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A Paradigm for the Scheduling of a Continuous Walking Beam Reheat Furnace using a Modified Genetic Algorithm

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Abstract:

The paper discusses the application of a paradigm for creating scheduling systems for steel reheating furnaces. The proposed paradigm utilises a modified version of a Genetic Algorithm (GA) to optimise such schedules via new ways of realising the crossover and mutation operations. The work was conducted in collaboration with the Thrybergh Combination Mill owned by CORUS- Sheffield (UK). The outcome of this research work is a novel scheduling system which links together the scheduling and furnace controls and is also able to accept new and already established mill heuristics. The proposed methodology is 'flexible' as well as 'generic' as it can be augmented easily in order to suit other industrial set-ups.

Keywords: Reheat furnace, scheduling, optimisation, genetic algorithms, simulation, time-delay.

1. Introduction

The reheat furnace performs a fundamental role in steel mills and is the primary mechanism for heating steel to the temperatures required for subsequent rolling and forming. Typically the reheat furnace is a refractory lined steel shell, with burners located along the furnace length to provide the necessary heat input. A stock movement mechanism is used to allow the steel to progress from the beginning of the furnace to the discharge end.

Cold stock is reheated to meet the rolling demand, however the problem is highly constrained. Steel stock items of different metallurgical grades, lengths, and cross-sectional areas (CSA) may be in the furnace at any one time and each of these different variations has specific heating requirements so as not to damage the stock or the subsequent rolling and forming equipment. In addition to this, the reheat furnace has to accommodate the different processing rates for certain material types, rolling mill demand and unforeseen delays. The present method of forming schedules for the furnace involves the application of heuristics, knowledge passing between different mill stages and experience. Whilst this method continues to be used successfully, its scope is limited to achieving product quality, and financial implications are not explicitly considered. This paper discusses a reheat furnace scheduling paradigm that was developed through a research project[1)] on the Thrybergh Combination Mill owned by CORUS-UK Ltd. The purpose of the paradigm is to aid the development of framework furnace scheduling systems which consider both product quality and process costs. This paper is organised as follows: Section 2 summarises a selection of schedule optimisation activities undertaken in steel processing environments, Section

3 reviews the rationale and details of the scheduling paradigm while Sections 4-7 outline the ideas behind the 4 tasks which form the Achilles' heel of this scheduling paradigm, namely the development of the optimiser, pre-processing of the orders, post-processing of the schedules, and managing the process interfaces. Results of the application of these paradigms are also presented and discussed. Finally, in Section 8 conclusions in relation to this overall study are drawn with landmarks for future exploitation of this new vision of scheduling clearly outlined.

2. A Selection of Scheduling Techniques Applied to Steel Processes

The optimisation of schedules for processes represents a direct way of improving the productivity associated with them. Materials manufacturing companies have undertaken many schedule optimisation projects, however, these have primarily considered continuous casting machines and soaking pits. The most plausible reason for the lack of literature in the area of reheat furnaces is the tendency by manufacturers to use well-understood heuristics to form production schedules, with the main purpose of the heuristics being the avoidance of problems in the rolling mill. Hence, the optimisation of schedules for continuous reheat furnaces is an area that deserves greater study.

Linkens and Yang[2)], developed a simulation model for an ingot based hot steel mill which developed could have been used for production scheduling and optimisation. An interesting point in this research is that the simulation model considers the complexities of the heat transfer, and hence the quality of heating is also considered in the subsequent schedule optimisation as well as the processing time. Deb and Chakraborti[3)] developed a hypothetical model of a bloom reheating furnace for the optimisation of furnace design and operational parameters i.e. burner locations and bloom speed. However, due to the hypothetical nature of the work, the model was not validated by comparison with a real furnace. Lally and Biegler [4)] used a Mixed Integer Linear Programming (MILP) approach to model the operation of a melt shop and a continuous caster. In this work, the number and positioning of gaps between the casting of different batches of molten steel (known as a “heat”) are optimised to synchronise the melting and casting processes, thus improving productivity and hence reducing costs. A larger castor-scheduling project is discussed in[5)]. In this approach, heuristics are used to group orders into sets to be processed continuously between necessary castor stoppages. The formation of groups is based upon the available facility capacities, maintenance schedules etc. An initial feasible schedule is then generated by arranging the orders in the group to give the smallest castor downtime possible without breaking any of the specified constraints. Subsequently, the schedule optimisation is performed by using a Travelling Salesman Problem (TSP) optimisation technique. The research is interesting in that it takes advantage of the several similarities between the TSP and castor scheduling to produce an optimisation system without reinventing the wheel. The article is useful for stimulating ideas, but since it does not contain definitions for constraints or the TSP-based optimiser, it is not possible to directly implement this research in other projects. An overview of the scheduling techniques applied to the continuous casting process can be found in[6)].

The reheat furnace scheduling problem is tackled in[7)] for a plate/sheet rolling mill. In this research, the optimisation of the processing time of the furnace and the fuel consumption are considered within the specified manufacturing constraints, and the sequencing of the slabs for the reheat furnace is posed as a constrained combinatorial optimisation problem. A branch-and-bound technique is used to find schedules in an iterative manner, and an upper cost bound is determined and updated during each cost evaluation stage of the tree. Models of the rolling mill, the reheat furnace, and slab charging heat loss are used by a total cost model which determines the total final cost based on the amount of fuel used and the production time taken. However, it is unclear what type of model is used for the reheat furnace and whether validation has been performed to ensure that the behaviour of the model is comparable to that of the real furnace. Therefore, it is also unclear whether the quality of the heating was considered in this research. A batch annealing furnace simulator which has been validated with process data is described in[8)]. A validated furnace model is a necessary step in producing any furnace operation optimisation system since it gives a degree of confidence in the optimisation process being able to produce results that can be obtained in practice. In this work the author optimises the diameters of coils of wire to maximise throughput while still achieving the required mechanical properties.

A wide variety of improvement activities either undertaken by the materials manufacturing community or aimed at them has been performed. However, there is no approach in the literature which directly considers the optimisation of furnace schedules while considering the ability of the furnace to process those schedules. This is achieved in this work by including the performance of the supervisory furnace control system and it's embedded processing constraints into the optimisation process.

3. The Reheat Furnace Scheduling Paradigm

The paradigm consists of the 4 following tasks:

- *Incorporate the ability of the furnace control into a schedule optimisation system*. The general aim of a process control system is to regulate variable(s) around an operating point, e.g. a reheat furnace control system which aims to satisfy the desired discharge temperature of the steel within it. Hence, ideally, schedules should be formed which cause as few obstacles as possible to the aims of the control system. An accurate way of achieving this is to incorporate the actual process control into the optimisation system. Therefore, the performance of the control can be compared for different schedules and an optimisation procedure can be initiated to find schedules that give improved performance with respect to the controlled variables. Furthermore, since the control system, and hence the model within it, have been thoroughly tested, both the industrial partners and the individual researchers can be satisfied that the outputs of the system are reliable. Hence, the control variable values obtained from simulations that encompass the process control are also accurate in relation to those obtained during the normal operation of the process. In this research, the controlled variables were the Mean Bulk Temperature (MBT)[1] and the Min-Max Temperature[2] error.

- *Pre-process the orders using the established mill practice heuristics*. All manufacturing facilities are governed by constraints, which can be imposed by the item being manufactured or the manufacturing processes themselves. Through years of experience, rules of ‘good practice’ have been developed which aim to reduce the onset of problems and / or limit the impact of necessary technicalities. For the optimisation of schedules to be successful, it is necessary that the original

[1] MBT – The average temperature of a stock item formed by considering all nodal temperatures calculated by the Finite Difference (FD) model.
[2] Min-Max Temperature – The difference between the highest and lowest nodal temperature calculated by the FD model.

orders be processed to comply with the established mill practices. Note that the established mill heuristics can also be incorporated into the optimisation process.

- *Post-process the schedules with the established mill practice heuristics and the heuristics derived from the analysis of production data.* After the sequential optimisation of the schedules has occurred, it is necessary to add further information to them to form practically realisable schedules. Although the optimised sequences of the orders have been formed, additional processing heuristics in the form of delays must be added. For the reheat furnace these can be known as delay heuristics, or process data extracted heuristics. The importance of these heuristics cannot be overstated since not only will they inform the individual scheduler in charge of the process as to what delays are required, but they will also improve the throughput estimates and therefore allow improved coordination with upstream and downstream processes.

- *Manage the process interfaces using a throughput adjustment mechanism*. There will always remain some uncertainty in any manufacturing environment, e.g. system failures. The formation of schedules that are tolerant to throughput changes is essential since in a serial production line the throughput rate will vary at each stage of the processing. However, there will be situations that occur as a result of unpredictable events that require direct actions to be taken. For example, increasing trends in the MBT error of the discharged stock items from the reheat furnace will require correctional action. Situations often arise due to the rolling process outstripping the processing capacity of the reheat furnace. Therefore, it is necessary to provide a mechanism by which a process can react to unpredictable events but without making unrealistic demands on the 'downstream' processes. This can be accomplished by a throughput adjustment mechanism which monitors the corresponding control variables and reduces the throughput in relation to the magnitude of the errors.

By following the above paradigm, the schedule optimisation systems can be formed for serial processing environments. The remainder of this paper is concerned with a description of the application of the paradigm on the Thrybergh Combination Mill.

4. Paradigm Task 1: Development of the Schedule Optimiser

The formation of a validated schedule optimiser is the most difficult and time-consuming part of forming a complete furnace schedule generation system. However, the process is simplified by first stating the overall purposes and of the schedule optimiser and then considering what are the prerequisites for an optimisation system. Indeed, the schedule optimiser should form the schedules that are optimal with respect to the product quality, and as a result the prerequisites for the optimisation can be summarised as follows:

- A method for comparing the optimality of the schedules such as a validated process model.
- A generic optimiser for refining the schedules.

4.1 A Validated Process Model

It is rarely the case that an 'off-the-shelf' validated process model is immediately available, instead models are generally developed using process knowledge and experience, and then validated by comparison with known data. However, recent trends in furnace control upgrades[9-11)] have led to installation of mathematical model based supervisory control systems, as was the case at the Thrybergh Combination Mill. Such control systems have a validated furnace model embedded within their structure, which can simulate the heating of stock items as they pass through the furnace. Hence, a validated model can be obtained through the analysis of the existing process control.

Overview of the Furnace Control

The furnace control divides the length of the furnace into 3 control zones known as the preheat, heating and soak zones as shown in Figure 1. Each zone has specific control strategies associated with it.

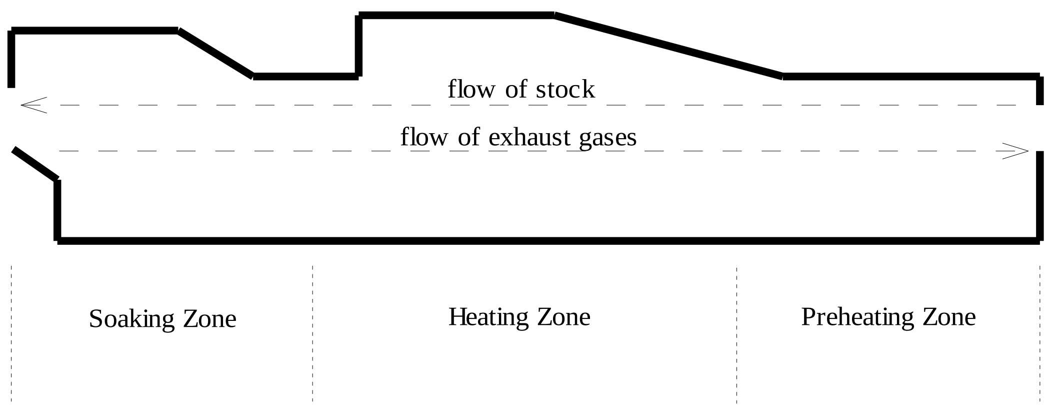

Figure 1. The Control Zones of the Furnace

The control utilises a calibrated 2-dimensional finite difference heat transfer model for calculating the temperature distributions of the stock as they pass through the furnace. Furnace temperatures and stock positions are obtained through communication with the SCADA (Supervisory Control and Data Acquisition) and MTS (Material Tracking System) respectively. A forward prediction of the final discharge temperature distribution is made using the model, the current zonal temperature set-points, and the zonal temperature increase/decrease capabilities of the furnace. For each stock item on which the prediction is performed, a set of ideal furnace set-points is generated. Consideration is then given to all the stock's ideal set-points to select an actual set of furnace set-points. A new set of furnace set-points is selected at every model iteration.

4.2 Development and Validation of a Furnace Simulator

Since the furnace simulator is part of an optimisation system, it must operate faster than in real-time. The original software, called INFERNO, was multi-threaded and designed to run on Microsoft Windows NT ™, a general-purpose operating system with a limited timing resolution for the scheduling of the threads. To this end the furnace control software and SCADA/MTS emulation software provided by CORUS UK Ltd were reverse-engineered and were transformed into a fast furnace simulator, which still contained the functionality of the original control but operated at a speed which was dictated by the power of the computer system and not by the timing resolution of the operating system. The validation of the furnace simulator was performed by comparing its operation with the original control and SCADA / MTS emulation software. A sample schedule was processed on both systems and the temperature data associated with the first item in the furnace was logged at every model iteration (20s) until the head item in the furnace was discharged. The recorded temperature data are listed in Figure 2.

Figures 2 and 3 illustrate the similarity of the furnace simulator to mimic the behaviour of the original control. Based on these results, the operation of the furnace simulator was considered representative of the original control.

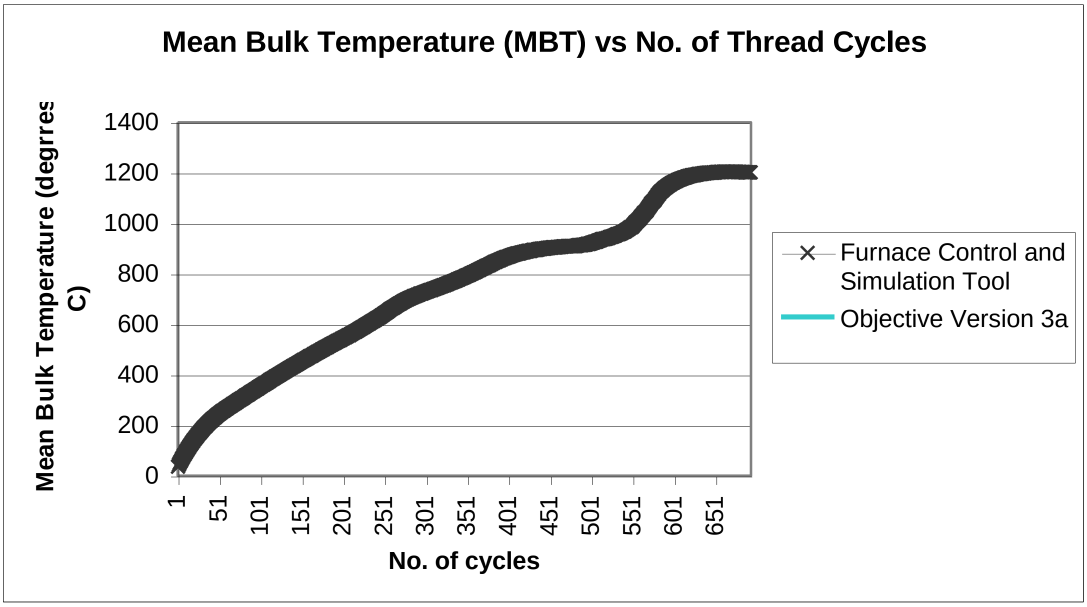

Figure 2. Comparison of the Head Stock Items Mean Bulk Temperature versus Time for the Original Furnace Control and Furnace Simulator.

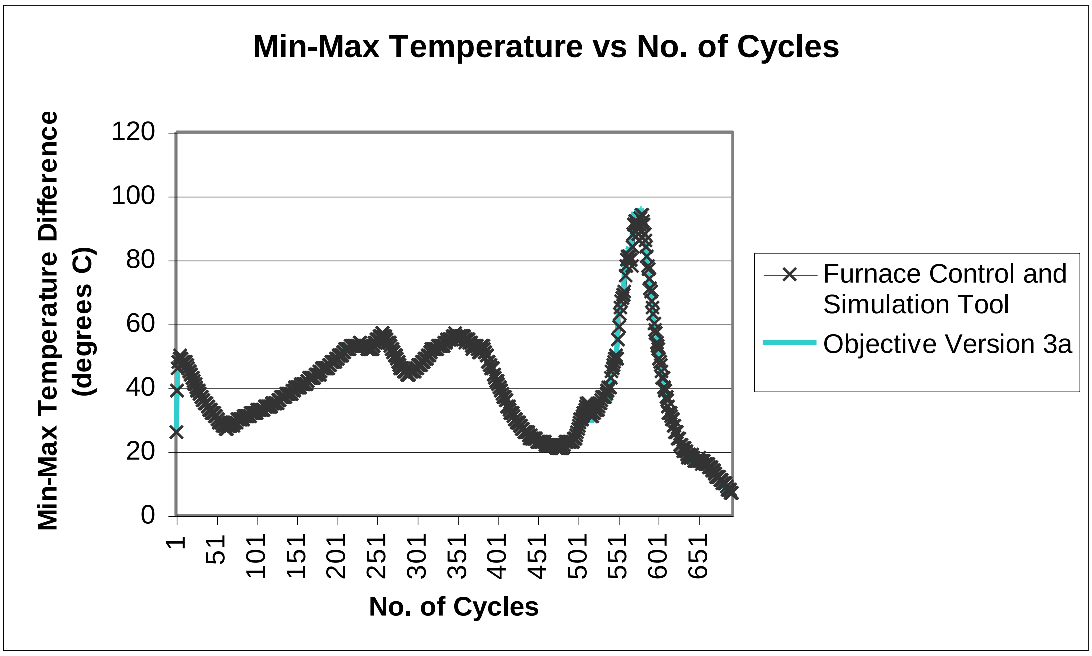

Figure 3. Comparison of the Min-Max Temperature Difference Measured Across the Cross-Section of the Head Stock Item versus Time for the Original Furnace Control and Furnace Simulator.

A Generic Optimiser

The purpose of the optimiser is to form schedules which will result in lower stock temperature errors at discharge. The general outline of the optimisation system is shown in Figure 4.

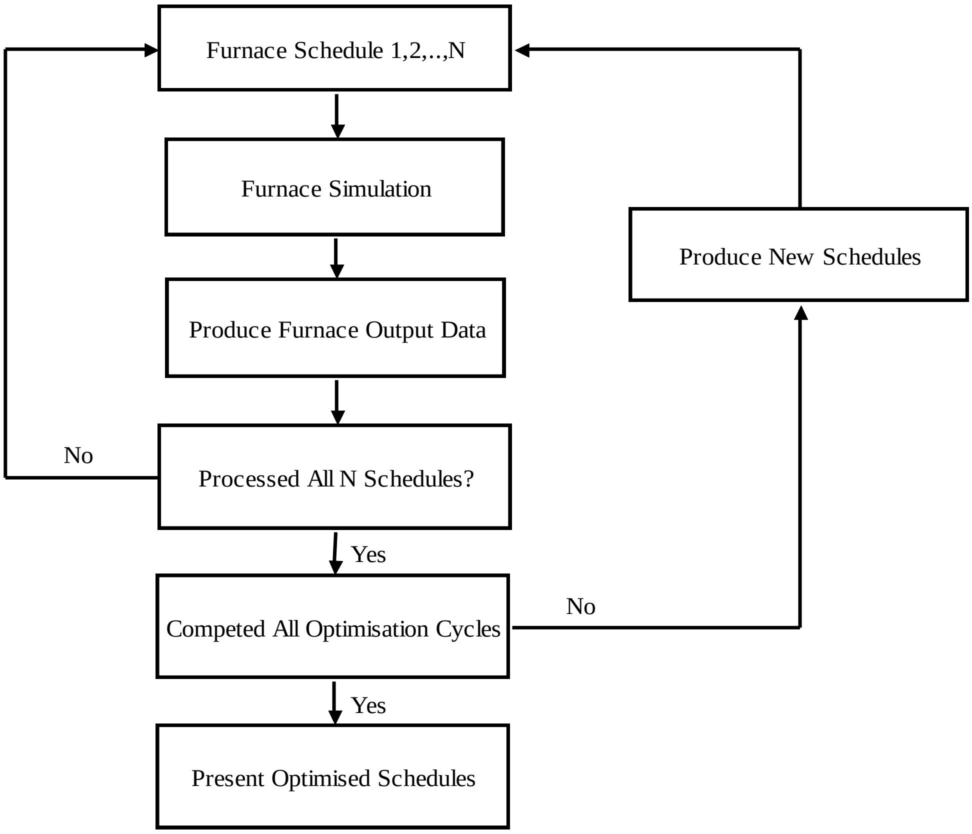

Figure 4. Outline of the Furnace Schedule Optimisation Scheme.

Genetic algorithms (GA)[12)] are generic optimisers that can be tailored to many different situations and have been widely applied to scheduling problems. For example, GAs have been used to schedule flowshops[13-14)], jobshops[15)], water supplies[16)], university class timetabling[17)], and nurse working shifts[18)].

A thorough introduction to GAs is given by Goldberg[19)]. Essentially GAs are population based stochastic sampling mechanisms which start with an initial population of solutions and iteratively refines the population based on set performance criteria. However, GAs belong to the Evolutionary Computation family of techniques and operate on the basis of natural evolution where there is a greater tendency for higher performing solutions to persist into future generations. For the purpose of this research a problem specific GA was developed to form the main optimisation mechanism, although other evolutionary or classical techniques could be used if desired. The furnace simulator provided the data which was used by the GA to assess each schedules performance with respect to the quality of the heating. The problem specific operators of the GA (crossover and mutation) were then used to form a new population of schedules, to be processed by the furnace simulator.

Modifying the GA

In the proposed schedule optimisation system the GA modifies the sequence of a fixed set of stock orders. Hence, the 'standard' GA operations could not have been used since infeasible schedules would have been produced. The problem with regards to single point crossover for a schedule consisting of 10 orders is illustrated in Figure 5. To be consistent with mill practice, 'crossover' should operate on an order and not an individual stock item. From Figure 5 it can be seen that the standard crossover operation has produced two new schedules that are both invalid since neither contains a full compliment of the original 10 orders. A modified mutation operator was devised, for example, two orders can be selected and their positions switched as shown in Figure 6.

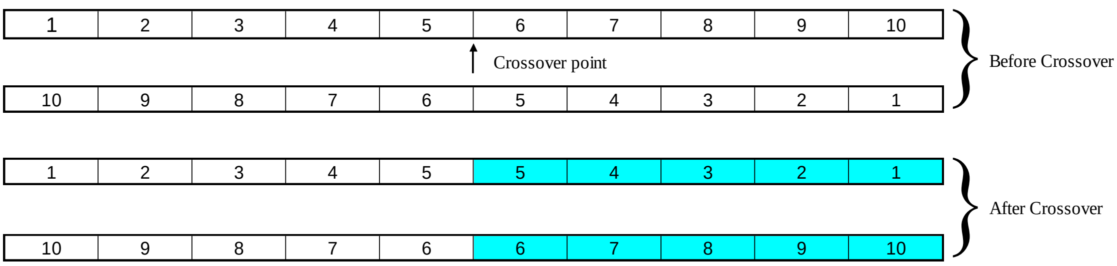

Figure 5. Illustration of the Formation of an Infeasible Schedule with Standard Single Point Crossover.

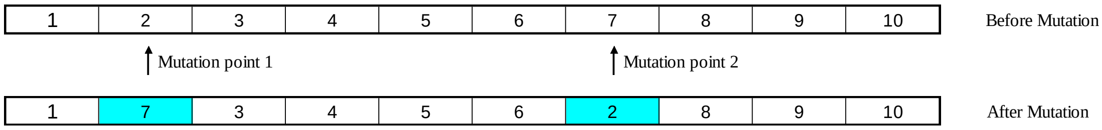

Figure 6. Illustration of the Mutation Operator for the Scheduling Problem.

- The specifications of the GA are as follows:
- Population size **30**;
- Maximum generations **150**;
- Number of optimum parameters (orders) **9**;
- Chromosome length assigned to each parameter **4**;
- Number of offspring **2**, **12**,**18**,**24**;
- Single point crossover;
- Stochastic selection;
- Ranking;
- Steady-state population breeding method.

Each of the 9 optimum parameters is an order consisting of a number of items of particular material type and CSA, and also have specified ideal discharge temperatures and allowable temperature errors. The preliminary objective function uses the aggregate sum of the MBT deviations and the Min-Max distribution temperatures upon discharge, weighted in favour of the MBT as shown in equation (1). This equation was used in 'INFERNO' for the determination of ideal setpoints for the individual stock items and is based on the MBT being the primary control variable since an unsatisfactory discharge MBT could result in the material being scrapped or damage to the rolling mill.

$$\text{Objective Function} = (\text{Min. Error} - \text{Max. Error}) + (4 \times \text{MBT deviations}) \quad (1)$$

The optimisation cycle continued upto a maximum of 150 generations although satisfactory performance was typically achieved within 100 generations. 10 runs were performed for each set of parameters to ensure repeatability of the results and Figure 7 shows the typical generational improvements obtained.

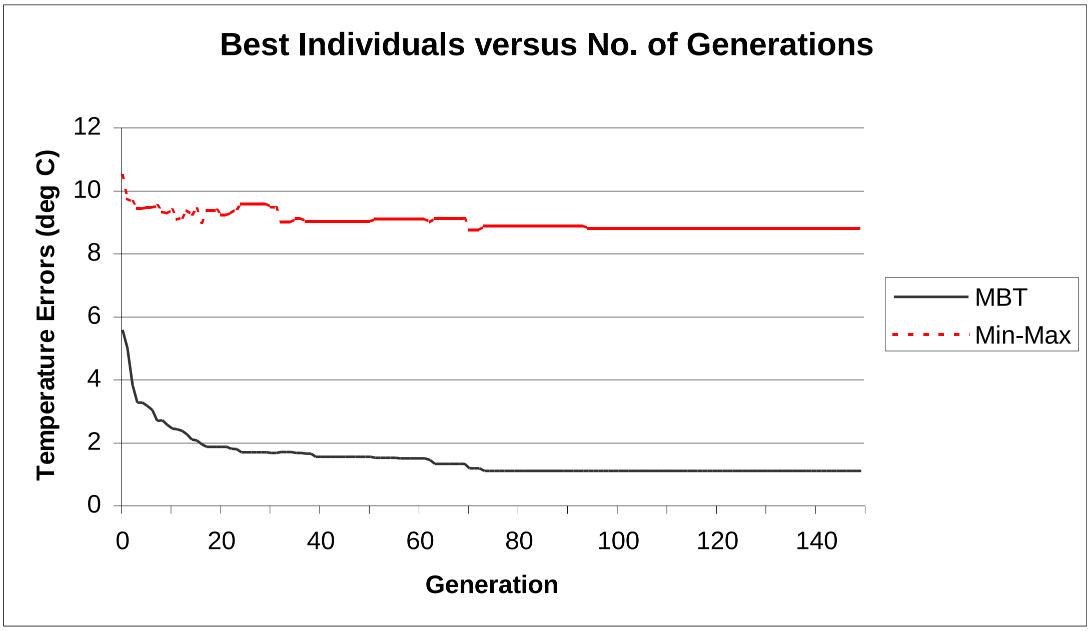

Figure 7. The Best Individuals MBT Errors and Min-Max Temperature Errors Per Generation.

The benefit of this approach to schedule optimisation lies in the fact that the performance of each schedule is judged on the performance of the control system to process that schedule efficiently and to provide the desired output temperatures. Therefore, scheduling and control are no longer separate activities and the schedules are generated which augment the capabilities of the furnace control.

5. Paradigm Task 2: Pre-process the orders using the established mill practice heuristics.

The furnace-scheduling problem is essentially a combinatorial problem, however a given set of orders cannot be arranged into any sequence and be processed by the mill. Each manufacturing facility has its own process constraints imposed upon it and the optimisation system must take these into account if it is to be successful. Typically, constraints specify that certain material types cannot be processed concurrently or that orders must be processed in groups based on product/stock dimensions. In the Thrybergh Combination Mill, the orders are sorted into bar/billet size groups and then processed. This operation consists of first sorting the orders into groups based on the finished bar size ranges, and then further dividing theses groups based on the CSA of the stock which is used to make the bar. A graphical representation of this is shown in Figure 8. The processing of items in bar / billet size groups not only reduces the number of mill set-ups, i.e. necessary technicalities, but also helps smooth the throughput rate which in turn aids the operation of the control to achieve the desired stock discharge temperatures, i.e. reduces the onset of problems.

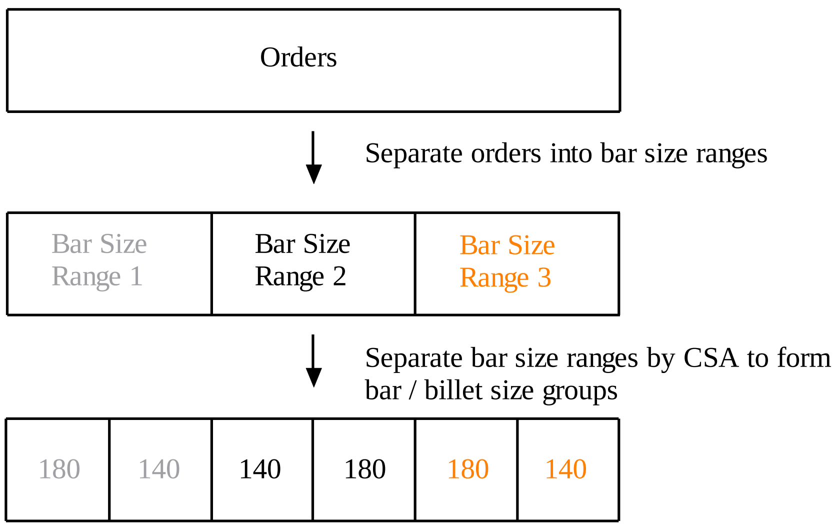

Figure 8. The sorting of the Bar / Billet Size Groups.

The order pre-processing stage splits the original orders into smaller groups. In this case the schedule optimisation process consists of the summation of the smaller group optimisations.

6. Paradigm Task 3: Post-process the schedules with the established mill practice heuristics and the heuristics derived from the analysis of production data.

The purpose of applying the post-process heuristics is to convert the optimised sequences of orders formed using Tasks 1 and 2 of the paradigm into practically realisable schedules. Established delay heuristics are used at the Thrybergh bar Mill to aid the reheating process or subsequent rolling process. Typically, the heuristics specify the addition of delays or extra distances between stock items of different material type or CSA. Figure 9 illustrates the process of applying post process delays.

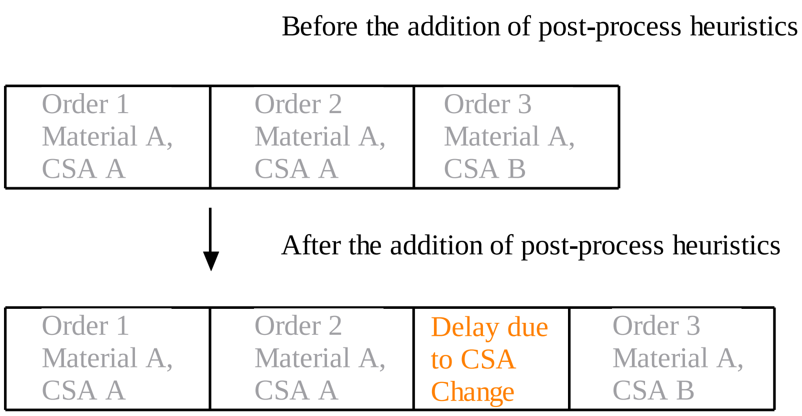

Figure 9. Addition of a Post-Process Delay.

It is possible to incorporate these heuristics into the optimisation phase, however, there are advantages to be obtained from incorporating delay heuristics **after** the schedule optimisation procedure is completed rather than **before**. Indeed, the inclusion of the delays prior to optimisation first increases the time required to simulate the processing of a schedule and hence the time required for the optimisation to complete. Secondly, since such delays are used to smooth certain transitions, e.g. from one CSA size to another, they can obscure the difficulty which the process control system can find in making such transitions. When the schedule optimisation is performed without the delays being present[3], the process control is faced with the worst-case scenarios and the difficulty associated with each transition is clear. The optimisation process is then driven towards minimising the effect of these transitions and the end result is the formation of schedules that are robust with respect to the fast throughput rates.

In addition to the established mill heuristics, further rules can be developed from analysing process data and hence integrated within the system. In a typical month, the Thrybergh Combination Mill is inactive for a proportion of the available production time. While this is due in part to the 'planned' delays, i.e. changes to the rolling mill to produce different size bars, the 'unplanned' delays remain the main cause. The purpose of the analysis was to gain a better understanding of the planned and the unplanned delays and determine whether there exist any correlation between the known processing changes and the delays. A systematic analysis of the process data was performed which considered what effects changes in CSA and material type in a production schedule had upon the discharge properties of the stock. From the analysis,

[3] It is believed that the incorporation of delays renders the optimisation process relatively easier to solve.

a set of recommended planned delays was proposed based on the expected delays associated with changes in CSA. Furthermore, the analysis of two types of planned delays was performed, stop delays and gap charge delays. For a stop delay, no movement of the stock occurs for a preset period, but for a gap charge delay stock is moved at the present throughput rate but no stock is input for a preset period. Figure 10 demonstrates the two types of planned delays.

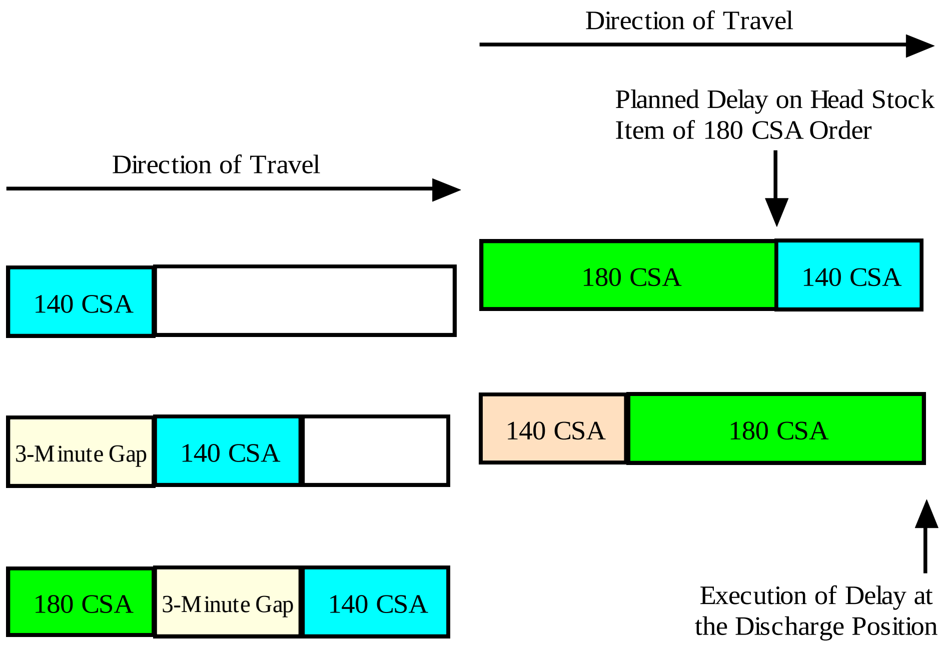

Figure 10. Illustrations of the Gap and Stop Delay Strategies.

The analysis was concerned with the furnace temperatures set-points and stock discharge errors obtained when using stop and gap charge delays. The following general conclusions were drawn:

- The gap charging strategy provides the best MBT error performance in the face of multiple material changes and hence is a good choice when accurate ideal MBT attainment is critical.

- The stop delay strategy is the most efficient with respect to the lowering of furnace zone temperatures and hence is a good choice for maximising productivity and minimising cost on less critical grades of steel.

Finally, after collating the pre-processing and post-processing rules, the optimisation system can be deemed to be complete.

7. Paradigm Task 4: Managing the process interfaces using a throughput adjustment mechanism.

Fluctuating production rates cause increasing and decreasing trends in stock discharge temperature errors. Also unpredictable events result in changes to the production rate. While it is not possible to eliminate these unpredictable events, efforts can be made to improve the control of the furnace-rolling mill interface. This in turn will inevitably lead to adjustments in the throughput rate to force the furnace set-point temperatures up or down when the MBT and/or the Min-Max temperature errors are seen to be moving out of the acceptable limits. This is a corrective measure that operates by monitoring the discharge temperatures of the stock items at the discharge and reacting to the observed trends.

A strategy was implemented which consisted of reducing the walk-rate if the MBT error of a newly discharged stock item fell within specified ranges. Since the prediction mechanism in the control calculates the heating requirements of stock items based on the calculated throughput rates, reducing this rate reduces the heat input per unit time. The mechanism first determines if the discharged stock item and the last item in the furnace are of the same material type and CSA. This check is performed so that the throughput adjustment mechanism does not interfere with the CSA change delays and the gap charges described earlier. If the material type and the CSA are the same, then appropriate adjustments to the walk rate are made. Table 1 shows a set of error ranges and associated throughput reductions that were tested, and Table 2 shows the schedule that was used. Figure 11 shows the effect on the MBT discharge error with and without the throughput adjustment when processing a schedule with several changes in the CSA. Similarly, Figure 12 shows the effect on the Min-Max temperature errors.

Table 1. Error Ranges and Associated Throughput Reductions.

MBT Error Ranges	Action
≥10; <15	10% reduction in throughput
≥15; <25	30% reduction in throughput
≥25	50% reduction in throughput
<-10; ≥-15	10% reduction in throughput
<-15; ≥-25	20% reduction in throughput
<-25	30% reduction in throughput

Table 2. A Schedule Incorporating Fast Changes in the CSA of the Billets

Order Number	Number of billets	Material Type	CSA (mm^2)
1	10	6	140
2	07	6	140
3	09	6	140
4	07	7	140
5	06	7	140
6	06	2	180
7	04	9	140
8	05	9	180
9	04	9	140

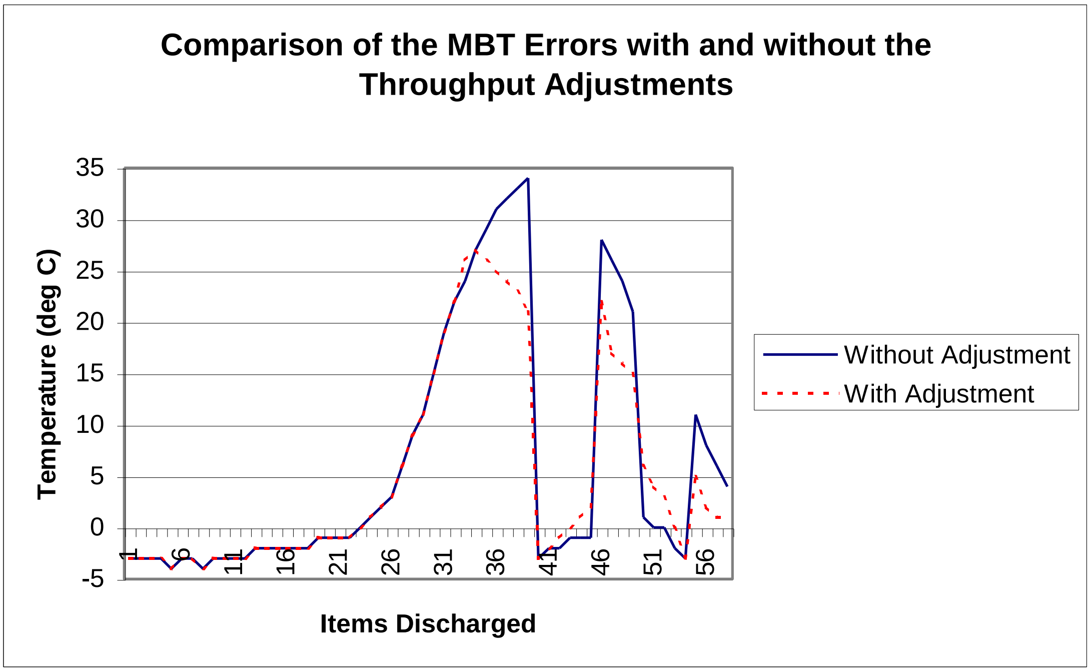

Figure 11. MBT Errors Obtained With and Without the Throughput Adjustments.

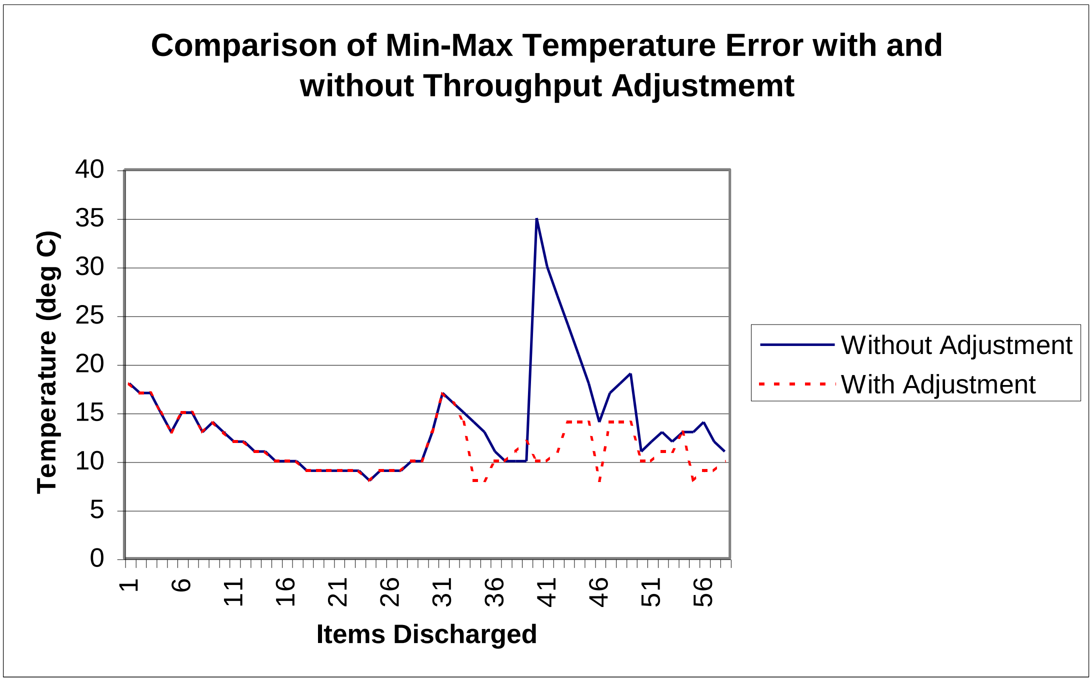

Figure 12. The Min-Max Temperature Errors Obtained With and Without the Throughput Adjustment.

The throughput adjustment mechanism successfully kept the MBT errors within the prescribed limits of $\pm 25^0 C$ and the Min-Max temperature error within the $\pm 40^0 C$ limits. It can also be seen that the Min-Max temperature errors have been smoothed without any explicit control, which indicates that the adjustment strategy was successful.

The trade-offs between the throughput and the heated quality can also be made; higher throughput rates can be achieved if larger error tolerances can be accepted. Using this strategy, specific throughput adjustments and error ranges can be tailored to different material types. A key feature of the mechanism is that only reductions in the throughput are made in reaction to the MBT errors. Hence, the mechanism places no demands on the rolling mill to operate at faster rates, which is consistent with current practice and also the through-process approach at the Thrybergh Combination Mill. Due to the slow dynamics of the heating process it is imperative that a rising/increasing error trend is identified significantly before the tolerance limits are reached. This is accomplished via a careful selection of the ranges and the percentage reduction in the throughput pertaining to them. Reducing the temperature at which significant throughput changes are made leads to reduced temperature errors and a slower throughput, the converse is true for increasing the temperature at which significant throughput changes are made.

8. Conclusions

- The optimisation of sequences of orders by the optimisation system to improve the MBT and Min-Max temperature errors has been demonstrated.

- The ability of the optimisation system to implicitly consider differences in CSA, material properties, and the positions of billets in the furnace, using limited information has been observed.

- The optimisation system has shown the ability to take into account the established mill processing heuristics and include the process data derived heuristics.

- Measures have been developed and implemented (in simulations) for incorporating estimated delays and reacting to unexpected events, which successfully reduced temperature errors.

- The throughput adjustment mechanism demonstrated the ability to avert unwanted increasing trends in MBT error through exploiting the sensitivity of stock temperatures to changes in throughput, and it is an effective interfacial process control mechanism which places no burden on the rolling mill to operate at a faster rate.

- Compromises between the acceptable temperature errors and the reductions in the throughput can be reached by an appropriate selection of the percentage reductions in the throughput rate.

In following the paradigm, a novel approach to the scheduling of the continuous walking beam reheat furnace has been developed. The performance of a schedule is judged by the optimisation system on the performance of the control to process that schedule efficiently and satisfy the heating requirements, and therefore a link is formed between the scheduling and subsequent control activities. It is hoped that the strategies developed for scheduling will be tested in real-time on the Thrybergh Combination Mill plant in the very near future.

9. Acknowledgements

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