

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.

7.3. TYPICAL ADDITION STRATEGY.

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.

7.3.7.4. 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.

7.3.7.2. 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.

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

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

The ratio: $s_{\text{man}}^2 / s_{\text{mpc}}^2$ 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

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

Substituting the degrees of freedom into standard tables used for the F-test [45], it can be seen that the ratio $s_{\text{man}}^2 / s_{\text{mpc}}^2 = 21.45$ 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 $n_2 - 1$.

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

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

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

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.

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

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

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

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 $\alpha = 0.05$ 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].

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

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.

7.4.4. Limitations

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 %.

Finally a simulation was done to compare the EAF under manual and MPC

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.

Electrical and Electronic Engineering