0.1 rad/s. At higher frequencies the singular values vary considerably (more than 6 dB) and poor setpoint following can be expected. The EAF is a slow varying process and most of the setpoints can be kept constant for the duration of the tap. Setpoint changes slower than 0.1 rad/s would be tracked efficiently by the four CVs analysed, and good setpoint following can be expected in this frequency range.

The large singular values at high frequencies however also imply that high frequency measurement noise would be amplified, potentially degrading system performance. The adaptive nature of the MPC controller should however be sufficiently effective to compensate for the non-ideal system characteristics.

The simulation study confirmed that good setpoint following could be achieved on the relative pressure, CO-fraction, carbon content and metal temperature for constant setpoints or linear increasing setpoints with low gradients. Overall setpoint following seem to improve when the weight of the liquid metal mass is reduced. A proper selection of the temperature setpoint profile and range proved to be efficient in reaching liquid metal mass and liquid metal temperature specifications simultaneously.

The slag foam depth seldom reached the minimum constraint, and the corrective action to avoid exceeding the constraint, seems to have little impact on the other CVs. The off-gas temperature however frequently reaches the maximum constraint, and control actions preventing the constraint from being exceeded, increase the CO-fraction and also the relative pressure significantly.

Although the original SVD plot (Figure 5.9) indicated that the system would show poor setpoint following, some adjustments to the system configuration (adding constraints, relaxing weights and specifying suitable setpoints) proved to be efficient in designing a system capable of reaching control objectives, as is suggested by Figure 5.11.

5.5.3. Sampling interval verification.

A sampling interval was chosen in Section 5.3 based on the time constants of the open loop system. As the time constants can vary considerably between open- and closed loop systems, a verification of the sampling interval is recommended to ensure that the controller is capable of capturing system dynamics. The discrete closed loop system was transformed into a continuous system, and the eigenvalues of the continuous closed loop **A**-matrix was used to determine the time constants. Similar to the open loop time constants, the closed loop time constants vary over a wide range, from 0.04 s to times exceeding the tapping time. More than half the time constants are however longer than 2 seconds, and using the same reasoning as given in Section 5.3, a sampling interval of 1 second is still considered a good trade-off between computational effort and accuracy of the discrete model, although not an ideal choice.

5.6. CONTROLLER IMPLEMENTATION.

The performance of the MPC controlled EAF was compared to that of the manually controlled EAF under typical operating conditions as described by Bekker [13]. The simulation was done in Microsoft Visual C++. This simulation study serves the purpose of showing that the controller is functionally effective, whilst a more thorough economic evaluation is presented in Chapter 7.

A linear MPC controller was implemented to control the non-linear plant described by Bekker [13]. This was done to represent a typical situation existing in industry where significant differences might exist between the plant and the model used by the controller. The non-linear model is also a better representation of the real EAF and results based on the non-linear plant model would thus be more accurate than results based on the linear model. The linearised model as described in Section 5.2 was therefore implemented as an internal model for the controller, whilst the complete non-linear model was used to simulate plant behaviour and to provide feedback to the controller where applicable. The constraints defined in Section 5.4 were used in both the linear and non-linear models, and the rest of the controller tuning was implemented as described in Section 5.4.

To ensure that the simulation is a realistic representation of reality, only continuous measurements (relative furnace pressure, off-gas temperature and CO-fraction in off-gas) are fed back to the controller continuously. Measurements of the carbon content and temperature of the liquid metal are only taken approximately 5 times during a tap [18]. For the simulation study these values are used as feedback to the controller only at the following discrete time intervals: t = 30, 45, 53, 59 and 64 minutes, based on plant data [13]. Slag foam depth is also updated at these 5 discrete intervals, although some plants have continuous measurements available. The liquid metal mass is not measured during the tap and no feedback is thus provided.

A comparison of the CVs under MPC and manual control is shown in Figures 5.12 – 5.18. Some prominent effects due to actions taken under manual control is highlighted and a complete discussion of the data used for manual control can be found in Bekker [6].

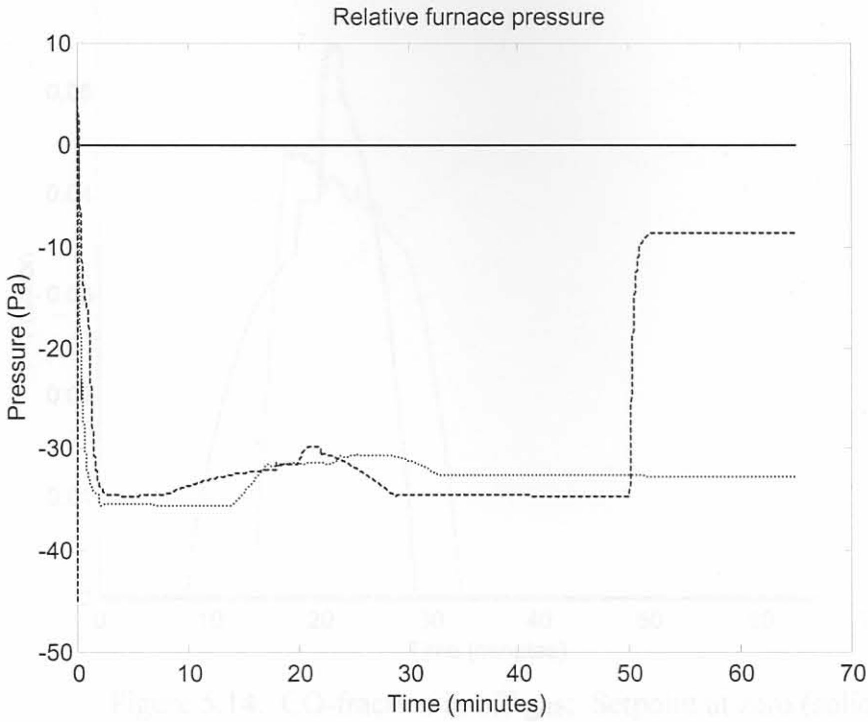

Figure 5.12. Relative furnace pressure: Setpoint (solid), Manual control (dashed) and MPC (dotted).

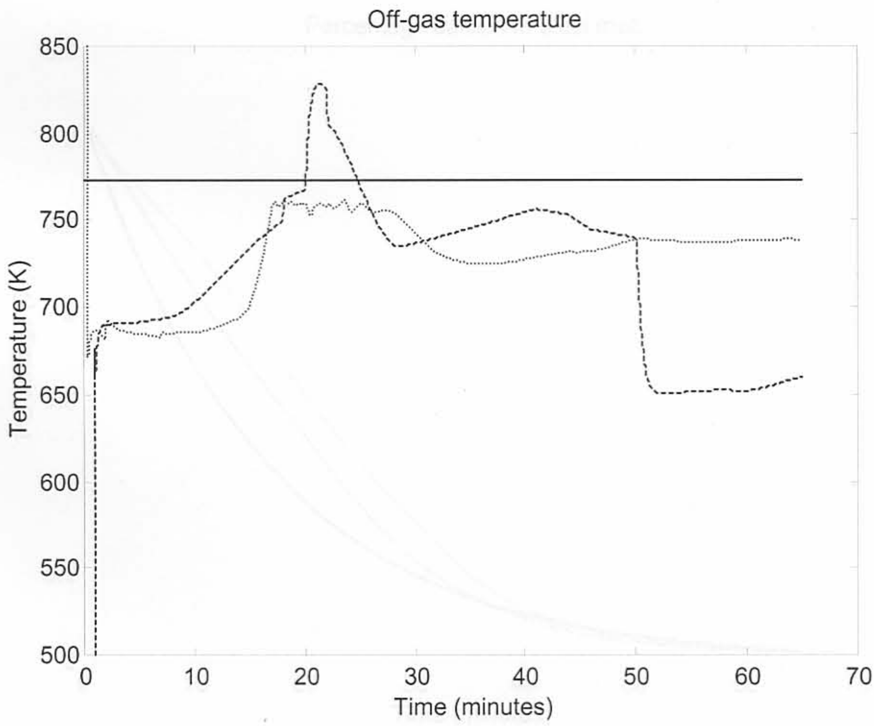

Figure 5.13. Off-gas temperature: Maximum limit (solid), Manual control (dashed) and MPC (dotted).

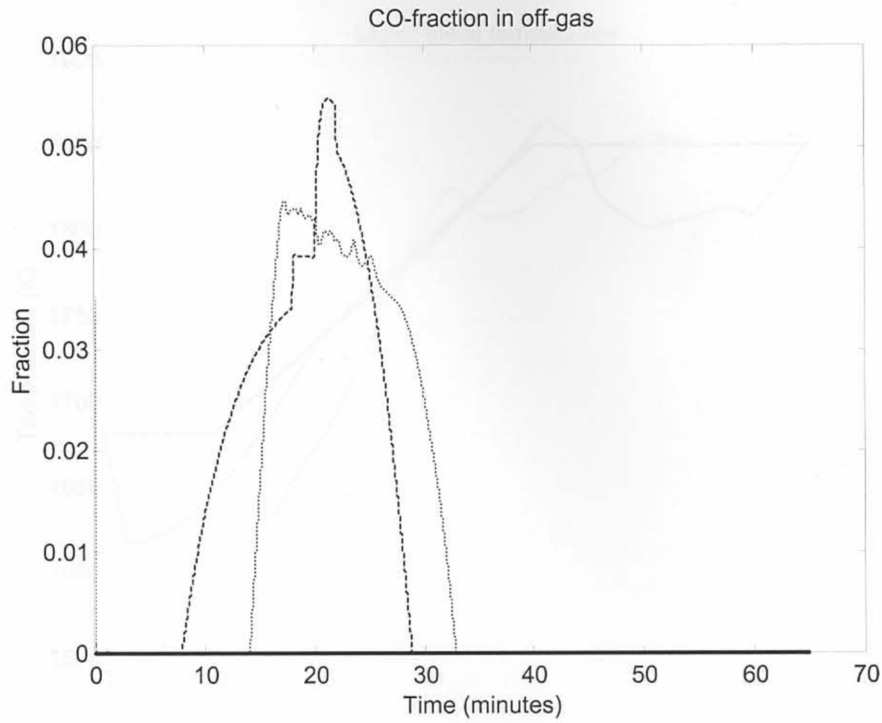

Figure 5.14. CO-fraction in off-gas: Setpoint at zero (solid), Manual control (dashed) and MPC (dotted).

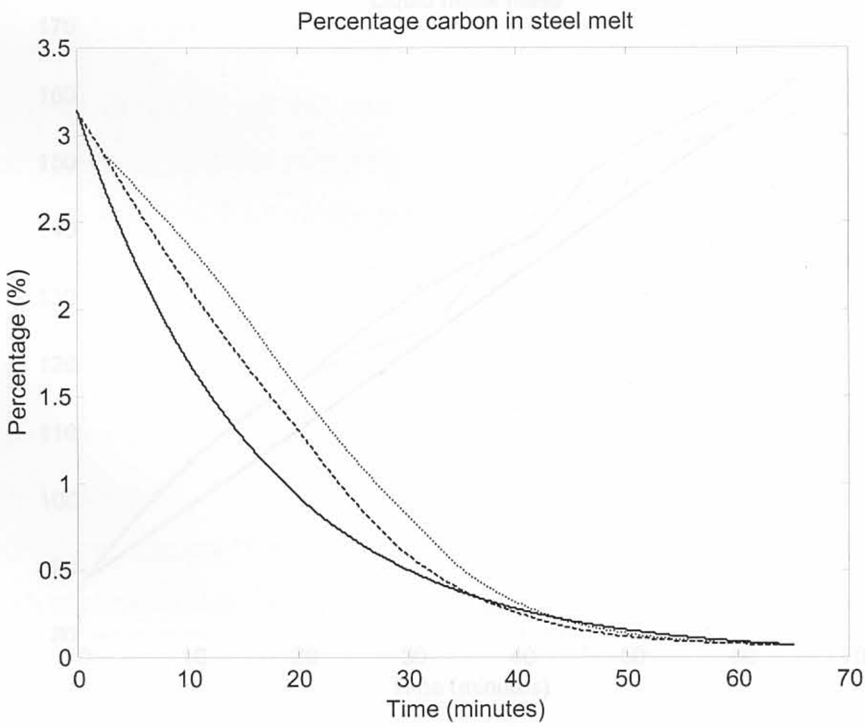

Figure 5.15. Percentage carbon in steel melt: Setpoint (solid), Manual control (dashed) and MPC (dotted).

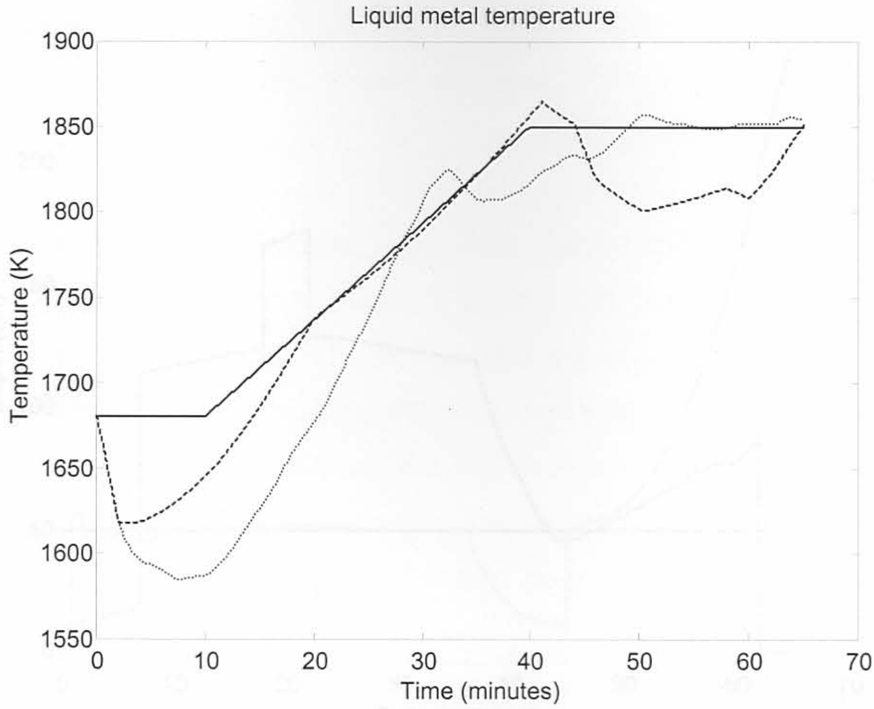

Figure 5.16. Liquid metal temperature: Setpoint (solid), Manual control (dashed) and MPC (dotted).

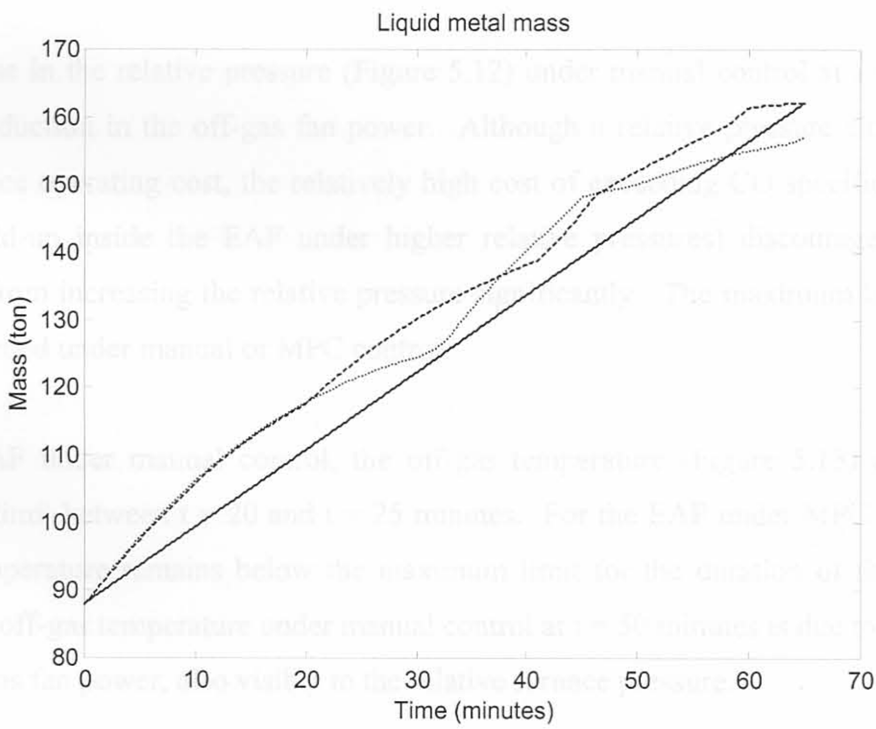

Figure 5.17. Liquid metal mass: Setpoint (solid), Manual control (dashed) and MPC (dotted).

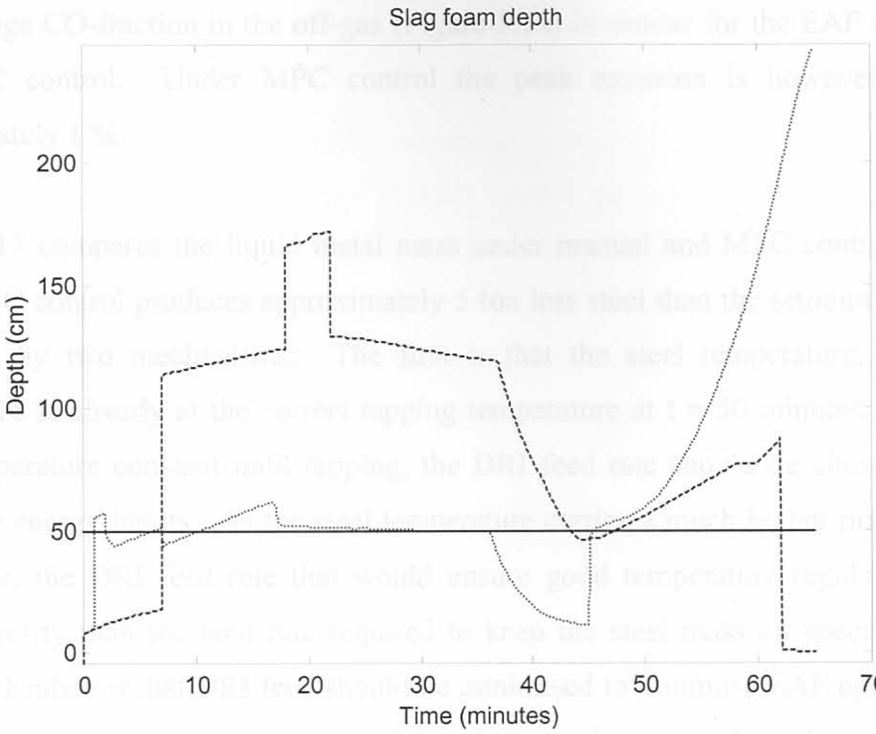

Figure 5.18. Slag foam depth: Setpoint (solid), Manual control (dashed) and MPC (dotted).

The increase in the relative pressure (Figure 5.12) under manual control at t = 50 min is due to a reduction in the off-gas fan power. Although a relative pressure closer to 0 Pa would reduce operating cost, the relatively high cost of exceeding CO specifications (due to CO build-up inside the EAF under higher relative pressures) discourages the MPC controller from increasing the relative pressure significantly. The maximum limit of 0 Pa is not exceeded under manual or MPC control.

For the EAF under manual control, the off-gas temperature (Figure 5.13) exceeds the maximum limit between t = 20 and t = 25 minutes. For the EAF under MPC control, the off-gas temperature remains below the maximum limit for the duration of the tap. The drop in the off-gas temperature under manual control at t = 50 minutes is due to a reduction in the off-gas fan power, also visible in the relative furnace pressure.

The average CO-fraction in the off-gas (Figure 5.14) is similar for the EAF under manual and MPC control. Under MPC control the peak emission is however reduced by approximately 1 %.

Figure 5.17 compares the liquid metal mass under manual and MPC control. The EAF under MPC control produces approximately 5 ton less steel than the setpoint. This can be explained by two mechanisms: The first is that the steel temperature, as shown in Figure 5.16 is already at the correct tapping temperature at t = 50 minutes. To keep the steel temperature constant until tapping, the DRI feed rate should be chosen such as to match the energy inputs. As the steel temperature carries a much higher priority than the steel mass, the DRI feed rate that would ensure good temperature regulation carries a higher priority than the feed rate required to keep the steel mass on specification. The other mechanism is that DRI feed should be minimised to minimise EAF operational cost. The cost associated with producing 5 ton less steel is less than the additional cost associated with charging an additional 5 tons of DRI, thus explaining the reduced DRI consumption and accompanying reduction in steel mass.

At t = 44 minutes, the percentage carbon in the steel melt dropped below the setpoint (Figure 5.15). The controller attempts to correct this error by injecting more graphite into the slag, thereby indirectly increasing the steel carbon content. The increased graphite injection however causes the slag foam depth to increase out of bounds from t = 44 minutes (Figure 5.18), as only a lower limit was specified for the slag foam depth (no penalization for higher foam depths). The slag foam depth would in reality only increase up to a level where overflowing would occur, but specification of an upper limit for the graphite injection rate should be capable of preventing this from occurring. The steps visible in the slag foam depth under manual control (between t = 0 and t = 30 minutes) are due to step changes in the graphite injection rate. The reduction in the slag foam depth from t = 36 minutes and the subsequent increase from t = 43 minutes, can mainly be attributed to the FeO content of the slag. The slag FeO content reaches a maximum at t = 43 minutes and then decreases until tapping. The inverse relation between the slag foam depth and the slag FeO content is clearly visible under manual control, but worsen the slag foam depth runaway under MPC control further.

5.7. CONCLUSION.

The design and analysis of an MPC controller was discussed and a simulation study presented comparing an EAF under manual control to one under MPC control. The controller reaches all control objectives whilst reducing the peak CO emission and maximum off-gas temperature compared to manual control. A much more thorough analysis of the economic feasibility of the MPC controller will be undertaken in Chapter 7, but functionally MPC proves being effective in controlling the EAF.

CHAPTER 6: THE EVALUATION OF CONTROL SYSTEMS.

6.1. INTRODUCTION.

Process control engineers are concerned with improving the performance of their plants, both functionally and economically. This often involves performing tests on the existing plant, to determine the benefits of new control strategies, or a different method of operating the plant. The problem with this approach is determining whether a real plant change (often with a small magnitude) has occurred, in the context of background noise and normal plant variations.

A wide range of statistical procedures is available to evaluate plant performance in the presence of disturbances. The use of these techniques in control applications however still seems to be the exception rather than the rule. As a consequence, plant improvement trials are often inappropriately designed, take too long, and lead to either no conclusion where a useful conclusion could have been reached, or the wrong conclusion [30].

In this chapter, some of the available evaluation techniques will be discussed and some other experimental considerations mentioned. An evaluation strategy will be suggested that will be followed in Chapter 7.

6.2. EXPERIMENTAL TECHNIQUES FOR COMPARATIVE EXPERIMENTS.

Comparative experimental techniques can roughly be divided into 3 categories: Replication, blocking and randomisation [31]. Most comparative experimental techniques form part of one of these categories or a combination of two or three.

Replication involves replicating each experiment performed immediately after the initial experiment. If two controllers, A and B, were to be compared using replication, the performance of controller A would be measured once, and the experiment repeated at least once immediately after the initial experiment. Controller B would then be switched on and the performance measured. The experiment involving controller B would then be repeated immediately afterwards. By using replication, the variations due to experimental error can be determined (from the replicated data) as well as the variations due to the different controllers. As the two sources of variations are separated, a much more accurate representation of the actual controller performance can be obtained.

Blocking is usually performed if it is expected that some disturbance exists which would cause data collected at different times or places to differ significantly. Experimental data collected within a block is compared, and not the data between blocks. For controller evaluation it can for example be expected that two operators would have different capabilities in controlling some plant variable effectively. A shift will then typically be selected as a block, to eliminate the variations due to different operator capabilities. The advantage of blocking is that the variations due to known parameters (e.g. operators, temperature differences, and different procedures on weekdays and weekend days) can be blocked out to improve the accuracy of the final estimate.

Blocking eliminates variances due to known disturbances and replication quantifies the experimental error more accurately. Random disturbances, disturbances with unknown frequencies and long term time trends are however not accounted for in any of the above-mentioned techniques. Randomisation is considered the most important basic principle in good experimentation [31], and ensures that successive errors are random and uncorrelated, thus eliminating the influence of any long term trends and systematic changes. A random testing sequence is easily created, by generating a series of random numbers, and assigning an experiment to a certain range of random numbers. If controllers A and B are to be compared, a random sequence consisting of zeros and ones can be generated, with all zeros indicating the use of controller A, and all ones indicating the use of controller B.

Replication, blocking and randomisation are seldom used in isolation. Two experimental combinations are described by Napier-Munn [30]: A replicated block experiment, and a randomised block experiment that was extended to a replicated randomised block experiment. For the third case described by Napier-Munn [30], a repeated on-off strategy, or blocking, was used, but a randomised block experiment is suggested, as time trends exist.

A method commonly employed by control engineers is a simple comparison of plant data before automation and after automation (e.g. single month-on, month-off trials). Although this may at first sight appear to use the blocking experimental procedure consisting of one block, the fundamental requirement of blocking is not satisfied, as operating conditions within the block are likely to change. Bergh *et al.* [32] quantified the benefits brought about by a supervisory control system (SCS), by comparing two months' data before implementation of the SCS to two months' data collected more than one year before, whilst a DCS was controlling the plant. Unless the improvement is large and the advantages hence obvious, this technique in general produces statistically invalid data. Changes in operating conditions will generally overwhelm the effects the experiment was designed to test for, invalidating any conclusions drawn.

Similar to this scenario, historical data is also used extensively to justify advanced control upgrades [33]. The "before and after" type experiments (improvement estimates relative to a base case) used by Marlin and co-workers [34] provides a useful framework in identifying control upgrade projects. These techniques however have severe shortcomings in producing statistically significant data required for controller evaluation [35]. Historical data might in many cases be the only method of control project justification. The infrastructure required for a new control strategy, or to perform comparative experiments, often contributes a major cost component to the proposed control upgrade project, favouring historical data analyses. Results based on historical data should however be examined with caution and a thorough statistical verification conducted to ensure that important trends are not overlooked. It is also suggested to perform a thorough audit after implementation of the new control strategy (using randomisation, blocking and/or replication) to verify the accuracy of recommendations based on historical data.

A number of further variations on the experimental procedures can be used to account for specific plant operating conditions. Craig and Henning [35] compared two controllers on a flotation circuit using a repeated on-off switching strategy, switching once per day. It is mentioned that a trial schedule was drawn up to alternate between the two controllers, and some form of randomisation was thus included. This experimental procedure can be classified as a random blocking experiment with a block size of 2 days. It might be argued that numerous changes might occur within each block, as there are for example four shifts per day. The dynamics of the system should however also be considered to ensure that the controllers are compared under typical operating conditions, and not just during the transient period. Craig and Henning [35] stated that the residence time of the circuit, as well as the frequency with which grades are analysed was used to determine the time between switching. Although knowledge of shifts could intuitively lead to a selection of a smaller block size, knowledge of plant dynamics should always carry an appropriate priority, and no experimental procedure attempted without sufficient process knowledge.

Instead of selecting the block size based on known disturbances, Craig and Henning [35] suggested switching as frequently as possible, but with each on-period significantly longer than the longest time constants of the process. These suggestions were further investigated by Oosthuizen, Craig and Pistorius [36] to determine the optimal switching time between two controllers, using a simple blocking experiment. It was concluded that an on-off switching time of 5 times the slowest time constant of the closed loop plant and controller would minimise the influence of external disturbances. A block experiment with a block duration of 10 times the slowest time constant of the plant is thus suggested. For a simple first order system, the time to reach a steady state is approximately equal to 5 times the slowest time constant. It is thus essential to ensure bumpless transfer of control between the two controllers to prevent the experiment from including only transient behaviour and no steady state behaviour. Randomisation was not included in the analysis [36], but it is expected that randomisation will yield better results (smaller resultant influence due to disturbances), even if the suggested switching time of 5τ is increased, as randomisation prevents biasing of the test data due to slow varying disturbances. If bumpless transfer of control is not possible, the best strategy might be a randomised block experiment with a block size larger than 5τ, but still as small as possible.

6.3. STATISTICAL TOOLS.

The test most commonly used for comparative experiments, is the t-test, of which 2 variations will be discussed. A brief discussion of analysis of variance will also be given. No statistical method is however valid, if the assumptions that are implicit to the test are ignored. The implicit assumptions for the t-test are the following [30]:

1. The data are normally distributed.
2. Each data point is a random independent sample of the population of all possible experimental outcomes, for the given system.
3. The two sample variances are estimates of the same population variance (i.e. they are not significantly different to each other).

For most processes the first assumption on normality can be accepted *a priori*, and the distribution can also be verified if necessary. The third assumption can also be checked easily using the F-test. The second assumption is a frequent cause of trouble as feed characteristics of processes vary with time and recovery or production is usually correlated with feed grade. Sequential measurements will thus not be random samples, but will depend to some extent on the preceding ones. Time trends in data raise the total variance and can also violate the assumption of sample independence [30].

t-tests are commonly used for comparing the means of two samples of data. In process control applications, the difference between the mean values of a controlled variable before and after automation can often be translated directly into increased profit. A null hypothesis is commonly stated which is assumed true until proven differently. In this case the null hypothesis would be that the two sample-means are identical. An alternative hypothesis is then stated that needs to be proven with a defined degree of statistical significance. In this example the alternative hypothesis will typically be that the two sample-means are significantly different from each other, or that one mean is larger than the other. A two-tailed test would be used for the first alternative hypothesis, and a one-tailed test for the second alternative hypothesis [31].

In most of the experimental techniques described in Section 6.2, experiments are carried out in pairs. The difference between each pair of measurements is in general of more importance than the absolute values. The t-test can be subdivided into a two-sample t-test and a paired comparison t-test.

For the two-sample t-test, the means of the two sample sets are calculated and compared using standard statistical formulas. If two controllers, A and B, were tested using a blocking technique, the mean of all the measurements for which controller A were used will be calculated, and compared to the mean of all the measurements where controller B was used. This is in general not a good comparison, since the variations between compounds will swamp any difference there may be between the two methods (Controllers A and B) [31]. A better approach would be to use the paired comparison t-test.

For the paired comparison t-test, the difference is calculated between each pair of data, provided that the data was generated in pairs. If the two controllers to be compared give similar results, the differences defined above would have a mean of zero. If one controller has a higher mean than the other does, the sample mean of the differences will be significantly different from zero. Standard statistical tables can be used to determine with a certain degree of significance if the means are really different. Napier-Munn [30] emphasises the advantages of the paired comparison t-test over the two-sample t-test, by calculating the number of paired measurements required to determine with 90 % confidence that a statistically significant increase has occurred for a given example. It was found that double the number of measurements was required for the two-sample t-test than for the paired t-test, clearly illustrating the increased sensitivity of the paired t-test.

In many process control applications, improved regulatory control due to a new control strategy enables the operator to move the setpoint of a controlled variable closer to a limiting value, thereby increasing process efficiency. This can typically be done in processes with constraints or in processes with non-linear performance functions [9]. Profits (determined by the performance function) are maximised by maintaining a controlled variable as close to its limits as possible. In statistical terms it can be said that a reduced variance enabled the operator to increase or decrease the mean. The advantages of a controller capable of reducing variations from the setpoint can however not be quantified by comparing the means, since no difference would exist between the means until the setpoint is changed. An analysis of the variances of the two controllers would have to be performed prior to changing the setpoint, to determine if the mean can be shifted due to a reduced variance whilst still staying within the operational region of the plant. Variances can be compared using the F-test. The ratio between the two variances can be calculated, and the significance level (of differences in the variances) read from standard tables.

Analysis of variance (ANOVA) is typically used if several groups exist in which the same experiments were conducted. If 4 operators for example control the same plant at different times, ANOVA can be used to determine if the observed product variations can be attributed only to natural process variations and experimental error, or if the operators have a significant influence on the final product quality. ANOVA is also used in blocking experiments to determine the influence of the separate blocks.

The basic principle ANOVA relies on, is that any measurement is made up of the sum of the population mean, influences that can be accounted for, and unaccounted factors including natural variations and experimental errors. The total variance of the sample thus consists of variances due to known causes (e.g. different operators) and natural variations that cannot be accounted for. ANOVA is in principle an arithmetical process of splitting up a total variance into its component parts [37]. Once the separate contributions to the total variance have been determined, the F-test can be used to compare the identified variances to the variance describing the experimental error. If the variances are significantly different, it can be concluded that the identified factors have a significant influence on the measurements, and their expected variances can be determined.

The statistical distribution of variances is described by the χ^2-distribution. An estimate of the variances is given by ANOVA, and the expected range of the variances can be calculated using the χ^2-distribution. In experiments where the difference between setpoints and process constraints are determined by the natural variations around the setpoints, an analysis of the sample variances will give insight into the magnitude of possible setpoint changes. A more detailed discussion of ANOVA is not within the scope of this work, and the complete statistical procedure can be found in Chatfield [31] and Davies [37], including a number of real test examples.

6.4. THE DURATION OF AN EXPERIMENT.

The duration of an experiment, and thus the number of repetitions required for each controller is determined by three factors: The degree of precision required, the amount of variability in the experimental material and the available resources to conduct the experiment, including time [38]. In general, the smaller the difference that needs to be detected, the more data is required.

The sample size of an experiment can be determined from the equations that are used to analyse the effects of the treatments. An example is shown for a one-tailed t-test, as is commonly used in testing the difference between recovery means, but a similar analysis can be done for the other tests described in Section 6.3. The equation used for a t-test is shown in Equation 6.1,

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)_{H_0}}{\hat{\sigma}_{\bar{x}_1 - \bar{x}_2}} \tag{6.1}$$

where $\bar{x}_1 - \bar{x}_2$ is the difference between the sample means, $(\mu_1 - \mu_2)_{H_0}$ is the hypothesised difference of the population means (= 0), and $\hat{\sigma}_{\bar{x}_1 - \bar{x}_2}$ is the estimated standard error of $(\bar{x}_1 - \bar{x}_2)$ given by Equation 6.2

$$\hat{\sigma}_{\bar{x}_1 - \bar{x}_2} = \sqrt{\sigma^2 (\frac{1}{n} + \frac{1}{n})}, \tag{6.2}$$

where σ^2 is the variance of the response variable which is assumed to be the same for both controllers. Assuming that both controllers are used equally often, the number of times each controller is used is thus equal to n and the total number of tests 2n. Substitution of the t-value for a defined level of significance, the difference in sample means to be tested $(\bar{x}_1 - \bar{x}_2)$ and the estimated standard error of the data $(\hat{\sigma}_{\bar{x}_1 - \bar{x}_2})$ thus yields the required value of n. The duration of the experiment can now be calculated by multiplying the duration of each test (controller on or off) as described in Section 6.2, by the number of tests (2n).

6.5. THREATS TO VALIDITY.

In the process of designing an appropriate experimental procedure, it is important to be aware of a number of threats to the validity of the results. If a threat is identified that might invalidate the results, the experimental procedure should be revised to eliminate the potential threat. Tien [39] classified the threats in 5 categories identifying 20 threats. Although many of these threats are applicable to the social sciences, many can be extended to the evaluation of engineering processes. A short discussion of the most important threats follows:

1. Internal validity.

   Extraneous events not representing typical operating conditions may occur during the test period. These incidents should be removed from the test-data if possible. Gradual deterioration of processes may occur, including cyclical deterioration that may be observed as a long time trend in product quality. Natural variations in the test-units, including variations in measurements need to be considered. Instrumentation changes or calibration may take place during the evaluation and should be accounted for if it cannot be avoided.

2. External validity.

   The sensitivity or responsiveness of a test subject may change since the test subject is aware of the test. An operator could for example control a plant better than normal during the test, since he is aware that his actions are being monitored.

3. Construct validity.

   Tests conducted under non-typical conditions can prevent the results from being extended to the general operational case.

4. Statistical conclusion validity.

   Manual intervention or the lack thereof, e.g. selecting which data should be omitted, is a serious threat if not conducted appropriately. This may lead to the rejection of a true hypothesis (type 1 error) or the non-rejection of a false hypothesis (type 2 error).

5. Conduct conclusion validity.

   Design complexity may preclude the complete and successful conduct of the evaluation. Economic infeasibility, including hidden and unanticipated costs, may lead to incomplete or inappropriate evaluation methods.

6.6. AN EVALUATION FRAMEWORK.

"The reason most evaluations or purposeful analyses fail – or are not valid – is because research or evaluation designs are lacking" [39]. According to Napier-Munn [30] plant improvement trials are often inappropriately designed, take too long and lead either to no conclusion when a useful conclusion could have been reached, or the wrong conclusion. "Unless a sensible design is employed, it may be very difficult or even impossible to obtain valid conclusions from the resulting data" [31]. It is thus clear that a clearly defined framework should be used to set up and conduct experiments, in order to draw any sensible conclusions.

The following evaluation framework is suggested by Chatfield [31]:

1. Process understanding.
2. Define the problem.
3. Determine which quantities should be measured.
4. Determine the accuracy of measurements and calibrate instrumentation.
5. If some variable is derived from other measurements, determine the distribution of the derived variable by examining the distribution of error through the system.
6. Make a list of factors influencing the value of the response variable.
7. Calculate the number of observations that should be made, based on statistical significance.
8. Decide which values should be used for each factor in each individual test run.
9. Set up a mathematical model to describe the testing procedure (e.g. the difference between two means).
10. Test the hypothesis and draw conclusions.

The framework suggested by Craig and Henning [35] starts where Chatfield's [31] framework ended, although some overlapping occurs. It elaborates much more on the experimental procedure, whilst Chatfield [31] focuses on the preliminary steps ensuring good experimental design. The framework proposed by Craig and Henning [35] follows:

1. State the hypothesis that needs to be tested, e.g. "The new controller is better than the old one".
2. Establish a base case to aid in experimental design.
3. Design an experiment to generate unbiased production data, which captures the economic performance of the control systems.
4. Monitor the experiment and make sure it is carried out as planned.
5. Analyse the generated data and determine the sample statistics for each.
6. Test and accept or reject the hypothesis.
7. Estimate the monetary benefits.
8. Do an economic project evaluation.

Marlin [34] proposed a benefit analysis method comprising three steps (points 1 to 3 in the following discussion). These steps however address a wide range of actions, mostly overlapping with the steps mentioned by Chatfield [31]. After the initial benefit analysis, two more steps (points 4 and 5) are mentioned, in some ways overlapping with the procedure proposed by Craig and Henning [35]. The method proposed by Marlin [34] is however not intended for experimental procedures, but mainly for the estimation of benefits from historical data. The procedure and a short discussion are given for completeness:

1. Interviews.

   The aim of this step is to become familiar with the plant operation, review control equipment, inspect field instrumentation, etc.
2. Basis and base case operation.

   This step identifies typical plant operation using the existing control system, identifies time periods where the plant operated in unusual modes, etc.

3. Opportunity identification.

   A brainstorming session usually initiates this step, after which feasible opportunities are identified. Potential benefits are calculated for the identified opportunities.

4. Conclusions based on benefits.

   Since the aim is to identify benefits and not test them, the conclusions include estimated control benefits, the control concept, control and process equipment needed, and the engineering effort required.

5. Control benefits calculation.

   The benefit is calculated taking the improvement, the value of the improvement, the unit throughput, the operational time and a service factor into account. These factors will be discussed in more detail in Section 6.6.

The evaluation framework suggested by Tien [39] is subdivided into 3 main steps:

1. A projected look at the range of program characteristics (from its rationale, through its operation and anticipated findings). This step also includes the identification of the problem that needs to be solved.
2. A prospective consideration of the threats to the validity of the final evaluation. The threats were discussed in detail in Section 6.4.
3. A more immediate identification of the evaluation design elements. This step is subdivided into the following categories:

3.1. The test hypothesis to be used.

3.2. The selection scheme of test groups.

3.3. The measuring framework, including the variables to be measured as well as a model describing their linkages.

3.4. The measurement method, e.g. the number of samples, test period, etc.

3.5. Selection of the analytical techniques to be used for data analysis.

Many of the steps proposed by Tien [39] overlap with those suggested by Chatfield [31], Craig and Henning [35] or combine several identified steps. The steps proposed by Craig and Henning [35] are in the final stage of the general control problem (GCP) whilst the preliminary steps (e.g. process understanding) would be covered, by solving the complete

GCP. It will thus be attempted to create a more comprehensive evaluation framework by combining the three suggested strategies. Although many of the steps may seem obvious (e.g. process understanding), their importance are often underestimated, and these steps will thus form part of the combined evaluation strategy.

The following combined evaluation strategy is thus proposed:

1. Process understanding.
2. Define the problem to be solved.
3. Determine the variables that should be measured.
4. Determine the accuracy of the measurements and calibrate instrumentation.
5. If some variable is derived from other measurements, determine the distribution of the derived variable by examining the distribution of error through the system.
6. Make a list of factors influencing the value of the response variable, which could invalidate the result.
7. State the hypothesis that needs to be tested.
8. Design an experiment to generate unbiased production data, which captures the economic performance of the control system. This step includes mathematical modelling of the test procedure, the number of observations required, the test period, a selection of analytical techniques to be used for analysis, etc.
9. Monitor the experiment and make sure it is carried out as planned.
10. Analyse the generated data and determine sample statistics for each.
11. Test and accept or reject the hypothesis.
12. Estimate the monetary benefits.
13. Do an economic project evaluation.

6.7. THE ECONOMIC EVALUATION OF CONTROLLERS.

The functional evaluation of a controller is often a simple process, since a display of trends is likely to provide sufficient proof of a controller's regulatory improvement. The economic performance evaluation is however a much more complicated process necessitating a carefully planned experiment. Such a scenario is described by Craig and Henning [35], for a flotation circuit. Although the regulatory improvement of the new controller is clearly discernible from time trends, a carefully planned experiment was required to measure an improved recovery (proportional to profit) in the presence of noise with a magnitude of approximately 10 times the measured improvement.

Marlin *et al.* [34] defined the following formula describing benefits.

$$\text{BENEFIT} = (\text{IMPROVEMENT}) \times (\text{INCREMENTAL VALUE}) \times (\text{UNIT THROUGHPUT}) \times (\text{TIME}) \times (\text{SERVICE FACTOR}) \qquad (6.3)$$

Knowledge of the improvement brought about by the new controller, the increase in profit due to an incremental change, the unit throughput per year, and the proportion of the time the plant and controller is operational, allows the calculation of the benefits of the new controller. The improvement can be estimated using any of the experimental techniques described above. For a multivariable process the determination of the incremental values is however a complicated process due to interactions between variables and possible non-linear characteristics. The format of the cost function (a combination of all the incremental values and cost of operation) can be rather complex and will depend on the plant configuration.

The fact that a controller can increase profit is in general not sufficient motivation for a control upgrade, or sufficient proof that the project is economically viable. An analysis of the expected cash cost and cash revenues associated with the project throughout the expected project life needs to be done. A diagram showing the typical characteristics of the cumulative cash flow for the duration of a project is shown in Figure 6.1 [40]. The aim of any project should be to ensure that the final positive cash flow at H is as large as possible, especially compared to the initial negative cash flow at D (see Figure 6.1). A detailed discussion of capital budgeting tools can be found in Allen [40], but a short discussion of the most commonly used capital budgeting tools follows.

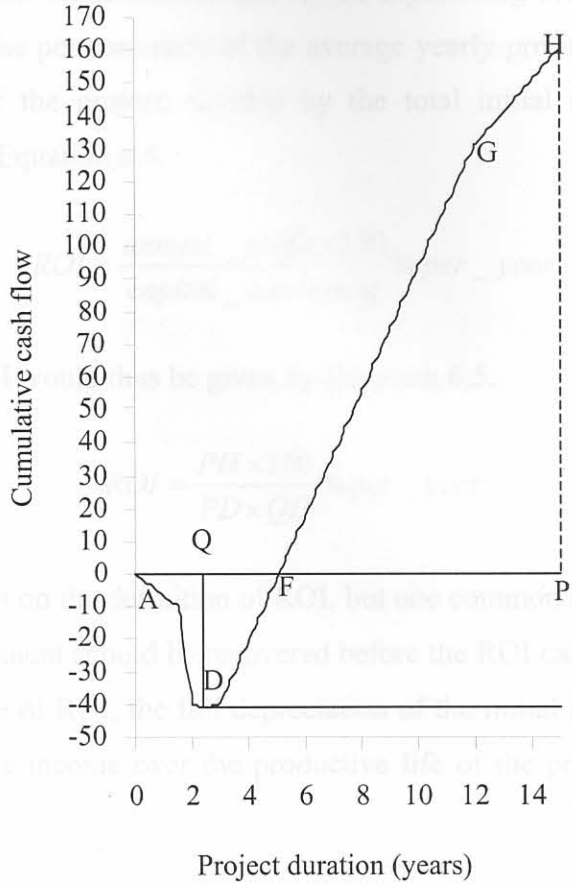

Figure 6.1. Typical cumulative cash flow diagram [40].

The simplest capital budgeting tool is the payback time. This is the time that elapses from the start of the project (A) to the breakeven point (F) (see Figure 6.1). The payback time thus indicates the time required in recovering early project expenditure and the cumulative investment, from the cumulative net project income [40]. The shorter the payback time, the more attractive the project appears.

One variation on the payback time is the time required to recover the initial investment. In this case the payback time would start at the time where the capital investment has all been spent, and not at the beginning of the project (A). Payback time provides no indication of the expected return on the investment and ignores everything in time beyond the breakeven point. It is thus very limited in its interpretation [40] and other more descriptive capital budgeting tools are often preferred.

The second tool is return on investment (ROI). In engineering economic evaluation, ROI is usually defined as the per cent ratio of the average yearly profit (net cash inflow) over the productive life of the project, divided by the total initial investment [40]. This definition is shown in Equation 6.4.

$$ROI = \frac{annual\_profit \times 100}{capital\_investment} \% per\_year \tag{6.4}$$

For Figure 6.1, the ROI would thus be given by Equation 6.5.

$$ROI = \frac{PH \times 100}{PD \times QD} \% per\_year \tag{6.5}$$

Several variations exist on the definition of ROI, but one common argument put forward is that the original investment should be recovered before the ROI can be calculated. For the calculation of this type of ROI, the full depreciation of the initial investment is calculated as a charge against the income over the productive life of the project [40], as shown in Equation 6.6.

$$ROI\_(including\_depreciation) = \frac{(PH - QD) \times 100}{PD \times QD} \% per\_year \tag{6.6}$$

Both payback time and ROI are very selective in the project cash flow information that they use, and both techniques ignore important relevant information regarding the changing pattern of cash flow with time and the time value of money [40]. Two other measures incorporating these factors will be discussed in turn.

In economic terms a project can be regarded as a series of cash flows throughout the project's lifetime. To take the time value of money into account, the annual cash flows have to be discounted to the time of evaluation before they can be compared and used as an evaluation measure [40]. The present value (PV) of a cash flow (C_t) at the end of project year t, is given by Equation 6.7, for i the applied discount rate.

$$PV = \frac{C_t}{(1+i)^t} \tag{6.7}$$

The net present value (NPV) of a complete project is the sum of the present values of the project's individual cash flows. The NPV is given by Equation 6.8, for n the complete project life in years.

$$NPV = \sum PV = \sum_{t=0}^{t=n} \frac{C_t}{(1+i)^t} \tag{6.8}$$

An effect of the discounting of the project cash flows, is that cash flows later in the life of the project make progressively smaller contributions to the project NPV [40]. Inaccurate estimates of the exact project lifetime or cash flows late in the project life would thus not influence the NPV significantly.

For a project to be viable in terms of generating a profit, the NPV should be positive. The discount rate would be determined by the effective cost of capital and the risk of the project [40].

Another economic measure used to determine project viability is the discounted cash flow rate of return (DCFR). It is also commonly referred to as interest rate of return and internal rate of return (IRR). DCFR is closely related to NPV, and is defined as the yearly discount rate that would yield a project NPV equal to zero [40]. The DCFR is thus determined by solving Equation 6.9 recursively, where 100I = project DCFR, % per year [40].

$$NPV = \sum_{t=0}^{t=n} \frac{C_t}{(1+I)^t} = 0 \tag{6.9}$$

A higher discount rate than the DCFR would thus yield a negative NPV and a lower discount rate a positive NPV. DCFR provides a measure of the rate of return expected over the whole project life, and thus the larger the value of the DCFR, the more economically attractive is the project [40].

The focus of this dissertation is the identification of suitable control strategies to increase profit, and the estimation of the profits attributable to advanced control. Specific cash flow calculations used to motivate control upgrades would depend on the level of automation of a specific steel plant, and can not be extended to a general case. Using the capital budgeting tools discussed above and the results of the simulation study presented in Chapter 7, an estimate of the economic viability of the suggested control strategy can be made to represent the scenario at a specific steel plant.

The advantages of a new control system are often not fully described by a benefit calculation. Some advantages that are difficult to quantify might include increased field instrument service factors, better operator displays, automated history data base, and better regulatory control which results in smoother plant operation [39]. Reduction in pseudo downtime, i.e. by preventing unscheduled plant shutdowns, by enabling fast recovery after plant disruptions, and by enabling fast plant start-ups and shutdowns are further unquantified advantages [35]. Tien [39] suggested listing these factors as additional advantages to the project, as it may be a determining factor in management decisions.

6.8. CONCLUSION.

A wide range of methods is available to ensure accurate evaluation of control systems. Unfortunately inappropriate techniques are often used to evaluate control systems or to justify implementation of new control systems, leading to invalid results. A number of experimental procedures were discussed (blocking, replication and randomisation), applicable to processes operating in noisy environments and which are subject to large natural variations. The most common statistical tools used for comparative experiments were discussed and a framework for experimental design presented that would ensure the generation of unbiased data. The process of translating a functional improvement into an economic benefit was also discussed briefly and some capital budgeting tools mentioned. The evaluation framework will form the basis of the economic evaluation presented in Chapter 7, and the tools described will be utilised where applicable.

CHAPTER 7. SIMULATION STUDY.

7.1. INTRODUCTION.

The MPC controller designed in Chapter 5 was evaluated by comparing a MPC controlled EAF to a manually controlled EAF (as is typically used). Although preliminary results obtained in Chapter 5 indicate some economic benefits due to improved regulatory control, a single comparative test provides a very inaccurate estimate of the real benefits (if any) due to the implementation of a new control strategy. The possibility exists that the experimental conditions favoured one controller more than the other, leading to biased results. It might also be the case that the MPC controller was tuned for a specific set of disturbances, and that it might be very ineffective if different disturbances are introduced.

To improve the accuracy of the comparison between the two control strategies (manual and MPC), a series of tests were conducted making use of the techniques described in Chapter 6. The composition of some of the MVs and also the magnitude of some of the disturbances were varied to represent natural variations occurring under typical EAF operating conditions. These natural variations had to be chosen carefully to represent scenarios where an operator would most likely not be capable of taking efficient corrective action, due to a lack of information. This would thus ensure that operators would respond similar to the behaviour described by Bekker [13] during the entire test.

For all the tests conducted, the MPC controller was thus compared to a base case representing typical operator behaviour, as obtained from plant data [13]. Although it might be argued that this approach favours the MPC controller, a comparison of furnace efficiency when operators respond to natural variations or ignore it, revealed that furnace efficiency is often degraded if operators are allowed to respond to natural variations [41]. The simulation study conducted is thus considered a reasonably accurate representation of results obtainable in practice.

7.2. MODELLING OF FEED VARIATIONS.

Many variations in feed quantities occur due to irregularities, e.g. blocking of pipes, failure of actuators, etc. In an industrial setup, data generated under non-typical operating conditions should be removed from the data set prior to data analysis [32]. In a simulation study it would thus serve no purpose to include these irregularities in the study, unless the robustness of the controller under these circumstances need to be evaluated. As an analysis of these irregularities is outside the scope of this simulation study, controller performance would only be evaluated under typical operating conditions including certain natural variations.

Natural variations in the off-gas fan power, slip-gap width, oxygen composition and graphite composition are negligible [18]. Variations in the feed rates of graphite, oxygen and DRI will occur due to irregularities that will not be included in the analysis. The composition of DRI can however vary within a certain range for a specific type of DRI.

The range of the percentage metallization (metallic iron - excluding iron oxides - as a percentage of the total iron content) may be as large as 88 % - 96 % [42], but more typical variations are approximately 5 % [5] between the minimum and maximum values. Since typical specifications for the percentage metallization [5,42] exceed the specification used in the model presented by Bekker [13], the percentage metallization suggested by Bekker [13] will be used as a minimum value, and the maximum value will be assumed to be 5 % higher. The variations in percentage metallization will be modelled as a slow linear drift from the maximum value (87.5 %), reaching the minimum percentage metallization (82.5 %) at the end of the simulation study. The percentage metallization will be assumed constant during a tap.

Although scrap selection attempts to classify scrap into well-defined groups, the selection process is often ineffective with the result that scrap compositions vary considerably [5]. Bekker [13] assumed that the scrap is of a high purity containing less than 0.5 % impurities. For the purpose of this analysis, the scrap composition will be modelled as a random variation in the carbon content with a range between 0 % and 0.5 % carbon.

The feed rate of flux additions to the slag is already modelled as a disturbance (based on plant data) [13] and no further modelling will be undertaken.

It is assumed that a proper control system is already in place for the electrical system of the EAF [13]. Some fluctuations will however still occur in the power transfer to the melt, which can be modelled as a variation in the efficiency of the power transfer. The efficiency of the power transfer will be modelled as a random fluctuation with a minimum of 0.66 and a maximum of 0.94, based on typical efficiencies obtained in industry [18]. The rate of fluctuations is not easy to determine since plant data is often logged at relatively slow frequencies. Fluctuations are however not completely random in nature and are to a certain extent dependent on previous values. A random power transfer coefficient (between 0.66 and 0.94) will thus be selected once per minute, and a linear interpolation will be used to calculate the power transfer coefficients between the random samples.

7.3. EVALUATION STRATEGY.

An evaluation strategy was suggested in Chapter 6, combining the suggestions of Tien [39], Chatfield [31] and Craig and Henning [35]. This strategy is similar to the evaluation procedure suggested by Montgomery [43], and all steps overlap to a certain extent. The strategy suggested in Chapter 6 will be followed in obtaining an accurate estimate of the benefits of an MPC controller. The steps are repeated below and a discussion is given in how these steps were applied to the experimental design.

7.3.1. Process understanding.

Process understanding is probably the most important step in solving a control problem. Chapter 2 gives an overview of the EAF from a metallurgical perspective. Chapter 3 covers a different aspect of process understanding in addressing the factors contributing to the cost of EAF operation. A combination of the information contained in these two chapters led to the design of the MPC controller as discussed in Chapter 5.

7.3.2. Define the problem to be solved.

The problem to be solved is to decrease the cost of producing a steel melt, without violating environmental or health standards. This problem was broken down into a number of control objectives in Chapter 3. These can be summarised as follows:

i) Limit the cost of feed materials and other inputs (Oxygen, DRI, Graphite and Off-gas fan power).

ii) Maximise throughput by ensuring that steel specifications are met at the tapping time. Steel specifications exist on the steel mass, carbon content and liquid steel temperature.

iii) Limit unnecessary losses in the off-gas stream by regulating the relative furnace pressure as close as possible to atmospheric pressure, without endangering the health of workers. Therefore the relative pressure must not exceed the 0 Pa level.

iv) Prevent financial penalties or possibly a plant shutdown due to excessive CO-emissions or a bag-house explosion. This is achieved by ensuring that the off-gas contains low enough concentrations of CO and that the off-gas temperature remains below the critical value of 773 K at the measurement point.

v) Ensure maximum heat transfer to the steel melt by ensuring that the slag foam depth is higher than the arc length (approximately 300 mm) for the duration of the tap.

7.3.3. Determine the variables to be measured.

The variables to be measured are dictated by the problem statement (see 7.3.2), and can be found by elaborating on the objectives defined above.

i) The cost of feed materials can be determined by measuring the feed rates of oxygen, DRI and graphite and also the power consumed by the off-gas fan.

ii) Measurements need to be taken of the steel temperature and carbon content at the tapping time. Since these two variables are not measured continuously, the number of measurements taken can have a large influence on the efficiency of the feedback controller. The number of measurements typically taken in industry and the time intervals at which measurements are typically taken will be used in the simulation study. The steel mass cannot be measured, but can be modelled accurately.

iii) The relative pressure needs to be measured.

iv) Off-gas temperature and the CO content of the off-gas need to be measured.

v) The slag depth needs to be measured (if instrumentation exists), or modelled accurately (as used in the simulation study).

7.3.4. Determine the accuracy of the measurements and calibrate instrumentation.

Due to the nature of this analysis (a simulation study), this step is not of much relevance. In an industrial setup the experiment would be affected severely by badly calibrated instrumentation, and also by the accuracy of measurements. An analysis of the robustness of the controller to inaccurate measurements is beyond the scope of this analysis, and this step was thus not considered.

7.3.5. Determine the distribution of a derived variable by examining the propagation of error through the system.

Since the steel mass cannot be measured directly, the measurement needs to be derived from other measurements. The feed rates of the inputs and also models containing the solid steel mass and temperature are used to determine the steel mass [13]. The measurements of feed materials are assumed to be very accurate, thus having a negligibly small variance and a mean equal to the feed rate. The largest prediction errors of the steel mass would probably be due to modelling inaccuracies and will not be influenced much by the accuracy of measurements. The propagation of error through the system would thus be negligible and is ignored for this analysis.

7.3.6. Make a list of factors influencing the value of the response variable, which could invalidate the result.

The response variable is in this case the cost of the steel melt. The cost is in turn dependent on the consumption of feed materials, the cost of any corrective action taken to reach steel specifications and the delay associated with the corrective action (reduced throughput), and also any financial penalties or bag-house repairs due to inefficient off-gas control. The profit would depend on the quality of the steel produced and on the cost to produce it. The cost is calculated based on the assumption that steel of the required quality will always be produced, even though corrective action may be required. The possibility of erroneous measurements of the steel quality is however not considered. The factors contributing to the cost of the melt will be discussed in turn. The threats to validity as defined in Chapter 6 are discussed in Section 7.3.7, but can also be classified under this heading.

The cost of the feed materials is determined by assuming a per-unit cost and multiplying it by the feed rates. Any price-fluctuations or inaccurate measurements of the feed rates would thus invalidate this cost estimate. For the purposes of a simulation study all measurements can be considered accurate. Price fluctuations may however change the operating strategy considerably, which should be updated accordingly.

The cost of additions made to reach steel specifications is in general small compared to the cost associated with the reduced throughput [18], if specifications were not met on the first attempt. This is however only a valid assumption if the EAF is the bottleneck in the process. If the capacity of the EAF exceeds that of the caster or other downstream processes, a time delay resulting from taking corrective action might have no impact on the throughput of the plant. In this case the cost of additions in taking corrective action might become significant. For the plant under consideration the EAF is the bottleneck [18] and the assumptions made would thus hold. For application on other plants some adjustments might be required.

The cost associated with exceeding emission regulations is not very accurate since the punishment may include a financial penalty and/or a plant shutdown. Emissions are furthermore not monitored continuously and an isolated case of exceeding the regulations would most likely not incur any financial penalty. A worst-case approach is however followed since legislation is continuously becoming stricter [44]. The cost attributed to financial penalties is the most likely cost component to invalidate the cost estimate of the steel melt. Many other consequences of excessive emissions are however not considered, including the cost of bad publicity, possible legal action due to the impact of pollution on the health of people living nearby, etc. The exaggerated cost is thus partly offset by the risks associated with some of the additional consequences.

7.3.7. Threats to validity.

Threats to the validity of the test were discussed in Chapter 6 [39]. These threats are repeated and their applicability to the evaluation process discussed. The threats to validity will be discussed under the following 5 topics: Internal validity, external validity, construct validity, statistical conclusion validity and conduct conclusion validity.

7.3.7.1. Internal validity.

Internal validity is concerned with the inclusion of extraneous events in the test data, e.g. calibration of instrumentation during the test period, and also with variations in the test unit (the EAF). During a simulation study none of these factors are much of a concern. Natural variations in feed materials will however occur, but a randomised experimental design would account for this.

7.3.7.2. External validity.

External validity is concerned with behavioural changes of a test subject since he/she is aware of a test being conducted. For a simulation study this is once again not a concern since the operator is assumed to respond identical under all conditions. The plant data used to model operator response might however not be a good indication of typical operator efficiency, since the operator might have been more alert due to his knowledge that test data were being generated. Due to this fact, the predicted improvement due to the new control strategy might be an underestimate of the real improvement. In an industrial experiment (not a simulation study) the responsiveness of operators during the experiment can be compared to historical data to determine if any significant change has occurred.

7.3.7.3. Construct validity.

Construct validity is concerned with the question whether the test results can be extended to the general case [38]. The inference space over which the results of the experiment would be valid is thus considered. To ensure that the experimental results are representative of the results obtainable in practice, it is essential to conduct tests under typical conditions and also to include all possible conditions in the test. These requirements are achieved by using real plant data to determine setpoints and also by ensuring that the EAF simulator represents the real EAF as closely as possible. The latter is done by e.g. only using continuous feedback on continuously measured variables and by feeding back discrete measurements at the same time intervals as described by Bekker [13]. The composition of some feed materials and the arc power is also varied to represent a wide range of possible operating conditions.

7.3.7.4. Statistical conclusion validity.

Statistical conclusion validity is concerned with manual intervention in determining which data should be omitted from the test data. Since all test data in a simulation study is generated under ideal conditions, no data need to be omitted.

7.3.7.5. Conduct conclusion validity.

Conduct conclusion validity is concerned with inappropriate or incomplete experimentation due to financial, time or other constraints. In a simulation study this is clearly not much of a concern. The number of tests required for a defined degree of significance can be calculated as described in Chapter 6 [38]. Very often the test period is however determined beforehand, based on time or financial constraints. To represent a scenario similar to this, a testing period of 1 month will be assigned to evaluate the controller. Any conclusions drawn will thus be based on results obtained during this test period, independent of the number tests as suggested in Chapter 6 [38].

7.3.8. State the hypothesis that needs to be tested.

A null hypothesis (H_0) is stated and also an alternative hypothesis (H_1):

H_0: Under manual control steel is produced at the same cost than under MPC control.

H_1: Steel is produced at a lower cost under MPC control than under manual control.

Since this analysis will be based on a comparison of the mean cost of the process under manual (μ_0) and MPC control (μ_{MPC}), the hypothesis can be restated in terms of the means:

H_0: $\mu_{MPC} = \mu_0$

H_1: $\mu_{MPC} < \mu_0$

The MPC controller will thus only be deemed effective if H_0 can be rejected with a sufficient degree of significance. For the purpose of this analysis, a confidence level of 95 % will be considered adequate and a value of $\alpha = 0.05$ will thus be used.

7.3.9. Design an experiment to generate unbiased production data, which captures the economic performance of the control system. This step includes selection of the test procedure, the number of observations required, the test period, a selection of analytical techniques to be used for the analysis, etc.

A complete randomised design will be used to conduct the experiment. Blocking will not be used since there is no proof suggesting that subdivision of the experiment into smaller time intervals will reduce the variability of the data. Although the composition of some of the feed materials shows time trends (percentage metallization of DRI), other variations are completely random in nature, suggesting that blocking won't be capable of removing the influence of those variables. Pairing or blocking of data if no significant difference between blocks exists, will probably be disadvantageous to the accuracy of the experimental outcome [45], and will thus not be used. It is furthermore considered good practice to keep an experiment as simple as possible.

The duration of the each test should be as short as possible and will depend on the characteristics of the system (e.g. time constants). Oosthuizen, Craig and Pistorius [36] showed that the optimal duration of each test is approximately 5 times the slowest time constant, if bumpless transfer of control is possible. This result was based on an analysis of a first order system, but since the linear model is mostly first order (except for the off-gas flow), the result holds. For batch processes like an EAF it would however not make sense to conduct a test with a duration shorter than one tap, since the process is optimised for the complete duration of a tap. The shortest possible duration of each test is thus 1 tap, and the testing schedule will be set up accordingly.

The number of observations required could be calculated using the formulas given in Chapter 6 [38]. For this analysis the time period of experimentation is however fixed to 1 month that translates into 420 tests (based on an average tap-to-tap time of 100 minutes, or 14 taps per day). The testing schedule with results is shown in Appendix A.

The economic performance of the controller can be calculated using the model suggested in Chapter 3. The cost of the melt will thus consist of the cost of the feed materials, the cost of corrective action and reduced throughput due to not meeting the steel specification on the first attempt, and the cost of additional delays due to ineffective off-gas control.

7.3.10. Monitor the experiment and make sure it is carried out as planned.

For a simulation study, this is a routine task. For experimentation on a real plant, it would however be much more complicated to ensure that the controllers are switched on and off according to a schedule [35], and also that no actions are taken that might invalidate the results.

7.3.11. Analyse the generated data and determine sample statistics for each.

Data recorded during the experiment is shown in Appendix A. The results are summarised in Table 7.1. The cost implication of corrective action was calculated assuming that temperature and composition adjustment can be done simultaneously if required.

The reduction in DRI consumption (3 tons lower) is accounted for in the average steel mass, which also decreased by approximately 3 tons. Oxygen consumption increased by almost 20 %, which is reflected in the lower average carbon content in the melt and also in the higher average tapping temperature. As oxygen is a relatively cheap feed material (see Chapter 2), the resultant cost of the melt was not increased significantly by the increased oxygen consumption. Graphite consumption decreased by more than 20 %, and is reflected in the 33 % reduction in the average slag foam depth.

The predicted cost decrease due to improved utilisation of feed materials is approximately 0.8 %. A large decrease was not expected since static furnace models are used extensively in industry to predict optimal feed additions to EAFs [18, 41]. Under manual control an average cost increase in excess of 7 % is however predicted due to exceeding specifications at tapping, or off-gas temperature limits. Large savings were expected for these cost components, as a dynamic model (as used by MPC) is clearly superior to a static model, especially if feedback is used.

Table 7.1. Summary of simulation results.

	Default values	Manual Control	MPC controlled	Unit
Average consumption of MVs				
DRI.	35.00	35.00	32.09	ton
Oxygen.	5414.00	5414.00	6480.95	kg
Graphite.	498.00	498.00	391.61	kg
Off-gas fan power.	1.32	1.32	1.50	MW
Average values of CVs				
Carbon content at tapping.	0.072 %	0.0782 %	0.0759 %	%
Tapping temperature.	1850	1842.04	1852.87	K
Steel mass.	162.1	163.31	160.37	ton
Average relative pressure.	-27.5	-27.43	-30.11	Pa
Average CO emission.	0.99 %	1.11 %	1.21 %	%
Average foam depth.	91.5	90.31	60.71	cm
Peak off-gas temperature.	829	841.52	762.13	K
Cost implication of increase/(decrease) in consumption per ton steel produced				
Scrap.	0 %	-0.22 %	0.33 %	
Electric Power.	0 %	-0.11 %	0.16 %	
Maintenance.	0 %	0.10 %	-0.15 %	
Hot metal.	0 %	0.10 %	-0.14 %	
DRI.	0 %	0.07 %	-0.84 %	
Electrodes.	0 %	0.04 %	-0.10 %	
Refractories.	0 %	0.03 %	-0.04 %	
Flux.	0 %	0.02 %	-0.04 %	
Labour.	0 %	0.01 %	-0.02 %	
Investment.	0 %	0.01 %	-0.02 %	
Oxygen.	0 %	0.01 %	0.13 %	
Off-gas power.	0 %	0.00 %	0.07 %	
Graphite.	0 %	0.00 %	-0.09 %	
Total	***0 %***	***0.07 %***	***-0.74 %***	
Cost implication of not reaching specifications or exceeding limits				
Number of tests conducted.		203	217	
Carbon specification not met.		30	0	Times
Tapping temperature not met.		72	0	Times
Off-gas temperature exceeded.		203	0	Times
Cost implication		***7.17 %***	***0 %***	
Resultant cost implication		**7.24 %**	**-0.74 %**	

Sample statistics of the test data are shown in Table 7.2.

Table 7.2. Sample statistics of EAF operating cost under MPC and manual control.

	Manual	MPC	Combined estimate
Mean.	7.24 %	-0.74 %	3.12 %
Standard deviation.	4.63 %	1.00 %	3.30 %

The combined estimate is the mean cost implication and the standard deviation of the data generated under manual and MPC control. The standard error (estimate of the standard deviation) was calculated using Equation 7.1 as described in Section 7.3.12. The combined estimate of the mean was calculated using standard formulas given in Chatfield [31], taking the different number of tests for each controller into account.

7.3.12. Test and accept or reject the hypothesis.

The null and alternative hypothesis stated in Section 7.3.8, are as follows:

H_0: $\mu_{MPC} = \mu_0$

H_1: $\mu_{MPC} < \mu_0$

Since a decrease in the mean cost is of interest and not a difference as such, a one-tailed t-test can be used to test the significance of the result. The implicit assumptions when conducting a t-test were given in Chapter 6.

The first assumption that the data is normally distributed, can be accepted without proof, since samples taken from any population (not necessarily normal) would tend towards a normal distribution as the number of samples increases [36]. Although this statement might not be true in a limited number of cases (e.g. a population consisting of the same constant number), it holds for most physical processes. The second assumption, that each data point is a random independent sample of the population of all possible experimental outcomes is also satisfied, since a carefully planned experiment was conducted to capture the plant behaviour under typical operating conditions. Randomisation would also ensure that disturbances are not correlated with the test sequence, although the DRI composition is a slowly decreasing function of time. The third assumption, that the two sample variances are estimates of the same population variance is clearly not satisfied, since the standard deviation under manual control is more than 4 times larger than the standard deviation under MPC control. Although the difference in standard deviations are obvious, an F-test will be conducted to test if the variation can not be attributed to natural variations. For the F-test a null- (H_{0F}) and alternative hypothesis (H_{1F}) will also be stated to determine if the variances (s_{man}^2 and s_{mpc}^2) differ significantly.

H_{0F}: $s_{man}^2 = s_{mpc}^2$

H_{1F}: $s_{man}^2 > s_{mpc}^2$

The ratio: s_{man}^2 / s_{mpc}^2 is used in the F-test and also the degrees of freedom. The result is summarised in Table 7.3.

Table 7.3. Data used in the F-test.

	Manual control	MPC control
Standard deviation (s).	4.63 %	1 %
Variance (s^2).	21.45	1
Samples in test.	203	217
Degrees of freedom.	202	216

The ratio: $s_{man}^2 / s_{mpc}^2 = 21.45$.

Substituting the degrees of freedom into standard tables used for the F-test [45], it can be seen that the ratio $s_{man}^2 / s_{mpc}^2 = 21.45$ exceeds both the 5 % and 1 % confidence intervals by far (approximately 10 times larger). H_{0F} can thus be rejected with 99 % confidence and the two sample variances are thus not estimates of the same population variance. The implicit assumptions in conducting a t-test are thus not satisfied and the t-test cannot be used efficiently for significance tests.

Davies [37] stated that the t-test could be seriously invalidated if variances that differ markedly are used in the testing procedure. This problem is however often overcome by making a transformation (e.g. log(x) instead of x), especially if there is some physical justification for the change. Davies [37] however furthermore stated that the t-test could still provide valuable information, even if large differences exist in the variances. It is however not possible to lay down precise rules, since the difference to be considered depends seriously on the degrees of freedom involved [37].

Since a large number of tests were conducted and a large difference is to be tested, the t-test would probably have provided sufficient proof. Exact tests do however exist for large differences in variances, and tables given in [45] will also be used in the test procedure.

For the t-test, only one variance can be used in the calculations. The best estimate of the population variance is obtained by applying Equation 7.1 [45] to the two sample variances, s_1 and s_2, and degrees of freedom, $n_1 - 1$ and $n_2 - 1$.

$$s^2 = \frac{(n_1 - 1)s_1^{\ 2} + (n_2 - 1)s_2^{\ 2}}{n_1 + n_2 - 2} \tag{7.1}$$

The test statistic, t, is then given by Equation 7.2.

$$t = \frac{\mu_0 - \mu_{MPC}}{s\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{7.2}$$

Table 7.4. Values used in determining the test statistic for the t-test.

μ_{MPC}	-0.74 %
μ_0	7.24 %
s_1	4.63 %
s_2	1 %
n_1	203
n_2	217

Using the values given in Table 7.4, the test statistic can be calculated as t = 24.77.

The 95 % and 99 % significance levels for the student's t-test with 418 degrees of freedom (or the normal distribution since a large number of samples were taken), is 1.645 and 2.33 respectively. H_0 can thus be rejected with both 95 % and 99 % confidence and a significant difference thus exists between the two means tested.

Although the null hypothesis can be rejected with 99 % confidence, another test is conducted taking the differences in variances into account. For the test used in Fisher [44], the ratio between the standard deviations (s_1 / s_2) is converted to an angle, θ, as indicated by Equation 7.3.

$$\frac{s_1}{s_2} = \tan(\theta) \tag{7.3}$$

A test statistic, d, is calculated using Equation 7.4.

$$d = \frac{\mu_0 - \mu_{MPC}}{\sqrt{s_1^{\ 2} + s_2^{\ 2}}} \tag{7.4}$$

Values for d are tabulated as a function of the angle, θ, and the number of samples (n_1 and n_2). If the calculated test statistic exceeds the tabulated value, the result is deemed significant.

Substitution of the values in Table 7.4, yields a test statistic, d = 1.68.

The tabulated value of d, for an angle of 80° (as calculated using Equation 7.3), is 1.645 and 2.326 for 95 % and 99 % confidence intervals respectively. According to this test the null hypothesis can thus be rejected with 95 % confidence, but not with 99 % confidence. As the required significance level was specified as α = 0.05 in Section 7.3.8, the null hypothesis can thus be rejected with the required degree of significance. Even if this test could not prove a difference in means with 95 % confidence, the large potential benefit predicted by the simulation study (cost reduction in excess of 7 %) would probably have been sufficient motivation to extend the test period to increase the accuracy of the estimate.

7.3.13. Estimate the monetary benefits.

The result of a test is often that a significant change in the mean of some physical quantity (e.g. level, grade, etc.) has occurred. In such a case the improvement needs to be multiplied by an incremental value (cost per unit improvement), the unit throughput, the time for which the benefit is to be calculated (e.g. one year) and the service factor. This was discussed in more detail in Chapter 6, as shown in Equation 7.5 [34].

$$\begin{aligned}\text{BENEFIT} = {} & \text{(IMPROVEMENT) x (INCREMENTAL VALUE) x} \\ & \text{(UNIT THROUGHPUT) x (TIME) x (SERVICE FACTOR)}\end{aligned} \tag{7.5}$$

Since the design of the MPC controller was based on economic objectives, the predicted 7.98 % improvement already takes the improvement multiplied by the incremental value (reduced cost per ton) and the service factor (reduction in unscheduled delays) into account. The predicted 7.98 % reduction in cost thus only needs to be multiplied by the annual cost of EAF operation to yield the annual benefit. A more accurate benefit prediction can also be obtained by dividing the predicted benefit into a component accounting for the reduced cost of feed per ton (0.74 %) and another component accounting for the increased service factor due to a reduction in unscheduled delays (7.17 %). The benefit will not be calculated since it would differ widely from plant to plant and also due to restrictions regarding confidentiality. A predicted cost reduction in excess of 7 % translates into a huge benefit, irrespective of the steel volume produced or the profit margins applicable.

7.3.14. Do an economic project evaluation.

An economic project evaluation would involve the calculation of the payback time, return on investment, net present value, discounted cash flow rate of return or another measure of the estimated project benefit, compared to the expenditure. A detailed analysis of project evaluation techniques is given by Allen [40], and the techniques mentioned were briefly discussed in Chapter 6. The simulation study showed a reduction in operating cost of approximately 8 %, which can easily be translated into an increase in profit. The capital expenditure required to implement the control strategy would however be highly dependent on the current level of automation, instrumentation, and other infrastructure required. The implementation cost is also highly variable, depending on skills of plant personnel, the method used for implementation, the packaging of the control algorithm and other factors. Future cash flows are also difficult to predict in the absence of confidential plant data. Due to these factors an analysis based on one plant would probably be a very poor approximation of the economic implication for another plant, and no thorough economic analysis will be performed.

In a typical industrial environment, the instrumentation required to conduct the tests would probably have been sufficient to allow implementation of the strategy if deemed efficient. Although a proper analysis would be of great help in convincing management of project feasibility, a reduction of 8 % in operating cost due to a different control strategy hardly needs any further justification.

7.4. DISCUSSION.

A simulation study was conducted to determine the economic benefits over manual control of implementing MPC on an EAF. A thorough experimental design was carried out prior to the simulation study to ensure that reliable data is generated and also that typical operating conditions are simulated. Disturbances were chosen in such a way to represent typical scenarios over which an operator would have little control, due to the lack of measurements. The simulations under MPC control were also designed to represent typical conditions experienced in industry, by only using continuous feedback on continuous measurements (relative pressure, off-gas temperature and composition), and by using discrete feedback on discrete measurements (composition and steel temperature). The evaluation strategy suggested in Chapter 6 was used to ensure the generation of reliable data.

An analysis of the data revealed that the cost per ton steel could be reduced by approximately 0.74 % by improved utilization of feed materials and energy sources. A small cost reduction was expected in improved feed material utilization, as static furnace models are used extensively in industry to predict optimal feed additions to EAFs. The major part of the savings can however be attributed to a reduction in unscheduled delays, due to improved dynamic process modelling (steel temperature and composition) and prediction of other possible causes of delays (e.g. exceeding the maximum off-gas temperature). The number of unscheduled delays was reduced to zero by the MPC controller. An increase in throughput of more than 7 % is predicted, due to the elimination of unscheduled delays.

After successful completion of the experiment, the data was analysed and the hypothesis tested to determine the significance of the indicated reduction (approximately 8 %) in operating cost. Since the variances of the data generated under manual and MPC control was due to different causes, the variances differed significantly (as indicated by an F-test). Two different versions of the t-test were therefore used in determining the significance of the result, one taking the difference in variances into account. Both tests showed with 95 % confidence that a reduction in operating cost is achieved using MPC compared to manual control. Although a thorough economic project evaluation was not possible due to confidentiality and a lack of information, it was shown that an 8 % reduction in operating cost could potentially result from a control upgrade.

One possible threat to the validity of the result is the fact that data from only one tap was used to predict operator behaviour in general. As the maximum off-gas temperature was exceeded during the tap for which data was collected, the simulation study indicates that the maximum off-gas temperature limit is exceeded for each tap under manual control (Table 7.1). This is an unlikely scenario, clearly indicating that operator behaviour is not modelled with sufficient accuracy. The result is however not completely invalid, and an analysis can be made excluding the off-gas temperature. Assuming that the maximum off-gas temperature limit is never exceeded under manual control (which is also an unlikely scenario, but the most conservative approach), the predicted reduction in operating cost would still be approximately 5 %. More comprehensive plant data would thus allow more accurate predictions to be made, but in the absence of such data it can be stated that, depending on operator skills, operating cost can be reduced by between 5 % and 8 %.

7.5. CONCLUSION.

Operating costs of EAFs can be reduced significantly by substituting conventional manual control with an advanced control strategy like MPC. All simulations were conducted assuming typical instrumentation configurations, and very limited expenditure on instrumentation is thus required to implement the strategy. A reduction in operating cost of between 5 % and 8 % is possible by utilising feed materials and energy more efficiently, and by increasing throughput by eliminating unscheduled delays.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS.

8.1. SUMMARY OF DISSERTATION CONTENTS.

In Chapter 1 a motivation of the project was presented and some background given to place the study's contribution to the literature in context.

Chapter 2 contained a technical overview of the EAF process, the simulation model used and control objectives typically specified in industry. The EAF model was expanded by modelling the slag foam depth.

In Chapter 3 the EAF was analysed from an economic perspective. The cost contribution of the feed materials was determined as well as the economic implication of not reaching the control objectives described in Chapter 2.

Chapter 4 provided the theoretical background on Model Predictive Control (MPC) and the applicability of MPC to the control problem was discussed.

Chapter 5 showed the design of a linear MPC controller based on economic objectives. The linearisation of the non-linear EAF model was discussed, and some implementation issues in ensuring representative simulations mentioned. The calculation of appropriate weights based on economic objectives was discussed, and the choices for other tuning parameters motivated. Finally a simulation was done to compare the EAF under manual and MPC control and to determine if all functional control objectives are met.

In Chapter 6 a theoretical background on the evaluation of systems was provided. The statistical and capital budgeting tools required were discussed and experimental techniques described, that would ensure the generation of statistically significant data in noisy environments. An evaluation framework was presented that would ensure that reliable data would be generated and that valid experimental results can be obtained.

Chapter 7 contained the final simulation study based on the experimental techniques and evaluation framework presented in Chapter 6. The MPC controller designed in Chapter 5 was compared to the EAF under manual control in the presence of typical disturbances, and subject to operational conditions typically found in industry. The data was analysed and hypothesis tested to determine if a statistically significant result could be obtained. The potential economic benefits of implementing an MPC controller was quantified and the major sources of potential savings identified.

The contribution can thus be summarized as follows:

1. The expansion of the available EAF model by modelling the slag foam depth.
2. The presentation of a structure to translate functional control objectives into economic objectives.
3. The design and simulation of an MPC controller, based on design criteria that would minimise the cost of EAF operation.
4. The suggestion of an evaluation framework to ensure that useful data are generated and that the data is analysed appropriately.
5. Quantifying the potential economic benefits of implementing an MPC controller on an EAF, based on a detailed simulation study.

8.2. CONCLUSIONS.

The slag foam depth is an important variable in minimizing heat losses in an EAF. The expansion of the existing EAF model to include the slag foam depth provides a useful framework to optimise the complete EAF steelmaking process. Although the slag foam depth model was not utilized to the maximum extent in the simulation study (definition as a state variable to be used in other state equations), further integration into the existing model can improve model accuracy significantly.

An analysis of the EAF steelmaking process from an economic perspective provides valuable insight into the relative importance of control objectives that are typically specified in industry. By adjusting the priorities of the control objectives according to their economic impact on the EAF steelmaking process, the process can be operated in an economically optimal way. MPC provides the infrastructure to specify the priorities of a number of control objectives based on economic considerations. Implementation of an MPC controller based on economic objectives proves to be effective in reducing the cost of EAF steelmaking without exceeding any of the physical limits.

Large potential economic benefits exist in the implementation of an advanced control strategy e.g. MPC on EAFs. Minor benefits (0.81 % reduction in operating cost) are predicted due to more efficient utilization of feed materials and energy inputs. As static furnace models are used extensively in industry in predicting optimal feed additions, limited benefits in improved feed material utilization were expected. The major portion of the predicted benefits (7.17 % reduction in operating cost) is due to the elimination of unscheduled delays. Unscheduled delays caused by not meeting steel temperature and composition specifications at tapping, or exceeding the maximum off-gas temperature can be eliminated completely using MPC. All these economic benefits were achieved without compromising the health of workers or by increasing emissions excessively. The simulations were also based on configurations and instrumentation typically available in industry. Expenditure in expanding available infrastructure and implementing the suggested control strategy should thus be limited.

The assumption that operators are not capable of responding to disturbances may favour the MPC controller to a certain extent, possibly biasing the results. Some of the assumptions required in deriving the economic cost model might also be invalidated under certain operating conditions, especially the assumptions concerned with influences that can not be quantified, e.g. the influence on the health of a number of workers. The major portion of the predicted economic benefits is however based on the elimination of unscheduled delays, which is modelled with sufficient accuracy. Due to modelling inaccuracies the predicted benefits might thus vary slightly from the actual benefits that can be achieved on a specific plant. The potential benefit (in excess of 8 %) is however of sufficient magnitude to ensure that the influences due to modelling inaccuracies are negligible.

8.3. RECOMMENDATIONS.

The following recommendations are made regarding future work on the EAF model and its application:

1. The model should be expanded to include the phosphorus, sulphur and manganese content of the melt and also the slag basicity. These variables were mentioned in the control objectives defined in Chapter 2, but were omitted from the final control objectives due to the lack of accurate models. Inclusion of these variables in the model would allow flux additions to the slag to be optimised, by adding flux additions to the current list of manipulated variables.
2. The relationship between electrode position, transformer tap position and power transfer to the melt should be incorporated into the model. The slag foam depth can also be incorporated into this model, to model power transfer more accurately. This would allow the electrical input to the EAF to be used as a manipulated variable and not as a disturbance input as is currently used.
3. Cooling water measurements of the furnace and duct walls need to be taken into account, as these are continuous measurements, compared to the discrete measurements used for the metal temperature. Accurate modelling of the relation between the cooling water temperature and the bath temperature can increase the efficiency of temperature feedback significantly.
4. The control strategy with all the models should be implemented on an industrial EAF. All the traditionally manually controlled variables should be substituted with automatic control to evaluate the efficiency of the MPC controller. The efficiency of the MPC controller based on economic objectives can be evaluated in this way, and also the accuracy of the simulator.

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Appendix A: Test schedule

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual	% C in scrap	DRI: %	%C	Tapping	Steel	Relative	CO	Avg Foam	Max off	Oxygen	DRI	Graphite	Off-gas fan
	1 = MPC	(Random)	metallization		Temp.	mass	Pressure	Emission	Depth	gas temp	(kg)	(ton)	(kg)	power (MW)
1	1	0.00	87.50	0.0738	1854	159.1	-32.3	0.95	60	762	6418	29.8	395	1.55
2	0	0.00	87.49	0.0721	1836	163.8	-27.5	0.988	86.2	828	5414	35	498	1.32
3	1	0.33	87.48	0.0768	1852	163.7	-28.7	1.31	55.6	762	6490	35.1	368	1.46
4	0	0.23	87.46	0.0778	1835	164.1	-27.4	1.1	90	842	5414	35	498	1.32
5	1	0.03	87.45	0.0713	1854	157.8	-32.8	0.92	61.9	762	6877	28.8	439	1.56
6	1	0.14	87.44	0.073	1853	160.3	-30.9	1.11	58.4	762	6479	31.2	386	1.52
7	1	0.23	87.43	0.0746	1852	158.4	-30.9	1.15	59.7	762	6653	29.2	400	1.52
8	0	0.45	87.42	0.0841	1834	164.3	-27.3	1.21	93.7	851	5414	35	498	1.32
9	0	0.47	87.40	0.0847	1834	164.4	-27.3	1.22	94.1	852	5414	35	498	1.32
10	1	0.01	87.39	0.0694	1856	157.7	-32.53	1.01	61.6	762	6924	28.6	444	1.55
11	0	0.30	87.38	0.0797	1835	164.2	-37.4	1.13	91	845	5414	35	498	1.32
12	0	0.02	87.37	0.0726	1836	163.8	-27.5	0.998	86.5	830	5414	35	498	1.32
13	1	0.04	87.36	0.0699	1856	157	-32.3	1.02	59.7	761	6826	27.8	425	1.55
14	0	0.34	87.35	0.0809	1834	164.2	-27.4	1.16	91.7	847	5414	35	498	1.32
15	1	0.15	87.33	0.0743	1854	159.6	-31	1.11	60.8	763	6532	30.3	401	1.52
16	1	0.04	87.32	0.0738	1854	159.4	-32.4	0.93	59.8	762	6475	30.2	398	1.55
17	0	0.01	87.31	0.0723	1836	163.8	-27.5	0.993	86.3	829	5414	35	498	1.32
18	1	0.00	87.30	0.071	1856	158.3	-31.7	1.05	63.2	763	6681	28.9	434	1.54
19	1	0.39	87.29	0.0761	1853	162.3	-28.4	1.39	56.6	762	6507	33.6	367	1.46
20	0	0.16	87.27	0.076	1836	164	-27.5	1.07	88.7	838	5414	35	498	1.32
21	0	0.15	87.26	0.0758	1836	164	-27.5	1.06	88.5	837	5414	35	498	1.32
22	0	0.04	87.25	0.073	1836	163.8	-27.5	1.01	86.8	831	5414	35	498	1.32
23	1	0.20	87.24	0.0758	1854	159.9	-30.1	1.2	60.8	762	6477	30.8	391	1.51
24	1	0.30	87.23	0.0764	1853	161.7	-28.7	1.33	58.7	762	6445	32.8	377	1.48
25	0	0.08	87.21	0.074	1836	163.8	-27.5	1.03	87.4	833	5414	35	498	1.32
26	1	0.30	87.20	0.0765	1852	162.7	-29.7	1.26	57.7	762	6363	33.9	366	1.48
27	1	0.22	87.19	0.0778	1853	160.1	-30.3	1.17	63.5	761	6435	30.8	398	1.51
28	0	0.40	87.18	0.0826	1835	164.2	-27.37	1.18	92.8	849	5414	35	498	1.32
29	0	0.18	87.17	0.0765	1836	164	-27.47	1.08	89	839	5414	35	498	1.32

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual 1 = MPC	% C in scrap (Random)	DRI: % metallization	%C	Tapping Temp.	Steel mass	Relative Pressure	CO Emission	Avg Foam Depth	Max off gas temp	Oxygen (kg)	DRI (ton)	Graphite (kg)	Off-gas fan power (MW)
30	1	0.41	87.15	0.0775	1852	165.3	-26.9	1.48	55	763	6517	37.1	364	1.41
31	1	0.49	87.14	0.0776	1850	168.9	-25.5	1.63	54.9	765	6765	41.4	383	1.38
32	1	0.47	87.13	0.0776	1852	166.9	-26.3	1.57	54.7	763	6594	39	366	1.4
33	0	0.32	87.12	0.0803	1835	164.1	-27.4	1.15	91.4	846	5414	35	498	1.32
34	1	0.25	87.11	0.0764	1852	160.1	-30.7	1.13	58.8	762	6479	31.1	381	1.51
35	0	0.31	87.10	0.08	1835	164.1	-27.4	1.14	91.2	845	5414	35	498	1.32
36	0	0.02	87.08	0.0771	1836	163.9	-27.5	1.09	89.4	840	5414	35	498	1.32
37	1	0.05	87.07	0.0722	1854	158.1	-32	1.04	61.3	762	6634	28.9	417	1.55
38	0	0.39	87.06	0.0823	1835	164.1	-27.4	1.18	92.7	849	5414	35	498	1.32
39	1	0.13	87.05	0.0721	1853	157.7	-31.8	1.06	61.6	762	6851	28.6	433	1.54
40	0	0.44	87.04	0.0838	1835	164.2	-27.3	1.2	93.5	851	5414	35	498	1.32
41	0	0.18	87.02	0.0765	1836	163.9	-27.5	1.08	89	839	5414	35	498	1.32
42	1	0.26	87.01	0.0749	1853	161	-30.4	1.18	57.8	762	6550	32.2	382	1.51
43	0	0.29	87.00	0.0795	1836	164	-27.4	1.13	90.9	844	5414	35	498	1.32
44	0	0.34	86.99	0.0809	1836	164.1	-27.4	1.16	91.8	847	5414	35	498	1.32
45	0	0.05	86.98	0.0733	1837	163.7	-27.5	1.01	87	832	5414	35	498	1.32
46	0	0.35	86.96	0.0811	1836	164.1	-27.4	1.16	91.9	847	5414	35	498	1.32
47	1	0.37	86.95	0.0759	1852	161.2	-29.2	1.32	58.4	762	6568	32.4	380	1.48
48	1	0.31	86.94	0.0751	1852	160.3	-30.1	1.25	60.3	762	6647	31.3	400	1.51
49	0	0.31	86.93	0.08	1836	164	-27.4	1.14	91.2	845	5414	35	498	1.32
50	0	0.15	86.92	0.0758	1837	163.8	-27.5	1.06	88.6	837	5414	35	498	1.32
51	1	0.21	86.90	0.0761	1853	159	-30.4	1.15	61.9	762	6592	30.1	402	1.51
52	0	0.12	86.89	0.075	1837	163.8	-27.5	1.05	88.1	836	5414	35	498	1.32
53	0	0.09	86.88	0.0743	1837	163.7	-27.5	1.03	87.6	834	5414	35	498	1.32
54	0	0.34	86.87	0.0809	1836	164	-27.4	1.16	91.8	847	5414	35	498	1.32
55	1	0.01	86.86	0.0715	1855	159.4	-31.6	1.03	59	762	6446	30.4	394	1.54
56	1	0.37	86.85	0.0771	1851	163.3	-27.7	1.4	56.4	762	6528	34.9	373	1.44
57	1	0.12	86.83	0.0752	1853	158.8	-31.4	1.04	61.6	762	6510	29.6	403	1.53
58	1	0.11	86.82	0.0749	1854	157.8	-31	1.11	63.2	762	6562	28.5	412	1.53
59	0	0.24	86.81	0.0781	1837	163.9	-27.4	1.11	90.1	842	5414	35	498	1.32
60	1	0.11	86.80	0.073	1853	157.4	-31	1.13	59.7	762	6610	28.4	402	1.52
61	0	0.16	86.79	0.076	1837	163.8	-27.4	1.07	88.7	838	5414	35	498	1.32
62	0	0.03	86.77	0.0728	1838	163.6	-27.5	1	86.7	830	5414	35	498	1.32

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual	% C in scrap	DRI: %	%C	Tapping	Steel	Relative	CO	Avg Foam	Max off	Oxygen	DRI	Graphite	Off-gas fan
	1 = MPC	(Random)	metallization		Temp.	mass	Pressure	Emission	Depth	gas temp	(kg)	(ton)	(kg)	power (MW)
63	1	0.36	86.76	0.0767	1852	161.5	-28.4	1.38	58.5	762	6529	32.8	380	1.46
64	0	0.23	86.75	0.0778	1837	163.9	-27.4	1.1	89.9	842	5414	35	498	1.32
65	1	0.42	86.74	0.0777	1853	164	-28.6	1.38	57.9	762	6397	35.4	365	1.46
66	0	0.14	86.73	0.0755	1838	163.9	-27.5	1.06	88.4	837	5414	35	498	1.32
67	1	0.20	86.71	0.0765	1853	157.9	-31.7	1.08	62.7	762	6476	28.7	394	1.53
68	1	0.02	86.70	0.0723	1855	159	-32.1	1.02	63.8	761	6583	29.7	427	1.55
69	0	0.09	86.69	0.0743	1838	163.7	-27.5	1.03	87.6	834	5414	35	498	1.32
70	0	0.07	86.68	0.074	1838	163.6	-27.5	1.02	87.3	833	5414	35	498	1.32
71	1	0.22	86.67	0.0753	1854	160.6	-29.4	1.24	59.5	763	6455	31.8	386	1.49
72	1	0.08	86.65	0.076	1853	159.9	-31.5	1.03	61.3	762	6288	30.8	385	1.53
73	0	0.08	86.64	0.0738	1838	163.6	-27.5	1.03	87.5	833	5414	35	498	1.32
74	1	0.22	86.63	0.0767	1853	161.3	-30.8	1.14	61.5	762	6417	32.4	391	1.52
75	1	0.02	86.62	0.072	1857	158.5	-31.5	1.06	57.7	762	6383	29.6	379	1.54
76	1	0.09	86.61	0.071	1855	158	-32.1	1.03	60.7	762	6832	29.3	426	1.54
77	1	0.05	86.60	0.072	1855	157.2	-31.5	1.06	60.2	762	6659	28.2	411	1.54
78	1	0.30	86.58	0.0775	1852	160.7	-30.9	1.12	59.3	762	6464	31.9	378	1.51
79	1	0.49	86.57	0.0786	1850	168.6	-26.1	1.58	55.8	765	6547	41	370	1.39
80	0	0.35	86.56	0.0811	1837	163.9	-27.4	1.16	92	847	5414	35	498	1.32
81	0	0.23	86.55	0.0778	1838	163.8	-27.4	1.1	89.9	842	5414	35	498	1.32
82	0	0.17	86.54	0.0763	1838	163.7	-27.5	1.07	88.9	839	5414	35	498	1.32
83	1	0.41	86.52	0.0772	1851	164.2	-29	1.27	56.2	762	6657	36	382	1.46
84	0	0.39	86.51	0.0823	1837	164	-27.4	1.18	92.7	849	5414	35	498	1.32
85	0	0.13	86.50	0.0752	1838	163.6	-27.5	1.05	88.3	836	5414	35	498	1.32
86	0	0.32	86.49	0.0803	1837	163.9	-27.4	1.15	91.4	846	5414	35	498	1.32
87	1	0.37	86.48	0.0771	1854	162.8	-27.7	1.43	56.9	763	6428	34.4	365	1.45
88	1	0.18	86.46	0.077	1852	161.4	-30.5	1.12	62.3	762	6468	32.5	404	1.51
89	1	0.43	86.45	0.0783	1850	167.7	-26.5	1.51	56.2	762	6492	39.9	372	1.41
90	1	0.10	86.44	0.0739	1853	158.3	-31.6	1.05	64.6	763	6733	29.4	434	1.53
91	1	0.29	86.43	0.0766	1854	160.6	-29.8	1.23	59.4	762	6409	31.8	374	1.5
92	1	0.19	86.42	0.0742	1853	160.9	-32.2	0.998	60.4	761	6638	32.2	409	1.54
93	0	0.34	86.40	0.0808	1837	163.9	-27.4	1.16	91.8	847	5414	35	498	1.32
94	0	0.00	86.39	0.0721	1839	163.5	-27.5	0.988	86.2	829	5414	35	498	1.32
95	0	0.26	86.38	0.0786	1838	163.8	-27.4	1.12	90.4	843	5414	35	498	1.32

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual	% C in scrap	DRI: %	%C	Tapping	Steel	Relative	CO	Avg Foam	Max off	Oxygen	DRI	Graphite	Off-gas fan
	1 = MPC	(Random)	metallization		Temp.	mass	Pressure	Emission	Depth	gas temp	(kg)	(ton)	(kg)	power (MW)
96	1	0.20	86.37	0.0749	1854	159.1	-30	1.21	57.6	762	6442	30.3	373	1.5
97	0	0.20	86.36	0.077	1838	163.7	-27.5	1.09	89.4	840	5414	35	498	1.32
98	1	0.48	86.35	0.0772	1849	166.6	-26.6	1.56	56.9	764	6739	38.8	394	1.41
99	0	0.37	86.33	0.0817	1838	163.9	-27.4	1.17	92.3	848	5414	35	498	1.32
100	0	0.45	86.32	0.0841	1837	164	-27.3	1.21	93.8	851	5414	35	498	1.32
101	0	0.20	86.31	0.077	1839	163.7	-27.5	1.09	89.4	840	5414	35	498	1.32
102	1	0.38	86.30	0.0781	1853	161.1	-28	1.41	58.8	762	6318	32.5	357	1.46
103	0	0.28	86.29	0.0792	1838	163.8	-27.4	1.13	90.8	844	5414	35	498	1.32
104	0	0.30	86.27	0.0797	1838	163.8	-27.4	1.14	91.1	845	5414	35	498	1.32
105	0	0.46	86.26	0.0844	1837	164	-27.3	1.21	94	851	5414	35	498	1.32
106	0	0.23	86.25	0.0778	1839	163.7	-27.4	1.1	89.9	842	5414	35	498	1.32
107	1	0.21	86.24	0.077	1852	159.8	-31.2	1.07	64.4	762	6599	30.8	418	1.52
108	1	0.02	86.23	0.0742	1854	158	-30.8	1.11	65	763	6490	28.7	420	1.53
109	1	0.10	86.21	0.0751	1853	158.4	-31.6	1.06	62.5	763	6437	29.4	398	1.53
110	1	0.10	86.20	0.0751	1852	158.3	-31.4	1.06	63.4	762	6520	29.1	412	1.53
111	0	0.22	86.19	0.0776	1839	163.7	-27.5	1.1	89.8	841	5414	35	498	1.32
112	0	0.13	86.18	0.0752	1839	163.5	-27.5	1.05	88.3	836	5414	35	498	1.32
113	1	0.45	86.17	0.0774	1854	164.1	-27.3	1.52	56.5	762	6400	35.8	358	1.43
114	0	0.27	86.15	0.0789	1839	163.7	-27.4	1.12	90.6	844	5414	35	498	1.32
115	0	0.37	86.14	0.0817	1838	163.8	-27.4	1.17	92.4	848	5414	35	498	1.32
116	1	0.13	86.13	0.0751	1853	159	-31.5	1.03	59.2	762	6586	30.5	397	1.53
117	0	0.28	86.12	0.0792	1839	163.7	-27.4	1.13	90.8	844	5414	35	498	1.32
118	0	0.11	86.11	0.0747	1840	163.5	-27.5	1.04	88	835	5414	35	498	1.32
119	0	0.31	86.10	0.08	1839	163.7	-27.4	1.14	91.3	845	5414	35	498	1.32
120	0	0.44	86.08	0.0837	1838	163.9	-27.3	1.2	93.6	851	5414	35	498	1.32
121	1	0.19	86.07	0.0731	1853	157.7	-32.1	1.09	62	762	6726	28.6	417	1.54
122	0	0.27	86.06	0.0789	1839	163.7	-27.4	1.12	90.6	844	5414	35	498	1.32
123	1	0.45	86.05	0.0775	1852	166.3	-26.1	1.57	53.4	763	6304	38.7	334	1.39
124	0	0.35	86.04	0.0811	1839	163.8	-27.4	1.16	92	847	5414	35	498	1.32
125	1	0.07	86.02	0.0734	1854	160.5	-30.8	1.09	59.3	762	6400	31.8	390	1.52
126	1	0.06	86.01	0.074	1854	157.3	-31.8	1.04	62.5	762	6599	28.3	413	1.54
127	1	0.43	86.00	0.077	1854	162.1	-28.1	1.39	54.6	762	6471	34.1	350	1.45
128	0	0.21	85.99	0.0773	1839	163.6	-27.5	1.09	89.6	841	5414	35	498	1.32

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual 1 = MPC	% C in scrap (Random)	DRI: % metallization	%C	Tapping Temp.	Steel mass	Relative Pressure	CO Emission	Avg Foam Depth	Max off gas temp	Oxygen (kg)	DRI (ton)	Graphite (kg)	Off-gas fan power (MW)
129	0	0.48	85.98	0.085	1838	163.9	-27.3	1.22	94.3	852	5414	35	498	1.32
130	0	0.41	85.96	0.0829	1839	163.8	-27.4	1.19	93.1	850	5414	35	498	1.32
131	0	0.21	85.95	0.0773	1840	163.6	-27.5	1.09	89.6	841	5414	35	498	1.32
132	0	0.28	85.94	0.0792	1839	163.6	-27.4	1.13	90.8	844	5414	35	498	1.32
133	0	0.04	85.93	0.073	1841	163.4	-27.5	1.01	86.9	831	5414	35	498	1.32
134	0	0.18	85.92	0.0765	1840	163.5	-27.5	1.08	89.1	839	5414	35	498	1.32
135	0	0.08	85.90	0.074	1840	163.4	-27.5	1.03	87.5	834	5414	35	498	1.32
136	0	0.44	85.89	0.0837	1839	163.8	-27.3	1.2	93.6	851	5414	35	498	1.32
137	0	0.33	85.88	0.0806	1839	163.7	-27.4	1.15	91.7	846	5414	35	498	1.32
138	0	0.32	85.87	0.0803	1839	163.7	-27.4	1.15	91.5	846	5414	35	498	1.32
139	0	0.15	85.86	0.0757	1840	163.5	-27.5	1.06	88.6	838	5414	35	498	1.32
140	1	0.20	85.85	0.0774	1853	160.5	-29.7	1.18	60.1	762	6285	31.8	372	1.5
141	1	0.36	85.83	0.0781	1852	161.2	-29.1	1.33	63	762	6441	32.4	390	1.48
142	1	0.15	85.82	0.0736	1854	157.5	-31.6	1.08	60.6	762	6645	28.7	406	1.53
143	1	0.09	85.81	0.0733	1854	158.5	-31.6	1.06	61.6	763	6685	29.9	417	1.53
144	0	0.39	85.80	0.0823	1839	163.7	-27.4	1.18	92.7	849	5414	35	498	1.32
145	1	0.09	85.79	0.075	1854	159.8	-31.4	1.06	61.7	762	6371	31	394	1.53
146	0	0.43	85.77	0.0834	1839	163.7	-27.4	1.2	93.5	850	5414	35	498	1.32
147	1	0.38	85.76	0.0783	1851	162.7	-28	1.39	58.4	762	6421	34.4	370	1.45
148	0	0.11	85.75	0.0747	1841	163.4	-27.5	1.04	88	835	5414	35	498	1.32
149	1	0.17	85.74	0.075	1853	158.1	-30	1.19	60.5	762	6528	29.2	396	1.5
150	0	0.17	85.73	0.0763	1840	163.4	-27.5	1.07	89	839	5414	35	498	1.32
151	0	0.36	85.71	0.0814	1840	163.6	-27.4	1.17	92.2	848	5414	35	498	1.32
152	0	0.33	85.70	0.0806	1840	163.6	-27.4	1.15	91.7	846	5414	35	498	1.32
153	1	0.02	85.69	0.0698	1856	157.8	-32.5	0.943	59.3	762	6802	29.4	423	1.55
154	1	0.06	85.68	0.0728	1854	157.6	-32.5	0.983	62.4	762	6649	28.9	419	1.55
155	0	0.32	85.67	0.0803	1840	163.6	-27.4	1.15	91.5	846	5414	35	498	1.32
156	1	0.07	85.65	0.0726	1854	157.9	-31.8	1.03	60.9	762	6701	29.5	416	1.53
157	1	0.24	85.64	0.0774	1852	160	-30.3	1.19	64.2	762	6418	31.3	399	1.51
158	0	0.02	85.63	0.0725	1842	163.2	-27.5	0.999	86.6	830	5414	35	498	1.32
159	0	0.23	85.62	0.0778	1841	163.5	-27.4	1.1	90	842	5414	35	498	1.32
160	0	0.04	85.61	0.073	1842	163.2	-27.5	1.01	86.9	831	5414	35	498	1.32
161	0	0.24	85.60	0.0781	1841	163.5	-27.4	1.11	90.1	842	5414	35	498	1.32

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual	% C in scrap	DRI: %	%C	Tapping	Steel	Relative	CO	Avg Foam	Max off	Oxygen	DRI	Graphite	Off-gas fan
	1 = MPC	(Random)	metallization		Temp.	mass	Pressure	Emission	Depth	gas temp	(kg)	(ton)	(kg)	power (MW)
162	1	0.18	85.58	0.0769	1854	158.8	-30.1	1.21	66.4	762	6437	29.7	411	1.51
163	0	0.43	85.57	0.0834	1840	163.7	-27.4	1.2	93.5	850	5414	35	498	1.32
164	0	0.32	85.56	0.0803	1840	163.5	-27.4	1.15	91.5	846	5414	35	498	1.32
165	0	0.07	85.55	0.0737	1842	163.3	-27.5	1.02	87.4	833	5414	35	498	1.32
166	1	0.23	85.54	0.0774	1851	158.9	-29.5	1.26	66.4	763	6625	29.9	427	1.49
167	1	0.16	85.52	0.0746	1852	159.8	-31	1.11	62.3	762	6680	31.4	417	1.52
168	0	0.16	85.51	0.076	1841	163.3	-27.5	1.07	88.8	838	5414	35	498	1.32
169	0	0.43	85.50	0.0834	1840	163.7	-27.4	1.2	93.5	850	5414	35	498	1.32
170	1	0.14	85.49	0.0762	1854	158.1	-30.5	1.13	63.7	763	6435	29.2	401	1.52
171	0	0.31	85.48	0.08	1841	163.5	-27.4	1.14	91.3	845	5414	35	498	1.32
172	0	0.11	85.46	0.0747	1842	163.3	-27.5	1.04	88	835	5414	35	498	1.32
173	1	0.28	85.45	0.0749	1853	159.3	-29.2	1.31	61.9	762	6629	30.6	406	1.49
174	0	0.33	85.44	0.0806	1841	163.5	-27.4	1.15	91.7	846	5414	35	498	1.32
175	0	0.36	85.43	0.0814	1840	163.6	-27.4	1.17	92.2	848	5414	35	498	1.32
176	1	0.16	85.42	0.0754	1853	158.3	-31	1.14	65.1	762	6564	29.3	419	1.52
177	0	0.22	85.40	0.0776	1841	163.4	-27.4	1.1	89.8	841	5414	35	498	1.32
178	0	0.07	85.39	0.0737	1842	163.2	-27.5	1.02	87.4	833	5414	35	498	1.32
179	0	0.01	85.38	0.0723	1842	163.1	-27.5	0.994	86.5	829	5414	35	498	1.32
180	0	0.27	85.37	0.0789	1841	163.4	-27.4	1.12	90.7	844	5414	35	498	1.32
181	1	0.01	85.36	0.0706	1855	157.8	-32.9	0.945	61	761	6732	29.4	423	1.56
182	0	0.38	85.35	0.082	1841	163.5	-27.4	1.18	92.6	848	5414	35	498	1.32
183	0	0.08	85.33	0.074	1842	163.2	-27.5	1.03	87.5	834	5414	35	498	1.32
184	1	0.14	85.32	0.0735	1856	158	-30.5	1.2	61.8	762	6511	29.2	402	1.52
185	1	0.25	85.31	0.0764	1853	161.7	-30.4	1.14	58.5	762	6501	33.6	386	1.51
186	1	0.35	85.30	0.0772	1853	162.9	-29.3	1.27	58.2	762	6388	34.8	368	1.49
187	1	0.32	85.29	0.0755	1853	162.4	-30.1	1.21	57.2	762	6583	34.5	383	1.5
188	0	0.46	85.27	0.0843	1840	163.6	-27.3	1.21	94	851	5414	35	498	1.32
189	1	0.06	85.26	0.0736	1853	158.2	-32.5	0.974	63.5	762	6646	29.4	427	1.55
190	0	0.32	85.25	0.0803	1841	163.4	-27.4	1.15	91.5	846	5414	35	498	1.32
191	1	0.27	85.24	0.0772	1854	162	-28.9	1.29	57.6	762	6209	33.8	353	1.47
192	0	0.24	85.23	0.0781	1842	163.3	-27.4	1.11	90.2	842	5414	35	498	1.32
193	0	0.36	85.21	0.0814	1841	163.5	-27.4	1.17	92.2	848	5414	35	498	1.32
194	1	0.17	85.20	0.0753	1852	158.5	-31	1.11	62.5	762	6558	29.7	408	1.52

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual	% C in scrap	DRI: %	%C	Tapping	Steel	Relative	CO	Avg Foam	Max off	Oxygen	DRI	Graphite	Off-gas fan
	1 = MPC	(Random)	metallization		Temp.	mass	Pressure	Emission	Depth	gas temp	(kg)	(ton)	(kg)	power (MW)
195	0	0.10	85.19	0.0745	1843	163.2	-27.5	1.04	87.9	835	5414	35	498	1.32
196	0	0.04	85.18	0.073	1843	163.1	-27.5	1.01	86.9	831	5414	35	498	1.32
197	1	0.23	85.17	0.0758	1855	162.1	-29.1	1.25	57.3	762	6327	34	367	1.48
198	1	0.31	85.15	0.0762	1853	161.2	-30.3	1.22	58.8	762	6433	32.9	376	1.5
199	0	0.35	85.14	0.0811	1841	163.4	-27.4	1.16	92.1	847	5414	35	498	1.32
200	0	0.22	85.13	0.0776	1842	163.3	-27.4	1.1	89.8	841	5414	35	498	1.32
201	1	0.01	85.12	0.0731	1853	156.7	-31.9	0.993	61.4	762	6529	28	408	1.54
202	1	0.11	85.11	0.0763	1852	159.3	-30.9	1.08	61.6	761	6364	30.7	391	1.52
203	1	0.13	85.10	0.0734	1854	157.6	-31.1	1.13	60.3	763	6513	29	395	1.53
204	0	0.19	85.08	0.0768	1842	163.2	-27.5	1.08	89.3	840	5414	35	498	1.32
205	0	0.24	85.07	0.0781	1842	163.3	-27.4	1.11	90.2	842	5414	35	498	1.32
206	0	0.11	85.06	0.0747	1843	163.1	-27.5	1.04	88	835	5414	35	498	1.32
207	1	0.33	85.05	0.0796	1851	162.8	-28.9	1.32	63.7	762	6277	34.3	383	1.47
208	1	0.31	85.04	0.0752	1853	161.6	-30.2	1.24	59.1	762	6504	33.5	384	1.51
209	0	0.39	85.02	0.0823	1842	163.4	-27.4	1.18	92.8	849	5414	35	498	1.32
210	1	0.30	85.01	0.0768	1853	161	-30.4	1.2	60	761	6377	32.7	376	1.51
211	1	0.04	85.00	0.0709	1856	157.6	-32.1	1.01	61.3	762	6677	29.1	419	1.55
212	1	0.30	84.99	0.0784	1851	161	-29.7	1.23	61.1	762	6390	32.7	382	1.49
213	1	0.47	84.98	0.0783	1852	163.8	-27.3	1.52	56	762	6386	36	352	1.43
214	0	0.10	84.96	0.0745	1843	163	-27.5	1.04	87.9	835	5414	35	498	1.32
215	1	0.25	84.95	0.0764	1854	159.3	-30.6	1.22	62.1	762	6354	30.7	382	1.51
216	1	0.20	84.94	0.0763	1854	159.4	-29.8	1.22	61.3	762	6393	30.9	386	1.5
217	1	0.03	84.93	0.0744	1853	159.1	-32.8	0.911	62.2	761	6435	30.6	405	1.56
218	1	0.18	84.92	0.0746	1852	158.3	-31.1	1.14	64.8	762	6600	29.5	419	1.53
219	1	0.15	84.90	0.0724	1856	159.2	-30.5	1.18	60.6	762	6602	30.8	406	1.53
220	1	0.24	84.89	0.0766	1851	159.2	-30.3	1.2	64	763	6502	30.5	404	1.51
221	1	0.21	84.88	0.0754	1852	159.3	-30.9	1.16	60.2	762	6485	30.9	389	1.52
222	0	0.01	84.87	0.0723	1844	163	-27.5	0.994	86.5	829	5414	35	498	1.32
223	0	0.47	84.86	0.0846	1842	163.5	-27.3	1.22	94.2	852	5414	35	498	1.32
224	1	0.23	84.85	0.0767	1853	159	-31.2	1.15	65.6	761	6487	30.2	408	1.53
225	1	0.36	84.83	0.0762	1855	160.7	-28.7	1.39	56.1	762	6303	32.6	346	1.48
226	0	0.21	84.82	0.073	1844	163	-27.5	1.01	87	831	5414	35	498	1.32
227	1	0.04	84.81	0.0741	1854	157.2	-32.3	1.01	64.5	762	6504	28.5	415	1.54

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual 1 = MPC	% C in scrap (Random)	DRI: % metallization	%C	Tapping Temp.	Steel mass	Relative Pressure	CO Emission	Avg Foam Depth	Max off gas temp	Oxygen (kg)	DRI (ton)	Graphite (kg)	Off-gas fan power (MW)
228	0	0.16	84.80	0.076	1843	163.1	-27.5	1.07	88.9	838	5414	35	498	1.32
229	0	0.06	84.79	0.0735	1844	163	-27.5	1.02	87.3	832	5414	35	498	1.32
230	0	0.19	84.77	0.0768	1843	163.1	-27.5	1.08	89	840	5414	35	498	1.32
231	1	0.05	84.76	0.0741	1855	157.9	-31.9	1.04	62.4	762	6368	29.3	396	1.54
232	0	0.31	84.75	0.08	1843	163.2	-27.4	1.14	91.4	845	5414	35	498	1.32
233	0	0.09	84.74	0.0742	1844	163	-27.5	1.03	87.7	834	5414	35	498	1.32
234	1	0.19	84.73	0.0766	1852	159.1	-30.6	1.15	65.6	763	6554	30.4	420	1.51
235	1	0.14	84.71	0.0726	1854	156.5	-31.4	1.15	62.9	762	6765	27.8	428	1.53
236	0	0.34	84.70	0.0808	1843	163.3	-27.4	1.16	91.9	847	5414	35	498	1.32
237	1	0.46	84.69	0.0788	1852	166.3	-26	1.6	58.6	763	6487	39	380	1.39
238	1	0.00	84.68	0.0708	1856	156.7	-31.8	1.04	62.7	762	6762	28.2	436	1.54
239	1	0.37	84.67	0.0793	1852	161.3	-27.6	1.44	60.5	762	6353	33.1	372	1.43
240	1	0.17	84.65	0.0741	1854	159.1	-31.2	1.08	59.9	762	6563	30.8	398	1.52
241	0	0.34	84.64	0.0808	1843	163.3	-27.4	1.16	91.9	847	5414	35	498	1.32
242	0	0.43	84.63	0.0834	1843	163.4	-27.4	1.2	93.5	850	5414	35	498	1.32
243	0	0.45	84.62	0.084	1842	163.4	-27.3	1.21	93.9	851	5414	35	498	1.32
244	0	0.30	84.61	0.0797	1843	163.2	-27.4	1.14	91.2	845	5414	35	498	1.32
245	0	0.20	84.60	0.077	1844	163.1	-27.5	1.09	89.5	840	5414	35	498	1.32
246	1	0.21	84.58	0.0765	1854	158.5	-30.9	1.14	64.3	762	6445	29.8	400	1.52
247	0	0.48	84.57	0.0849	1842	163.4	-27.3	1.22	94.4	852	5414	35	498	1.32
248	1	0.33	84.56	0.076	1852	160.5	-30.8	1.14	58.5	762	6678	32.8	391	1.51
249	0	0.44	84.55	0.0837	1843	163.3	-27.3	1.21	93.7	851	5414	35	498	1.32
250	1	0.06	84.54	0.0751	1852	157.7	-31.5	1.06	66.6	762	6524	28.9	428	1.54
251	1	0.05	84.52	0.0743	1854	157.8	-32.5	0.955	60.5	762	6339	29.3	385	1.55
252	1	0.08	84.51	0.0744	1853	157	-31.2	1.1	64	762	6517	28.2	413	1.53
253	1	0.20	84.50	0.0765	1852	159	-30.4	1.17	62.9	762	6512	30.5	404	1.51
254	0	0.27	84.49	0.0789	1844	163.1	-27.4	1.12	90.7	844	5414	35	498	1.32
255	1	0.41	84.48	0.0773	1852	163.5	-37.8	1.45	57.6	762	6410	35.7	367	1.44
256	1	0.17	84.46	0.0721	1855	158	-31.8	1.08	58.8	762	6609	29.8	394	1.54
257	1	0.11	84.45	0.0752	1853	158.9	-31.9	1.01	60.8	762	6446	30.6	394	1.53
258	1	0.39	84.44	0.0782	1852	162.6	-29.1	1.32	58	762	6315	34.8	358	1.47
259	1	0.05	84.43	0.0746	1853	157.5	-32.3	0.981	65.4	762	6585	28.9	426	1.55
260	1	0.31	84.42	0.0786	1851	160.3	-29.8	1.21	62.1	762	6337	32	378	1.5

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual	% C in scrap	DRI: %	%C	Tapping	Steel	Relative	CO	Avg Foam	Max off	Oxygen	DRI	Graphite	Off-gas fan
	1 = MPC	(Random)	metallization		Temp.	mass	Pressure	Emission	Depth	gas temp	(kg)	(ton)	(kg)	power (MW)
261	1	0.11	84.40	0.0767	1851	158.8	-30.9	1.07	65.6	762	6463	30.3	413	1.52
262	1	0.05	84.39	0.0731	1853	157.3	-31.7	1.02	61	762	6610	28.9	412	1.54
263	1	0.21	84.38	0.0769	1850	159.8	-31.6	1.04	62.5	761	6532	31.5	405	1.53
264	0	0.13	84.37	0.0752	1845	162.9	-27.5	1.05	88.4	837	5414	35	498	1.32
265	1	0.40	84.36	0.08	1852	161.6	-26.8	1.56	63.6	762	6312	33.3	378	1.43
266	0	0.38	84.35	0.082	1844	163.2	-27.4	1.18	92.7	848	5414	35	498	1.32
267	1	0.05	84.33	0.0733	1854	159	-31.8	0.981	60.5	762	6388	30.8	391	1.54
268	0	0.10	84.32	0.0745	1845	162.9	-27.5	1.04	87.9	835	5414	35	498	1.32
269	1	0.25	84.31	0.0742	1854	160.4	-30.9	1.17	58.4	762	6445	32.4	377	1.52
270	0	0.45	84.30	0.084	1844	163.2	-27.3	1.21	93.9	851	5414	35	498	1.32
271	0	0.09	84.29	0.0742	1845	162.8	-27.5	1.03	87.8	834	5414	35	498	1.32
272	1	0.01	84.27	0.0757	1854	158	-31.6	1.02	66.2	762	6395	29.3	417	1.54
273	1	0.40	84.26	0.0777	1853	163.7	-27.9	1.42	55.4	762	6351	36.3	348	1.45
274	0	0.09	84.25	0.0742	1846	162.8	-27.5	1.03	87.8	834	5414	35	498	1.32
275	1	0.36	84.24	0.0767	1853	163	-27.5	1.4	54.6	762	6432	35.7	357	1.43
276	0	0.05	84.23	0.0732	1846	162.8	-27.5	1.01	87.1	832	5414	35	498	1.32
277	0	0.20	84.21	0.077	1845	162.9	-27.5	1.09	89.5	840	5414	35	498	1.32
278	1	0.02	84.20	0.0725	1854	157.5	-32.6	0.912	63	762	6678	29.3	429	1.55
279	0	0.21	84.19	0.0773	1845	162.9	-27.5	1.09	89.7	841	5414	35	498	1.32
280	0	0.34	84.18	0.0808	1844	163.1	-27.4	1.16	92	847	5414	35	498	1.32
281	0	0.01	84.17	0.0723	1846	162.7	-27.5	0.994	96.5	829	5414	35	498	1.32
282	0	0.01	84.15	0.0723	1846	162.7	-27.5	0.994	96.5	829	5414	35	498	1.32
283	1	0.35	84.14	0.0758	1854	161.4	-29.4	1.32	58.9	763	6408	33.5	372	1.49
284	1	0.43	84.13	0.0789	1850	165.9	-25.9	1.6	60.1	763	6499	38.6	391	1.39
285	1	0.43	84.12	0.0785	1852	162.9	-28	1.44	60	763	6512	35.2	385	1.45
286	1	0.05	84.11	0.0743	1854	159.9	-31.6	0.99	61.3	762	6331	31.7	392	1.53
287	1	0.38	84.10	0.0781	1854	163.1	-27.7	1.44	56.1	763	6218	35.6	341	1.44
288	1	0.25	84.08	0.0788	1852	159.9	-29.2	1.25	63.7	763	6282	31.6	383	1.48
289	1	0.11	84.07	0.0721	1854	156.9	-32.2	1.07	61.4	762	6622	28.4	410	1.55
290	1	0.14	84.06	0.0753	1854	157.4	-30.7	1.1	62.1	762	6423	28.9	394	1.53
291	1	0.39	84.05	0.0772	1854	163	-28.8	1.34	55.7	762	6269	35.5	343	1.47
292	1	0.07	84.04	0.074	1854	158.1	-31.5	1.07	64.2	763	6543	29.6	420	1.54
293	1	0.19	84.02	0.0767	1852	157.4	-31	1.12	61.7	762	6395	28.9	384	1.52

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual	% C in scrap	DRI: %	%C	Tapping	Steel	Relative	CO	Avg Foam	Max off	Oxygen	DRI	Graphite	Off-gas fan
	1 = MPC	(Random)	metallization		Temp.	mass	Pressure	Emission	Depth	gas temp	(kg)	(ton)	(kg)	power (MW)
294	1	0.44	84.01	0.0785	1851	168.1	-25.5	1.6	55.3	763	6489	41.6	366	1.38
295	1	0.03	84.00	0.0746	1853	157.6	-32.2	0.99	63.2	762	6410	29.1	405	1.54
296	0	0.31	83.99	0.08	1845	163	-27.4	1.14	91.4	846	5414	35	498	1.32
297	0	0.29	83.98	0.0794	1845	163	-27.4	1.13	91.1	845	5414	35	498	1.32
298	1	0.39	83.96	0.0775	1852	162.3	-28.4	1.37	56.7	762	6430	34.9	362	1.46
299	0	0.27	83.95	0.0789	1846	163	-27.4	1.12	90.7	844	5414	35	498	1.32
300	0	0.43	83.94	0.0834	1845	163.1	-27.4	1.2	93.6	850	5414	35	498	1.32
301	1	0.28	83.93	0.077	1851	162.7	-30.1	1.17	59.2	762	6489	35.1	389	1.5
302	0	0.29	83.92	0.0794	1846	163	-27.4	1.13	91.1	845	5414	35	498	1.32
303	1	0.14	83.90	0.0742	1853	158.1	-31.6	1.07	63.2	762	6579	29.9	412	1.53
304	0	0.16	83.89	0.076	1846	162.8	-27.5	1.07	88.9	838	5414	35	498	1.32
305	1	0.20	83.88	0.0764	1853	160	-30.7	1.13	60.4	762	6304	31.9	376	1.51
306	0	0.26	83.87	0.0786	1846	162.9	-27.4	1.12	90.6	843	5414	35	498	1.32
307	0	0.30	83.86	0.0797	1846	162.9	-27.4	1.14	91.3	845	5414	35	498	1.32
308	0	0.11	83.85	0.0747	1847	162.7	-27.5	1.04	88.1	835	5414	35	498	1.32
309	1	0.06	83.83	0.0741	1853	156.9	-32.3	1	62.9	761	6493	28.4	409	1.54
310	0	0.26	83.82	0.0786	1846	162.9	-27.4	1.12	90.6	843	5414	35	498	1.32
311	1	0.37	83.81	0.0782	1852	160.7	-29.4	1.28	56.4	762	6422	32.6	381	1.46
312	1	0.14	83.80	0.0756	1854	158.9	-30.9	1.12	60.7	762	6353	30.7	383	1.52
313	0	0.03	83.79	0.0728	1847	162.6	-27.5	1	86.9	831	5414	35	498	1.32
314	0	0.20	83.77	0.077	1846	162.8	-27.5	1.09	89.6	840	5414	35	498	1.32
315	0	0.21	83.76	0.0773	1846	162.8	-27.5	1.09	89.7	841	5414	35	498	1.32
316	0	0.36	83.75	0.0814	1846	163	-27.4	1.17	92.3	848	5414	35	498	1.32
317	1	0.48	83.74	0.0784	1852	162.2	-27.1	1.59	59.8	762	6347	34.4	363	1.43
318	0	0.11	83.73	0.0747	1847	162.7	-27.5	1.04	88.1	835	5414	35	498	1.32
319	1	0.46	83.71	0.0784	1852	164	-27.2	1.53	59.3	762	6344	36.5	367	1.43
320	0	0.01	83.70	0.0723	1848	162.5	-27.5	0.994	86.6	829	5414	35	498	1.32
321	0	0.38	83.69	0.082	1846	163	-27.4	1.18	92.7	848	5414	35	498	1.32
322	0	0.24	83.68	0.0781	1847	162.8	-27.4	1.11	90.3	842	5414	35	498	1.32
323	1	0.34	83.67	0.0773	1850	162.9	-28.33	1.33	58.1	762	6442	35.4	377	1.46
324	1	0.46	83.65	0.0769	1853	162.9	-27.9	1.47	57	763	6550	35.6	373	1.44
325	1	0.42	83.64	0.0789	1852	164.2	-26.4	1.56	58	764	6405	37.1	368	1.4
326	0	0.07	83.63	0.0737	1848	162.6	-27.5	1.02	87.5	833	5414	35	498	1.32

Test no.	Controller 0 = manual 1 = MPC	Inputs % C in scrap (Random)	DRI: % metallization	Results %C	Tapping Temp.	Steel mass	Relative Pressure	CO Emission	Avg Foam Depth	Max off gas temp	Feed materials consumed Oxygen (kg)	DRI (ton)	Graphite (kg)	Off-gas fan power (MW)
327	1	0.15	83.62	0.0778	1852	158.6	-31.9	1.03	65.2	762	6359	30.2	400	1.54
328	0	0.19	83.61	0.0767	1847	162.7	-27.5	1.08	89.4	840	5414	35	498	1.32
329	1	0.04	83.60	0.0756	1853	157.5	-31.9	1.02	66.7	762	6415	28.8	418	1.54
330	1	0.12	83.58	0.0743	1853	158	-31.7	1.06	64.8	762	6569	29.5	421	1.54
331	1	0.33	83.57	0.0776	1852	165.5	-29.4	1.19	56.8	762	6382	38.5	371	1.47
332	0	0.19	83.56	0.0767	1847	162.7	-27.5	1.08	89.4	840	5414	35	498	1.32
333	1	0.45	83.55	0.0781	1851	165.7	-27.2	1.45	57.6	762	6657	39	389	1.42
334	0	0.34	83.54	0.0808	1846	162.9	-27.4	1.16	92	847	5414	35	498	1.32
335	0	0.47	83.52	0.0846	1846	163	-27.3	1.22	94.3	852	5414	35	498	1.32
336	0	0.42	83.51	0.0831	1846	163	-27.4	1.2	93.4	850	5414	35	498	1.32
337	0	0.09	83.50	0.0742	1848	162.6	-27.5	1.03	87.8	834	5414	35	498	1.32
338	1	0.26	83.49	0.0789	1851	160.4	-28.9	1.28	62.5	762	6292	32.3	380	1.47
339	1	0.42	83.48	0.0773	1852	162.9	-29.1	1.36	59.1	762	6458	35.4	377	1.48
340	1	0.04	83.46	0.0745	1855	157.5	-32.8	0.958	62.6	762	6335	29.2	392	1.56
341	0	0.48	83.45	0.0849	1846	163	-27.3	1.23	94.5	852	5414	35	498	1.32
342	1	0.35	83.44	0.079	1852	160.7	-29.4	1.3	63.3	762	6421	32.7	389	1.49
343	0	0.36	83.43	0.0814	1847	162.9	-27.4	1.17	92.4	848	5414	35	498	1.32
344	0	0.02	83.42	0.0725	1849	162.5	-27.5	0.999	86.7	830	5414	35	498	1.32
345	1	0.47	83.40	0.0782	1850	165.5	-26.2	1.58	56	762	6436	38.7	362	1.39
346	0	0.12	83.39	0.075	1848	162.6	-27.5	1.05	88.3	836	5414	35	498	1.32
347	1	0.15	83.38	0.0767	1853	157.4	-30.9	1.13	67.2	762	6553	28.9	425	1.53
348	0	0.02	83.37	0.0725	1849	162.4	-27.5	0.999	86.7	830	5414	35	498	1.32
349	0	0.05	83.36	0.0732	1849	162.5	-27.5	1.01	87.2	832	5414	35	498	1.32
350	1	0.25	83.35	0.0775	1852	159.5	-31.1	1.19	61.4	761	6397	31.5	386	1.49
351	0	0.03	83.33	0.0728	1849	162.4	-27.5	1	86.9	831	5414	35	498	1.32
352	1	0.13	83.32	0.0753	1853	158	-30.5	1.14	63.9	762	6453	29.8	406	1.52
353	1	0.48	83.31	0.0784	1851	164.3	-26.7	1.56	57.6	763	6465	37.3	367	1.42
354	0	0.44	83.30	0.0837	1847	162.9	-27.3	1.21	93.8	851	5414	35	498	1.32
355	0	0.14	83.29	0.0755	1848	162.6	-27.5	1.06	88.6	837	5414	35	498	1.32
356	1	0.21	83.27	0.0772	1852	160.7	-29.8	1.19	62.4	762	6337	32.8	389	1.5
357	1	0.44	83.26	0.0766	1852	164.7	-28.1	1.39	55.7	762	6540	37.9	370	1.44
358	1	0.15	83.25	0.0781	1853	159.4	-31.6	1.02	63.3	761	6301	31.4	389	1.53
359	0	0.31	83.24	0.08	1848	162.7	-27.4	1.14	91.5	846	5414	35	498	1.32

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual 1 = MPC	% C in scrap (Random)	DRI: % metallization	%C	Tapping Temp.	Steel mass	Relative Pressure	CO Emission	Avg Foam Depth	Max off gas temp	Oxygen (kg)	DRI (ton)	Graphite (kg)	Off-gas fan power (MW)
360	0	0.44	83.23	0.0837	1847	162.9	-27.3	1.21	93.8	851	5414	35	498	1.32
361	1	0.43	83.21	0.0777	1852	164.6	-26.5	1.56	55.5	763	6427	37.8	360	1.41
362	0	0.43	83.20	0.0834	1847	162.9	-27.4	1.2	93.6	850	5414	35	498	1.32
363	1	0.48	83.19	0.0796	1851	163.9	-26.7	1.57	60.9	762	6403	36.6	378	1.41
364	1	0.46	83.18	0.0811	1850	166.5	-25	1.72	61	763	6241	39.5	369	1.37
365	0	0.05	83.17	0.0732	1849	162.4	-27.5	1.01	87.2	832	5414	35	498	1.32
366	1	0.37	83.15	0.0785	1853	161.6	-29.1	1.32	60.6	762	6332	33.9	371	1.48
367	0	0.34	83.14	0.0808	1848	162.7	-27.4	1.16	92	847	5414	35	498	1.32
368	0	0.06	83.13	0.0735	1849	162.4	-27.5	1.02	87.4	833	5414	35	498	1.32
369	1	0.20	83.12	0.078	1853	157.7	-30.9	1.12	64.7	762	6383	29.5	395	1.52
370	0	0.03	83.11	0.0728	1849	162.4	-27.5	1	86.9	831	5414	35	498	1.32
371	1	0.07	83.10	0.0755	1853	159.7	-31.6	1.01	65.3	762	6318	31.6	405	1.54
372	1	0.31	83.08	0.0769	1853	161.5	-29.7	1.24	57.7	761	6318	34.1	361	1.49
373	0	0.49	83.07	0.0852	1847	162.9	-27.3	1.23	94.7	853	5414	35	498	1.32
374	1	0.11	83.06	0.0756	1853	158.1	-31.7	1.09	69.3	762	6548	29.6	437	1.54
375	1	0.24	83.05	0.0757	1853	157.4	-30.9	1.15	63.3	761	6651	29.4	411	1.52
376	1	0.35	83.04	0.0774	1853	163.1	-29.3	1.27	57.4	762	6349	35.9	363	1.48
377	1	0.18	83.02	0.0788	1852	158.1	-30.5	1.13	66.2	762	6333	29.8	399	1.52
378	1	0.39	83.01	0.0786	1851	160.8	-27.3	1.48	58.4	762	6335	33.3	360	1.43
379	0	0.35	83.00	0.0811	1848	162.7	-27.4	1.16	92.2	847	5414	35	498	1.32
380	1	0.36	82.99	0.0782	1851	163.6	-27.9	1.37	57.9	762	6335	36.4	367	1.44
381	1	0.06	82.98	0.0738	1854	156.5	-31.9	1.04	63.6	762	6615	28.4	419	1.54
382	1	0.16	82.96	0.0749	1852	157	-32.2	1.03	63.5	762	6468	28.8	402	1.54
383	1	0.22	82.95	0.0754	1853	159.2	-31.1	1.13	59.9	761	6499	31.4	389	1.52
384	0	0.09	82.94	0.0742	1850	162.4	-27.5	1.03	87.8	834	5414	35	498	1.32
385	0	0.26	82.93	0.0786	1849	162.6	-27.4	1.12	90.64	843	5414	35	498	1.32
386	1	0.06	82.92	0.0735	1855	156.9	-32.4	0.98	64.8	762	6598	28.8	425	1.55
387	0	0.37	82.90	0.0817	1848	162.7	-27.4	1.17	92.6	848	5414	35	498	1.32
388	0	0.16	82.89	0.076	1849	162.4	-27.5	1.07	89	838	5414	35	498	1.32
389	0	0.49	82.88	0.0852	1848	162.8	-27.3	1.23	94.7	853	5414	35	498	1.32
390	0	0.06	82.87	0.0735	1850	162.3	-27.5	1.02	87.4	833	5414	35	498	1.32
391	1	0.07	82.86	0.0739	1854	155.9	-31.4	1.12	66.1	761	6602	27.4	429	1.54
392	0	0.03	82.85	0.0728	1850	162.3	-27.5	1	86.9	831	5414	35	498	1.32

	Controller	Inputs		Results							Feed materials consumed			
Test no.	0 = manual 1 = MPC	% C in scrap (Random)	DRI: % metallization	%C	Tapping Temp.	Steel mass	Relative Pressure	CO Emission	Avg Foam Depth	Max off gas temp	Oxygen (kg)	DRI (ton)	Graphite (kg)	Off-gas fan power (MW)
393	1	0.47	82.83	0.08	1852	166.5	-26.3	1.59	57.1	762	6170	39.7	346	1.4
394	1	0.23	82.82	0.077	1851	161.3	-31	1.1	61	762	6479	33.8	397	1.52
395	1	0.14	82.81	0.0758	1855	158.8	-30.2	1.18	64.7	762	6405	30.7	405	1.52
396	1	0.43	82.80	0.0783	1851	164	-26.9	1.52	56.7	763	6355	37.1	359	1.42
397	1	0.08	82.79	0.0746	1855	157.5	-31.4	1.08	63.9	762	6482	29.4	411	1.54
398	0	0.00	82.77	0.072	1851	162.2	-27.5	0.99	86.4	829	5414	35	498	1.32
399	0	0.38	82.76	0.0819	1849	162.7	-27.4	1.18	92.8	849	5414	35	498	1.32
400	1	0.34	82.75	0.0772	1851	161.5	-30.4	1.17	59.2	761	6536	34.4	384	1.5
401	1	0.44	82.74	0.08	1850	165.7	-26.2	1.58	61.6	763	6396	38.8	386	1.4
402	0	0.50	82.73	0.0855	1848	162.8	-27.3	1.24	94.9	853	5414	35	498	1.32
403	1	0.43	82.71	0.0788	1851	163.1	-28.4	1.39	57.6	763	6311	36	355	1.45
404	1	0.41	82.70	0.0777	1852	163	-27.5	1.45	55.6	763	6342	36.1	350	1.43
405	1	0.11	82.69	0.0762	1854	157.6	-31	1.1	65.9	763	6345	29.3	404	1.53
406	0	0.20	82.68	0.077	1850	162.4	-27.5	1.09	89.6	840	5414	35	498	1.32
407	0	0.40	82.67	0.0825	1849	162.6	-27.4	1.19	93.1	849	5414	35	498	1.32
408	0	0.26	82.65	0.0786	1850	162.5	-27.4	1.12	90.7	843	5414	35	498	1.32
409	0	0.31	82.64	0.08	1849	162.5	-27.4	1.14	91.5	846	5414	35	498	1.32
410	1	0.12	82.63	0.0769	1852	159	-31.6	1.03	62.3	762	6322	31.2	389	1.53
411	1	0.30	82.62	0.0767	1852	161.9	-30.5	1.13	60.1	762	6549	34.7	397	1.5
412	1	0.20	82.61	0.0769	1855	159	-30.7	1.16	61.5	762	6275	31.2	376	1.51
413	1	0.23	82.60	0.0771	1853	161.4	-27.8	1.33	58.9	763	6262	34	369	1.46
414	1	0.16	82.58	0.0762	1854	158.3	-31.7	1.03	64.2	761	6451	30.5	405	1.54
415	1	0.49	82.57	0.0793	1850	165.1	-25.8	1.66	60.7	765	6603	38.5	398	1.39
416	1	0.08	82.56	0.0758	1853	156.9	-31.8	1.01	63.2	762	6440	28.9	402	1.54
417	1	0.27	82.55	0.0774	1851	161.8	-29.6	1.22	60.5	762	6339	34.4	380	1.49
418	1	0.23	82.54	0.0798	1851	158.8	-30.5	1.15	65.4	762	6238	30.8	384	1.51
419	0	0.10	82.52	0.0744	1851	162.2	-27.5	1.04	88	835	5414	35	498	1.32
420	0	0.50	82.51	0.0855	1849	162.7	-27.3	1.24	94.9	853	5414	35	498	1.32