The Development of an Expert System and Adaptive Process Models for Hot Mill Setup

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ABSTRACT

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A study was performed to develop new techniques for rolling mill setup and supervisory control. The study was based around three main components, namely a mathematical model of the process, its associated adaptation and an expert system. A novel architecture was developed to integrate the three components into a setup control system, along with some additional functions. The objective of the mill setup system is to determine the optimum mill actuator set points and control targets prior to the rolling of the slab. It is the function of the mill setup and supervisory control system to ensure that the material produced is of prime quality and that a high productivity level is achieved.

The novel control architecture incorporates three main components. Firstly, process models are used to predict the states of the rolling process prior to rolling. These models predict the rolling load, motor power and strip temperature, thermal camber of the work rolls, deflection of the mill stack and the profile and shape of the strip. Adaptation ensures that there is good agreement between measurements and the model predictions. The adaptation is split into two main levels. A Kalman filter is used to predict short term errors in the process model from one pass to the next. Long term variations in the process are tracked using the recursive least squares algorithm. Finally the expert system is used to schedule the mill, diagnose possible faults occurring within the process and to supervise the activities of the other components in the control system.

The system is demonstrated in simulation and comparisons are made with and without the expert system control. The results show that there are distinct improvements to be gained with the application of artificial intelligence to an industrial control problem, in this case a hot aluminium rolling mill.

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TABLE OF CONTENTS

NOMENCLATURE

A	=	strip cross sectional area
A_B	=	back-up roll cross sectional area
A,B,C	=	state transition matrices
A_W	=	work roll cross sectional area
a	=	set of model parameters
B	=	length of work barrel
C	=	strip crown
C_{DF}	=	roll deflection
C_{FL}	=	roll flattening
C_{mech}	=	mechanical crown of rolls
Cp_1	=	specific heat of strip
Cp_2	=	specific heat of roll
C_{TH}	=	thermal crown
E	=	motor power
E_B	=	back-up roll Young's modulus
E_W	=	work roll Young's modulus
E_2	=	Young's modulus of work roll
f	=	forward slip
f	=	total horizontal force acting on a given cross section
G	=	torque
G_B	=	back-up roll shear modulus
G_W	=	work roll shear modulus
h_1	=	entry strip thickness
h_2	=	exit strip thickness
h_m	=	average strip thickness in roll bite
h_n	=	strip thickness at neutral plane
I_B	=	back-up roll moment of inertia
I_W	=	work roll moment of inertia
J	=	cost function

J_B	=	back-up roll bending
J_W	=	work roll bending
K	=	filter gain vector
K	=	strip profile
k	=	flow stress of strip
k^*	=	modified flow stress of strip
k_B	=	back-up roll shape factor (4/3)
k_W	=	work roll shape factor (4/3)
k_1	=	thermal conductivity of strip
k_2	=	thermal conductivity of roll
L	=	length of strip wave
L	=	length of the arc of contact
L_B	=	distance between back-up roll bending cylinders
L_{cc}	=	distance between roll load cylinders
L_n	=	length of arc of contact to neutral plane
L_W	=	distance between work roll bending cylinders
L'	=	deformed length of arc of contact
ΔL	=	elongation of strip in longitudinal length
P	=	rolling load
P	=	error covariance matrix
Q	=	variance of system state
Q_p	=	geometric factor in load model
R	=	height of wave
R	=	work roll radius
R	=	universal gas constant, 8.314 (J/mol/K)
R	=	variance of system measurement
R'	=	deformed roll radius
s	=	normal pressure between roll and strip
T_A	=	ambient air temperature
T_{B1}	=	strip entry temperature to the roll bite
T_{B2}	=	strip exit temperature from roll bite

T_L	=	Leidenfrost temperature
T_W	=	coolant wash temperature
T_{W1}	=	strip temperature into entry wash
T_{W2}	=	strip exit temperature from exit wash
T_1	=	initial strip temperature for pass
T_2	=	final strip temperature for pass
t	=	time
u(x)	=	roll flattening at point x
V_T	=	threshold speed
v	=	noise on system measurements
v_1	=	entry strip speed
v_2	=	exit strip speed
v_m	=	mill speed
W	=	strip width
w	=	noise on system state
w	=	strip wedge
y	=	system observation
z	=	measured system observation
α	=	alloy strength factor
α_1	=	thermal diffusivity of strip
α_2	=	thermal diffusivity of roll
β	=	forgetting factor
δ	=	draft
ϵ	=	strain
ε	=	strip shape (I units)
ε	=	strip strain (shape)
ϵ_1	=	strip emissivity
ϕ	=	roll bite angle
ϕ	=	length of strip perimeter
ϕ_n	=	roll bite angle at neutral plane
Γ_{ARM}	=	lever arm ratio

η	=	motor efficiency
λ	=	elastic recovery constant
λ	=	weighting function
ν_2	=	Poisson's ratio of work roll
θ	=	adaptation coefficient
ρ_1	=	density of strip
ρ_2	=	density of strip
σ	=	Stefan Boltzmann constant
σ	=	standard deviation of noise v
σ_1	=	entry tension
σ_2	=	exit tension
τ	=	interfacial shear stress
ω_1	=	flow stress modification factor for inhomogeneous deformation
ω_2	=	flow stress modification factor for thick stock
ξ	=	shape change coefficient
ζ	=	imprinting ratio

Subscripts

c	=	strip centre line
1e	=	strip drive side edge
2e	=	strip non-drive side edge

CHAPTER 1

Introduction

Recent years have seen a rapid increase in the computational capabilities of industrial control systems. Consequently complex control algorithms are now used in many processes that would not have been possible 20 years ago. Accurate mathematical models are now run in real time alongside the process in both the closed loop controllers and their associated supervisory systems. There is, however, always the need for these models to incorporate an adaptation scheme that will maintain and further improve the model performance. Model inaccuracies may lie in both the input data and internal model structure and it is the values of these components that adaptation will aim to adjust to attain optimum model performance.

The increase in the use of computer technology has resulted in an upsurge of interest in the area of artificial intelligence (AI). AI concepts and algorithms that were developed earlier this century are now being put to the test. The notion that intelligence can be embedded into an industrial control systems is indeed an exciting prospect. The goal of an entirely intelligent machine is still a remote prospect. However, some degree of intelligence has been incorporated into industrial control systems using such techniques as fuzzy logic, neural networks and expert systems. It is the latter which is of interest in this thesis.

The industrial application in this thesis is the hot rolling of aluminium. This thesis introduces an architecture for the integration of an expert system, process models and adaptation. The knowledge base within the expert system stores strategies which an experienced operator would use to ready the rolling mill to roll aluminium. The models provide forward predictions of process parameters, while the adaptation ensures model accuracy is maintained.

Chapter 2 contains background information on the various processing routes involved in forming aluminium into thin strip, in particular hot and cold rolling and strip casting. The chapter goes on to describe the parameters used to define the quality of the strip produced from the metal forming processes. The various levels of control within a hot mill are discussed together with some examples of mill actuation and instrumentation. The position of the control system described in this thesis within the overall process control hierarchy is defined, together with an illustrative example of how correct control leads to better performance. The chapter concludes with a survey of the literature relevant to this thesis.

In Chapter 3, the process models used within the control system are defined. An overview is first presented of the four primary process model blocks that describe the rolling process. These four model blocks are used to predict the rolling load, the main motor power and the strip temperature, thermal camber of the work rolls, the deflection of the mill stack and finally the profile and shape of the strip. Each model is discussed in detail in separate sections within this chapter.

The accuracy of the models, discussed in Chapter 3, is maintained with the use of adaptation and this is described in Chapter 4. The chapter begins by explaining why there is the need for adaptation and demonstrates how it interacts with the process models. It then goes on to define the method of producing first order derivatives needed when adapting the models. Later sections discuss the two levels of adaptation that track long term and short term variations within the process. The chapter concludes with a description of some implementation considerations that must be made to adapt the models in an on-line application.

Chapter 5 demonstrates how an expert system is used to encapsulate operator strategies and control rules into a knowledge base. The first section introduces the concepts of AI and shows why the rolling process is a suitable application for AI techniques. The primary components of an expert system are described together with some examples of typical language constructs. The knowledge base within the rolling mill expert system is defined and it is shown how the strategies and rules have been grouped into three main blocks. These are used to store strategies concerning mill scheduling, diagnostics and monitoring model and adaptation performance. Each of the rule groups is described in a separate section within the chapter. The concluding section presents the novel architecture that integrates the expert system with the process models and adaptation. Other constituents of the control system are also described here.

Finally Chapter 6 presents the conclusions from the work presented in this thesis. The original aspects of the work are highlighted, in particular the novel architecture that encapsulates a combination of technologies into one system. The thesis demonstrates an innovative approach to the control of the rolling process using an expert system. The references are listed at the end of the thesis, together with a list of the author's publications related to this thesis and to the subject of metal rolling.

It is the aim of this thesis to demonstrate how some of the control tasks required for supervisory control can be co-ordinated using an expert system. The main functions required at the supervisory level are:

I) A set of control strategies for setting the actuator set points prior to rolling.

ii) A suite of process models and their associated adaptation schemes, along with control of the updating of the adaptation algorithms.

iii) Measurement diagnostics and validation.

iv) Selecting suitable targets for the closed loop controllers.

CHAPTER 2

Background

This chapter gives an introduction to the processes involved in forming aluminium into thin strip. The principal metal forming techniques are casting and rolling. Alting [1] provides a summary of the manufacturing routes. A number of different combinations of these processes are required to produce strip of the desired thickness, surface finish and microstructure. Further processing of the strip may be necessary to either alter its surface finish or its metallurgical properties. Davis [2] gives detailed information about aluminium alloy composition and characteristics. The desired physical properties of the final aluminium product will be dependent upon its final application. The end use for the aluminium strip or foil include, beverage can production, the automotive industry, household aluminium foil and building construction. Hayter [3] and IOM [4] provide some illustrative examples of aluminium products. Although the specific application of each of these end users is different, each requires aluminium strip of the highest quality. In particular they demand consistency in the material's surface finish, geometry and metallurgy.

The manufacturers of flat, rolled products are driven by an economic need to maintain the highest efficiency possible, see Nussbaum [5] and Frampton [6]. This efficiency will be based upon the amount of high quality strip they produce, the production rates and the amount of scrapped material, for example see Barnes [7]. To further complicate the problem the production of a variety of final products is commonly required in a single production line. These products are distinguished from one other by the particular aluminium alloy, strip width and finish gauge. In the production environment, aluminium products are grouped into batches and it is rare that the process will reach a completely steady state condition.

During each processing stage that the strip undergoes, careful control is required of both the strip's geometry and metallurgy as outlined by Brooks [8]. Traditionally experienced operators are used, who using their own knowledge of the process are able to manually control the various process variables to meet the quality conditions. With the drive to become more efficient, aluminium producers are seeking to install automatic control systems which remove process variability.

The first section of this chapter presents an overview of the hot rolling process which is the main focus of attention in this thesis. Also described is cold rolling which is down stream of the hot rolling process. Consequently control on the hot mill will have a direct influence on how the cold mill is controlled. The second section outlines the main levels of control which are required in a modern aluminium production plant. The importance of controlling the initial setup of the process is highlighted. A summary is also presented of the main types of hot mill actuation and instrumentation that is currently available. The third section presents a definition of the problem to be examined in this thesis, together with a description of the case study to be considered. An illustrative example is given of how good supervisory control can improve the performance of the rolled product. The chapter concludes with the literature survey covering all aspects of the control of the rolling process.

2.1 Metal forming processes

The next two sub-sections provide an overview of the processes involved in hot and cold rolling and thin strip casting, Nussbaum [9] provides a very detailed description of each process involved in an aluminium plant. The third sub-section provides more detail on the mechanics of hot rolling. The final sub-section highlights the important factors which govern the production of good quality strip.

2.1.1 Hot forming processes

The forming of aluminium into thin strip requires several separate processes depending upon the desired final strip thickness, surface finish and metallurgical properties. Figure 2.1 shows the main operations which are involved in producing strip at a thickness of around 3mm to 8mm. The manufacture of aluminium strip commences with a process known as direct chill (DC) casting, some details are provided by Ocenasek [10]. The molten aluminium product is poured into a mould where it cools to form an ingot. This ingot is further processed by cutting it into shorter blocks and then scalping the surfaces. Scalping involves milling around 15mm off of the large flat surfaces to remove any oxides and segregates and to also present a smooth surface for rolling. The slabs produced in this way will be typically 500mm thick by 1000mm wide by 6000mm long. A batch of these slabs will then be placed into a preheat furnace for approximately 12 hours and heated to a temperature of around 500°C. This allows the complete homogenisation of the slab's microstructure to take place. At this higher temperature the material's yield stress is lower and forming of the material into thin strip is easier.

The slab's thickness is reduced by passing it through a combination of hot mills until the final thickness is produced. A Metals Society publication [11] compares different mill configurations. The principal mechanism involved in rolling is to apply a sufficiently large load to the material as it passes between a pair of rotating steel rolls, so that it goes into yield and undergoes plastic deformation. For hot rolling Roberts [12] provides a great deal of background information and although written for hot steel mills much of the material is still applicable to aluminium. The gap between the work rolls is set such that the strip will be reduced by a prescribed amount. The gap is actually set to a distance slightly smaller than the desired strip thickness to allow for the stretch of the mill housing and rolls when the rolling load is applied to the strip. The rolls are driven by motors which provide the power required to force the material through the roll bite so that it is deformed to its new thickness.

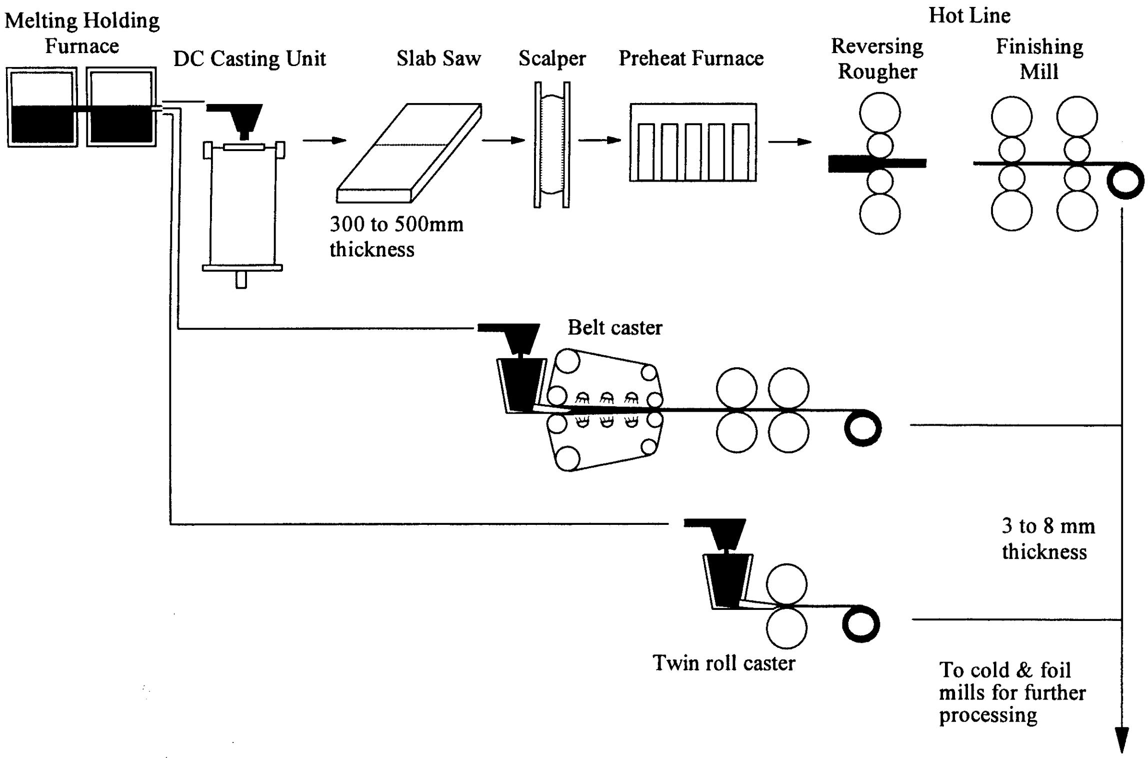


Figure 2.1 Hot processing of aluminium

Recently the development of strip casting processes for aluminium has meant that a 'nearer net shape' product can be produced, see Regan [13] and Birat [14]. This means the cast material has dimensions closer to those required for the final end product. There are two main types of continuous caster, twin roll and belt.

Twin roll casting involves pouring molten aluminium from a specially designed tip through a pair of rotating rolls, described by Cook [15]. The metal solidifies when it comes into contact with the rolls which are cooled internally with coolant sprays. The material is coiled once it leaves the caster and a shear will cut the material once a coil of sufficiently large size has been produced. Strip of around 3mm can be produced using this technique and the production rate is around 5m/min. Once the caster has reached a steady state condition, the process production time can be several days long. This makes it an ideal process for aluminium producer's interested in a single or a small product range.

The belt caster involves injecting molten aluminium in between a pair of counter rotating belts. The distance between the belts gradually tappers down, so that as the material solidifies, its thickness reduces to the desired gauge. The material is then passed to a hot mill at a gauge of around 20mm where it is further reduced in thickness and then coiled. Strip leaving the hot line can either be passed to the cold mill for further processing or cut into lengths for use as plate.

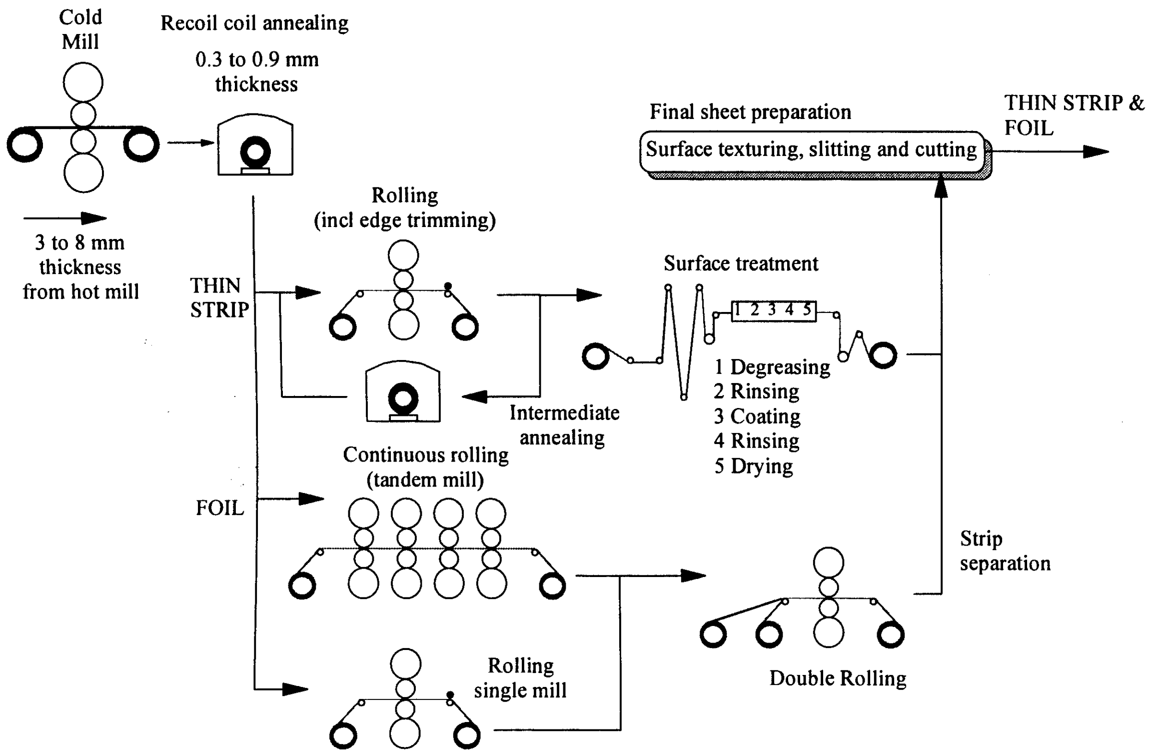


Figure 2.2 Cold processing of aluminium

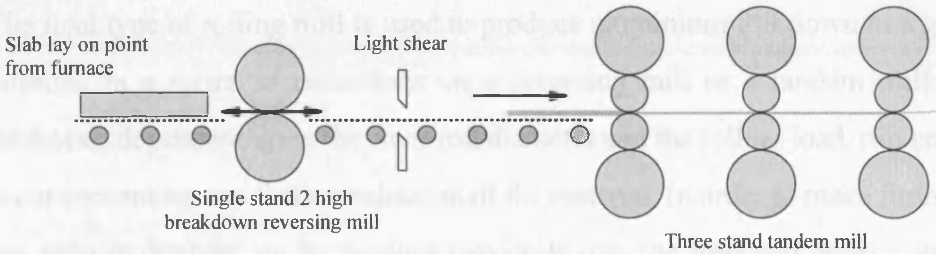
2.1.2 Cold rolling processes

Figure 2.2 shows the principal processes involved in producing strip at gauges ranging from a few millimetres to a few microns in thickness. The coils of aluminium produced from either hot rolling or continuous casting are passed to a cold mill. Again Roberts [16] is a useful reference, although steel biased. An Institute of Material publication [17] provides background material for aluminium rolling. A series of cold mill reductions will take place where the strip is reduced down to a thickness of approximately 0.3mm. During each reduction the strip is uncoiled, passed through the mill and then recoiled again on the other side of the mill. The temperature of the strip will increase from ambient temperature to around 80 °C. Reheating of the coil may be required to allow annealing to take place and consequently the production of the correct microstructure.

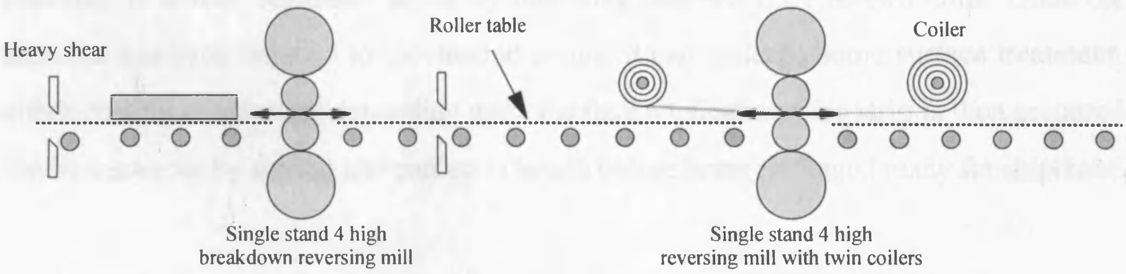
The final type of rolling mill is used to produce aluminium foil down to a gauge of a few microns in a series of reductions on a reversing mill or a tandem mill. At a certain thickness, dependent upon the work roll diameter and the rolling load, roll end contact will occur preventing any further reduction of the material. In order to make further reductions, the strip is doubled up by feeding two coils into the mill and coiling the doubled up material. It is then separated again by uncoiling and recoiling as two coils. Once the material has been reduced to the desired gauge, it can undergo some surface treatment, either coating or texturing depending upon the final application. The strip is then prepared for the customer by slitting and cutting to length before being packaged ready for shipment.

2.1.3 Mechanics of hot rolling

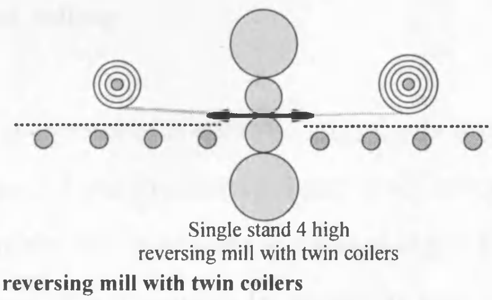
The primary metal forming process of interest in this thesis is the hot rolling of aluminium, see Starling [18]. Figure 2.3 shows the three main types of hot lines. From an initial DC cast thickness of 500mm the slab is reduced to a gauge of just a few millimetres, by a series of passes through one or two hot mills. Its thickness may then be further reduced by passing the strip through a cold mill and then a foil mill, as described above. Before hot rolling commences the slab is preheated in a furnace to a temperature of typically 500°C. This allows the slab to become fully homogenised and eliminates the effects of macrosegregation formed when the slab was cast. Hot rolling normally commences on a reversing breakdown mill where the slab is reduced in thickness by successively passing it from one side of the mill to the other. As the slab's thickness is reduced, its length will become longer and consequently a sufficiently long table is required to accommodate the strip. This table consists of a series of rollers which are motor driven and are capable of moving the slab from the furnace to the mill, for transfer to another mill or for shearing. The head and tail ends of the strip are often sheared to remove defects which can occur as the strip enters and leaves the rolls. The change in width of the strip during rolling is relatively small. However, some spread of material does occur during hot rolling, typically 25mm over a 1500mm wide strip. The strip edges can be trimmed when the strip is coiled to give a smooth edge finish.



i) Two high single stand reversing mill and three stand tandem mill



ii) Four high single stand reversing mill and four high single stand reversing mill with twin coilers



iii) Four high single stand reversing mill with twin coilers

Figure 2.3 Hot line configurations

Once the strip is reduced to a thickness of typically 24mm it will typically be at a temperature of 450 °C. Thereafter the strip must be coiled up, firstly to prevent too much heat loss to the surroundings and secondly so that its length can be accommodated in the production line. At this stage the strip can either be processed by a tandem mill or by a reversing mill. The tandem mill configuration consists of a series of stands, typically three or four. As the material passes through the mill, its thickness is reduced by each stand. The material is then coiled after the final stand at a temperature of around 300 °C. Such a mill requires a considerable capital investment, but has a larger production rate. The reversing mill type of configuration consists of a pair of coilers on either side of the mill. In some cases the same mill used to breakdown the slab is used for these final passes, as shown in Figure 2.3. In other cases a dedicated mill is used, the strip being passed from the breakdown mill along the connecting roller table. In the reversing mill the strip is passed from one coiler through the mill and then recoiled on the opposite side of the mill. A series of three or four passes are required to achieve the desired strip thickness. Having been reduced to a gauge of around 3mm the coiled strip is then allowed to cool before being passed from the hot mill to the cold mill.

In addition to the mill types described above, a number of different mill stack configurations exist. The two high configuration consists of a pair of work rolls, with the material passing between the rolls. By adding another pair of rolls, usually termed back-up rolls outside the existing work rolls, the stack becomes a four high mill. The added support of the back-up rolls has the advantage of allowing the work roll diameter to be reduced and consequently a reduction of the required rolling load. An additional pair of intermediate rolls can be added to the stack to form a six high mill. Such a configuration offers some additional control of the strip's geometry.

2.1.4 Definition of strip quality parameters

At all stages in these processes it is desirable to control the quality of the strip, which is mainly dependent upon its geometric and metallurgical properties as well as its surface finish. The strip geometry is defined by the following parameters as given by Ginzburg [19]:

i) Centreline gauge is defined as the thickness midway across the strip's width h_c.

ii) Profile is the difference between the strip centre and edge thicknesses expressed as a percentage ratio, defined by:

$$K = \frac{h_c - \dfrac{(h_{1e} + h_{2e})}{2}}{h_c} \times 100\,\% \tag{2.1}$$

iii) Wedge is the difference between the two edge thicknesses expressed as a percentage ratio, defined by:

$$w = \frac{(h_{1e} - h_{2e})}{h_c} \times 100\,\% \tag{2.2}$$

iv) Shape is defined as the deviation of the strip from perfect flatness in the longitudinal direction, defined by:

$$\epsilon = \frac{\Delta L}{L} = \left(\frac{\pi\ R}{2\ L}\right)^2 \tag{2.3}$$

and in terms of I units, which is a common conversion factor used when expressing shape:

$$\varepsilon = \left(\frac{\pi\ R}{2\ L}\right)^2 \times 10^5 \quad (I\ units) \tag{2.4}$$

v) Percentage of strip in the longitudinal direction which is within the quality limits.

Figure 2.4 also gives a definition of these parameters.

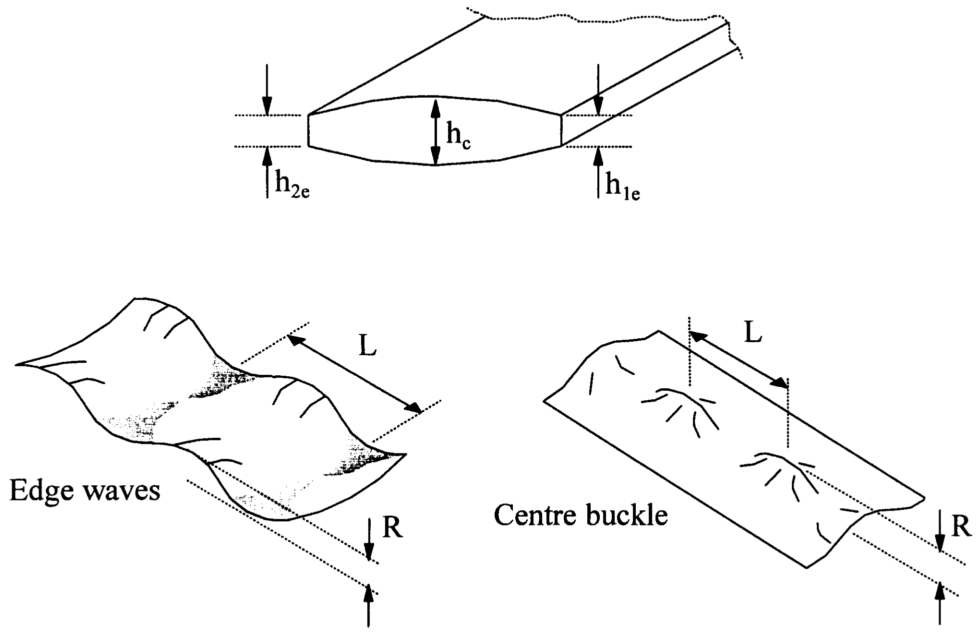


Figure 2.4 Definition of strip geometric properties

The microstructure and hence the strength of aluminium is influenced by the addition of alloying elements. For example, Mg, Cu, Zn and Si are added to increase the aluminium's strength for use as can end, structural panels or auto body parts. Aluminium in its pure soft form is more commonly used for food packaging where a higher strength is not required. The addition of the alloying elements means that the temperature time transition of the material is critical if the correct grain size and phases are to be produced. This results in constraints being imposed on the process, typically the strain rate during rolling and limits on the strip temperature after hot and cold rolling. Sheppard [20] and Langdon [21] provide descriptions of the main factors influencing microstructural evolution during rolling.

The surface finish of the aluminium is also an important parameter, see an Aluminium Association publication [22]. Surface marks can occur if the work rolls become worn or damaged in some way. Hot spots on the work rolls can produce a band running along the length of the strip. This can be due to faulty roll coolant equipment or because the controlled coolant spray level is allowed to drop too low. Another surface problem is caused by mill vibration when the roll speed reaches a critical resonant point and this can lead to mills having to run at lower speeds.

Production engineers are also interested in ensuring that the production line is run with as near maximum capacity as possible to achieve high productivity. The process speed, handling time, the amount of scrapped strip and the mill down time being the primary contributors to the productivity.

2.2 Control of the rolling process

In order to meet the quality and productivity demands for the rolling process, aluminium producers require sophisticated controllers which will automate as much of the operation as possible. Examples of such systems may be found in Bryant [23], IOM [24] and MacAlister [25]. Such automation replaces the traditional function of the mill operator, who uses his or her expertise to control the various process variables to produce good quality strip. One drawback from using operators is that this inevitably introduces some variability, as not all operators have identical skill levels. Process automation introduces both a consistent and an accurate degree of control.

2.2.1 Control hierarchy

Control of the rolling process is normally divided into three main levels. Figure 2.5 shows a block diagram of how these levels are split up for a rolling mill automation system.

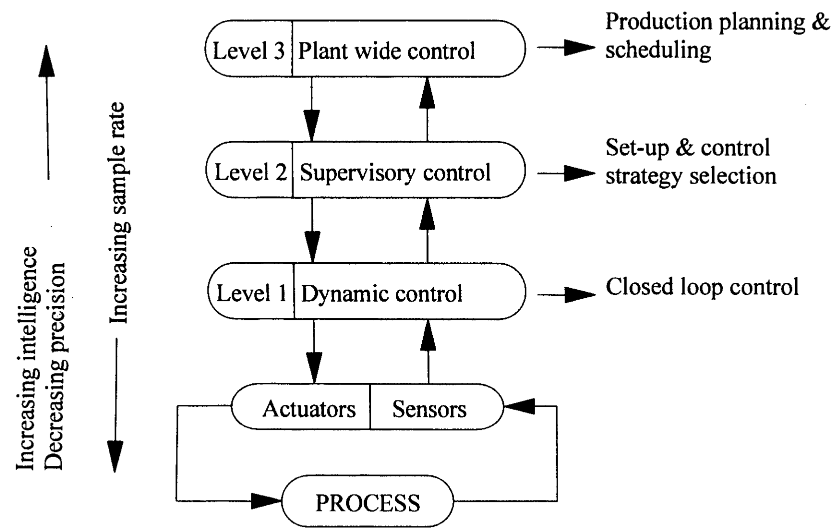


Figure 2.5 Process control hierarchy

Level 1 is concerned with controlling the inner closed loops of the system. These loops control the quality of the strip within a single coil. Measurements are fed into the controllers where the error is determined by comparison with the desired target value for the particular parameter. Modifications are then made to chosen actuators to eliminate this error. Variations in the exit gauge, strip temperature, profile and shape are typical parameters which are controlled at this level, Ginzburg [26], [27] and Beattie [28]. When designing the controllers particular consideration has to be made to the frequency response characteristics and the interacting nature of the rolling process.

The second level of control is usually termed supervisory control. This level is concerned with controlling the mill as a whole. The primary role is to provide suitable actuator set points and target values for the closed loops to aim for. For example, a run speed is required for the main mill motor to ramp up to, once the material has entered the roll bite. A suitable target strip profile is required by the closed loop profile controller in order to adjust the actuators during rolling. This control level also includes diagnostics to ensure that process measurements taken are valid and that the mill is producing good quality product. It is at this level that the thesis describes a novel approach to rolling mill process control. A full description of the requirements is given later in this chapter.

The third level of control is concerned with looking at the overall plant and evaluating the processing route for a given set of slabs. The task is traditionally performed by the scheduling engineer who looking at the order book, must decide in what sequence the slabs are to be rolled and how they will move around the production plant. The engineer must take into account how much room is available in the waiting bays, the length of mill down time due to maintenance and operate closely to a just in time philosophy. Similar products will be batched together to avoid variations in the mill operation. There will, however, be inevitable product changes which must be handled by the supervisory controller.

2.2.2 Rolling mill actuation

The actuators which are available to control the rolling process vary from mill to mill as does the degree of instrumentation. Ginzburg [29] describes the primary profile and flatness actuation available. The most common mill actuation scheme used to control the strip temperature is to use a combination of mill speed and strip cooling. Increasing the mill speed has the effect of increasing the temperature of the strip as it exits from the roll bite. This is due to the shorter contact time between the strip and the rolls and the strip and the coolant and hence a lower loss of heat. In some cases the mill speed cannot be modified because the aluminium product requires a specific strain rate. In this case control of the strip coolant provides a further temperature actuator. Additional coolant can be sprayed onto the strip to remove heat. Conversely the flow of coolant over the strip can be restricted with the use of a compressed air jet being blown onto the strip which has the effect of modifying the coolant wash length.

For strip profile a large variety of actuators are available, all of which in some way influence the roll gap profile and hence the strip profile. The four most common techniques used to control the strip profile are:

i) The rolling load is directly related to the reduction taken. By modifying the exit gauge for a given pass it is possible to influence the rolling load and hence the roll gap profile. When using this control method, careful checks are necessary to ensure that no problems are introduced for future passes, such as producing strip with dimensions longer than the maximum roller table length. Using such a control strategy is restricted to the setup level only.

ii) The work roll stack deflection can be influenced using work roll bend. This is, the application of a load between the work rolls using hydraulic cylinders to either push the roll ends apart or to bring them closer together. The work roll bend can be modified dynamically which enables it to be used by the closed loop controllers.

iii) The temperature and hence the thermal expansion of the work rolls can be affected by spraying more or less coolant onto them. This coolant comes from spray bars fitted with a number of nozzles spaced across the work roll barrel length. By setting the spray flow rate at different levels across the strip width it is possible to control the thermal camber and hence the strip profile. Work roll thermal camber control has a long time delay associated with it and for this reason it is most commonly used at the mill setup level, see Atack [30].

iv) The final type of profile actuator is based around the principle of replacing the work roll or the back-up roll with a specially modified roll or mechanism. Matsumoto [31] and Ginzburgh [32], compare around 54 patented types of profile actuation and examine their comparative control ranges. The type of actuation available is divided into three main groups:

a) The work rolls are modified usually with a special ground profile so that the roll gap profile is changed and the strip profile is affected. The controlling action can only be modified by changing the work rolls and the mill will be scheduled so as to roll products compatible with the particular ground camber.

b) The work rolls and/or the back-up rolls are replaced with a mechanism which allows the camber of the rolls to be modified when the mill is setup. Typical examples include: Side shifting work rolls which allow the roll camber seen by the strip to be varied by moving the work rolls axially, outlined by Nakajima [33]. The work rolls and back-up rolls can be rotated so that they cross at the strip centre-line, again providing a modification to the roll camber seen by the strip, for example see Kishi [34].

c) The top back-up roll is replaced with a hollow shell which contains hydrodynamic pads which can be controlled dynamically to influence the work roll to back-up roll load distribution and hence the roll gap profile, described by Morel and Bosh [35].

2.2.3 Rolling mill process measurements

The instrumentation which is available to the process controllers will vary from mill to mill. Ginzburg [36] presents a good summary of the available instrumentation for hot mill process control. The most common measurements which can be made are summarised below:

I) *Rolling load* is measured from the roll load cylinder pressure or alternatively if the mill is only fitted with screws then strain gauges can be fitted between the back-up roll bearings and the mill housing.

ii) *Main motor power* can be computed by measuring the motor voltage and motor current being drawn during rolling and knowing the motor characteristics.

iii) *Strip gauge* is measured using an isotope or X-ray source. As the strip passes through the source the amount of absorption is measured using a detector and hence the strip thickness is determined from previous calibrations of the instrument's absorption characteristics. Stayte [37] presents some recent advances in this area.

iv) *Strip profile* is measured by using multiple isotope or X ray sources across the strip width so that the thickness is measured at a series of points. The strip profile is calculated from the centre and edge strip thickness measurements. A description can be found in Shaw [38].

v) *Strip shape* is not commonly measured in aluminium hot mills. Techniques are available to either measure the latent shape of the strip, by passing the strip over a roll which is split into a number of independent zones. Each zone measures the tension within the strip and hence the strain and strip shape can be calculated. Manifest or visible strip shape is measured using lasers which can determine the size of any bad shape present as waves. One such device is described by Beattie [39].

vi) *Strip temperature* measurement is performed by using a contact thermocouple probe which is placed onto the strip either when it is being transferred from the furnace to the mill or when it is coiled up. Non-contact temperature measurement is performed using a pyrometer to measure the radiant energy emitted from the strip's surface. Metcalfe [40] describes one such product.

Such measurements will not be available at every processing stage of the slab. Typically temperature measurements can only be made if the strip remains underneath the pyrometer for a period long enough to ensure that the data acquisition is successful. The energy of the isotope sources used to measure strip profile and gauge are only strong enough to penetrate to a gauge of approximately 20mm which means that measurements of these parameters will be unavailable above this thickness. Other on-line measurements which one would like to have such as the size of the thermal camber on the work rolls cannot be directly measured at present. It is common to use process models to determine parameters which are not measured due to the lack of suitable instrumentation. Chapter 3 describes a set of process models which are used to provide predictions of such states.

2.3 Case Study

2.3.1 Description of process

The chosen case study for the thesis is a single stand reversing mill with twin coilers. The mill parameters are given in Table 2.1.

	Work roll	Back-up roll
Diameter (mm)	845.0	1492.0
Barrel length (mm)	2450.0	2450.0
Roll material	Cast steel	Cast steel
Ground camber (microns)	-200.0 parabolic	0.0
Cylinder centres (mm)	4000.0	
Work roll coolant spray pitch (mm)	72.0	
Coolant temperature (°C)	56.0	

Table 2.1 Mill parameters

Such a mill is used to breakdown slabs of aluminium from an initial thickness of 480mm to 3mm in typically 23 passes for the relatively hard aluminium alloy, AA5182. Table 2.2 gives the composition of this alloy. Table 2.3 gives a typical fixed schedule used to roll the material.

Alloy element	Si	Fe	Cu	Mn	Mg	Ni	Sn
Percentage of composition	0.25	0.7	0.1	0.1	8.0	0.05	0.05

Table 2.2 Composition of aluminium alloy AA5182

Initial slab condition								Target values	
Slab No	No of passes	Alloy	Width (m)	Slab length (m)	Slab gauge (m)	Temp (°C)	Profile (%)	Temp (°C)	Profile (%)
1	23	5182	1.68	5.9	0.480	480	0.0	300	0.7

Rolling schedule								Measurements			
Pass No	Exit gauge (m)	Roll speed (m/s)	Bend (Tonnes)	Spray level centre	Spray level edge	Entry tension (N/m²)	Exit tension (N/m²)	Load (Tonnes)	Power (MW)	Temp (°C)	Profile (%)
1	0.460	1.40	35	10	10	0.0	0.0	2115	8.40		
2	0.440	1.40	35	10	10	0.0	0.0	1909	6.74		
3	0.420	1.40	35	10	10	0.0	0.0	1997	7.85		
4	0.395	1.40	35	10	10	0.0	0.0	2020	9.20		
5	0.370	1.40	35	10	10	0.0	0.0	1977	8.61		
6	0.345	1.40	35	10	10	0.0	0.0	1994	9.51		
7	0.320	1.40	35	10	10	0.0	0.0	1878	8.34		
8	0.295	1.40	35	10	10	0.0	0.0	1879	8.41		
8	0.270	1.40	35	10	10	0.0	0.0	1758	7.96		
10	0.245	1.40	35	10	10	0.0	0.0	1726	7.99		
11	0.220	1.40	35	10	10	0.0	0.0	1679	7.78		
12	0.190	1.40	35	10	10	0.0	0.0	1703	8.52		
13	0.160	1.40	35	10	10	0.0	0.0	1713	8.35		
14	0.130	1.40	55	10	10	0.0	0.0	1717	8.28		
15	0.100	1.40	80	10	10	0.0	0.0	1760	8.23		
16	0.070	1.50	80	10	10	0.0	0.0	2145	10.74	487	
17	0.048	2.20	85	10	10	0.0	0.0	2277	14.66		
18	0.035	2.50	90	10	10	0.0	0.0	1795	9.63	478	
19	0.025	2.60	95	10	10	0.0	0.0	1861	8.48		
20	0.018	3.10	35	10	10	0.0	0.0	1936	9.11	452	
21	0.012	2.25	35	10	10	0.0	9e6	2605	6.60	385	
22	0.006	2.70	45	10	10	9.0e6	1.7e7	1746	5.45	356	
23	0.003	1.80	75	10	10	1.7e7	2.4e7	1531	1.61	308	0.78

Table 2.3 Typical schedule

The control actuators available on this particular mill is roll speed to control the strip temperature and work roll bend plus work roll cooling sprays to control strip profile. The mill in question also has instrumentation available to measure the rolling load, main motor power, strip temperature on certain passes and the strip profile on the final pass. Figure 2.6 shows a summary of the parameters involved in defining a pass on a single stand reversing mill.

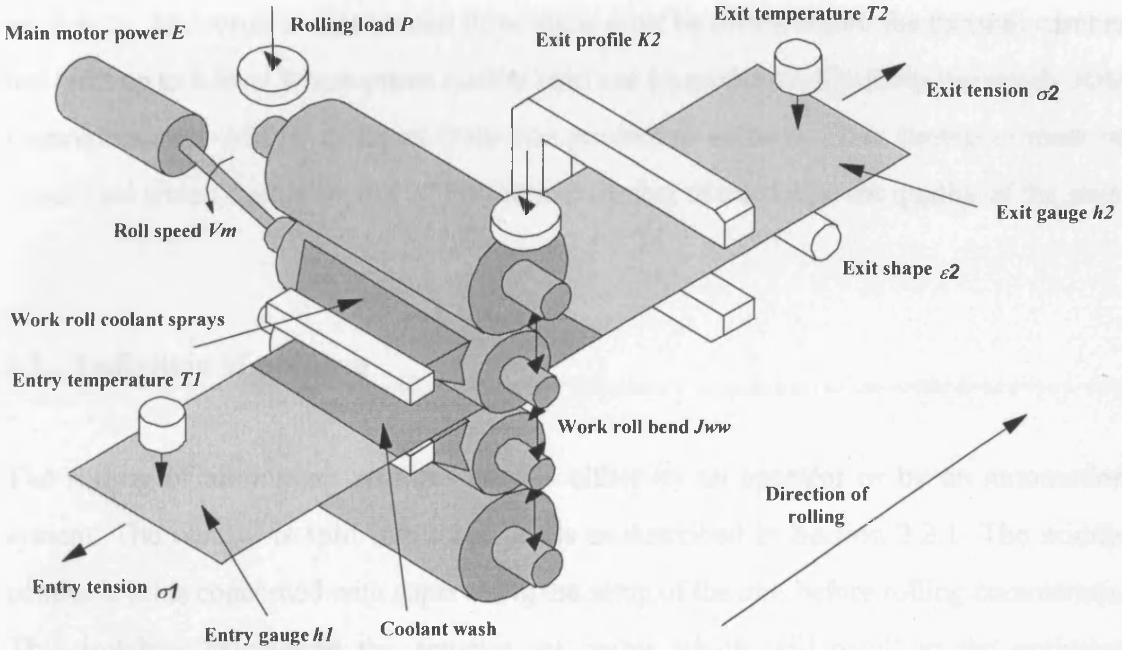


Figure 2.6 Single stand reversing mill with twin coilers

The rolling of aluminium is a batch process, which means that similar slabs are grouped together in a rolling sequence and each batch will consist of around five slabs. The slabs will be similar, in that they will be of the same product type. The characteristics which define a product are usually the aluminium alloy, strip width, the final gauge and final temperature. The slabs within each batch may however have some variation in their metallurgical composition and initial lay-on temperature. Such variations from batch to batch and from slab to slab will result in changes in the operating point of the mill. This operating point will be dependent upon the aluminium product being rolled, the particular schedule parameters and the mill conditions such as the thermal camber and the coolant properties.

The work rolls in the mill are changed every three or four days because of the effect of roll wear which can cause marking on the strip surface. The roll wear is caused by contact of the aluminium strip with the roll and thus the width of the wear will be dependent upon the width of the strip rolled. After the rolls are taken out of the mill they will be reground to remove the effects of wear.

After the rolls are replaced or after a long delay, there will be no thermal camber on the work rolls. The result is that around three slabs must be rolled before the thermal camber has built up to a level where prime quality strip can be produced. Similarly the steady state thermal camber will be different from one product to another. Thus strategies must be developed which enable control of the thermal camber to maximise the quality of the strip.

2.3.2 Definition of problem

The rolling of aluminium requires control either by an operator or by an automation system. The control is split into three levels as described in Section 2.2.1. The middle control level is concerned with supervising the setup of the mill before rolling commences. This involves calculating the actuator set points which will result in the optimum performance of the process. This means producing the maximum possible within specification strip despite variations in the process operating point. The actuators available in the selected case study are mill speed, work roll coolant sprays and work roll bend.

The performance of the mill is measured by the percentage of the strip which meets the target quality parameters given in Section 2.1.4. Trade-offs between these quality parameters can often occur as explained by Robinson [41]. For example ensuring that flat strip is produced whilst ensuring that the strip profile is as close to the target value as possible. Likewise, the level of coolant being sprayed onto the mill may have to be maintained above a threshold value to avoid surface marking of the strip. This may be in conflict with the requirements for thermal camber control.

The roll gap must be set so that the desired reduction of the material is achieved. In order to compensate for the mill stretch, the gap setting procedure requires a prediction of the steady state rolling load. This rolling load prediction also provides a means of checking that the proposed reduction will not exceed the mechanical limits of the mill. A prediction of the rolling power also ensures that the desired mill run speed will not overload the main mill motors.

In order to perform the above tasks information about the process must be gathered from either measurements, see Section 2.2.3 or from a set of process models, see Chapter 3. The models are used both as a forward prediction of parameters and to provide states within the process. Further, by differentiating the models, see Section 4.2, it is possible to obtain estimates of the actuator sensitivities which can be used for both mill setup and for closed loop control.

Maintaining the on-line accuracy of the process models is important if they are to provide information used to control the process. Model adaptation is used to recursively update parameter estimators which when applied to the models maintain their accuracy, see Chapter 4. Such model adaptation requires careful control to ensure that only validated measurements are passed to the algorithm.

Validating the measurements can be performed by comparing the measured data with previously logged information obtained from previous similar slabs. Measurements may also be validated by looking at the amount of scatter during the data logging interval or by cross checking several independent measurements and looking for consistency.

2.3.3 Illustrative example

To illustrate why there is the need for mill setup consider the following example:

Before the strip is threaded into the mill a steady state run speed is required. This provides the main mill motor speed controller with a target speed, allowing the mill to be accelerated smoothly up to run speed. Once the mill is operating at steady state, the strip temperature leaving the mill should be as close as possible to the desired target. This temperature will be specified in order that the required strip metallurgical properties are achieved. It is the task of the mill setup system to calculate the target run speed which will produce strip at the desired temperature.

Once operating at run speed, the closed loop temperature controller will make adjustments to the mill speed to ensure that the exit strip temperature is maintained at the target temperature. It is also assumed that a non-contact measurement of the strip exit temperature is available. Figures 2.7 and 2.8 show simulations of the variation of the mill speed and the exit strip temperature for one pass on a single stand reversing mill. The simulation was performed using the process models described in Chapter 3 and with a closed loop temperature controller described by Beattie [28]. The graphs in Figure 2.7 show the effect of using a larger target run speed than is actually required. The resultant initial strip exit temperature produced is larger than the desired temperature of 270°C. Following the threading of the strip, the closed loop temperature controller adjusts the mill speed until the desired temperature is achieved. The result is that the head end of the strip will not have the same metallurgical properties as the body of the strip. Consequently the commercial value of such a coil will be lower than if it was rolled having a consistent quality along its entire length.

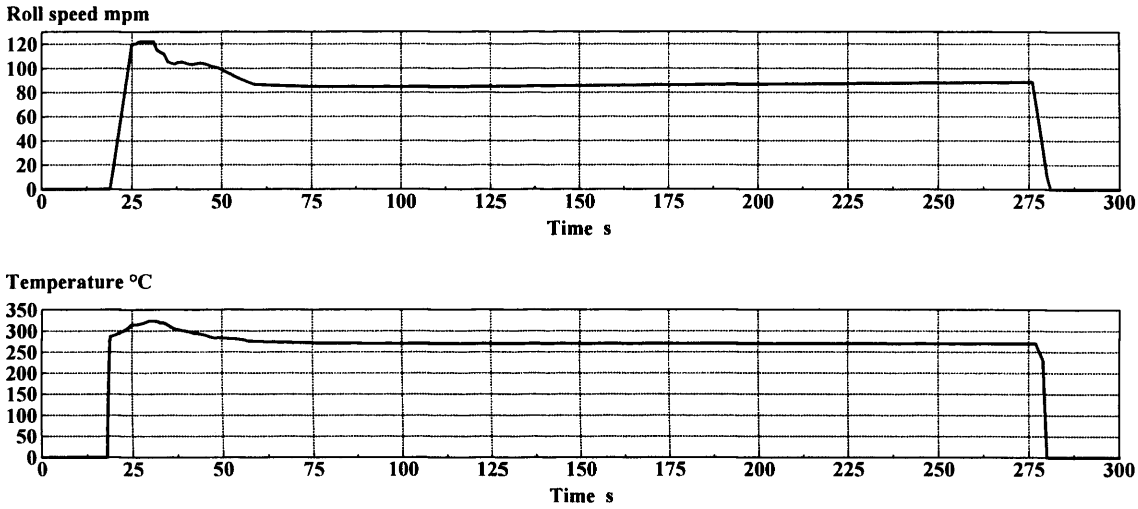


Figure 2.7 Strip temperature variation with poor initial speed set point

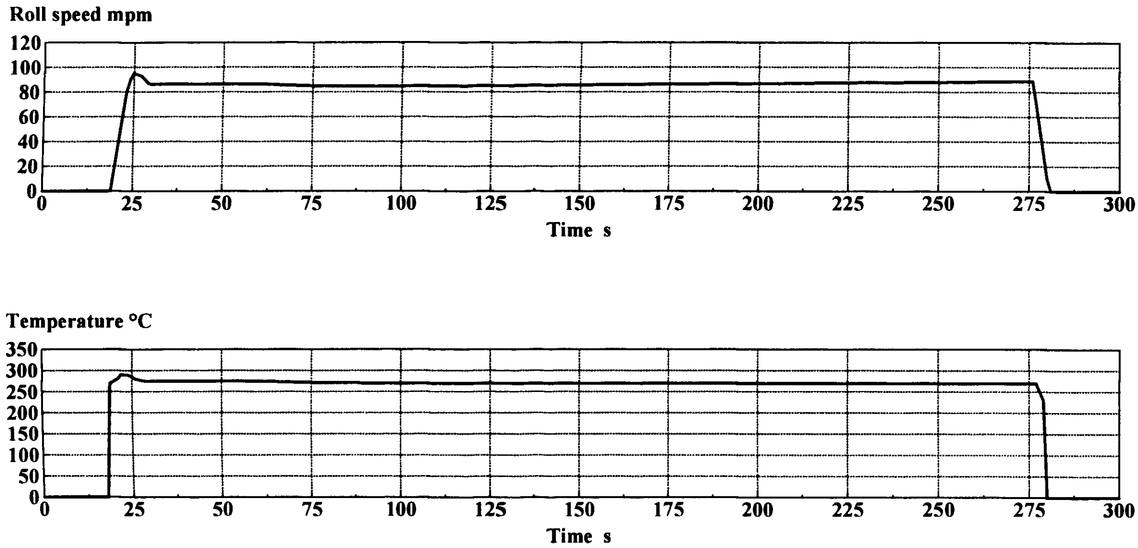


Figure 2.8 Strip temperature variation with good initial speed set point

The graphs in Figure 2.8 show the effect of using a target run speed which is close to that which is required at steady state. Subsequently once the strip is threaded the initial adjustment required to the run speed by the closed loop temperature controller is small. Hence the amount of off specification strip is now smaller than that shown in the previous figure.

2.4 Literature survey

This section presents a survey of the literature relevant to this thesis. Many of the references cited in this section are referred to again within the body of the thesis where the reference is of particular relevance. The survey is split into four key areas. First a brief summary is presented of the literature relevant to rolling mill process models. The survey continues with closed loop control applications within the rolling industry. The publications on mill setup are then discussed and finally a summary is made of plant wide control literature. Particular emphasis is placed on papers which have some AI content because of there particular relevance to this thesis.

There is a large body of published material on the modelling of the rolling process. Many models to calculate the mechanics of both hot and cold rolling have been developed. Sandmark [92] reviews and compares a number of different rolling models, including Seibel [94], Orowan [93], Alexander and Ford [42] and Sims [43]. Each model the deformation within the roll bite and develop expressions for the rolling load, deformed roll radius and forward slip. Three papers Hollander [44], Seredynski [104] and Kimura [45] provide a summary of the modelling involved in predicting the strip temperature, both within and outside of the roll bite. Sheppard and Wright [99] develop the fundamental flow stress constitutive equations for hot rolling of aluminium. Lenard [102] presents a summary of the frictional conditions within the roll bite, including attempts at measurement. The modelling of the work roll thermal camber has been investigated by a number of people including Bryant [23], Saer [46], Goodwin [47], Schipper [48] and Atack [30]. The calculation of the heat removal rate of work roll cooling sprays has been investigated by Davenport [49] The models fall into two main groups: solving the thermal conduction problem using a finite difference method or solving the heat conduction equations directly to give an expression for the roll temperature mesh, usually producing equations involving Bessel functions.

The deflection of the mill stack is another area where a number of papers has been published for a variety of mill stack configurations and actuators. Many are derived from the original work of Shohet [50]. Most use a discrete sampling of cross-directional variables to form a full width model of the roll stack. These account for non-linearity due to roll flattening, the variation of pressure distribution both axially and through the bite and conditions where partial roll contact occurs. Allwood [51] presents a fast roll stack model based on a matrix formulation and Misaka [110], Ogawa [114] and Huggins [52] are typical examples of roll deflection models based on classical roll bending theory. Shape and profile modelling are also well served within the literature. They range from very simple models based upon the principle of inheriting strip profile from one pass to the next and at the same time imprinting a new profile onto the strip from the roll gap, see Matsumoto [113] and Nakajima [53]. More complex iterative models take into account the variation of pressure distribution with the roll bite, lateral flow of the material and the effect on the tension distribution within the strip see for example Cresdee [54].

The advent of computer technology, firstly analogue and then digital, has seen a rapid and continual growth in the implementation of new closed loop control algorithms. These algorithms control the gauge, profile, shape and temperature of the rolled product. The earliest and most widely used gauge control principle was developed by the British Independent Steel Research Association (BISRA) . The strategy for controlling gauge is largely dependent upon the type of mill. Large tandem mills require regulation of each stand whilst maintaining mass flow and tension between the stands. Both conventional and multivariable control techniques have been applied. Hoshino [55] adopts an observer based approach to tandem mill gauge control problem, Postlethwaite [56] treats the mill as a single system applying H_∞ optimisation and Hearns [57] treats each stand as an individual system again applying multivariable techniques. Gauge control on single stand mills is considered by Nishida [58] and Kikuchi [59] who both examine an observer based approach to the control problem.

Shape control is mostly considered on cold mills, although some work is now being done on hot mills, see Beattie [39]. Papers consider and compare the use of different actuators for the control of shape. Any shape error is categorised into an appropriate polynomial form so that it can be corrected using the most suitable actuator. The papers by Naganuma [60], McDonald [61] and Carney [62] all develop models for predicting shape together with the control algorithms to divide shape correction between the appropriate actuator. Fuzzy logic has also been used to control shape. Hasegawa [63] and Jung [64] use fuzzy sets to categorise the shape defects and then infer the best corrective action to be taken using a knowledge base. Profile control is largely performed on the hot mills and practical control has only recently been possible due to recent advances in profile measurement. Beattie [65] describes a profile control system for an aluminium hot mill. Colas [66] and McNeilly [67] describe systems which integrate shape and profile control together for hot strip mills.

The control of temperature is more common within the steel industry to ensure the correct strip microstructure is produced. Ditzhuijzen [68] is a detailed summary of temperature control on a steel mill and Beattie [28] outlines a temperature control system for an aluminium hot mill.

There are many papers describing mill setup systems for both aluminium and steel mills. They are normally based around a suite of process models coupled with adaptation algorithms to adapt the models from pass to pass and slab to slab. Atack [106], [69], MacAlister [25], [70], [71] and Silvestrini [72] are some examples of such system for both aluminium and steel mills. None of these papers discuss in any detail the strategies which are to be used to setup the rolling mill. One paper by Stirling [73] uses an expert system for setup of a stainless steel rolling mill. Becker [74] describes how optimisation how has been used to determine rolling schedules given a set of target values for rolling load on each pass. Cotter [75] uses optimisation to determine the number of passes required to roll a particular product. The use of expert systems is more widespread in the plant wide scheduling of a production plant for tracking the location of coils within the plant, scheduling the order that coils should be rolled, surface inspection and shape defects.

Fujimoto [76] describes an expert system for the sequencing of slabs to be rolled in plant based upon the current order book. Haataja [77] describes the use of an expert system for surface inspection of steel strip. Hosoda [78] develops rules for transporting coils around a steel plant. Ishikawa [79] developed an expert system for determining the order that coils should be rolled in steel plant. Konishi [80] has used an expert system for foil rolling to classify shape defects and identify the optimum actuator corrections. Lassila [81] uses a knowledge base to aid scheduling through a large steel works from the furnaces through to a plate mill. Ng [82] is concerned with identifying and diagnosing abnormal plan view shape of plates from a steel mill using an expert system. Stohl [83] develops a rule base for scheduling within a steel plant. Other AI techniques are also now being used for the control and modelling of the rolling process. For example, Chung [84] uses a neural network in the prediction of material flow stress. Portmann [85] and Straub [86] use neural networks within classical process models to give estimates of certain model parameters. Fuzzy logic has been applied both to setup, Sakawa [87], and to shape control, Jung [64]. All these papers demonstrate that AI techniques can be applied to the rolling process with some significant improvements to the plant performance.

2.5 Conclusions

This chapter has presented a summary of the main processing routes in the production of aluminium strip. The various types of hot and cold mill lines have been presented together with the different types of mill stand configurations. A definition has been given of how the quality of the rolled product can be defined. A review has been made of the various control levels involved within a rolling mill control system. The actuators and instrumentation available on a rolling mill have been discussed. The problem to be addressed within this thesis is given together with an illustrative example which shows the advantages of introducing supervisory control at level 2 within the control hierarchy. Finally a review has been made of the literature relevant to this thesis.

CHAPTER 3

Metal Rolling Process Modelling

3.1 Overview

Mathematical modelling has proven to be a valuable tool to describe the metal rolling process, for example Kimura [88]. Models are used on-line within the controllers to provide forward predictions of parameter states and adaptive control gains. Due to the recent improvements in computer technology it is now possible to run complex models on-line, see Atack [69]. Such models still have to make a number of simplifying assumptions to reduce their running time to the order of a few seconds. Thus, there must be a trade off between the model accuracy and its computation time. One solution is to build into the models, algorithms which can compensate for any inaccuracies. Adaptation algorithms serve this purpose and Chapter 4 gives a description.

Off-line models are used as tools for simulating the process and for validating control strategies. The conditions that apply to models running on-line, also apply to off-line models where process simulations are required in the order of a few minutes. Again the models must be calibrated to ensure they correctly reflect the process. More complex models, which for example use the finite element technique to compute the deformation within the roll bite may still take many hours of computation time to converge to a solution.

This section will outline the mathematical models used to describe the hot rolling of aluminium, see Atack and Abbott [89]. The simplifying assumptions made in order to reduce the complexity of the models are stated. These models together with the appropriate adaptation schemes have been used on-line to control the rolling process. The evaluation of the process models' first order partial derivatives and the adaptation schemes for these models are described in detail in Chapter 4.

The models described in this chapter are divided into four groups.

i) **Rolling load, motor power and strip temperature.** The model for the cooling of the strip, includes the effect of heat transfer to air, the coolant wash and the work rolls. The model can be used to investigate the control of strip temperature using external strip cooling sprays and mill speed. The rolling load model considers the effect of the material's flow stress, roll bite friction and roll gap geometry. An accurate prediction of the rolling load is important when setting the roll gap in order to compensate for mill stretch. The main motor power prediction allows the roll speed to be modified without risk of overloading the main mill motors.

ii) **Thermal camber.** During rolling the work rolls expand due to heat conduction from the strip. The temperature of the roll in contact with the strip will be greater than that at the roll end. This temperature gradient causes a differential expansion of the roll along its length which is termed the thermal camber. Thermal camber is controlled by modifying the coolant to roll heat transfer coefficient. This is done using special spraybars fitted with variable level sprays. The thermal camber control range can be determined from the thermal camber model.

iii) **Stack deflection.** When the rolling load is applied to the mill stack, the rolls will bend and bed together. Flattening occurs between the work rolls and the strip and between the back-up rolls and the work rolls. The deflection and flattening can be influenced by profile control actuators such as work roll bend or side shifting rolls. Again the model can be used to investigate the control action of such actuators on the deflection of the work rolls.

iv) Profile and shape. Combining the thermal camber, stack deflection and roll flattening results in a roll gap profile. This will then imprint itself onto the strip. However, profile is not only dependent on the roll gap profile, but the entry profile to the mill and how it is attenuated in the roll bite. Flatness or shape depends upon how the profile changes as the passes are rolled.

Figure 3.1 shows the order in which these process models are run and how they interact with two further blocks which complement the process models. These two additional modules are:

i) Partial derivatives. These compute the model derivatives with respect to a variety of different independent variables. They are used by other components within the overall control structure in particular the closed loop controllers and the model adaptation.

ii) Adaptation. The purpose of the adaptation is to maintain the accuracy of the models by adjusting pre-defined model coefficients using a suitable adaptation algorithm. The model accuracy is evaluated by comparing the predictions with the corresponding measurements from the process.

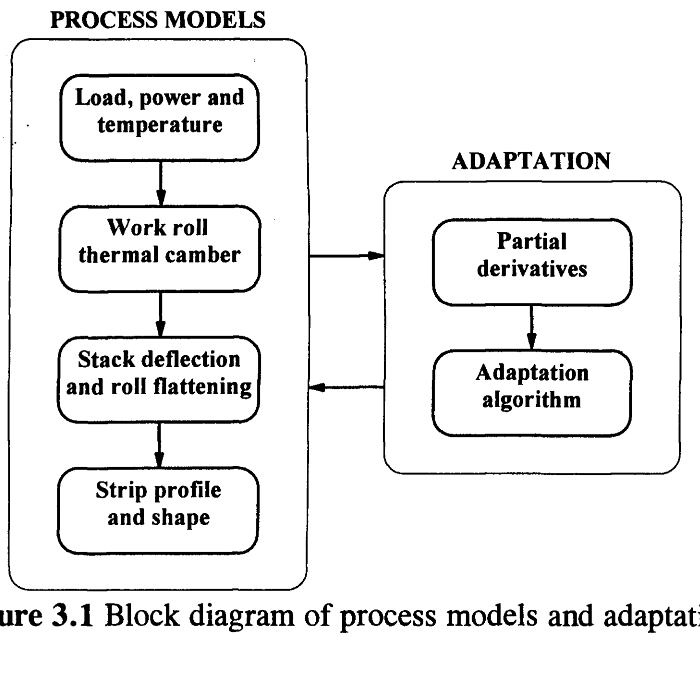


Figure 3.1 Block diagram of process models and adaptation

Although not discussed here there is a further model group which is important within the metal rolling industry. That is the models describing the microstructure of the material at each stage of rolling. Such models predict material properties such as the grain size, the degree of recrystallisation and texture. Microstructural control of the material during rolling is critical if it is to have the desired final properties. The temperature history of the material to a large extent determines the material's microstructure. Other factors such as the strain rate may impose restrictions on the systems controlling the process. For this reason both control and scheduling of the strip's temperature are important if the desired microstructure is to be achieved.

Figure 3.2 shows in more detail how the various process models interact with each other. Each of the modules shown in this figure is explained in this chapter.

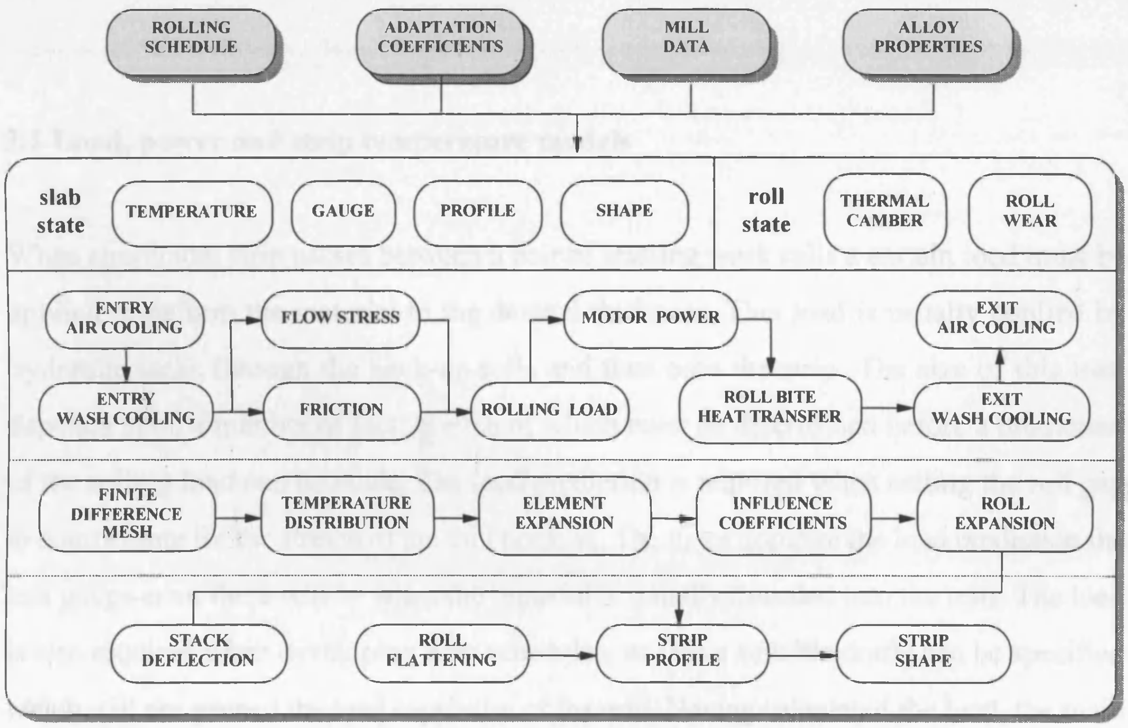


Figure 3.2 Process model modules

The figure also shows the various sets of input parameters passed to the models.

These are:

i) Rolling schedule The details used to define the initial slab state and the parameters required to roll each pass.

ii) Adaptation coefficients The adaptation coefficients which are used to calibrate the process models.

iii) Mill data This includes the roll and stack dimensions, the roll material properties and details of the roll and strip cooling configuration.

iv) Alloy properties These are the characteristics of the particular aluminium alloy being rolled and includes thermal, mechanical and microstructural properties.

3.2 Load, power and strip temperature models

When aluminium strip passes between a pair of rotating work rolls a certain load must be applied to deform the material to the desired thickness. This load is usually applied by hydraulic jacks through the back-up rolls and thus onto the strip. The size of this load depends upon a number of factors each of which must be determined before a prediction of the rolling load can be made. The load prediction is required when setting the roll gap to compensate for the stretch of the mill housing. The more accurate the load prediction the less gauge error there will be when the material is initially threaded into the mill. The load is also required when developing new schedules, so that a suitable drafts can be specified which will not exceed the load capability of the mill. Having calculated the load, the main motor power is relatively easy to evaluate. Again an accurate prediction of power is required to ensure that the motor limits are not exceeded when the schedule is developed. Predictions of strip temperature are required to ensure that the schedule is compatible with the microstructural requirements of the material.

3.2.1 Roll bite geometry

Figure 3.3 shows the basic roll bite geometry for rolling. The material enters the roll bite with a thickness of h_1 and is gradually reduced down between the work rolls, finally exiting with a thickness of h_2. The size of the reduction made or the draft δ is given by:

$$\delta = (h_1 - h_2) \tag{3.1}$$

Assuming a circular arc of contact, the average thickness of material within the roll bite h_m is given by:

$$h_m = \frac{1}{3}(h_1 + 2h_2) \tag{3.2}$$

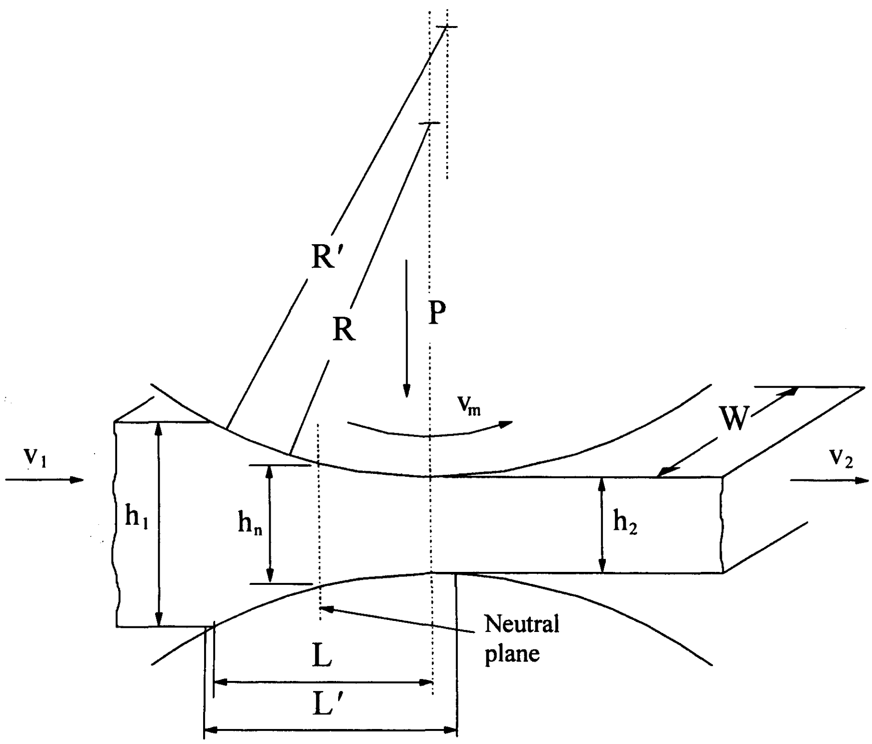


Figure 3.3 Roll bite geometry

The mass flow for the rolling process relating the entry and exit states may be written down as:

$$v_1 \, h_1 = v_2 \, h_2 \tag{3.3}$$

This assumes that there is little or no lateral spread of material from one side of the bite to the other, that is no significant change in the materials width W. Under normal rolling conditions the work rolls are rotating at a speed of v_m, which is slower than v_2 but faster than v_1. As a consequence there is a point within the roll bite where the strip is travelling at the same speed as the roll. This point is termed the neutral plane of the strip. The strip thickness at this point is h_n and is calculated within the rolling load model. The ratio between the strip speed at the neutral plane and that at the exit from the bite is termed the forward slip f, given by:

$$f = \frac{(v_2 - v_m)}{v_m} \tag{3.4}$$

The contact length L between the work roll of radius R and the strip may be written as:

$$L = \sqrt{R\ \delta} \tag{3.5}$$

Provided it is assumed that the angles involved are small, Hosford and Caddell [90]. The ratio of h_m / L is an important geometric characteristic as it describes the operating region of the material; thin or thick stock. Now when the rolling load P is applied to the work rolls, roll flattening occurs such that the roll's radius becomes larger. This has the effect of modifying the arc of contact to a longer length L':

$$L' = \sqrt{R'\ \delta} \tag{3.6}$$

where R', the deformed roll radius is given by the equation derived by Hitchcock [91]:

$$R' = R\left(1 + \frac{C}{\delta}\frac{P}{W}\right) \tag{3.7}$$

and C is a constant dependent upon the roll material, given by:

$$C = \frac{16\ (1 - \nu_2^2)}{\pi\ E_2} \tag{3.8}$$

where ν_2 is the work roll Poisson's ratio and E_2 is the work roll Young's modulus.

3.2.2 Rolling load

The fundamental mechanics of rolling have been discussed in numerous papers, primarily covering the hot and cold rolling of steel. These models can be extended to aluminium as the basic rolling mechanics are the same. A review of twenty-one rolling models may be found in Sandmark [92]. The model presented here uses results obtained by Orowan [93], which is generally accepted as the basis for most modern rolling theories. Within this model a number of assumptions are made:

i) The arc of contact between the strip and the work roll is a circle of constant radius R' from entry to exit. It is also assumed that the exit plane is tangential to the roll.
ii) The roll bite angle is small such that $\sin\phi=\phi$ and $\cos\phi=1$.
iii) Following Siebel [94], the interfacial shear stress between the strip and the rolls is constant along the arc of contact.
iv) Conditions within the roll bite are assumed to be constant, in particular the flow stress, strain rate and temperature.
v) The strip is fully plastic within the roll bite, the elastic zone at the entry and exit of the bite is assumed to have little or no effect on the rolling load.
vi) There is no significant change in the strip width and the ratio of the strip width to its thickness is such that the material is deformed under plane strain conditions.
vii) The material obeys the Von Mises yield criteria.

3.2.3 Derivation of load model

Referring to Figure 3.4 the forces exerted on the surface of a single element of strip per unit width for both top and bottom planes is:

$$\frac{\partial f}{\partial \phi} = 2\, R'\, s\, \phi \pm 2\, R'\, \tau \qquad \textbf{(3.9)}$$

where f is the total horizontal force acting on a given cross section, ϕ is the roll bite angle, s is the normal pressure between roll and strip and τ is the interfacial shear stress.

The use of the ± arises because the direction of the shear stress changes from one side of the neutral plane to the other due to the difference in the relative speeds of the roll and the strip.

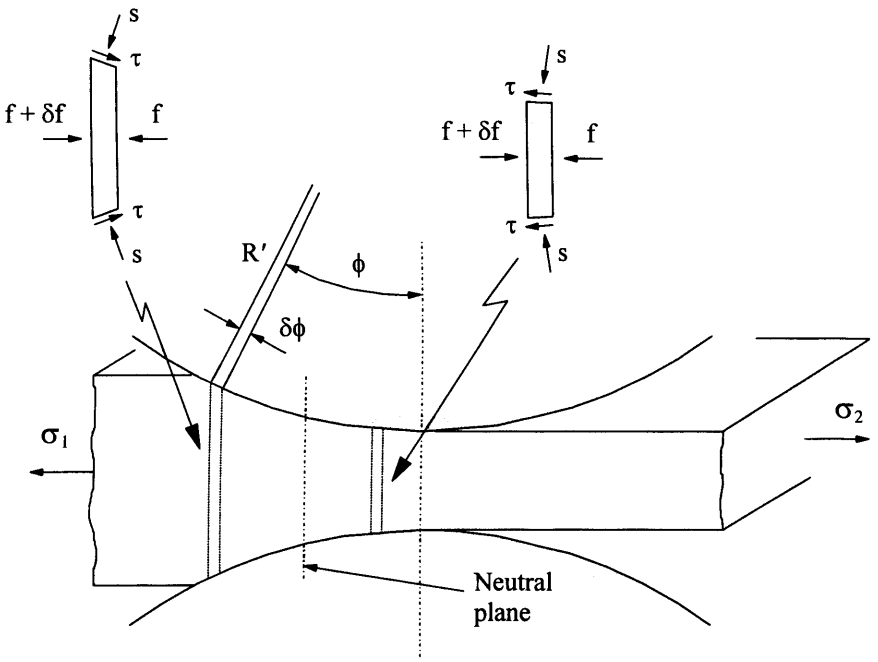


Figure 3.4 Rolling load analysis

Orowan went on to show that the relationship between the horizontal force f and the normal pressure s is given by:

$$f(\phi) = h(\phi)\,(s - k^{*}) \tag{3.10}$$

where $h(\phi)$ is the gauge thickness at the roll bite angle ϕ and the modified flow stress, k^* is introduced which corrects the flow stress k for thick stock and takes into account inhomogeneous deformation.

Now substituting Equation (3.10) into Equation (3.9) we obtain:

$$\frac{\partial[h(\phi)(s - k^{*})]}{\partial\phi} = 2\,R'\,s\,\phi \pm 2\,R'\,\tau \tag{3.11}$$

From the roll gap geometry it can be shown that:

$$h(\phi) = h_2 + R^{/} \phi^2 \tag{3.12}$$

Differentiating Equation (3.12) with respect to ϕ gives:

$$\frac{\partial h}{\partial \phi} = 2 R^{/} \phi \tag{3.13}$$

Substituting Equation (3.12) into (3.11) and using the result from (3.13) yields:

$$\frac{\partial(s - k^*)}{\partial \phi} = \frac{2 R^{/} k^* \phi}{h_2 + R^{/} \phi^2} \pm \frac{2 R^{/} \tau}{h_2 + R^{/} \phi^2} \tag{3.14}$$

Dividing Equation (3.14) through by k^* produces:

$$\frac{\partial\left(\frac{s}{k^*} - 1\right)}{\partial \phi} = \frac{2 R^{/} \phi}{h_2 + R^{/} \phi^2} \pm 2 \left(\frac{\tau}{k^*}\right) \frac{R^{/}}{h_2 + R^{/} \phi^2} \tag{3.15}$$

Now the rolling load per unit width $\bar{P}$ is found by integrating the area under the s vs ϕ curve from the entry side (angle of ϕ_1) to the exit side (angle of 0):

$$\frac{\bar{P}}{k^*} = R^{/} \int_0^{\phi_n} s(\phi)^+ \, d\phi + R^{/} \int_{\phi_n}^{\phi_1} s(\phi)^- \, d\phi \tag{3.16}$$

Putting in the appropriate boundary conditions for entry and exit stress on the strip (σ_1 and σ_2 respectively) , yields the rolling load per unit width as:

$$\bar{P} = k^* L^{/} \left[2 \sqrt{\frac{h_2}{\delta}} \arctan \sqrt{\frac{\delta}{h_2}} - 2 \left(\frac{\tau}{k^*}\right) \sqrt{\frac{R^{/}}{\delta}} \ln \left(\frac{h_n}{\sqrt{h_1 h_2}}\right) - 1 - \frac{\sigma_1}{k^*} \right] \tag{3.17}$$

and the angle at the neutral plane ϕ_n as:

$${}_n = \sqrt{\frac{h_2}{R^{/}}} \tan \left[\frac{1}{2} \arctan \sqrt{\frac{\delta}{h_2}} + \frac{1}{4} \left(\frac{k^*}{\tau}\right) \sqrt{\frac{h_2}{R^{/}}} \left(\ln \left(\frac{h_2}{h_1}\right) - \frac{\sigma_1}{k^*} + \frac{\sigma_2}{k^*} \right) \right] \tag{3.18}$$

The gauge at the neutral plane h_n can be calculated by substituting ϕ_n for ϕ in Equation (3.12):

$$h_n = h_2 + R' \phi_n^2 \tag{3.19}$$

The total rolling load P is calculated using the equation below:

$$P = k^* W L' Q_p \tag{3.20}$$

where Q_p is the geometric function in square brackets in Equation (3.17).

3.2.4 Correction of flow stress

Within the rolling load model it has been stated that the flow stress k is corrected to account for thick stock and for inhomogeneous deformation, to produce a modified flow stress, k^* given by:

$$k^* = \omega_1 \omega_2 k \tag{3.21}$$

Lalli [95] showed that ω_1, the modification factor accounting for inhomogeneous deformation, that is the material not remaining plane during compression within the roll bite, can be written as:

$$\omega_1 = \sqrt{\left(1 - 4\left(\frac{\tau}{k}\right)^2 c^2\right)} \tag{3.22}$$

where c is given by:

$$c = 0.6 \qquad for \ \frac{h_m}{L'} \leq 1.0 \tag{3.23}$$

and

$$c = 1.1 - \frac{1}{2}\frac{h_m}{L'} \qquad for \ \frac{h_m}{L'} > 1.0 \tag{3.24}$$

the modification factor ω_2 which corrects for thick stock material when the ratio of h_m / L'

becomes greater than 1.0, then following MacGregor and Palme [96]:

$$\omega_2 = 1.0 \qquad for \ \frac{h_m}{L^{/}} \leq 1.0 \tag{3.25}$$

$$\omega_2 = 0.75 + 0.25 \frac{h_m}{L^{/}} \qquad for \ 1.0 < \frac{h_m}{L^{/}} \leq 8.0 \tag{3.26}$$

and

$$\omega_2 = 2.75 \qquad for \ \frac{h_m}{L^{/}} > 8.0 \tag{3.27}$$

3.2.5 Model iterations

Within the load, power and strip temperature model it is necessary to set up two iteration loops in order to converge the models to a solution. This is necessary for two reasons:

i) The inter-dependence of the deformed roll radius and the rolling load, see Equations (3.7), and (3.17). Starting with the deformed roll radius set equal to the undeformed roll radius, the model calculates the rolling load P. This then gives a new estimate for $R^{/}$ and the procedure is repeated until convergence is achieved.

ii) The dependence of the entry bite temperature T_{B1} on the entry strip speed v_1 and consequently upon the forward slip. This relationship can be seen from Equations (3.3) and (3.28).

$$v_2 = v_m (1 + f) \tag{3.28}$$

The forward slip calculation within the rolling load model is dependent upon the flow stress and therefore the bite entry temperature. A starting value for the forward slip is chosen and the load, power and strip temperature models are iterated until the forward slip converges.

The second iteration loop is placed around the first with both loops placed around the load, power and strip temperature models.

3.2.6 Main motor torque and power

The torque G that is required to rotate one work roll, assuming that a roll separating force P is acting in the middle of the arc of contact is given by:

$$G = \frac{L^{/}}{2} P \qquad \textbf{(3.29)}$$

Within the process models the calculation of torque is split into two regimes; one model being applied for thick material and one for thin material. The model used for thick stock material extends Equation (3.29) with a parameterised form for the calculation of the length of the lever arm. The model following on from work initially carried out by Denton and Crane [97], takes the form of:

$$G = 2\, \Gamma_{ARM}\, L^{/}\, P \qquad \textbf{(3.30)}$$

where the lever arm ratio Γ_{ARM} is calculated from the parameteric model:

$$\Gamma_{ARM} = \Gamma_1 + \Gamma_2 \left[\frac{2\,R^{/}}{h_1}\right] + \Gamma_3 \sqrt{\frac{2\,R^{/}}{h_1}} \qquad for \left[\frac{2\,R^{/}}{h_1}\right] \leq 25.0 \qquad \textbf{(3.31)}$$

and

$$\Gamma_{ARM} = \Gamma_1 + 25.0\,\Gamma_2 + 5.0\,\Gamma_3 \qquad for \left[\frac{2\,R^{/}}{h_1}\right] > 25.0 \qquad \textbf{(3.32)}$$

The method of determining the constants $\Gamma_{1,}\Gamma_2$ and Γ_3 is discussed in Chapter 4.

The model for thin material follows that developed by Darby [98], which calculates the torque by taking the difference between the interfacial shear stress at the entry and exit sides of the neutral plane, thus:

$$G = 2\, R'\, W\, \tau\, (L' - 2\, L_n) \tag{3.33}$$

where τ is calculated by from:

$$\tau = k \left(\frac{\tau}{k} \right) \tag{3.34}$$

For both thick and thin material the total motor power is given by the following equation:

$$E = \frac{G\, v_m}{R\, \eta} \tag{3.35}$$

where is the η motor efficiency.

3.2.7 Flow stress

For a particular aluminium alloy a prediction is required of the yield or flow stress of the material. This is the value of the stress at which the material will start to yield and undergo permanent plastic deformation and this is an important parameter within the rolling load model.

The flow stress k is calculated using a constitutive equation, see Sheppard & Wright [99] which takes the form:

$$k = \alpha\, \epsilon^{\frac{B}{T_{BI}}} \ln \left[\left(\frac{Z}{A} \right)^{\frac{1}{n}} + \sqrt{\left(\left(\frac{Z}{A} \right)^{\frac{2}{n}} + 1 \right)} \right] \tag{3.36}$$

where Z is the temperature compensated strain rate given by:

$$Z = \boldsymbol{\theta} \exp \left(\frac{Q}{R'\, T_{BI}} \right) \tag{3.37}$$

The strain rate $\dot{\epsilon}$ is given by:

$$\dot{\epsilon} = \frac{V_m}{\sqrt{R\ \delta}} \ln\left(\frac{h_1}{h_2}\right) \qquad \textbf{(3.38)}$$

and the strain ϵ is given by:

$$\epsilon = \ln\left(\frac{h_1}{h_2}\right) \qquad \textbf{(3.39)}$$

The constants α, A, Q, B and n are determined experimentally for a range of different aluminium alloys, Atack [100].

3.2.8 Roll bite friction

In order to accurately predict the rolling load, a model of the variation of the friction between the strip surface and the work rolls must be developed. When the material is relatively thick (above 30mm) it is generally agreed that friction is relatively unimportant due to the nature of the deformation. This means that the interfacial shear stress τ is large enough to yield the material's surface, so that the τ/k ratio (the friction) is equal to 0.5. The shearing of the material occurs because at thicker gauges the material's flow stress is lower than that at thin gauges. Below a gauge of 30mm the friction becomes smaller than 0.5 and shearing of the materials's surface no longer occurs. The model developed by Abbott [101] assumes that the friction is a function of the strip bite entry temperature T_{B1}, the roll speed and the geometrical ratio h_m / L'. The model has the following form:

$$\left(\frac{\tau}{k}\right) = A_1\ T_{BI}^{A_2} \left(\frac{h_m}{L'}\right)^{A_3} (V_m + A_5)^{A_4} \qquad \textbf{(3.40)}$$

Subject to the following constraint:

$$\max\left(\frac{\tau}{k}\right) = 0.5 \qquad \textbf{(3.41)}$$

Figure 3.5 shows a plot of the variation of the friction with strip bite entry temperature. The coefficients A_1 to A_5 are constants which are computed when the model is calibrated. The constants will vary from alloy to alloy and from mill to mill, because factors such as the mill lubrication properties, roll roughness and strip surface finish will greatly influence the friction. Attempts to directly measure the friction in the laboratory have been attempted by Lenard and Malinowski [102]. Here pressure pins mounted into the work roll are used to measure the shear stress and the pressure distribution under different hot rolling conditions.

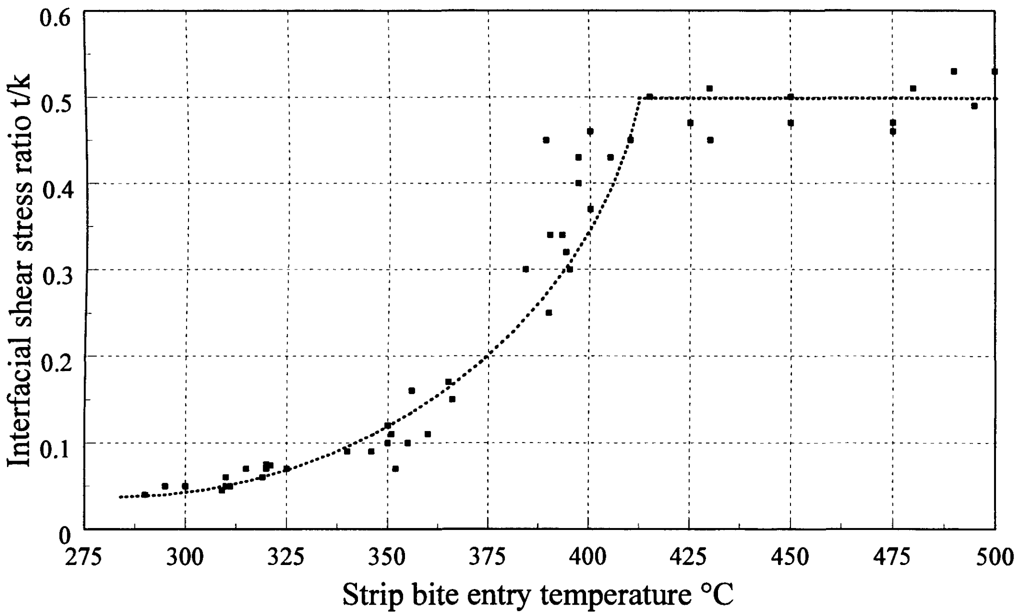


Figure 3.5 Variation of friction with strip bite entry temperature

3.2.9 Strip temperature models

There are four main mechanisms by which the strip will gain or lose heat during rolling. These are:

i) By contact with air when heat is lost due to radiation and natural convection.

ii) By forced convection when the strip moves through the coolant wash.

iii) By conduction of heat from the strip to the work rolls when the strip passes through the roll bite.

iv) Heat is generated within the strip due the plastic deformation.

On some mills actuators are fitted which are used to control of the amount of coolant falling onto the strip. The most common control method is to use compressed air jets to blow the coolant off of the strip which has the effect of fixing the coolant wash length. Additional banks of sprays can be installed over the strip which are switched on or off to allow more or less strip cooling to take place. Figure 3.6 shows the five temperature zones that the strip will go through for one pass on a single stand reversing mill.

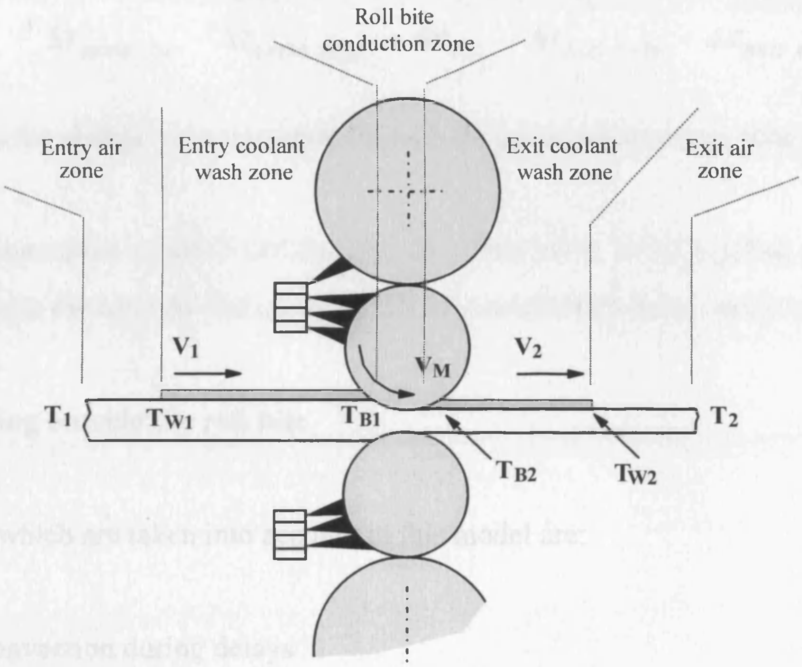


Figure 3.6 Strip temperature model zones

Within the strip temperature model a single point on the strip is tracked as it passes through the various temperature zones. The position of this point can be varied from the head to the tail end of the strip, so that variation in the strip's temperature along it's length can be predicted.

The change in temperature of the strip from entry T_1 to exit T_2 is given by:

$$T_2 = T_1 - \Delta T_{ENTRY\ AIR} - \Delta T_{ENTRY\ WASH} - \Delta T_{BITE} - \Delta T_{EXIT\ WASH} - \Delta T_{EXIT\ AIR} \quad \textbf{(3.42)}$$

where ΔT_i is the change in temperature through the given temperature zone i.

The strip temperature model is divided into two main parts; firstly dealing with the heat transfer outside the roll bite and secondly the heat conduction to the work rolls.

3.2.10 Cooling outside the roll bite

The factors which are taken into account in this model are:

i) Natural convection during delays
ii) Radiation losses
iii) Forced convection losses when the slab is moving through air
iv) Heat extracted by the coolant wash

The assumption is made that because aluminium is a good conductor of heat, there will be no significant through thickness variation in the temperature. The general equation governing the temperature T of the slab is given by:

$$\frac{dT}{dt} = -\frac{\phi\, h\, (T - T_A)}{A\, \rho_1\, C_{p1}} \quad \textbf{(3.43)}$$

where A is the strip cross sectional area, ϕ is the perimeter length of the strip cross section and T_A is the ambient temperature. If it is assumed that the heat transfer coefficient h is not a function of temperature then Equation (3.43) can be integrated to give:

$$T_{exit} - T_A = (T_{entry} - T_A) \exp\left(\frac{\phi\ h\ t}{A\ \rho_1\ C_{p1}}\right) \qquad \textbf{(3.44)}$$

For each of the cooling modes the appropriate heat transfer coefficient h and ambient temperature T_A is used.

3.2.11 Air heat transfer coefficient

For the losses due to radiation the Stefan Boltzmann equation is applicable, Holman [103], which is written as:

$$\frac{dT}{dt} = -\frac{\phi\ \epsilon_1\ \sigma}{A\ \rho_1\ C_{p1}} \left[(T + 273)^4 - (T_A + 273)^4\right] \qquad \textbf{(3.45)}$$

If Equation (3.45) is written in the form of Equation (3.43) then following Serendynski [104] the mean heat transfer coefficient for the rate of heat loss from the strip's surface h_R is given by:

$$h_R = \frac{\epsilon_1\ \sigma}{(T - T_A)} \left[(T + 273)^4 - (T_A + 273)^4\right] \qquad \textbf{(3.46)}$$

The heat transfer coefficient due to natural and forced convection of a horizontal plate in air, h_C follows that of Holman [103] and is given by:

$$h_C = 1.43\ (T - T_A)^{0.33} \qquad \textbf{(3.47)}$$

Now by adding together Equations (3.46) and (3.47) gives the total heat transfer coefficient h_A:

$$h_A = h_C + h_R \qquad \textbf{(3.48)}$$

Substituting h_A for h in Equation (3.44) gives the strip exit temperature T_{exit} from the air cooling zone for a given strip entry temperature T_{entry} into the air cooling zone:

$$T_{exit} = T_A + (T_{entry} - T_A) \exp\left(\frac{\phi\, h_A\, t}{A\, \rho_1\, C_{p1}}\right) \tag{3.49}$$

3.2.12 Coolant wash heat transfer

Investigations by Bamberg and Prinz [105] have shown that the heat transfer coefficient for the coolant wash is a function of the strip temperature, strip speed and chemical composition of the coolant. Laboratory tests have been done, Atack et al [106] to measure the heat lost from a plate under various conditions. The following heat transfer coefficient for the coolant washover h_W has been derived for strip at a temperature T and moving with a velocity V_S:

$$h_W = A_1 \qquad for\ V_S < V_T\ \ and\ \ T > T_L \tag{3.50}$$

$$h_W = A_1 + A_3(V_S - V_T)^{A4} \qquad for\ V_S \geq V_T\ \ and\ \ T > T_L \tag{3.51}$$

$$h_W = A_1 \exp(A_2(T_L - T)) \qquad for\ V_S < V_T\ \ and\ \ T \leq T_L \tag{3.52}$$

$$h_W = A_1 \exp(A_2(T_L - T)) + A_3(V_S - V_T)^{A4} \qquad for\ V_S \geq V_T\ \ and\ \ T \leq T_L \tag{3.53}$$

The base heat transfer coefficient A_1 is calibrated to suit the specific mill and alloy which the model is describing. Substituting h_W for h in Equation (3.44) gives

$$T_{exit} = T_W + (T_{entry} - T_W) \exp\left(\frac{\phi\, h_W\, t}{A\, \rho_1\, C_{p1}}\right) \tag{3.54}$$

Further temperature models can be produced for the effects of air jets or strip sprays by calculating the appropriate heat transfer coefficient for the cooling effect, along with the length of the temperature zone.

3.2.13 Roll bite heat transfer

The roll bite heat transfer model is based upon that developed by Bradley et al [107]. The principal is that heat is generated within the strip during plastic deformation and there is heat conduction into the rolls along the arc of contact. Figure 3.7 shows how the heat conduction problem is defined.

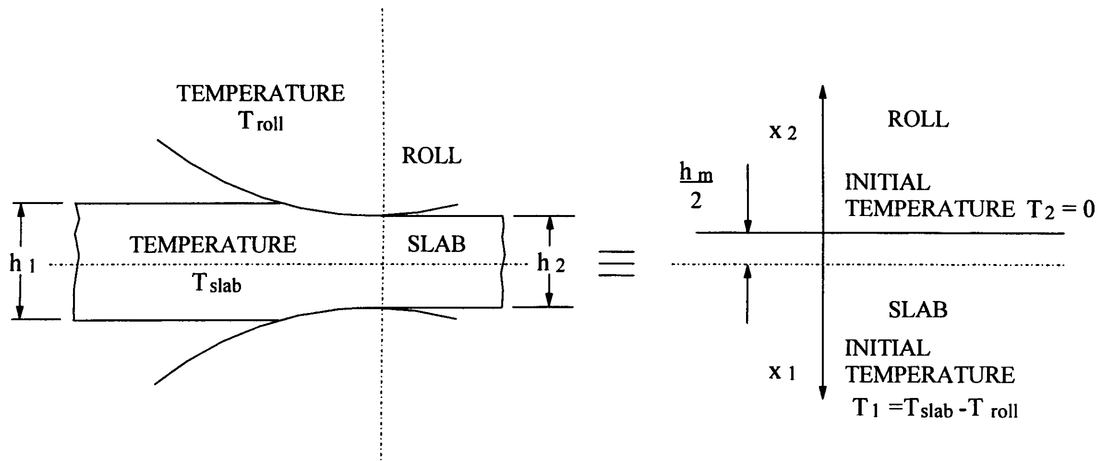


Figure 3.7 Roll bite heat transfer analysis

It is assumed that:

i) The strip and roll can be considered as semi-infinite planes initially at uniform although different temperatures.

ii) There is no thermal resistance to heat flow at the strip to roll interface.

iii) The heat is generated at a uniform rate per unit volume within the strip.

iv) The heat conduction is predominantly in the radial or through thickness direction.

v) Temperatures are normalised with respect to the initial roll temperature.

The heat conduction equations based on the above assumptions are:

For the slab:

$$\frac{\partial^2 \bar{T}_1}{\partial x_1^2} + \frac{\Phi}{k_1} = \frac{1}{\alpha_1} \frac{\partial \bar{T}_1}{\partial t} \qquad \textbf{(3.55)}$$

where

$$\bar{T}_1(x_1,t) = T_{slab}(x_1,t) - T_{roll}(0,0) \tag{3.56}$$

and

$$\bar{T}_{slab} = T_{slab}(x_1,0) - T_{roll}(0,0) \tag{3.57}$$

and for the roll:

$$\frac{\partial^2 \bar{T}_2}{\partial x_2^{\,2}} = \frac{1}{\alpha_2}\frac{\partial \bar{T}_2}{\partial t} \tag{3.58}$$

where

$$\bar{T}_2(x_2,t) = T_{roll}(x_2,t) - T_{roll}(x_2,0) \tag{3.59}$$

The initial condition for the slab is:

$$\bar{T}_1(x_1,0) = \bar{T}_{slab} \tag{3.60}$$

and for the roll:

$$\bar{T}_2(x_2,0) = 0 \tag{3.61}$$

The boundary conditions are:
at the strip to roll interface:

$$\bar{T}_1(0,t) = \bar{T}_2(0,t) \qquad for\ t > 0 \tag{3.62}$$

and

$$k_1 \frac{\partial \bar{T}_1(0,t)}{\partial x_1} = -\,k_2 \frac{\partial \bar{T}_2(0,t)}{\partial x_2} \tag{3.63}$$

At a considerable distance from the interface it is assumed that
for the slab:

$$\lim_{x_1 \to \infty} \bar{T}_1(x_1,t) = \bar{T}_{slab} \tag{3.64}$$

and for the roll:

$$\lim_{x_2 \to \infty} \bar{T}_2(x_2, t) = 0 \qquad \textbf{(3.65)}$$

The heat generated within the strip is given by:

$$\phi = \frac{\dfrac{E\,\eta}{v_2\, h_2\, W} + (\sigma_2 - \sigma_1)}{t_C} \qquad \textbf{(3.66)}$$

where the contact time t_C is:

$$t_C = \frac{h_m\, L}{v_2\, h_2} \qquad \textbf{(3.67)}$$

Using Laplace transforms the partial differential Equations (3.55) and (3.58) are solved in conjunction with the boundary conditions. The solution for the variation in strip temperature with respect to x_1 and t is given by:

$$\bar{T}_1(x_1, t) = \bar{T}_{slab} + \frac{\alpha_1\, \phi}{k_1} - \frac{1}{1 + \dfrac{k_1}{k_2}\sqrt{\dfrac{\alpha_2}{\alpha_1}}} \left[\left(\bar{T}_{slab} + \frac{\alpha_1\, \phi\, t}{k_1} \left(t + \frac{x_1^2}{2\,\alpha_1} \right) \right) \right.$$
$$\left. \times\, erfc\left(\frac{x_1}{2\sqrt{\alpha_1\, t}} \right) - \frac{\alpha_1\, \phi\, x_1}{k_1} \sqrt{\frac{t}{\pi \alpha_1}} \exp\left(\frac{x_1^2}{4\,\alpha_1\, t} \right) \right] \qquad \textbf{(3.68)}$$

Equation (3.68) can be differentiated to give the rate of heat flow at the interface of the strip and the roll:

$$k_1 \frac{\partial\, \bar{T}_1(0, t)}{\partial\, x_1} = \frac{k_1}{1 + \dfrac{k_1}{k_2}\sqrt{\dfrac{\alpha_2}{\alpha_1}}} \left[\frac{\bar{T}_{slab}}{\sqrt{\pi\, \alpha_1\, t}} + \frac{2\,\alpha_1\, \phi}{k_1} \sqrt{\frac{t}{\pi\, \alpha_1}} \right] \qquad \textbf{(3.69)}$$

Integrating Equation (3.69) with respect to time gives the total quantity of heat flow across the interface for the given contact time.

$$Q = \frac{2\,k_1}{\sqrt{\pi\,\alpha_1}\left(1 + \frac{k_1}{k_2}\sqrt{\frac{\alpha_2}{\alpha_2}}\right)}\left[\bar{T}_{slab}\sqrt{t_C} + \frac{2\,\alpha_1\,\Phi}{3\,k_1}\,t_C^{\frac{3}{2}}\right] \tag{3.70}$$

The strip exit temperature T_{B2} for a given bite entry temperature T_{B1} is:

$$T_{B2} = T_{B1} - \frac{2\,Q}{\rho_1\,C_{p1}\,h_m} + \frac{\Phi\,t_C}{\rho_1\,C_{p1}} \tag{3.71}$$

The models given in this section allow the temperature of the workpiece to be predicted for a series of passes, from being brought out of the furnace as a thick slab to being coiled up as thin strip after its final pass.

3.3 Work roll temperature and thermal camber

When the hot strip comes into contact with a work roll, heat is conducted across the interface and the work roll temperature increases from ambient to a steady state value. Those portions of the work roll not in contact with the strip will be at a lower temperature, as there is no heat being conducted into the roll's surface. As a result, the roll will have a differential radial expansion along its length. The difference between the roll radial expansion at the strip's centre line and that at the barrel edge is termed the thermal camber of the work roll. Tracking the variation in the thermal camber is important because of its effect on strip profile and shape.

This section will describe how the thermal camber can be calculated, following the work of Beeston and Edwards [108]. The finite difference method is used to solve the partial differential equations describing the heat conduction within the work roll.

It is assumed that the development of thermal camber is a long term phenomenon governed only by the radial and axial temperature distribution within the work roll. Any circumferencial variation in temperature caused by the rotation of the roll is assumed to have little or no effect on the camber. The heat transfer from the workpiece to the roll is considered to be evenly distributed around the roll as is the cooling effect of the sprays. The axial spacing of the nodes is set to correspond to the spray pitch. To determine the temperature distribution within the roll, the roll is discretised into a finite difference grid as shown in Figure 3.8. In the radial direction the nodes are organised such that, close to the surface the distance between the nodes is less than that deep within the body of the roll.

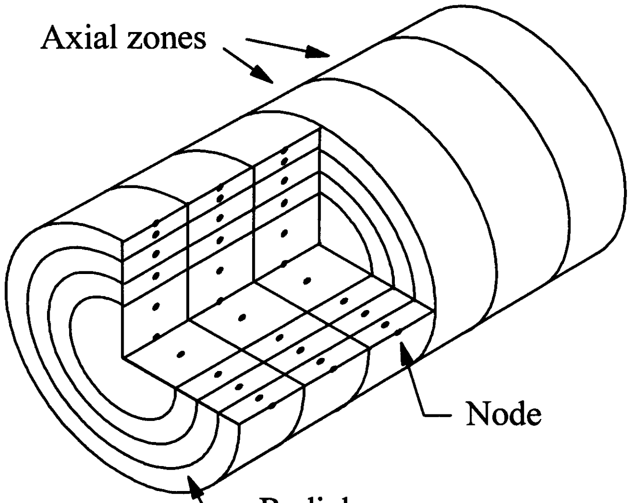


Figure 3.8 Work roll discretization

At points (r,z), the variation of temperature T with time t is given by the partial differential equation governing the heat conduction within a cylinder:

$$\frac{1}{\alpha_2}\frac{\partial T}{\partial t} = \frac{\partial^2 T}{\partial r^2} + \frac{1}{r}\frac{\partial T}{\partial r} + \frac{\partial^2 T}{\partial z^2} \tag{3.72}$$

Equation (3.72) is solved numerically using the finite difference method, such that Equation (3.72) may be written in dimensionless form as:

$$\frac{dT_{ij}}{d\tau} = \left(\frac{1}{\Delta r^*}\right)^2 \left[T_{ij+1}\left(1 + \frac{1}{2j-1}\right) + T_{ij-1}\left(1 - \frac{1}{2j-1}\right) - 2T_{ij} \right. \\ \left. + \left(\frac{\Delta r^*}{\Delta x^*}\right)^2 \left[T_{i+1j} + T_{i-1j} - 2T_{ij}\right]\right] \tag{3.73}$$

where

$$\tau = \frac{k_2\, t}{\rho_2\, C_{p2}\, R^2} \tag{3.74}$$

$$r^* = \frac{r}{R} \tag{3.75}$$

$$x^* = \frac{x}{R} \tag{3.76}$$

The boundary conditions for the roll are:

$$\frac{\partial T}{\partial r^*} = 0 \,, \qquad r^* = 0 \tag{3.77}$$

$$\frac{\partial T}{\partial x^*} = 0 \,, \qquad x^* = 0 \tag{3.78}$$

$$\frac{\partial T}{\partial r^*} = - \frac{R\ h_r(x)}{k_2} \left[T - T_C(x)\right] + q_i^* , \qquad r^* = 1 \tag{3.79}$$

$$\frac{\partial T}{\partial x^*} = - \frac{R\ h_{re}}{k_2} \left[T - T_{ce}(x)\right] \,, \qquad x^* = \frac{L}{R} \tag{3.80}$$

where L=B/2.

Figures 3.9 and 3.10 show the nomenclature used in this model.

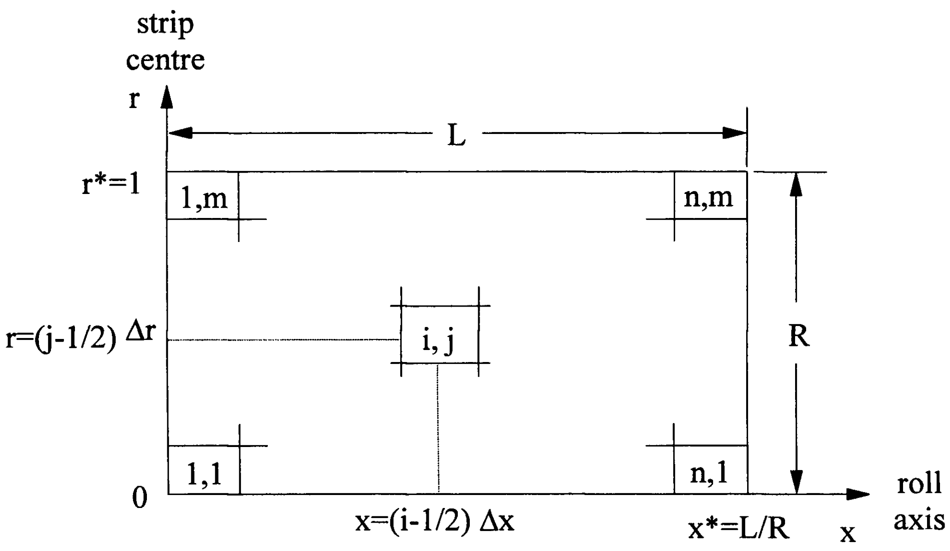


Figure 3.9 Work roll elements

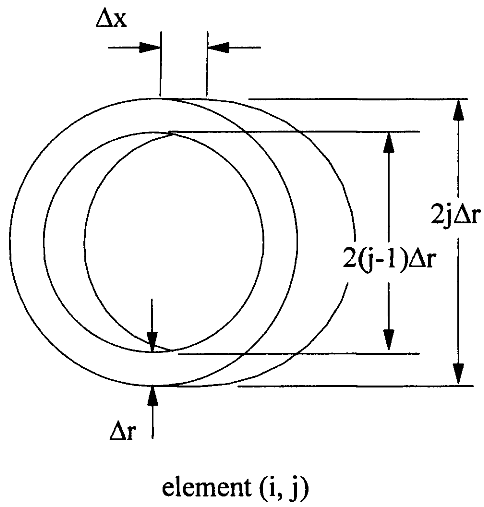


Figure 3.10 Work roll radial element

The heat input into each surface radial node is given by:

$$q_i^* = \frac{q}{2\ \pi\ k_2\ \Delta r^*}\ ,\ i \leq p \qquad \textbf{(3.81)}$$

$$= 0\ ,\qquad i > p$$

and total heat transferred to the roll is:

$$q = q_{total} - q_{strip} \qquad \textbf{(3.82)}$$

where

$$q_{total} = \frac{E\,\eta + v_2\,h_2\,(\sigma_2 - \sigma_1)}{4\,\pi\,W\,R^{/}} \tag{3.83}$$

and

$$q_{strip} = \frac{C_{p2}\,\rho_2\,v_2\,h_2\,(T_{B2} - T_{B1})}{2\,\pi\,W\,R^{/}} \tag{3.84}$$

The size of the finite difference mesh and time step is set to ensure that problem meets the Fourier stability criteria given by Equation (3.85).

$$\frac{\Delta\,\tau}{\Delta\,r^{*}\Delta\,x^{*}} < 0.5 \tag{3.85}$$

The model evaluates the temperature distribution within a quarter of the roll cross section as it is assumed that the problem is symmetrical about the strip centre line and the roll axis. The heat transfer coefficient used in Equation (3.79) was determined in the laboratory, Atack et al [109]. The coefficient is determined for different types of spray nozzles and for combinations of nozzles operating at different spray levels.

The expansion of each roll section is calculated from the radial temperature distribution using the work roll material's coefficient of thermal expansion. It is firstly assumed that the restraining effect of adjacent axial elements can be neglected. Expansions found in this way are then smoothed to take into account the restraining effect of the combination of the axial elements. The surface expansion of the roll is computed by using a Green's function to produce a set of influence coefficients relating the surface displacements to the internal stress distribution within the roll. The thermal camber at the strip edge is calculated by taking the difference between the roll expansion at the strip centreline and that at the strip edge.

3.4 Stack deflection

3.4.1 Work roll axis deflection

When the rolling load is applied to the roll stack, the work rolls and the back-up rolls will deflect. Flattening will also occur between the work rolls and back-up rolls and between the work rolls and the strip. The model of the stack must firstly be configured for the number of rolls in the stack, in this case there are four rolls. Different model configurations must be used for other stack sizes such as a two high or six high mill. The models must also consider the effect of any profile actuators which are fitted to the mill, such as work roll bend or if there is the ability to shift the work rolls sideways.

The model of the four roll stack presented here is based upon the work by Misaka and Yokoi [110]. Figure 3.11 shows the top two rolls of the stack and the associated nomenclature.

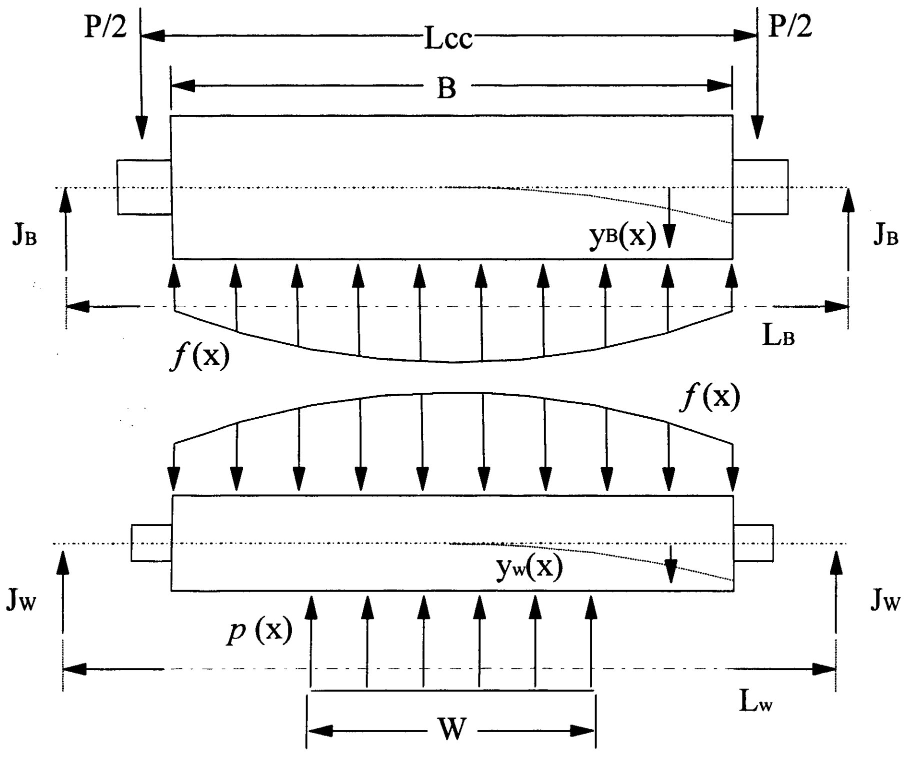


Figure 3.11 Stack deflection model notation

The work roll axis deflection is computed by firstly making the assumption that the pressure distribution between the work roll and the strip may be written down as a quartic equation:

$$P(x) = \frac{P_s}{W}\left(\alpha_1\left(\frac{x}{W}\right)^4 - \beta_1\left(\frac{x}{W}\right)^2 + \gamma_1\right) \quad \textbf{(3.86)}$$

The total strip to work roll load P_s takes into account the effect of any roll bending either on the work rolls J_W or on the back-up rolls J_B. The work roll to back-up roll is also assumed to have a quartic pressure distribution of the form:

$$f(x) = \frac{P}{B}\left(\alpha_2\left(\frac{x}{B}\right)^4 - \beta_2\left(\frac{x}{B}\right)^2 + \gamma_2\right) \quad \textbf{(3.87)}$$

To solve the problem the assumption is made that the pressure distribution between the work roll and the strip is a known function in this it is assumed to be linear. Thus, in Equation (3.87) α_1 and β_1 are set to 0 whilst γ_1 is set to 1. There now remain three unknowns in the problem, namely α_2, β_2 and γ_2. Three independent equations are now required for the problem to be solvable.

The compatibility equation for contact between the work roll and the back-up roll can be expressed as:

$$y_W(x) - y_B(x) + m\,[f(x) - f(0)] + g(x) = 0 \quad \textbf{(3.88)}$$

where m is a constant used to define the inter-roll flattening produced when two cylinders come into contact, see Loo [111]. The term $g(x)$ is the unloaded roll separation and is therefore the difference between the back-up roll camber and the work roll camber. Here camber is the sum of the roll thermal camber, the initial ground camber and the camber produced due to roll wear.

The equations for the work roll and back-up roll deflections, $y_W(x)$ and $y_B(x)$ can be written down from beam theory, see Case and Chilver [112]. The roll axis deflection at a point x is the sum of the bending moment and the shear force being applied to the roll.

So for the back-up roll $y_B(x)$ is written down as:

$$y_B(x) = \frac{1}{E_B I_B}\left[\frac{M_0 x^2}{2} - \int_0^x\!\!\int_0^x x\int_0^x f(\zeta)\,d\zeta\,dx\,dx + \int_0^x\!\!\int_0^x\!\!\int_0^x \zeta f(\zeta)\,d\zeta\,dx\,dx\right] + \frac{k_B}{A_B G_B}\int_0^x\!\!\int_0^x f(\zeta)\,d\zeta\,dx \tag{3.89}$$

and for the work roll $y_W(x)$ is written down as:

$$\begin{aligned} y_W(x) = \frac{1}{E_W I_W}\Bigg[& -\frac{M_0 x^2}{2} + \frac{x^2}{2}\left(\frac{PL_{cc}}{4} - \frac{J_B L_B}{2} - \frac{J_W L_W}{2} - P_S^*\right) \\ & + \int_0^x\!\!\int_0^x x\int_0^x f(\zeta)\,d\zeta\,dx\,dx - \int_0^x\!\!\int_0^x\!\!\int_0^x \zeta f(\zeta)\,d\zeta\,dx\,dx - \int_0^x\!\!\int_0^x x\int_0^x P(\zeta)\,d\zeta\,dx\,dx \\ & - \int_0^x\!\!\int_0^x\!\!\int_0^x \zeta P(\zeta)\,d\zeta\,dx\,dx\Bigg] + \frac{k_W}{A_W G_W}\left[\int_0^x\!\!\int_0^x P(\zeta)\,d\zeta\,dx - \int_0^x\!\!\int_0^x f(\zeta)\,d\zeta\,dx\right] \end{aligned} \tag{3.90}$$

where

$$M_o = \frac{PL_{cc}}{4} - \frac{J_B L_B}{2} - \int_0^{B/2} f(x)\,x\,dx \tag{3.91}$$

and

$$P_S^* = \int_0^{W/2} P(x)\,x\,dx \tag{3.92}$$

Performing the integrals in Equations (3.89) and (3.90) produces equations relating $y_W(x)$ and $y_B(x)$ to α_2, β_2 and γ_2 , which may then be substituted into Equation (3.88). The assumption is now made that the back-up roll and work roll must come in contact at at least two positions along the roll barrel length. These two positions are firstly at the barrel edge and secondly at a point a quarter of the way along the barrel. If x is set to B/4 and B/2 and then substituted into Equation (3.88) two equations are produced with α_2, β_2 and γ_2 being the only unknowns. Finally if Equation (3.87) is integrated along the work roll to back-up roll contact length and the result set to the rolling load, a third equation is produced. The solution may now be found by solving these three equations simultaneously to produce equations for α_2, β_2 and γ_2. Substituting these coefficients into the equation for $y_W(x)$ produces a prediction for the work roll stack deflection.

3.4.2 Work roll to strip flattening

The assumption made about the uniform work roll to strip pressure distribution, in the previous section, means that the work roll to strip flattening must be computed separately. When the strip comes into contact with the work rolls, the load between the two surfaces causes the rolls to flatten. The amount of flattening produced is dependent upon the rolling load applied, the roll material and the roll gap geometry. Within this analysis, following Matsumoto [113], it is assumed that the load distribution between the strip and the work roll is a known function $p'(\xi,\zeta)$, where the co-ordinates ξ and ζ are defined in Figure 3.12.

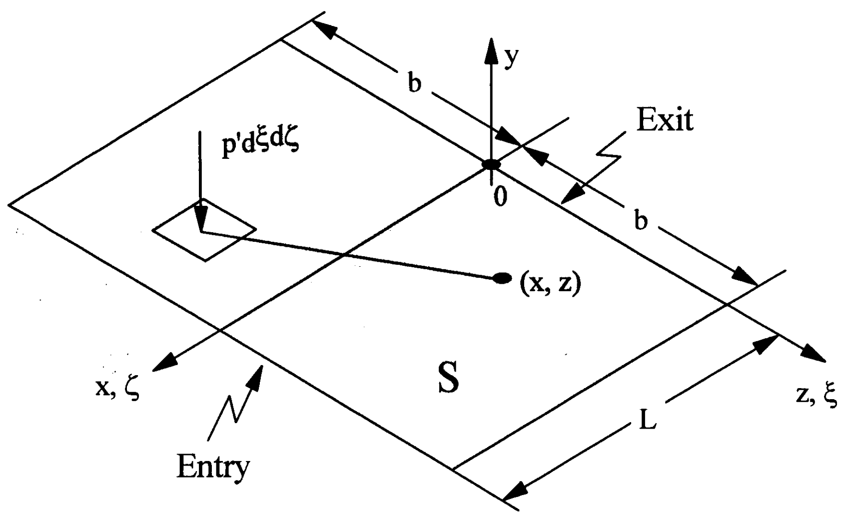


Figure 3.12 Flattening of work roll to strip contact area

The expression to give the roll flattening at the co-ordinates (x,z) is given by:

$$u(x,z) = \int_S \frac{1 - \nu_2^2}{\pi E_2} \frac{p'(\xi,\zeta)}{\sqrt{(x - \xi)^2 + (z - \zeta)^2}} \, dS \qquad \textbf{(3.93)}$$

where S is the contact surface between the work roll and the strip. It is now assumed that p' varies uniformly both across the strip width and along the arc of contact between the strip and the roll. Using this assumption the flattening of the roll at any position x is found by integrating Equation (3.93), thus:

$$u(x) = \frac{1 - \nu_2^2}{\pi E_2} P \left[\ln\left(\frac{b + x + \sqrt{(b + x)^2 + L^2}}{-b + x + \sqrt{(b - x)^2 + L^2}} \right) \right.$$
$$\left. + \frac{(b + x)}{L} \ln\left(\frac{L + \sqrt{(b + x)^2 + L^2}}{b + x} \right) + \frac{(b - x)}{L} \ln\left(\frac{L + \sqrt{(b - x)^2 + L^2}}{b - x} \right) \right] \qquad \textbf{(3.94)}$$

where b is W/2

3.5 Strip profile and shape

Predictions of strip profile and shape are required to control the geometry of the strip. The profile across the strip width is generated because the roll gap profile will be imprinted onto to the strip as the material passes through the roll bite. This roll gap profile is produced by summing the work roll effects described in the previous two sections. Namely the work roll thermal camber, stack deflection and roll flattening. In addition the effects of the initial ground camber on the rolls and roll wear must be taken into account when calculating the roll gap profile. Shape is generated within the strip because of the differential gauge across the strip's width. Consequently there is then a mismatch between the length of material at the edges and that at the centre of the strip. Some of this mismatch is accommodated by lateral flow of the material, whilst the remainder produces a strain distribution within the strip. Once this strain distribution reaches a certain level, bad shape will be produced which will manifest itself as visible waves or pockets on the strip.

3.5.1 Strip profile model

The mechanisms by which strip profile is created within the roll gap is a complex modelling problem. A simplified model has been developed which can be used on-line and which is also amenable to adaptation. The profile model follows that of Ogawa et al [114]. The mechanical camber on the work rolls can be calculated by:

$$C_{mech} = 2\ (-C_{TH} + C_{DF} + C_{FL}) \qquad \textbf{(3.95)}$$

This equation assumes that the camber will be the same for both top and bottom work rolls. The sign of the thermal crown C_{TH} is indicating that a roll with a greater expansion in the centre of the strip than at the edge is termed a positive camber. The strip profile model is based around the following single equation:

$$C_i = \zeta_i\ C_{i\ mech} + (1 - \zeta_i)\ C_{i-1} \qquad \textbf{(3.96)}$$

which expresses the exit strip crown C_i to be composed of a proportion of the crown entering the mill C_{i-1} plus a proportion of the mechanical crown on the work rolls. The term ζ is called the imprinting ratio, whilst the term $(1 - \zeta)$ is called the hereditary factor. The strip profile may then be calculated from:

$$K_i = \frac{C_i}{h_2} \times 100\% \tag{3.97}$$

The imprinting ratio is expressed by:

$$\zeta = 1 - 0.88 \times 0.073 \sqrt{\frac{W}{h_2}} \qquad for\ 0.073 \sqrt{\frac{W}{h_2}} < 1 \tag{3.98}$$

and

$$\zeta = 1 - 0.88 \qquad for\ 0.073 \sqrt{\frac{W}{h_2}} \geq 1 \tag{3.99}$$

As the strip enters and exits the roll gap it passes through elastic regions, see Figure 3.13.

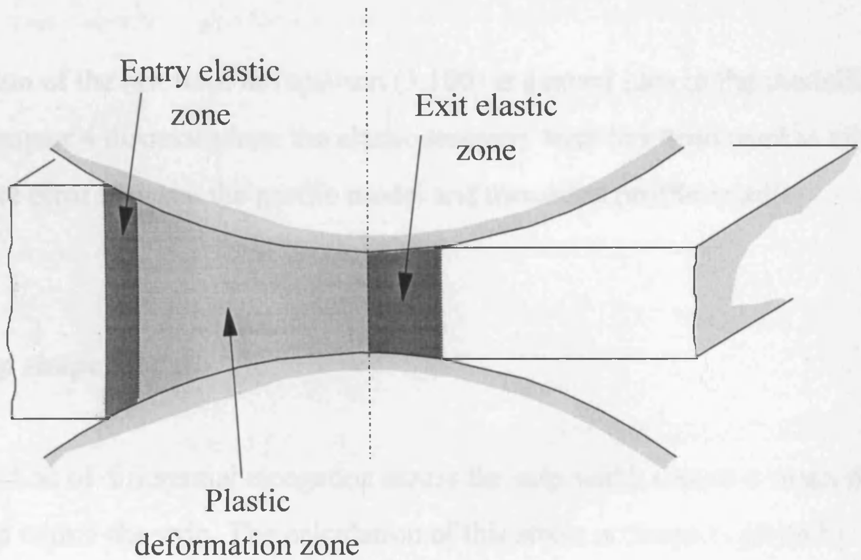


Figure 3.13 Elastic and plastic regions

The size of these elastic regions generally increases as the strip becomes thinner. The work of Jouet et al [115] introduced the concept of secondary deformation taking place at the roll bite exit. This effect causes a modification of the strip profile across the strip width. As the rolling load is removed from the strip as it leaves the roll bite, relaxation of the strip occurs, Kalpakjan [116]. Such relaxation increases with the application of forward tension onto the strip. The consequence of this mechanism is that Equation (3.96) must be modified to take into account the secondary deformation effect. Here it is postulated that Equation (3.96) can be modified by the addition of a elastic recovery term as shown below:

$$C_i = \zeta_i \, C_{i\ mech} + (1 - \zeta_i) \, C_{i-1} + \frac{\lambda \sqrt{h_2}}{10000} \tag{3.100}$$

The elastic recovery constant λ is used to calibrate the profile model for steady-state rolling conditions and the method for determining λ is discussed in Chapter 4.

If Equation (3.100) is expressed in terms of strip profile then it becomes:

$$K_i = \frac{\zeta_i \, C_{i\ mech}}{h_2} \times 100 + (1 - \zeta_i) \, K_{i-1} + \frac{\lambda}{\sqrt{h_2} \; 100} \ \% \tag{3.101}$$

The addition of the last term in Equation (3.100) is a novel idea in the modelling of strip profile. Chapter 4 discusses how the elastic recovery term has been used to eliminate the steady state error between the profile model and measured profile results.

3.5.2 Strip shape model

The generation of differential elongation across the strip width causes a strain distribution to be setup within the strip. The calculation of this strain or shape is given by:

$$\varepsilon_i = \xi_i \, (k_i - k_{i-1} + \varepsilon_{i-1}) \tag{3.102}$$

which relates the exit shape ε_i to the entry shape ε_{i-1} plus the difference between the entry and exit profile. The shape change coefficient ξ is defined as:

$$\xi = 0.1715 \left(\log \frac{W^2}{472\ h_1^{1.5}} \right)^2 \qquad \textbf{(3.103)}$$

which specifies how much of the profile change made during a particular pass can be accommodated by lateral flow of the material.

The work of Shoet and Townsend [117] investigated experimentally how much profile change could be made before bad shape is manifested. Following from the equations that they developed the shape limits for a particular pass are given by:

$$\textit{Max positive profile change} = \frac{1}{\xi}\ 100 \times 15 \left(\frac{h_2}{W} \right)^{1.64} \qquad \textbf{(3.104)}$$

and

$$\textit{Max negative profile change} = -\frac{1}{\xi}\ 100 \times 15 \left(\frac{h_2}{W} \right)^{1.64} \qquad \textbf{(3.105)}$$

Due to the lack of strip shape measurement at present for the hot rolling of aluminium, the shape model is difficult to calibrate. However it is possible to observe bad shape during rolling at certain gauges and relate this back to profile changes made within the roll bite. Consequently Equations (3.104) and (3.105) can be calibrated to produce profile change limits for a given gauge.

3.6 Conclusions

This chapter has presented a survey of the process models which give predictions of the rolling mill parameters. The chapter opened with a discussion about how the models are interlinked. The next four sections described in detail the components of each model block. The model blocks described produce predictions of the rolling load, main motor power, strip temperature, work roll thermal camber, stack deflection, shape and profile. It can be concluded that the models presented describe in some detail the mechanisms involved in the rolling of aluminium. The models can be used to produce predictions of the key quality parameters which are important in the control of the rolling process. Novel and interesting aspects of this chapter include the presentation of a unified rolling load model for both thick and thin stock material, the solution of the roll bite heat conduction problem and the formulation of the strip profile and shape model.

CHAPTER 4

Adaptation of Process Models

4.1 Introduction

This chapter describes the algorithms used to adapt the process models described in Chapter 3. Feldmann [118], MacAlister [119], Stephens [120], Randall [121], [122] and Atack [123], [124], [125] describe model adaptation schemes for both aluminium and steel rolling. The adaptation described in these papers quite specific to the applications and to the model configuration. The aim of adaptation is to ensure that model predictions are in good agreement with measurements made when rolling, see Bilkhu [126]. Measurements of the rolling load, main motor power, strip temperature and strip profile are compared with the corresponding model predictions and adjustments made to model parameters. The models described in the previous chapter are non-linear. In order to make them amenable to adaptation the models are firstly linearised about an operating point. The method adopted for doing this is to evaluate the model partial derivatives directly and this is discussed in the second section of this chapter.

Sections two and three present the adaptation algorithms and show how they are applied to the rolling process models, see Reeve [127] for a review of adaptation for use on a steel mill. Adaptation is split into two levels. The first level is used to compensate for long term variations in the process. Long term adaptation is run after each slab has been rolled and new adaptation coefficients calculated and used for the next slab predictions. The second level of the adaptation algorithm is used to track short term variations in the process. The short term algorithm is run after each pass to estimate the slab state. Within each section results from the algorithms are presented.

The final section in this chapter presents details on the implementation considerations which were made to ensure the algorithms operated successfully. This section also contains techniques which can be used by an expert system to improve the performance of the model adaptation. Details of how this is done are presented in Chapter 5.

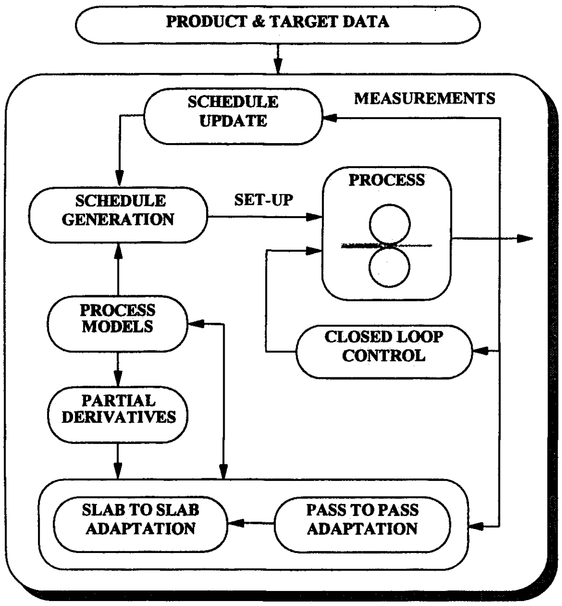


Figure 4.1 Interaction of process model adaptation with other control functions

Figure 4.1 shows a block diagram of a rolling mill setup and control system, see Stephens [128]. The interactions between the adaptation, process models and the derivatives are shown.

4.1.1 The need for model adaptation

There are several reasons why the models require adaptation, see Eykhoff [129] and Gevers [130]. These include:

i) A number of simplifying assumptions were made in describing the process mathematically. Such simplifications inevitable lead to model inaccuracies in some parts of their operating range.

ii) Model data, such as the aluminium flow stress or mill coolant heat transfer coefficient are measured off-line and may not completely describe the true situation on-line. The application of inaccurate or uncertain input data to the models leads to errors in the model predictions.

iii) Although the models are calibrated off-line, such a calibration is fixed. The use of an on-line adaptation algorithm allows the models to track long term variations in the operating point of the process. For example, the coolant properties will change with time, as will the roll bite friction.

iv) There will be short term variations in the process caused by slight differences in the alloy composition of the aluminium, differences in the initial geometry of the slab or inaccuracies in the measured slab temperature.

Figures 4.2 to 4.6 show the process models without any adaptation plotted against the corresponding actual plant measurements. Figure 4.2 shows that the unadapted rolling load model is over predicting by an average of 20%. The results for the power model in Figure 4.3 show better agreement although some points lie outside the ±10% error region. The strip temperature predictions in Figure 4.4 show that the model temperature error can be as high as 40°C for some passes of the schedule. Finally the strip profile predictions are offset from the 0% error line. It is clear that improvements in the model prediction accuracy should be made before they are used on-line and this can be achieved using adaptation.

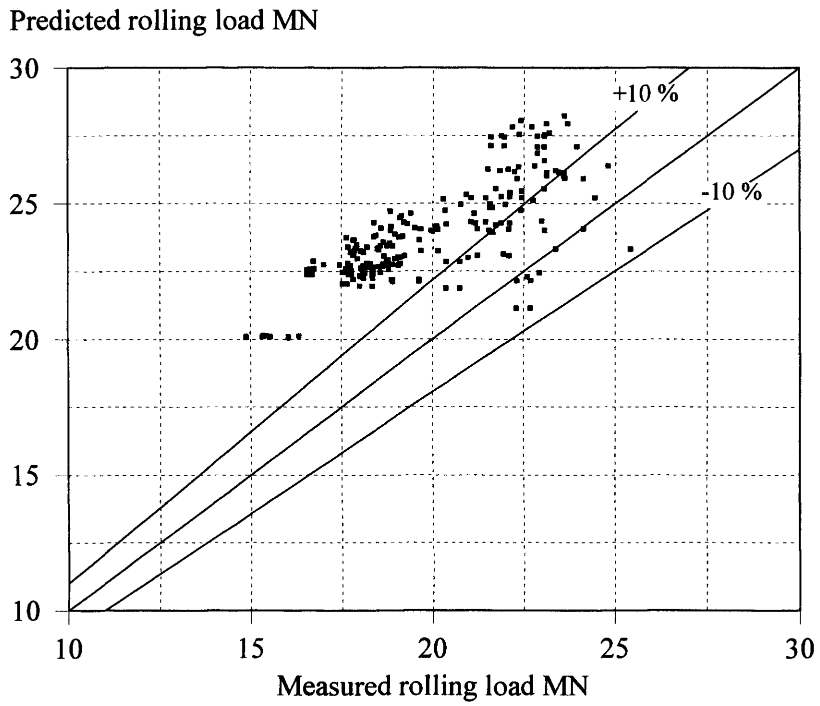


Figure 4.2 Graph of predicted against actual measured rolling load for the unadapted models

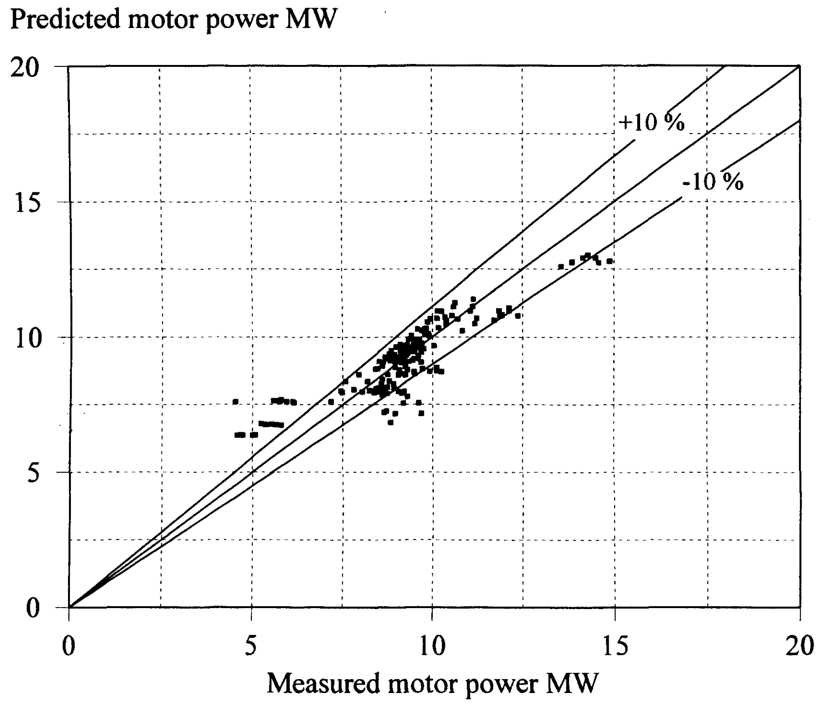


Figure 4.3 Graph of predicted against actual measured motor power for the unadapted models

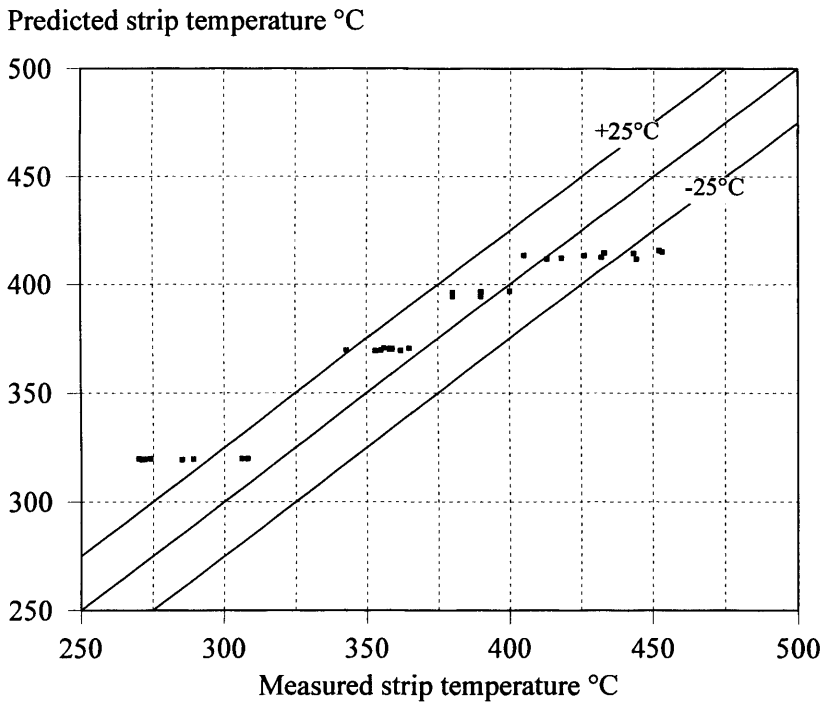


Figure 4.4 Graph of predicted against actual measured strip temperature for the unadapted models

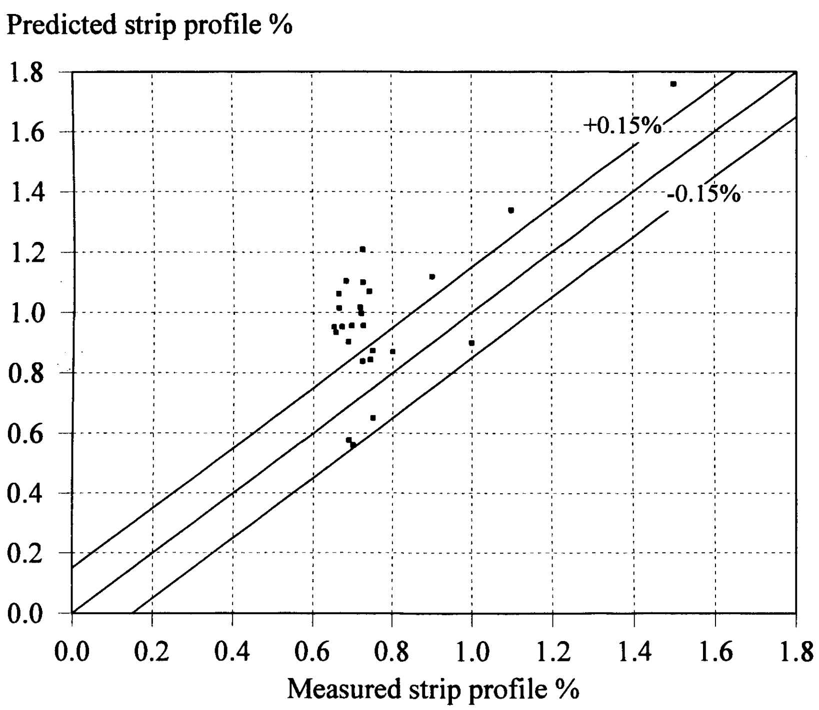


Figure 4.5 Graph of predicted against actaul measured strip profile for the unadapted models

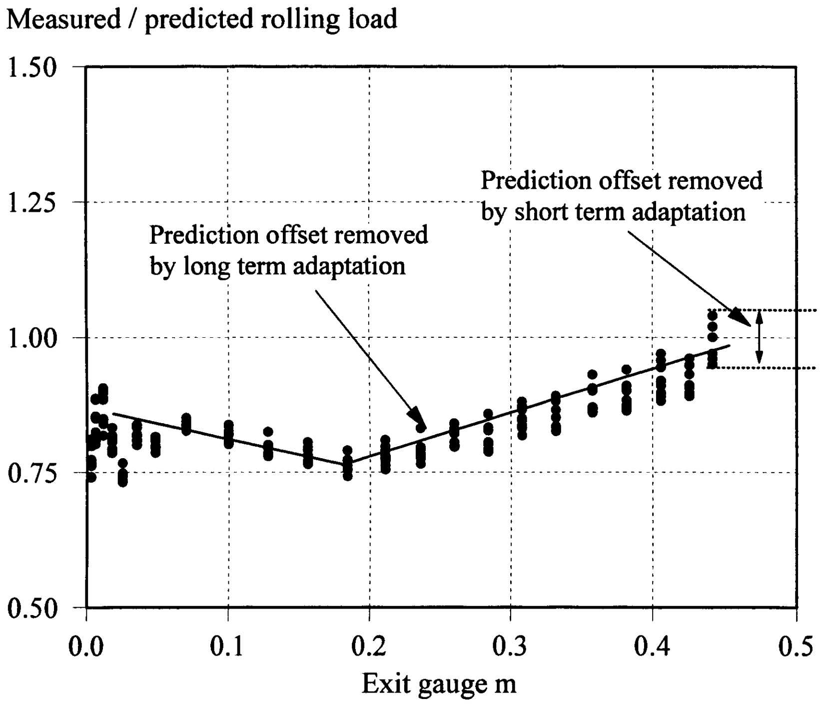


Figure 4.6 Graph showing ratio of measured to predicted rolling load and distribution of error in process model

Figure 4.6 shows the load data given in Figure 4.2 plotted on a pass by pass basis and presented as the ratio of the measured to the predicted load. From the graph two types of error in the prediction can be seen. Firstly the fact that they are offset by a varying amount from pass to pass. Secondly that they are offset from slab to slab. The first type of offset will be removed with long term adaptation and the second type by the short term adaptation.

4.2 Derivation of model derivatives

In order that the models described in Chapter 3 can be used to control the rolling process it is firstly necessary to differentiate them with respect to defined independent variables. This enables linear control theory to be directly applied. There are two applications within rolling mill automation where derivatives are required. The first being closed loop control gains and the second being the model adaptation.

Evaluation of the derivatives for the load, power and strip temperature models is performed in two parts. Firstly obtaining the partial derivatives for each of the individual models and then secondly combining these derivatives to produce a total derivative for a given pass. The computation of the profile model derivatives is performed in a similar manner. The form of the profile model is, however, much simpler making its differentiation relatively straightforward.

4.2.1 Partial derivatives

Bryant [23] describes the evaluation of derivatives for a steel tandem mill. Before commencing with this task, it must first be decided which parameters are the dependent variables and which are the independent variables for each model. The dependent variables are selected as the measurement set, namely the rolling load, main motor power, strip temperature and the strip profile. Whilst the independent variables are selected as the control actuators and the adaptation coefficients. In this case, the control actuators are the mill speed v_m and the work roll bend J_w The selected adaptation coefficients are multipliers to the material flow stress, coolant wash HTC, motor torque and the elastic recovery constant. In practice, the independent variables includes other model parameters so that the derivatives set is as general as possible., So, for example, adaptation can be performed using the strip thermal properties.

4.2.2 Load, power and strip temperature model derivatives

The model defining the rolling load given in Chapter 4 can be written as a function of its independent variables thus:

$$P = f_1(x_1,\ k^*,\ \tau/k,\ R^{/}) \qquad \textbf{(4.1)}$$

where x_1 is defined by:

$$x_1 = (\theta_i,\ v_m,\ T_1) \qquad \textbf{(4.2)}$$

and θ_i the adaptation coefficients are given by:

$$\theta_i = (\theta_1,\ \theta_2,\ \theta_3) \qquad \textbf{(4.3)}$$

where

$$\hat{k} = k\ \theta_1 \qquad \textbf{(4.4)}$$

$$\hat{G} = G\ \theta_2 \qquad \textbf{(4.5)}$$

and

$$\hat{A}_1 = A_1\ \theta_3 \qquad \textbf{(4.6)}$$

where ^ indicates an estimation of the given parameter.

Now if Equation (4.1) is perturbed with respect to each independent variable, the rolling load P can be expressed by the following equation:

$$P = P_o + \frac{\partial P}{\partial x_1}\delta x_1 + \frac{\partial P}{\partial k^*}\delta k^* + \frac{\partial P}{\partial \tau/k}\delta \tau/k + \frac{\partial P}{\partial R^{/}}\delta R^{/} \qquad \textbf{(4.7)}$$

This equation is a linearization of the load about an operating point P_0. Each of the partial derivatives in Equation (4.7) are calculated by direct differentiation of the rolling load model. For each of the load, power and strip temperature models it is possible to write down a function relating each model to its set of independent variables.

Thus for roll flattening:

$$R' = f_2(x_1,\ P) \tag{4.8}$$

for the flow stress:

$$k = f_3(x_1,\ T_{B1}) \tag{4.9}$$

for the roll bite friction:

$$\frac{\tau}{k} = f_4(x_1,\ T_{B1}) \tag{4.10}$$

for the strip temperature from the entry air cooling zone:

$$T_{W1} = f_5(x_1,\ v_1) \tag{4.11}$$

for the strip temperature from the entry wash cooling zone:

$$T_{B1} = f_6(x_1,\ T_{W1},\ v_1) \tag{4.12}$$

for the strip temperature exiting from the roll bite:

$$T_{B2} = f_7(x_1,\ T_{B1}) \tag{4.13}$$

for the strip temperature from the exit wash cooling zone:

$$T_{W2} = f_8(x_1,\ T_{B2},\ v_2) \tag{4.14}$$

for the strip temperature from the exit air cooling zone:

$$T_2 = f_9(x_1,\ T_{W2},\ v_2) \tag{4.15}$$

and for the motor torque:

$$G = f_{10}(x_1,\ k,\ \tau/k) \tag{4.16}$$

Each of the Equations (4.8) to (4.16) is differentiated to obtain an equation similar to (4.7). Thus a complete set of partial derivatives for each of the models is obtained. An examination of the above equations reveals that there are some interrelationships between the various models. In particular the rolling load model and the roll flattening model. If Equation (4.1) is perturbed by a small amount δx_1 then the following equation is obtained:

$$\delta P = \left\{ \frac{\partial f_1}{\partial x_1} + \frac{\partial f_1}{\partial k} \cdot \frac{dk}{dx_1} + \frac{\partial f_1}{\partial \tau/k} \cdot \frac{d\tau/k}{dx_1} + \frac{\partial f_1}{\partial R'} \cdot \frac{dR'}{dx_1} \right\} \delta x_1 \qquad \textbf{(4.17)}$$

Similarly perturbing Equation (4.7) by a similar amount δx_1 gives:

$$\delta R' = \left\{ \frac{\partial f_2}{\partial x_1} + \frac{\partial f_2}{\partial P} \cdot \frac{dP}{dx_1} \right\} \delta x_1 \qquad \textbf{(4.18)}$$

Substituting Equation (4.18) into (4.17) and rearranging gives the derivative for the rolling load:

$$\delta P = \left\{ \frac{\dfrac{\partial f_1}{\partial x_1} + \dfrac{\partial f_1}{\partial k} \cdot \dfrac{dk}{dx_1} + \dfrac{\partial f_1}{\partial \tau/k} \cdot \dfrac{d\tau/k}{dx_1} + \dfrac{\partial f_1}{\partial R'} \cdot \dfrac{\partial f_2}{\partial x_1}}{1 - \dfrac{\partial f_1}{\partial R'} \cdot \dfrac{\partial f_2}{\partial P}} \right\} \delta x_1 \qquad \textbf{(4.19)}$$

Now the computation of the total derivatives for the mill, for example $\partial T_2/\partial T_1$ or $\partial T_2/\partial v_m$ requires the multiplication of the various temperature partial derivatives. A general technique is described in Section 4.2.2 which allows the temperature derivatives to be calculated.

4.2.3 Strip profile model derivatives

The calculation of the strip profile model partial derivatives follows a similar procedure to that for the load, power and strip temperature models. The stack deflection model can be expressed as:

$$y_W = f_{11}(x_2) \qquad \textbf{(4.20)}$$

where:

$$x_2 = (\theta_4, P, J_W) \tag{4.21}$$

and where:

$$\hat{\lambda} = \lambda\, \theta_4 \tag{4.22}$$

and λ is the dynamic recovery constant.

The strip profile model can be written down as:

$$K_i = f_{12}(x_2, y_W, K_{i-1}) \tag{4.23}$$

For a given pass, i, the strip profile model derivatives can be obtained by differentiation of Equations (4.20) and (4.23). The effect of modifying the adaptation coefficient θ_4 over a group of passes can be computed by multiplying the appropriate derivatives together.

4.2.4 Perturbation analysis

The perturbation analysis is used to calculate the total derivatives for the strip temperature models for a single pass on a reversing mill. Referring to Figure 3.6, the partial derivatives for the five temperature zones shown are combined together and coupled with the mass flow equation. The procedure uses the derivatives calculated in the previous section, effectively performing the chain rule operation using matrix algebra.

Perturbing Equations (4.11) through to (4.15) with respect to the independent variables produces for T_{WI}:

$$\frac{\Delta T_{WI}}{T_{WI}} = \frac{\Delta x_1}{x_1} \frac{\partial T_{WI}}{\partial x_1} \frac{x_1}{T_{WI}} + \frac{\Delta v_1}{v_1} \frac{\partial T_{WI}}{\partial v_1} \frac{v_1}{T_{WI}} \tag{4.24}$$

for T_{BI}:

$$\frac{\Delta T_{BI}}{T_{BI}} = \frac{\Delta x_1}{x_1}\frac{\partial T_{BI}}{\partial x_1}\frac{x_1}{T_{BI}} + \frac{\Delta T_{WI}}{T_{WI}}\frac{\partial T_{BI}}{\partial T_{WI}}\frac{T_{WI}}{T_{BI}} + \frac{\Delta v_1}{v_1}\frac{\partial T_{BI}}{\partial v_1}\frac{v_1}{T_{BI}} \qquad \textbf{(4.25)}$$

for T_{B2}:

$$\frac{\Delta T_{B2}}{T_{B2}} = \frac{\Delta x_1}{x_1}\frac{\partial T_{B2}}{\partial x_1}\frac{x_1}{T_{B2}} + \frac{\Delta T_{BI}}{T_{BI}}\frac{\partial T_{B2}}{\partial T_{BI}}\frac{T_{BI}}{T_{B2}} \qquad \textbf{(4.26)}$$

for T_{W2}:

$$\frac{\Delta T_{W2}}{T_{W2}} = \frac{\Delta x_1}{x_1}\frac{\partial T_{W2}}{\partial x_1}\frac{x_1}{T_{W2}} + \frac{\Delta T_{B2}}{T_{B2}}\frac{\partial T_{W2}}{\partial T_{B2}}\frac{T_{B2}}{T_{W2}} + \frac{\Delta v_2}{v_2}\frac{\partial T_{W2}}{\partial v_2}\frac{v_2}{T_{W2}} \qquad \textbf{(4.27)}$$

and finally for T_2:

$$\frac{\Delta T_2}{T_2} = \frac{\Delta x_1}{x_1}\frac{\partial T_2}{\partial x_1}\frac{x_1}{T_2} + \frac{\Delta T_{W2}}{T_{W2}}\frac{\partial T_2}{\partial T_{W2}}\frac{T_{W2}}{T_2} + \frac{\Delta v_2}{v_2}\frac{\partial T_2}{\partial v_2}\frac{v_2}{T_2} \qquad \textbf{(4.28)}$$

Now if Equation (3.3) is perturbed the following equation is obtained:

$$\frac{\Delta v_1}{v_1} = \frac{\Delta v_2}{v_2} - \frac{\Delta h_1}{h_1} + \frac{\Delta h_2}{h_2} \qquad \textbf{(4.29)}$$

which therefore means that the ratio $\Delta v_2/v_2$ can be directly substituted for $\Delta v_1/v_1$ in Equations (4.24) and (4.25).

Now v_2 is a function of the mill speed and the forward slip, which in turn is itself related to the strip temperature at the entry to the roll bite, thus:

$$v_2 = g_1(x_1, T_{BI}) \qquad \textbf{(4.30)}$$

Perturbing this equation produces:

$$\frac{\Delta v_2}{v_2} = \frac{\Delta x_1}{x_1}\frac{\partial v_2}{\partial x_1}\frac{x_1}{v_2} + \frac{\Delta T_{BI}}{T_{BI}}\frac{\partial v_2}{\partial T_{BI}}\frac{T_{BI}}{v_2} \qquad \textbf{(4.31)}$$

It is now possible to combine Equations (4.24) to (4.28) along with (4.31) into the following matrix form:

$$X_j = A\ Y \tag{4.32}$$

where $X_j \in \mathbb{R}^6$ for $1 \le j \le 3$ is defined by the vectors:

$$X_1 = \begin{pmatrix} \dfrac{\theta_i}{T_{W1}} \dfrac{\partial T_{W1}}{\partial \theta_i} \dfrac{\Delta\theta_i}{\theta_i} \\[2ex] \dfrac{\theta_i}{T_{B1}} \dfrac{\partial T_{B1}}{\partial \theta_i} \dfrac{\Delta\theta_i}{\theta_i} \\[2ex] \dfrac{\theta_i}{T_{B2}} \dfrac{\partial T_{B2}}{\partial \theta_i} \dfrac{\Delta\theta_i}{\theta_i} \\[2ex] \dfrac{\theta_i}{T_{W2}} \dfrac{\partial T_{W2}}{\partial \theta_i} \dfrac{\Delta\theta_i}{\theta_i} \\[2ex] \dfrac{\theta_i}{T_2} \dfrac{\partial T_2}{\partial \theta_i} \dfrac{\Delta\theta_i}{\theta_i} \\[2ex] \dfrac{\theta_i}{v_2} \dfrac{\partial v_2}{\partial \theta_i} \dfrac{\Delta\theta_i}{\theta_i} \end{pmatrix} \quad X_2 = \begin{pmatrix} 0 \\[2ex] 0 \\[2ex] \dfrac{v_m}{T_{B2}} \dfrac{\partial T_{B2}}{\partial v_m} \dfrac{\Delta v_m}{v_m} \\[2ex] 0 \\[2ex] 0 \\[2ex] \dfrac{v_m}{v_2} \dfrac{\partial v_2}{\partial v_m} \dfrac{\Delta v_m}{v_m} \end{pmatrix} \quad X_3 = \begin{pmatrix} \dfrac{T_1}{T_{W1}} \dfrac{\partial T_{W1}}{\partial T_1} \dfrac{\Delta T_1}{T_1} \\[2ex] 0 \\[2ex] 0 \\[2ex] 0 \\[2ex] 0 \\[2ex] 0 \end{pmatrix} \tag{4.33}$$

$A \in \mathbb{R}^{6\text{x}6}$ is defined by the following matrix which will be invertible provided it is nonsingular.

$$A = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & -\alpha_{v_2} \\ -\beta_{T_{W1}} & 1 & 0 & 0 & 0 & -\beta_{v_2} \\ 0 & -\gamma_{T_{B1}} & 1 & 0 & 0 & 0 \\ 0 & 0 & -\delta_{T_{B2}} & 1 & 0 & -\delta_{v_2} \\ 0 & 0 & 0 & -\epsilon_{T_{W2}} & 1 & -\epsilon_{v_2} \\ 0 & -\varepsilon_{T_{B1}} & 0 & 0 & 0 & 1 \end{pmatrix} \tag{4.34}$$

and $Y \in \mathbb{R}^6$ is the vector:

$$Y = \left(\frac{\Delta T_{WI}}{T_{WI}}, \frac{\Delta T_{BI}}{T_{BI}}, \frac{\Delta T_{B2}}{T_{B2}}, \frac{\Delta T_{W2}}{T_{W2}}, \frac{\Delta T_2}{T_2}, \frac{\Delta v_2}{v_2} \right)^T \tag{4.35}$$

By inverting the matrix A, the derivatives can be calculated by multiplying through by the appropriate X_j containing the independent variables:

$$A^{-1} X_j = Y \tag{4.36}$$

The remaining terms in A are defined as:

$$\alpha_{v_2} = \frac{v_1}{T_{WI}} \frac{\partial T_{WI}}{\partial v_1} \tag{4.37}$$

$$\beta_{T_{WI}} = \frac{T_{WI}}{T_{BI}} \frac{\partial T_{BI}}{\partial T_{WI}} \tag{4.38}$$

$$\beta_{v_2} = \frac{v_1}{T_{BI}} \frac{\partial T_{BI}}{\partial v_1} \tag{4.39}$$

$$\gamma_{T_{BI}} = \frac{T_{BI}}{T_{B2}} \frac{\partial T_{B2}}{\partial T_{BI}} \tag{4.40}$$

$$\delta_{T_{B2}} = \frac{T_{B2}}{T_{W2}} \frac{\partial T_{W2}}{\partial T_{B2}} \tag{4.41}$$

$$\delta_{v_2} = \frac{v_2}{T_{W2}} \frac{\partial T_{W2}}{\partial v_2} \tag{4.42}$$

$$\epsilon_{T_{W2}} = \frac{T_{W2}}{T_2} \frac{\partial T_2}{\partial T_{W2}} \tag{4.43}$$

$$\epsilon_{v_2} = \frac{v_2}{T_2} \frac{\partial T_2}{\partial v_2} \tag{4.44}$$

and

$$\varepsilon_{T_{BI}} = \frac{T_{BI}}{v_2} \frac{\partial v_2}{\partial T_{BI}} \tag{4.45}$$

The derivatives derived in this section may now be used for on-line control. The application discussed in the next two sections is their use within the model adaptation schemes.

4.3 Long term adaptation scheme

The purpose of the long term adaptation is to determine adaptation coefficients which will track variations in the process for a group of similar slabs. The coefficients which are calculated will characterise the long term operating point for the particular product. The parameters selected to distinguish one product from another will vary from mill to mill. The alloy code, strip width, desired finish temperature and finish gauge can be used to identify the product.

The long term adaptation is run after all the passes have been rolled, when the measured data for every pass will become available. The results presented in this section were produced using measurements from a batch of twenty five slabs of a single product type.

4.3.1 Recursive least squares adaptation algorithm

This section describes the recursive least squares algorithm (RLS) used to estimate the long term adaptation coefficients, see Chen [131] and Cowan [132].

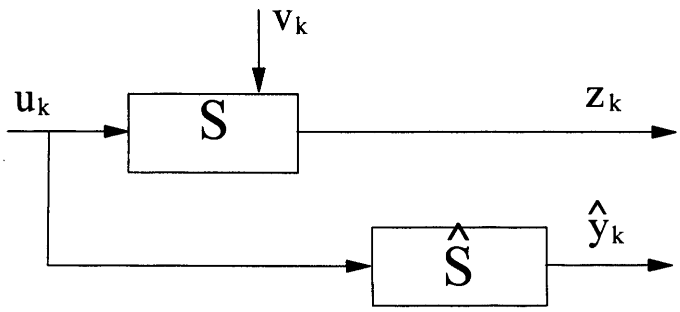


Figure 4.7 Block diagram of process S and model $\hat{S}$

Referring to Figure 4.7, for a given process S it is possible to measure certain parameters y which are contaminated with noise v to give an observation z, thus for the kth such set of observations:

$$z_k = y_k + v_k \tag{4.46}$$

The noise is of the form such that for a sequence of such measurements $i= 1,2...,k$ the noise has the following statistical properties:

$$E\{v_i\} = 0 \tag{4.47}$$

and the v_i are uncorrelated, having variance σ^2 thus:

$$E\{v_i v_j^T\} = \sigma^2 \delta_{ij} \qquad for\ all\ i, j \tag{4.48}$$

where E is the expectation operator and δ is the Kronecker delta function.

At the same time it is also possible to make an estimate of the parameter y based upon the inputs u to the system using a non-linear model shown as $\hat{S}$ in Figure 4.7.

$$\hat{y}_k = f(u_k) \tag{4.49}$$

Now assume that $\hat{S}$ can be expressed as:

$$\hat{y}_k = a_k^T u_k \tag{4.50}$$

where $a_k \in \mathbb{R}^P$ is a vector of parameters that model the kth measurement and $u_k \in \mathbb{R}^P$ is a vector of input data for the kth measurement. The problem now posed is to estimate the values of the model parameters a_k that will minimise the difference between the measurement z_k and the prediction $\hat{y}_k$. This is done by minimizing the least squares cost function J. For k measurements this is written as:

$$J = \sum_{i=1}^{k} \left[a_i^T u_i - z_i\right]^2 \tag{4.51}$$

Solving this equation produces the least squares algorithm, see Plackett [133] and Lawson [134] thus:

$$\hat{a}_k = \left[u_k u_k^T\right]^{-1} \left[u_k z_k\right] \tag{4.52}$$

Provided $u_k u_k^T$ is nonsingular then an estimate $\hat{a}_k$ can be found for a_k. This can be further developed into a recursive form which is known as the recursive least squares algorithm, see Young [135]. The three stage RLS algorithm is given in Equations (4.53) to (4.55).

$$\hat{a}_{k+1} = \hat{a}_k + K_{k+1} (z_{k+1} - u_{k+1}^T \hat{a}_k) \tag{4.53}$$

$$K_{k+1} = P_k u_{k+1} [I + u_{k+1}^T P_k u_{k+1}]^{-1} \tag{4.54}$$

$$P_{k+1} = P_k - P_k u_{k+1} [I + u_{k+1}^T P_k u_{k+1}]^{-1} u_{k+1}^T P_k \tag{4.55}$$

where $P \in \mathbb{R}^{PxP}$ is the error covariance matrix and $K \in \mathbb{R}^P$ is the gain vector. The error between the estimate and the actual value of a_k is given by the estimation error vector:

$$\tilde{a}_k = \hat{a}_k - a_k \tag{4.56}$$

The estimates have the following statistical properties:

$$\mathrm{E}\{\hat{a}_k\} = 0 \tag{4.57}$$

and the variance-covariance matrix P_k^* is given by:

$$P_k^* = \mathrm{E}\{\tilde{a}_k \tilde{a}_k^T\} \tag{4.58}$$

By noting that:

$$P_k^* = \sigma^2 P_k \tag{4.59}$$

and substituting into the RLS algorithm given above, we get an algorithm which weights the contribution made from each measurement. Less precise measurements having a higher variance will be weighted less heavily than more precise measurements. Thus:

$$K_{k+1} = P_k^* u_{k+1} [\sigma^2 + u_{k+1}^T P_k^* u_{k+1}]^{-1} \tag{4.60}$$

$$P_{k+1}^* = P_k^* - P_k^* u_{k+1} [\sigma^2 + u_{k+1}^T P_k^* u_{k+1}]^{-1} u_{k+1}^T P_k^* \tag{4.61}$$

Equation (4.53) together with Equations (4.60) and (4.61) constitutes the recursive least squares regression algorithm. Information about the accuracy and rate of convergence of the estimates can be obtained by examining the diagonal elements of the P_k^* matrix.

A final modification to the algorithm can now be made by introduction of a forgetting factor β which when substituted into the RLS algorithm produces a fading memory implementation of the filter.

Consider the noise v_i associated with a group of k measurements thus:

$$E\{v_i v_i^T\} = diag(\sigma_1, \sigma_2, \ldots, \sigma_k) \qquad \textbf{(4.62)}$$

Introducing the forgetting factor to weight more recent measurements more heavily than old measurements gives a weighting matrix W given by:

$$W = diag(\sigma_1, \beta^1\sigma_2, \ldots, \beta^{k-1}\sigma_k) \qquad \textbf{(4.63)}$$

It can be shown that the fading memory implementation of the filter is given by:

$$K_{k+1} = P_k^* u_{k+1} [\beta\sigma^2 + u_{k+1}^T P_k^* u_{k+1}]^{-1} \qquad \textbf{(4.64)}$$

$$P_{k+1}^* = P_k^* - P_k^* u_{k+1} [\beta\sigma^2 + u_{k+1}^T P_k^* u_{k+1}]^{-1} u_{k+1}^T \frac{P_k^*}{\beta} \qquad \textbf{(4.65)}$$

where $0 < \beta \leq 1$

The filter defined by Equation (4.53) together with Equations (4.64) and (4.65) is the form of the RLS algorithm which has been used for long term adaptation of the process models.

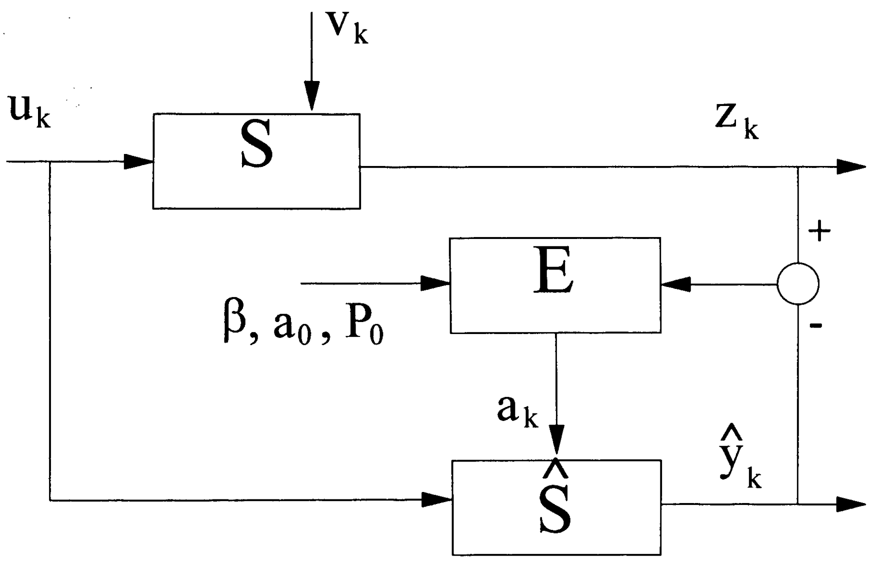


Figure 4.8 Block diagram of adaptation algorithm being applied to model $\hat{S}$

Figure 4.8 shows a modification of Figure 4.7 to include the RLS algorithm shown as E. The starting values a_0 and P_0 for the algorithm and control of the forgetting factor β are considered in Section 4.5.

4.3.2 Recursive least squares formulation for long term adaptation

The RLS algorithm is used in two different ways to adapt the process models. The first case is where it is used directly to identify the value of unknown model parameters. This method is applied to the estimation of the torque model parameters for thick stock material and is described in Section 4.3.3.

The second way that the RLS is used is to estimate the offset of adaptation coefficients which have a nominal value of 1.0. Such coefficients are used to multiply model parameters for example as shown in Equation (4.4). The formulation of the RLS algorithm for this second case is described below.

A vector $\theta \in \mathbb{R}^4$ of coefficients are introduced to adapt the models:

$$\theta_k = (\theta_1, \theta_2, \theta_3, \theta_4)^T \tag{4.66}$$

The coefficients being defined by Equations (4.4) to (4.6) and (4.22). The problem now posed is to calculate the change in the coefficient vector away from a nominal operating point which will minimise the difference between measurements and predictions. For the kth prediction of the parameter y, Equation (4.50) can be rewritten as:

$$\hat{y}_k = \hat{y}_k^0 + \sum_{i=1}^{N} b_k^{T\,i}\, \Delta\theta_k^i \tag{4.67}$$

where $\hat{y}_k^0$ is the nominal model prediction, N is the number of coefficients and:

$$\Delta\theta_k = (\Delta\theta_1, \Delta\theta_2, \Delta\theta_3, \Delta\theta_4)^T \tag{4.68}$$

The RLS algorithm given in Equations (4.53) together with Equations (4.64) and (4.65) is used to estimate the value of $\Delta\theta_k$ as each set of measurements becomes available. For the purposes of adapting the load, power, strip temperature and profile models the following vectors and matrices will apply:

$$a_k = \Delta\theta_k \tag{4.69}$$

the adaptation coefficients are updated after each batch of measurements is applied to the adaptation algorithm, using:

$$\theta_k = \theta_{k-1} + \Delta\theta_k \tag{4.70}$$

Initially:

$$\theta_k = (1,1,1,1)^T \tag{4.71}$$

after every update:

$$\Delta\theta_k = (0,0,0,0)^T \tag{4.72}$$

The measurement vector z_k is replaced by:

$$z_k = z_k^/ - \hat{y}_k^0 \tag{4.73}$$

where:

$$z_k^/ = \left[P_m, G_m, T_m, K_m\right]^T \tag{4.74}$$

and:

$$\hat{y}_k^0 = \left[P_p, G_p, T_p, K_p\right]^T \tag{4.75}$$

subscript m denotes a measured quantity and subscript p denotes a nominal model prediction.

Finally the b_k matrix is defined as:

$$b_k = \begin{pmatrix} \frac{\partial P_k}{\partial \theta_1} & \frac{\partial P_k}{\partial \theta_2} & \frac{\partial P_k}{\partial \theta_3} & 0 \\ \frac{\partial \tau_k}{\partial \theta_1} & \frac{\partial \tau_k}{\partial \theta_2} & \frac{\partial \tau_k}{\partial \theta_3} & 0 \\ \frac{\partial T_k}{\partial \theta_1} & \frac{\partial T_k}{\partial \theta_2} & \frac{\partial T_k}{\partial \theta_3} & 0 \\ 0 & 0 & 0 & \frac{\partial K_k}{\partial \theta_4} \end{pmatrix} \tag{4.76}$$

The profile model is independent of the load, power and strip temperature models because measurements are used in the calculation of strip profile.

The next sections present the results from the implementation of the RLS algorithm for long term adaptation.

4.3.3 Torque model for thick stock material

The torque model is split into two regimes as described in Section 3.2.3. For each of these regimes an adaptation scheme has been designed. For thick stock three model parameters are estimated over the operating region of the model. The equation for the lever arm ratio can be obtained by rearranging Equation (3.30):

$$\Gamma^m_{ARM} = \frac{G_m}{2\ L^{\prime}\ P_m} \tag{4.77}$$

where G_m is the measured torque and P_m is the measured rolling load. The length of the arc of contact $L^{\prime}$ is calculated from Equation (3.6) and $R^{\prime}$ is calculated using Equation (3.7) by substituting P_m for P. This means that the lever arm Γ^m_{ARM} can be estimated solely based upon measurements. The measured lever arm Γ^m_{ARM} is substituted for z_k in the RLS algorithm, Equation (4.53). The model of the lever arm given in Equations (3.31) and

(3.32) may written as:

$$\Gamma_{ARM} = \left[1.0 \ , \ \frac{2R'}{h_1} \ , \ \sqrt{\frac{2R'}{h_1}} \right] \begin{bmatrix} \Gamma_1 \\ \Gamma_2 \\ \Gamma_3 \end{bmatrix} \qquad for \left[\frac{2\ R'}{h_1} \right] \le 25.0 \tag{4.78}$$

and

$$\Gamma_{ARM} = \left[1.0 \ , \ 25.0 \ , \ 5.0 \ \right] \begin{bmatrix} \Gamma_1 \\ \Gamma_2 \\ \Gamma_3 \end{bmatrix} \qquad for \left[\frac{2\ R'}{h_1} \right] > 25.0 \tag{4.79}$$

which is in the form of:

$$\Gamma_{ARM} = u_{k+1}^{T} \, a_k \tag{4.80}$$

where:

$$a_k = (\Gamma_1, \Gamma_2, \Gamma_3)^T \tag{4.81}$$

and:

$$a_0 = (0.78, \ 0.017, \ -0.163)^T \tag{4.82}$$

The results in Figures 4.9 to 4.11 show the estimated torque model coefficients at the end of each slab for the selected batch of twenty five similar slabs. After some initial movement in the parameters the coefficients settle down to a steady value. The accuracy of the model predictions with the long term adapted torque model are given later in this section.

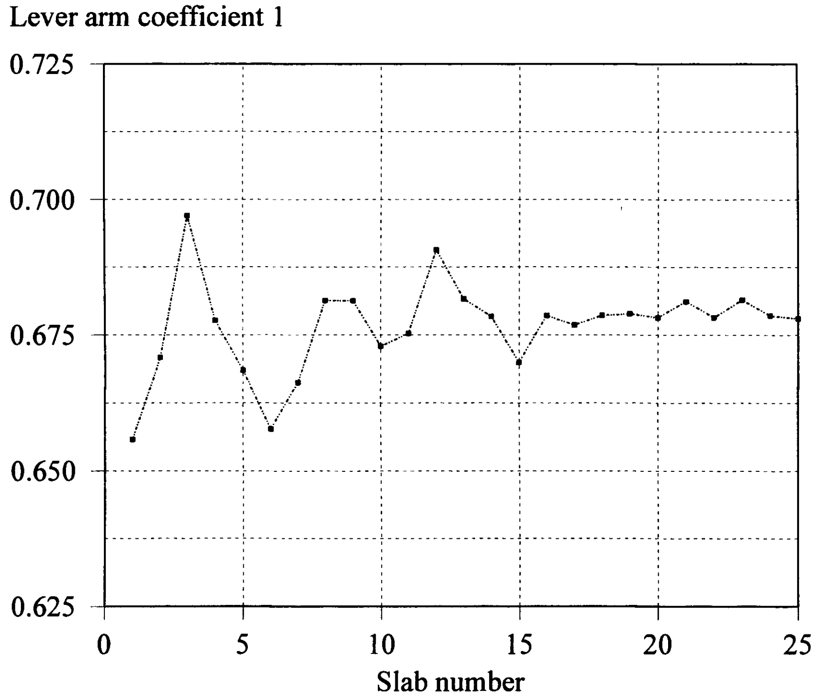


Figure 4.9 Variation in estimated lever arm coefficient 1 for sample of twenty five slabs

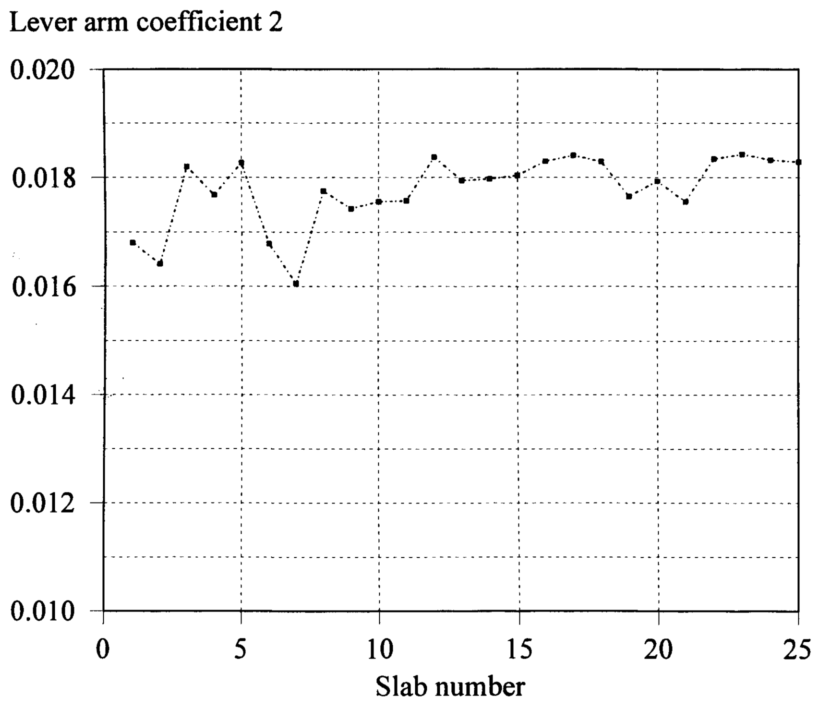


Figure 4.10 Variation in estimated lever arm coefficient 2 for sample of twenty five slabs

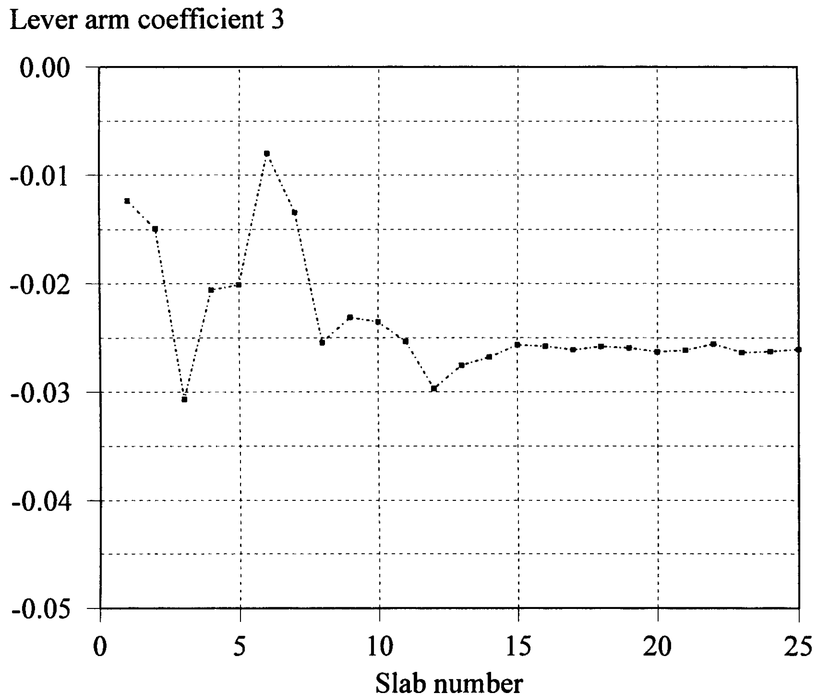


Figure 4.11 Variation in estimated lever arm coefficient 3 for sample of twenty five slabs

4.3.4 Adaptation of load and temperature model for thick stock material

Section 4.3.2 described how the RLS algorithm can be posed in order that it can be applied to the estimation of long term adaptation coefficients. The models applicable for thick stock material are applied above a bite entry gauge of 20mm. For the particular sample schedule, this means that the models must be adapted over a series of 20 passes. The method adopted was to divide the passes into groups by defining gauge breakpoints. Each breakpoint has associated with it an adaptation coefficient. When measurements fall in between two breakpoints the appropriate adaptation coefficients are updated. Different breakpoints are defined for the flow stress (θ_1) and for the coolant wash HTC (θ_3). Figure 4.12 shows the estimated coefficients for flow stress after the sample twenty five slabs. Note that the coefficient is primarily less than 1 to correct for the over estimation of the load shown in Figure 4.2. At a given entry gauge the adaptation coefficient is calculated from the two breakpoints that it bisects using the following equation:

$$\theta_k = \theta_{i-1}^b + \frac{(\theta_i^b - \theta_{i-1}^b)}{(h_i^b - h_{i-1}^b)}(h_1 - h_{i-1}^b) \qquad \textbf{(4.83)}$$

where θ_i^b is the adaptation coefficient at the gauge breakpoint h_i^b and θ_{i-1}^b is the adaptation coefficient at the gauge breakpoint h_{i-1}^b and:

$$h_i^b \geq h_1 \geq h_{i-1}^b \qquad \textbf{(4.84)}$$

Figure 4.13 shows the estimated coefficients for the coolant wash HTC. A different set of breakpoints are applied because the strip temperature measurements are made primarily at thinner gauges. Equations (4.83) and (4.84) are also applicable to the calculation of the coefficient for the coolant wash HTC.

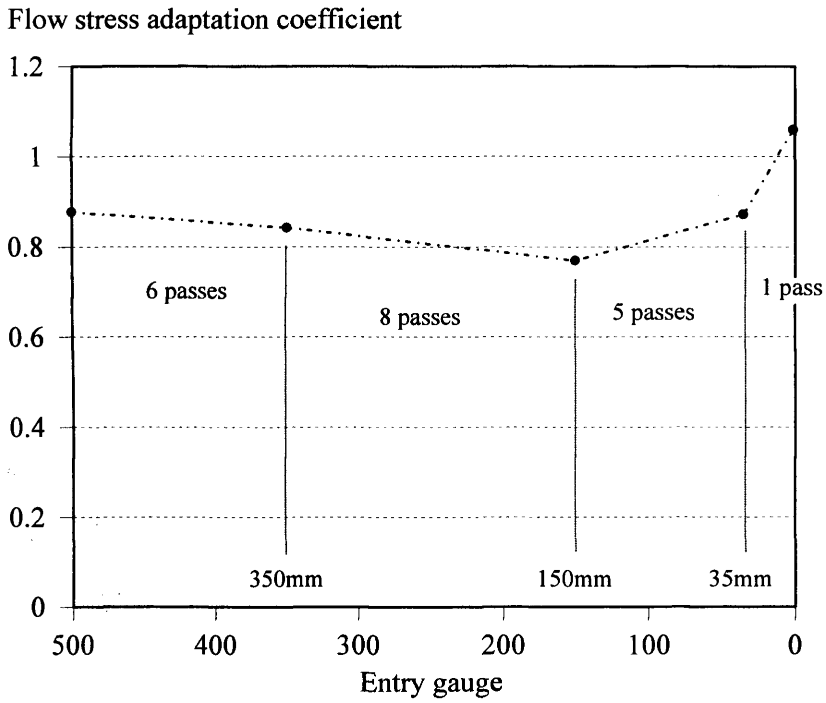


Figure 4.12 Piecewise linearisation of adaptation coefficient for flow stress

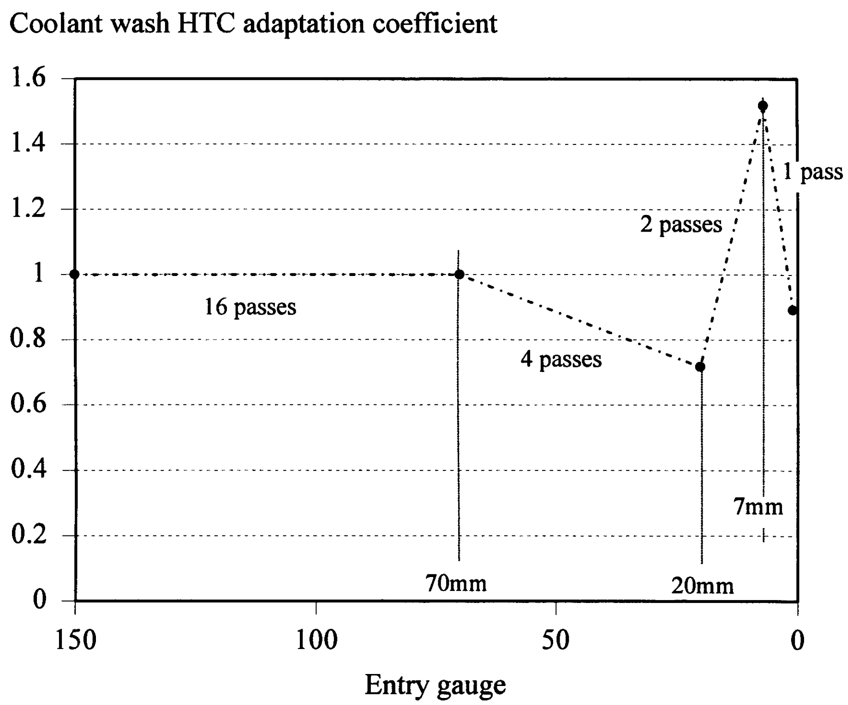


Figure 4.13 Piecewise linearisation of adaptation coefficient for coolant wash HTC

4.3.5 Adaptation of load, torque and temperature model for thin stock material

As the gauge of the aluminium strip becomes thinner, friction within the roll bite becomes an important factor in predicting the load and power. In order to ensure that the models remain accurate within this operating region the adaptation is performed on the load and power models using a coefficient for each model and for each pass. With the sample schedule three passes fall into the thin stock material region.

Figures 4.14 and 4.15 show the variation in the adaptation coefficients estimated for the load and the power for the final pass of the schedule.

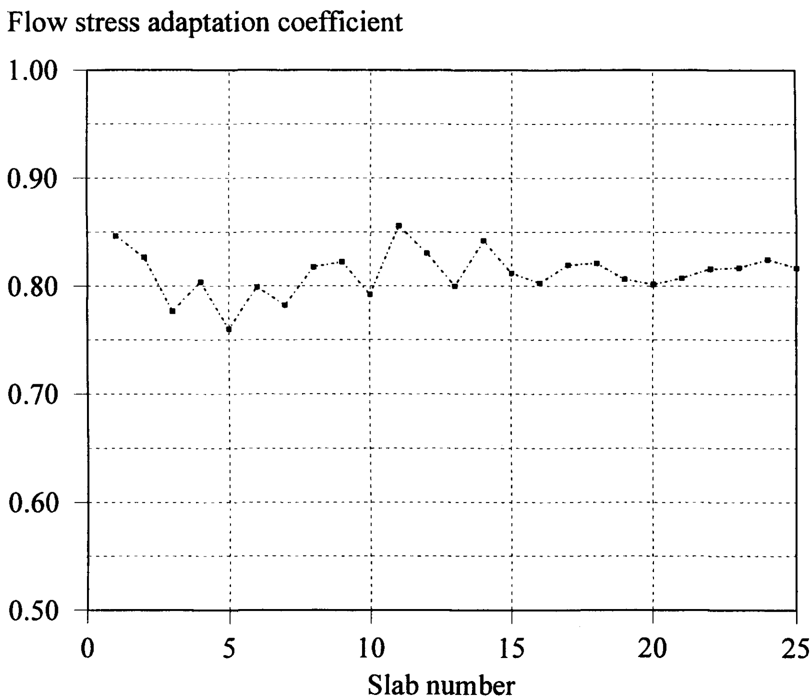


Figure 4.14 Variation in estimated flow stress coefficient for pass number 23 of the sample of twenty five slabs

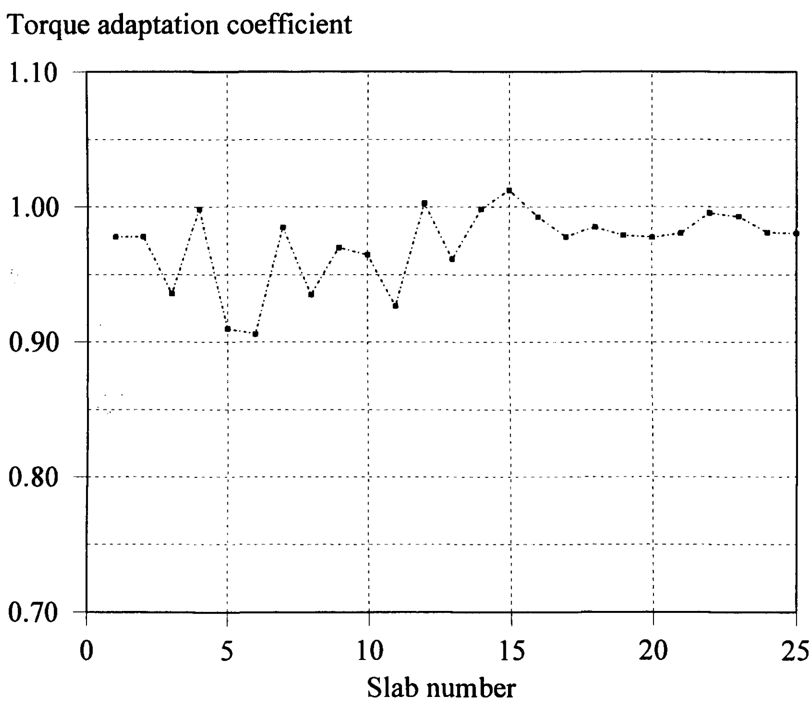


Figure 4.15 Variation in estimated torque coefficient for pass number 23 of the sample twenty five slabs

4.3.6 Long term adaptation results for thick and thin stock material

This section presents the results from running the long term adaptation scheme for the load, power and strip temperature models. Figures 4.16 to 4.18 show scatter graphs of the actual measured versus predicted results for the adapted models and these graphs may be directly compared to those in Figures 4.2 to 4.4 which show the same results for the unadapted models. Table 4.1 compares the mean and standard deviation of the model error for the two sets of results. In all cases the long term adaptation shows an improvement of roughly a factor of 2 in the standard deviation and significant improvements in the offset of the results which can be seen from the mean value. Figure 4.19 shows the ratio of the measured to predicted rolling load with the long term model adaptation. Comparing this figure to Figure 4.6 it can be seen that the overall model offset has been reduced and there is also some improvement in the slab to slab variation in the model error.

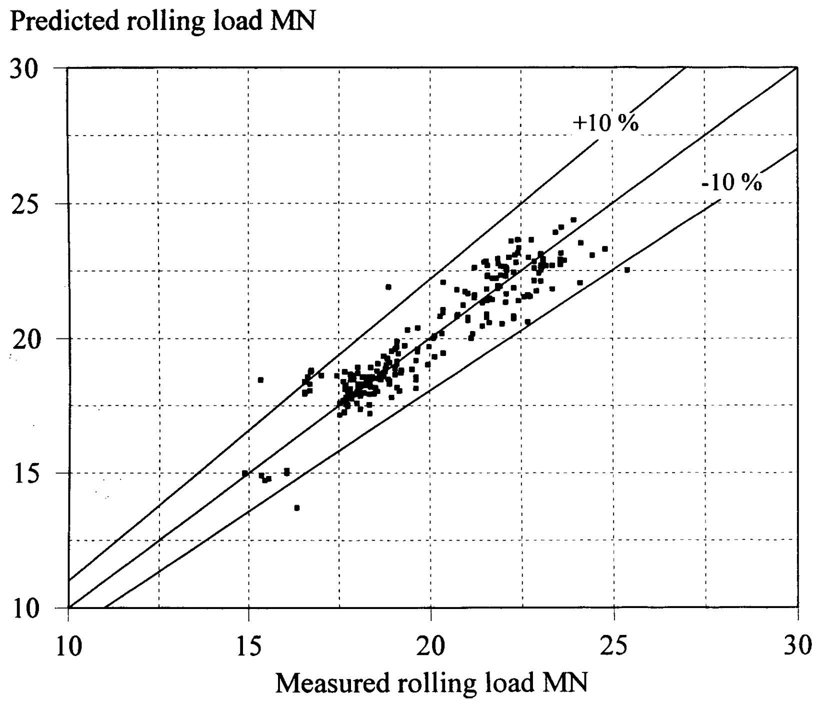


Figure 4.16 Graph of predicted against actual measured rolling load for long term adapted models

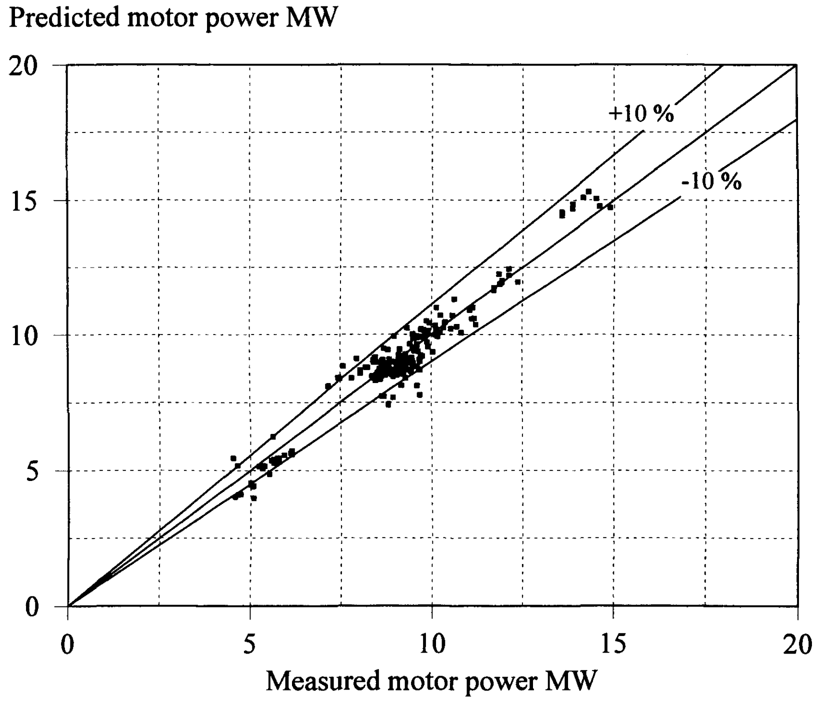


Figure 4.17 Graph of predicted against actual measured motor power for long term adapted models

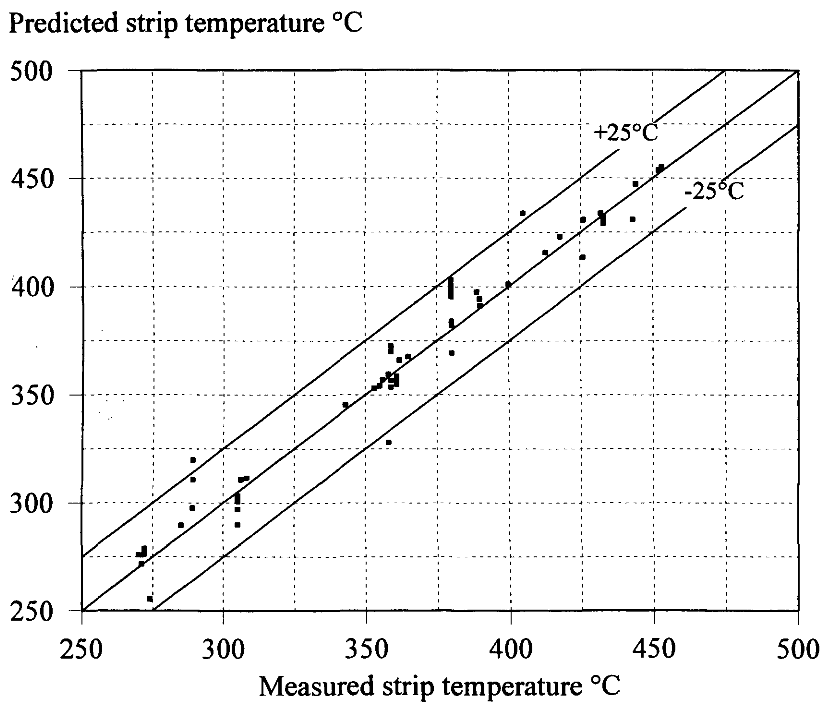


Figure 4.18 Graph of predicted against actual measured strip temperature for long term adapted models

Model	Unadapted models		Long term adapted models	
	Mean	Standard deviation	Mean	Standard deviation
Rolling load	-20.34%	8.90%	-0.14%	5.38%
Motor power	-2.05%	12.73%	0.98%	8.49%
Strip temperature	-11.96°C	22.38°C	-3.80°C	12.82°C
Strip profile	-0.21%	0.17%	0.04%	0.06%

Table 4.1 Comparison of statistical data for unadapted and long term adapted models

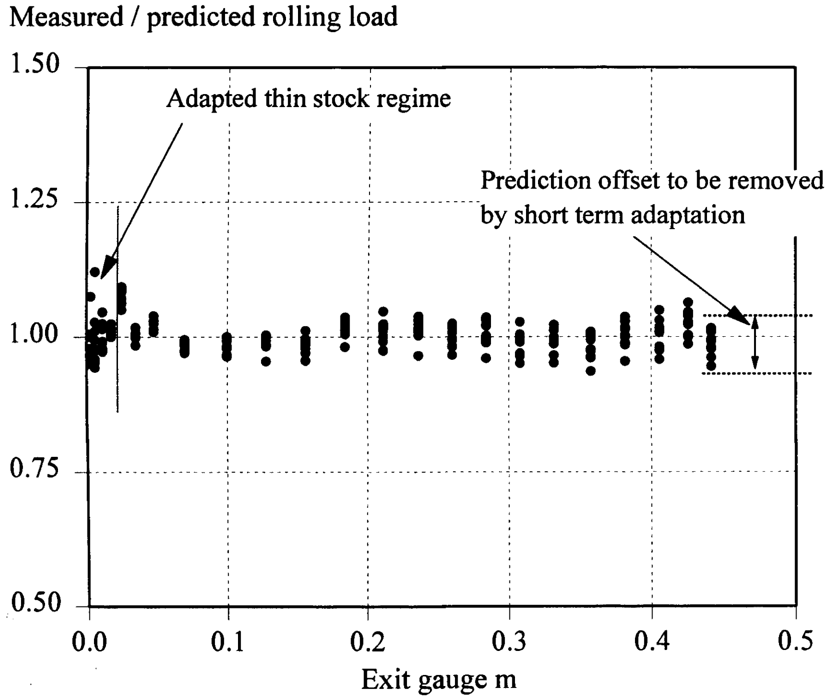


Figure 4.19 Graph showing ratio of actual measured to predicted rolling load with long term adaptation

4.3.7 Adaptation of strip profile model

The aim of the strip profile adaptation is to recursively estimate a value for θ_4 which when multiplied by the elastic recovery constant λ results in a better prediction of strip profile. The sample data used in this study has a single profile measurement made on the final pass. For this reason only one level of adaptation is applicable and this is done on a long term basis. The RLS algorithm is again used and its formulation for the profile model was described in Section 4.3.2. The estimate for λ is applied to every pass of the schedule using Equation (3.101). The results for the set of sample slabs are shown in Figures 4.20 and the improvement in the model prediction is shown in table 4.1. The value of the calculated adaptation coefficient θ_4 is given in Figure 4.21.

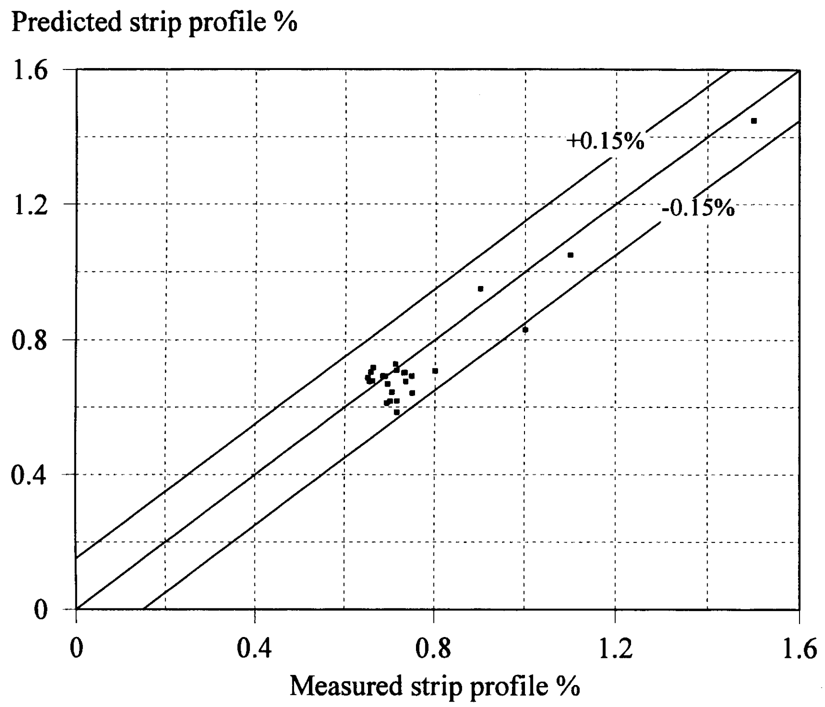


Figure 4.20 Graph of predicted against actual measured strip profile for long term adapted models

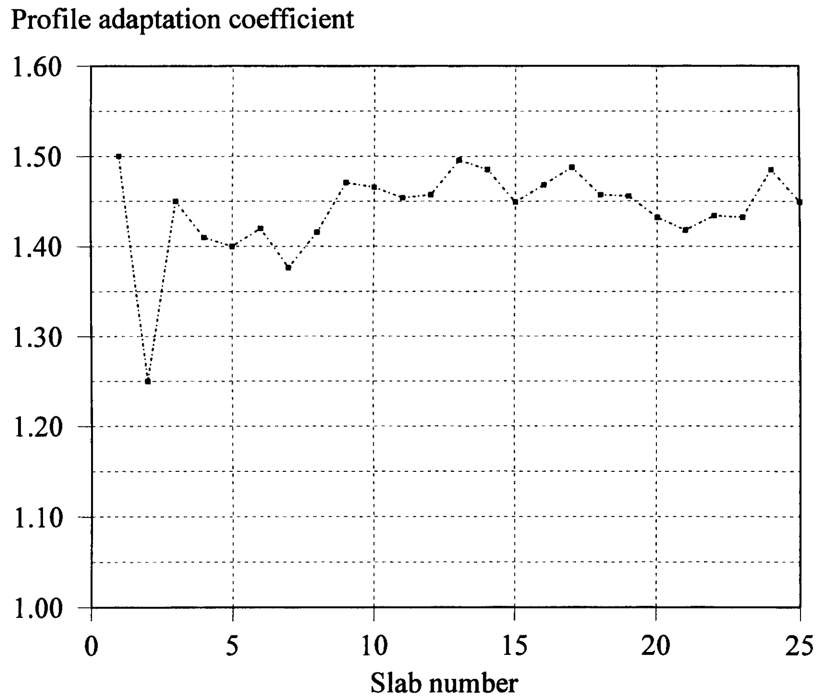


Figure 4.21 Variation in estimated dynamic recovery constant for sample of twenty five slabs

4.4 Short term adaptation algorithm

The purpose of the short term adaptation algorithm is to track changes in rolling conditions from one slab to the next. Such variations can be caused by differences in the material metallurgical properties, the accuracy of the initial strip temperature measurement or the slab's physical dimensions, such as its initial width or thickness. If variations occur to any one of these parameters the predictions made by the model will be initially offset because the input data set to the model will be incorrect. The role played by the short term or pass by pass adaptation is to identify and remove any offset in the short term data supplied to the process models.

4.4.1 Extended Kalman filter

This section describes the Extended Kalman filter algorithm (EKF) which has been used to estimate the short term adaptation coefficients, see Borrie [136] and Kalman [137]. The algorithm is derived directly from the Kalman filter estimator and its applicability to rolling mill adaptation is discussed. Randall [138] first pointed out that the discrete form of Extended Kalman filter could be used as an estimator to adapt rolling mill models on a pass to pass basis. Each pass is deemed the kth sampling interval for the filter.

A linear discrete time and stochastic system can be modelled with the following equations:

$$\hat{x}_{k+1} = A\,\hat{x}_k + B\,u_k + \Gamma\,w_k \tag{4.85}$$

$$\hat{z}_{k+1} = C\,\hat{x}_k + v_k \tag{4.86}$$

where v is the measurement noise and w is the system disturbance. In the context of the Kalman filter $x \in \mathbb{R}^n$ is the state vector, where n is the number states. Figure 4.22 shows a block diagram of such a system where S is the process and $\hat{S}$ is the model of the process. The states x of the process may or may not be measured.

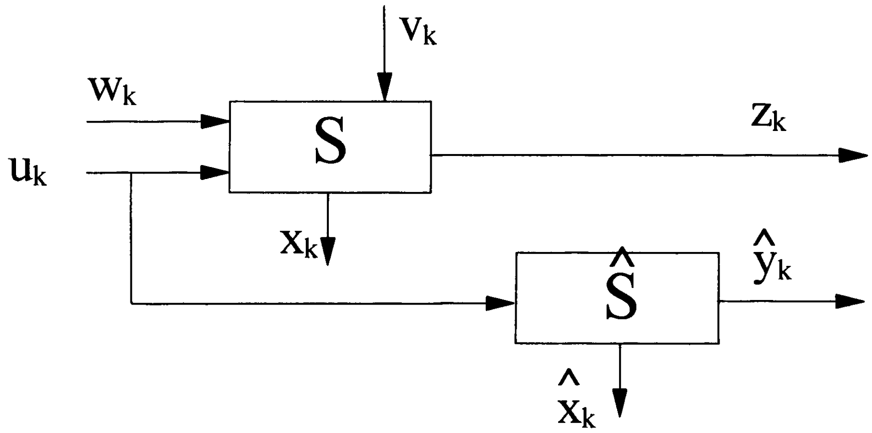


Figure 4.22 Block diagram of system with measurements z_k and states x_k

The noise is of the form such that it has zero mean:

$$E\{v_k\} = E\{w_k\} = 0 \tag{4.87}$$

and the noise is uncorrelated such that:

$$E\{v_i v_j^T\} = R\,\delta_{ij} \tag{4.88}$$

$$E\{w_i w_j^T\} = Q\,\delta_{ij} \tag{4.89}$$

with:

$$E\{v_i w_j^T\} = 0 \qquad \textit{for all } i, j \tag{4.90}$$

The recursive solution to the problem of estimating the system state x was first obtained by Kalman [139]. The estimate of x at time interval k+1 is based upon the state at time k and the a priori information contained within the state transition matrix $A \in \mathbb{R}^{n\times n}$, thus:

$$\hat{x}_{k+1|k} = A\,\hat{x}_k \tag{4.91}$$

the hat indicates that the state is an estimate and not based upon measurements. The error covariance matrix $P_{k+1|k} \in \mathbb{R}^{n\times n}$ for the state estimate is calculated from:

$$P_{k+1|k} = A\,P_k A^T + \Gamma Q \Gamma^T \tag{4.92}$$

Equations (4.91) and (4.92) together form the prediction stage of the Kalman filter estimator. It can be shown that the correction of these state estimates which can be made after the measurements become available, see Young [140] and Bozic [141], are given by the following:

$$\hat{x}_{k+1} = \hat{x}_k + K_{k+1}(z_{k+1} - C_{k+1}\hat{x}_{k+1|k}) \qquad \textbf{(4.93)}$$

$$K_{k+1} = P_{k+1|k}C^T[R + C P_{k+1|k}C^T]^{-1} \qquad \textbf{(4.94)}$$

$$P_{k+1} = P_{k+1|k} - P_{k+1|k}C^T[R + C P_{k+1|k}C^T]^{-1} C P_{k+1|k} \qquad \textbf{(4.95)}$$

Equations (4.93) to (4.94) form the correction stage of the Kalman filter. $K_k \in \mathbb{R}^n$ is usually termed the Kalman filter gain vector. The error covariance matrix P_k of the estimated errors is given by:

$$P_k = \mathrm{E}\{\tilde{x}_k \tilde{x}_k^T\} \qquad \textbf{(4.96)}$$

where the error in the estimate is given by:

$$\tilde{x}_k = \hat{x}_k - x_k \qquad \textbf{(4.97)}$$

The rolling process is inherently non-linear for this reason the linear representation given by Equations (4.85) to (4.86) will only be approximate. For a non-linear system Equation (4.85) can written as:

$$\hat{x}_{k+1} = f(\hat{x}_k, u_k) + \Gamma w_k \qquad \textbf{(4.98)}$$

where *f* represents the non-linear relationship for the state transition.

To take into account this non-linearity Equation (4.91) is replaced by:

$$\hat{x}_{k+1|k} = \hat{x}_k + \int_{t_k}^{t_{k+1}} f(\hat{x}_k, u_k)\, dt \qquad \textbf{(4.99)}$$

This equation together with Equations (4.92) to (4.95) represent the EKF algorithm which has been used in this section to adapt the process models on a pass by pass basis. The way in which the algorithm has been applied is discussed in the follow sections.

4.4.2 Extended Kalman filter formulation for pass by pass adaptation

This section describes how the EKF algorithm described above is formulated so that it can be used to estimate process model parameters on a pass by pass basis. The coefficients selected for use in the short term adaptation are defined by x_k in Equation (4.100).

$$x_k^T = (\theta_1, \theta_2, T_k) \tag{4.100}$$

where θ_1 and θ_2 are defined in Equations (4.4) and (4.5).

As in the case with the long term adaptation, the problem of estimating the coefficients is cast such that the change in the coefficients away from the current operating point x is calculated by the adaptation algorithm. In this case Δx_k is given by:

$$\Delta x_k^T = (\Delta\theta_1, \Delta\theta_2, \Delta T_k) \tag{4.101}$$

and the updated coefficient is calculated using:

$$x_k = x_{k-1} + \Delta x_k \tag{4.102}$$

Equation (4.86) can be written down in terms of the rolling mill parameters as:

$$\begin{pmatrix} \Delta P_{k+1} \\ \Delta \tau_{k+1} \\ \Delta T_{k+1} \end{pmatrix} = \begin{pmatrix} \dfrac{\partial P_k}{\partial \theta_1} & \dfrac{\partial P_k}{\partial \theta_2} & \dfrac{\partial P_k}{\partial T_k} \\ \dfrac{\partial \tau_k}{\partial \theta_1} & \dfrac{\partial \tau_k}{\partial \theta_2} & \dfrac{\partial \tau_k}{\partial T_k} \\ \dfrac{\partial T_k}{\partial \theta_1} & \dfrac{\partial T_k}{\partial \theta_2} & \dfrac{\partial T_k}{\partial T_k} \end{pmatrix} \begin{pmatrix} \Delta\theta_1 \\ \Delta\theta_2 \\ \Delta T_k \end{pmatrix} \tag{4.103}$$

and Equation (4.91) can be written down as:

$$\begin{pmatrix} \Delta\theta_{1,k+1} \\ \Delta\theta_{2,k+1} \\ \Delta T_{k+1} \end{pmatrix} = \begin{pmatrix} \dfrac{\partial\theta_{1,k+1}}{\partial\theta_{1,k}} & \dfrac{\partial\theta_{1,k+1}}{\partial\theta_{2,k}} & \dfrac{\partial\theta_{1,k+1}}{\partial T_k} \\ \dfrac{\partial\theta_{2,k+1}}{\partial\theta_{1,k}} & \dfrac{\partial\theta_{2,k+1}}{\partial\theta_{2,k}} & \dfrac{\partial\theta_{2,k+1}}{\partial T_k} \\ \dfrac{\partial T_{k+1}}{\partial\theta_{1,k}} & \dfrac{\partial T_{k+1}}{\partial\theta_{2,k}} & \dfrac{\partial T_{k+1}}{\partial T_k} \end{pmatrix} \begin{pmatrix} \Delta\theta_{1,k} \\ \Delta\theta_{2,k} \\ \Delta T_k \end{pmatrix} \qquad \textbf{(4.104)}$$

Thus the matrices A, C and $\hat{z}_{k+1}$ are defined for the EKF algorithm. The prediction stage of the algorithm defined by Equation (4.99) is obtained by running the process models to obtain the estimates of the exit slab state.

4.4.3 Short term adaptation for load and power models

The previous two sections described the EKF algorithm which is suitable for predicting short term variations in rolling mill process parameters. In this section the results from running the algorithm are presented. The coefficients selected for use in this algorithm, Equation (4.100) are weighted by means of the term $\Gamma Q \Gamma^T$ in Equation (4.92) so that either flow stress or strip temperature is used as the observer within the model. Each of these parameters is capable of adapting the load model to remove any disagreement with the measured data. Which to use, is discussed in Chapter 5. The short term adaptation is run after every pass, up to the pass where the strip is deemed to be thin stock, at which the point the algorithm is stopped and only long term adaptation is applied. The formulation of the EKF algorithm for use with the rolling mill process models was discussed in Section 4.4.2.

4.4.4 Torque model adaptation

The torque model coefficient for short term adaptation is updated after each pass has been run. Figure 4.23 shows the variation in the estimated torque model parameter with long term adaptation being run to remove the overall model offset. Figure 4.24 shows a comparison between the measured and predicted motor power for each pass with the long term adaptation being run. It can be seen that there is a good agreement between the values shown in the graph.

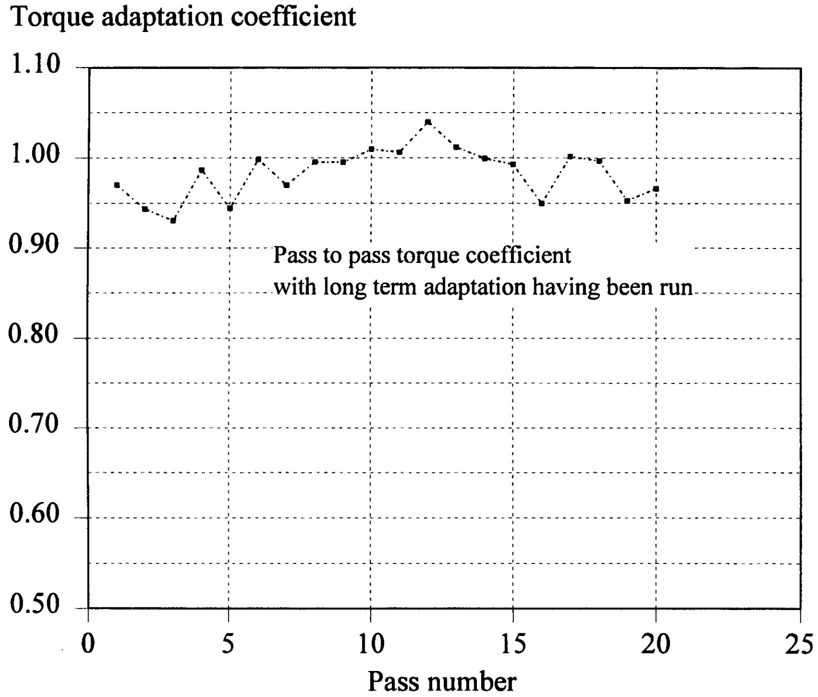


Figure 4.23 Variation in estimated torque coefficient

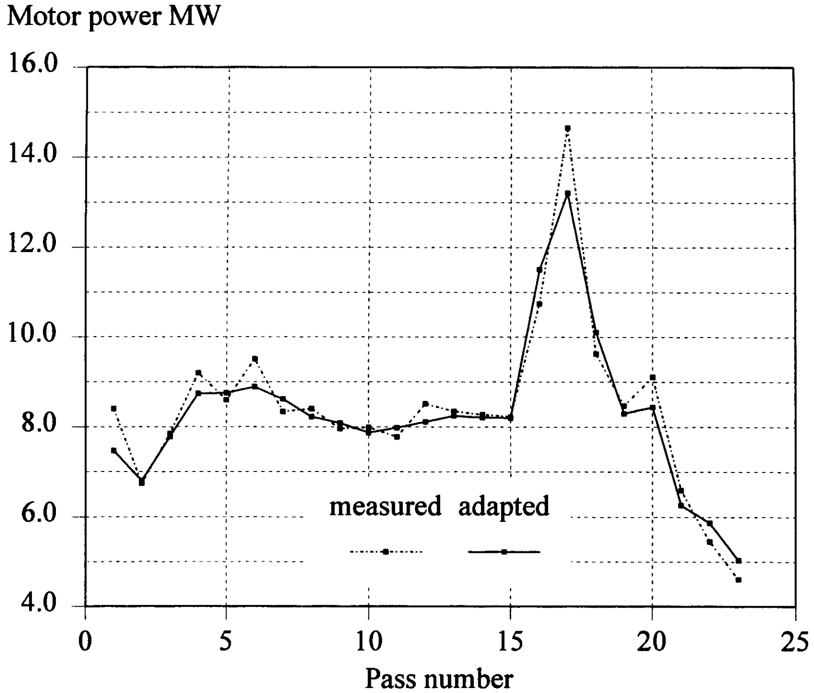


Figure 4.24 Comparison of pass by pass actual measured and adapted motor power

4.4.5 Flow stress as an observer

The load model is corrected for short term adaptation after each pass has been run. It is possible to use flow stress to perform this correction. The assumption is that not every slab will have identical material properties and that the flow stress will be affected by such variations. Figure 4.25 shows the variation in the estimated flow stress parameter with the long term adaptation being run. The average value for the coefficient is less than 1.0, 0.955 in fact which corresponds to the flow stress offset for the current slab. Figure 4.26 shows a comparison between the measured and predicted rolling load for each pass with the long term adaptation being run. It can be seen that there is a good agreement between the values shown in the graph.

4.4.6 Strip temperature as an observer

Instead of assuming that the error in the rolling load is due to the flow stress offset it is also equally valid to assume that an error in the measured initial slab temperature was made. In this case the EKF algorithm is used to correct the observed temperature state based upon the measurement of rolling load. Figure 4.27 shows the estimated strip temperature when the lay-on temperature is correctly measured. In this case flow stress is used to correct for any load error. The second temperature prediction curve shows the effect of an error of 20°C in the lay-on temperature measurement. The algorithm corrects for the temperature offset after 3 passes have been rolled. After these 3 passes it is assumed that the temperature state has been corrected. The EKF is switched so that flow stress is used to correct the rolling load and the any flow stress offset is identified. Figure 4.28 shows a comparison between the measured and model predicted rolling load using the temperature observer. The error in the rolling load for first two passes is caused by the incorrect strip temperature being applied to the process models.

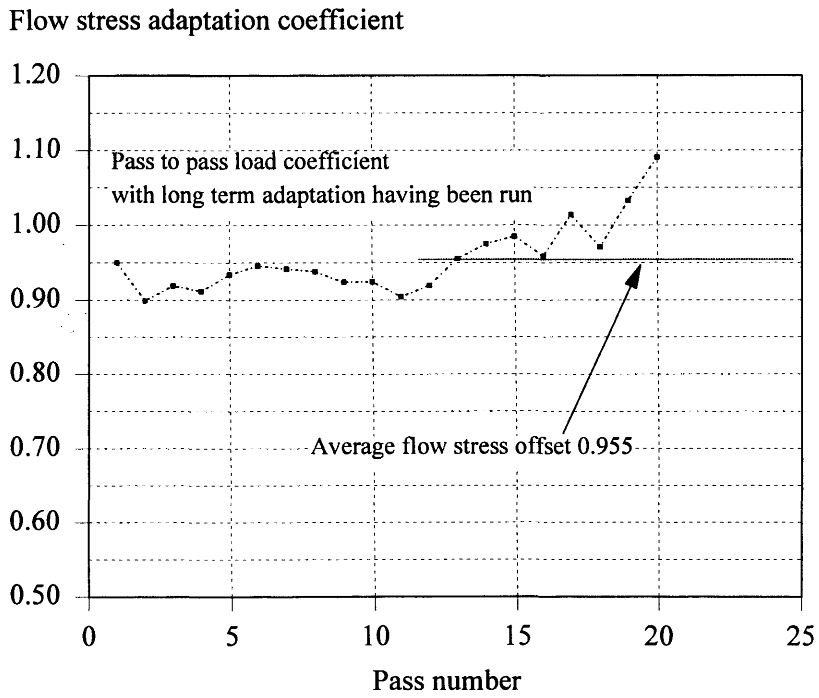


Figure 4.25 Variation in estimated flow stress coefficient

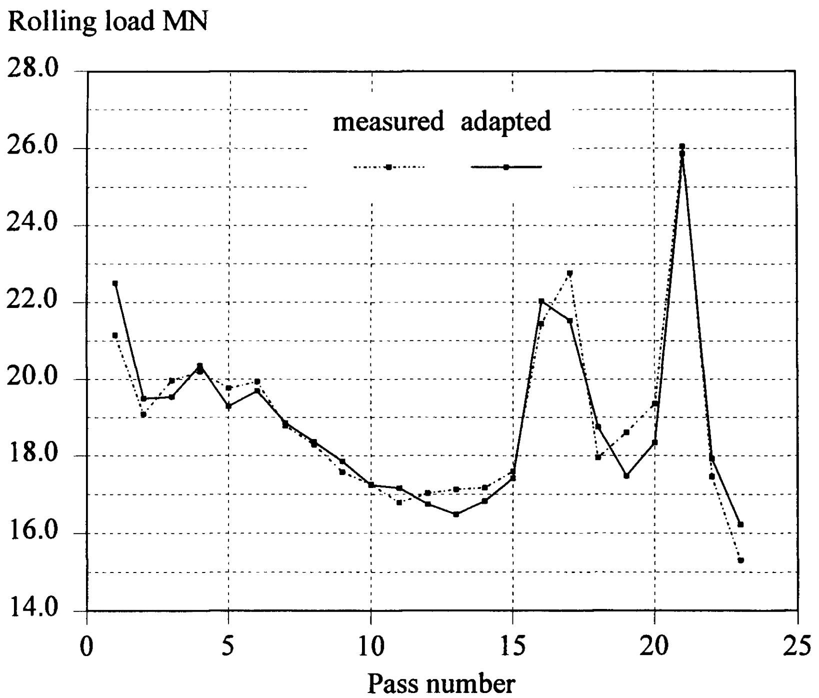


Figure 4.26 Comparison between actual measured and adapted rolling load with flow stress as adaptor

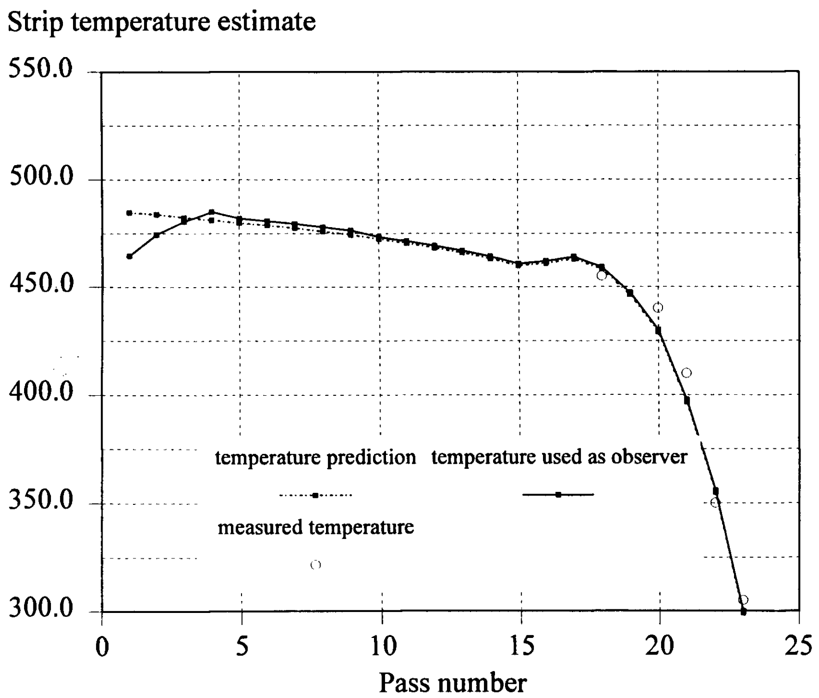


Figure 4.27 Estimates of strip exit temperature

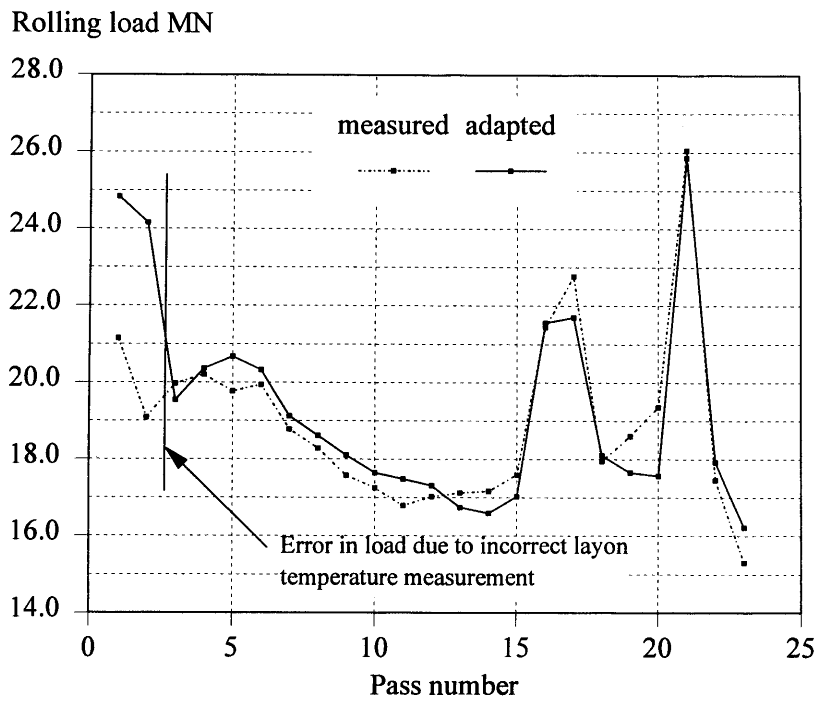


Figure 4.28 Comparison of actual measured and predicted rolling load with offset in lay-on temperature measurement

4.4.7 Short term adaptation

The results shown below for the load, power and strip temperature models show the improvement that is made when the short term adaptation and long term adaptation are run together. Figures 4.29 to 4.31 show scatter graphs of the measured versus predicted results for the adapted models and these graphs may be directly compared to those in Figures 4.2 to 4.4 and Figures 4.16 to 4.18 which show the same results for the unadapted and long term adapted models. Table 4.2 compares the mean and standard deviation of the model error for the three sets of results. In all cases there is improvement in the performance of the models over the case when just the long term adaptation is used. Figure 4.32 shows the ratio of the measured to predicted rolling load with the long term and the short model adaptation. Comparing this figure to Figures 4.6 and 4.19 it can be seen that the overall model offset has been reduced by the long term adaptation and the slab to slab variation in the model error is also less than in the previous two graphs.

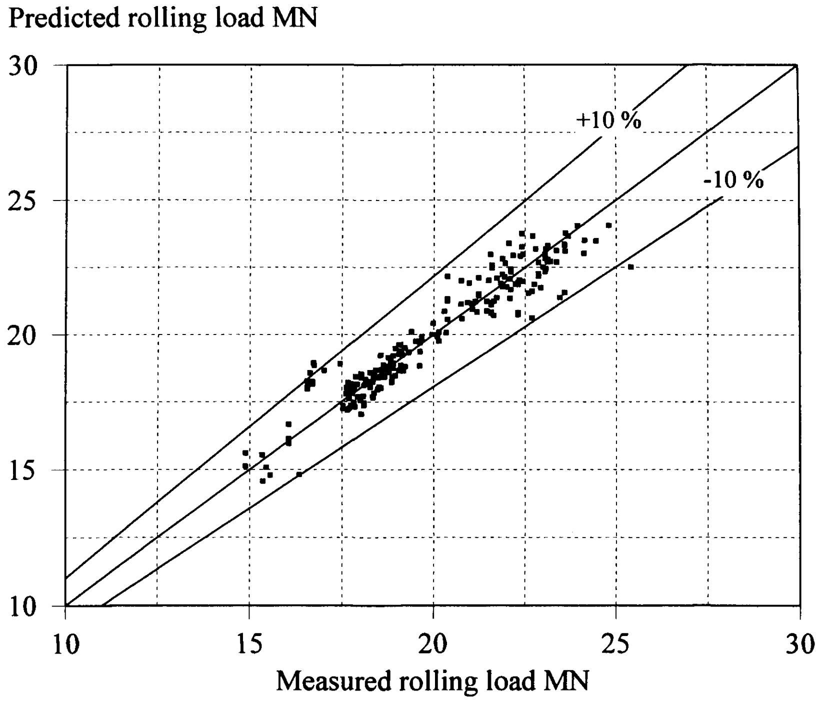


Figure 4.29 Graph of measured against actual measured rolling load for long and short term adapted models

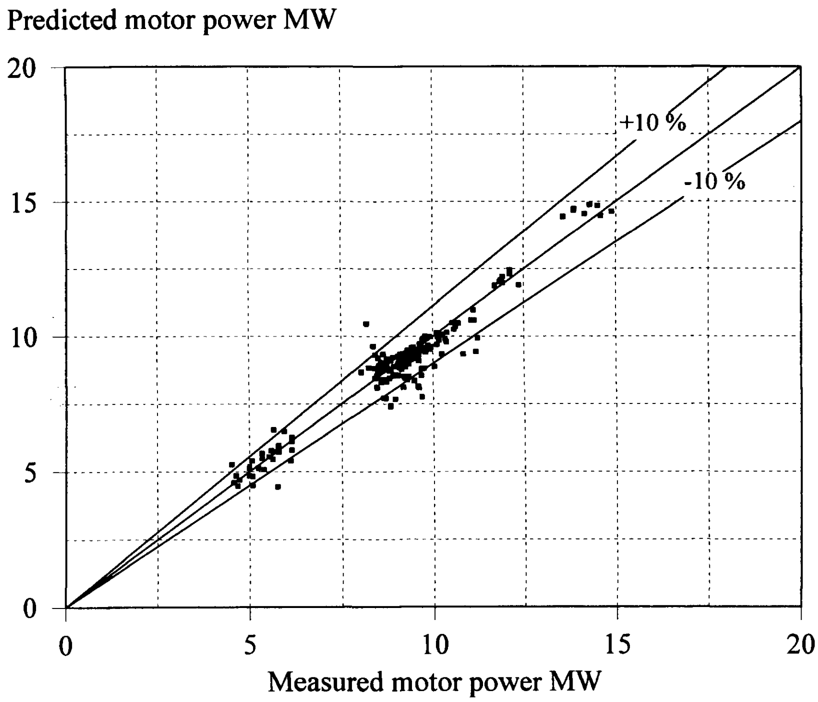


Figure 4.30 Graph of predicted against actual measured motor power for long and short term adapted models

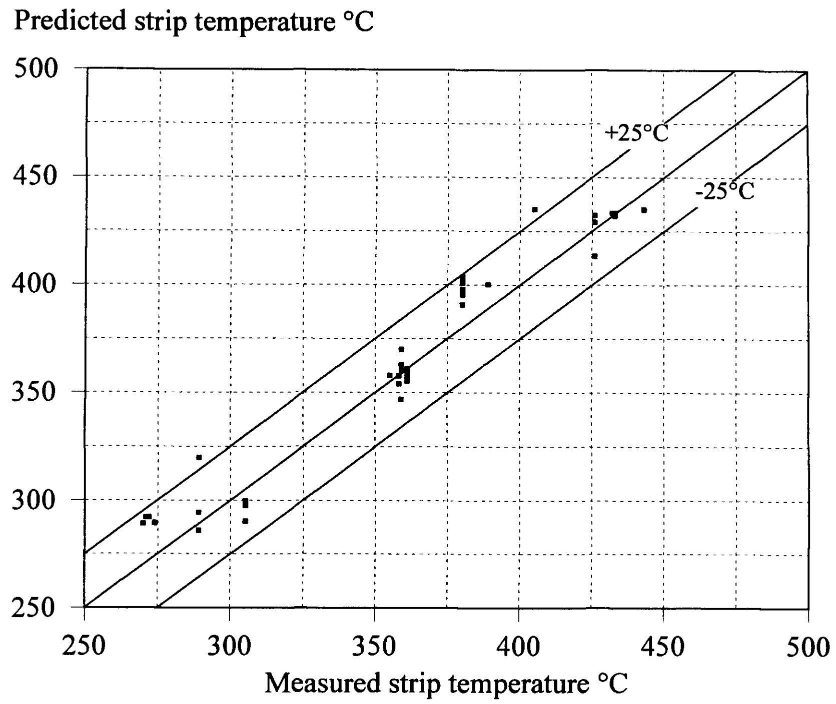


Figure 4.31 Graph of predicted against actual measured strip temperature for long and short term adapted models

Model	Unadapted models		Long term adapted models		Short and long term adapted models	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Rolling load	-20.34%	8.90%	-0.14%	5.38%	-0.12%	3.57%
Motor power	-2.05%	12.73%	0.98%	8.49%	0.87%	6.02%
Strip temperature	-11.96°C	22.38°C	-3.80°C	12.82°C	3.72°C	9.41°C
Strip profile	-0.21%	0.17%	0.04%	0.06%	0.04%	0.06%

Table 4.2 Comparison of statistical data for unadapted and long term adapted models

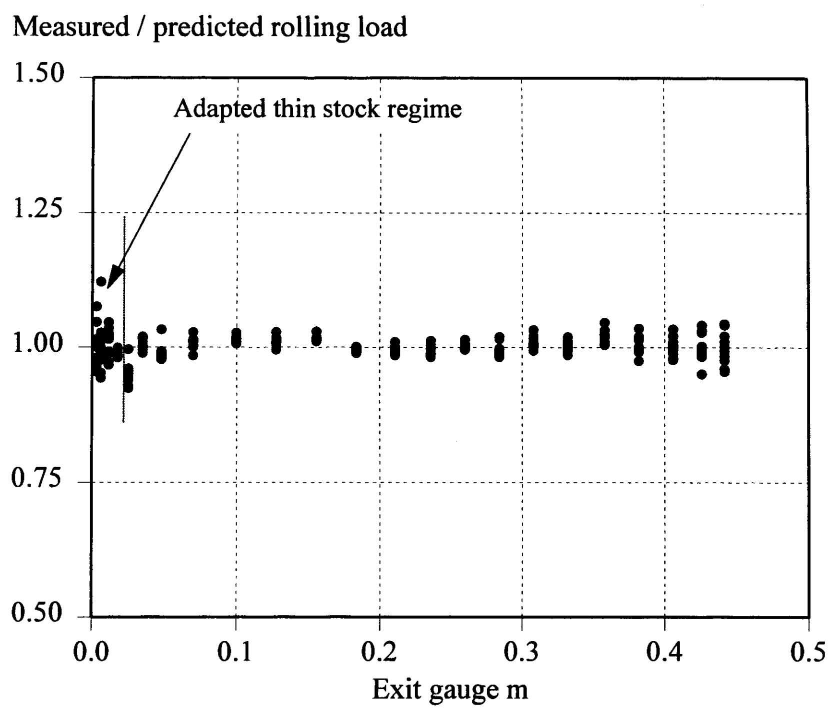


Figure 4.32 Graph showing ratio of actual measured to predicted rolling load with long term and short term adaptation

4.5 Implementation considerations

This section describes some considerations applied when implementing the adaptation algorithms, see Isermann [142] and Wittenmark [143]. All the techniques described here improve the performance of the adaptation scheme. They also provide mechanisms in the form of parameters whereby the functionality of adaptation algorithms can be influenced from an external source. In the case of this thesis such an external source is in the form of an expert system. Adaptation control strategies are described in Chapter 5 that allow the parameters to be adjusted for given scenarios and thus the adaptation is controlled.

4.5.1 Selection of weights

Within the two adaptation algorithms presented in Sections 4.3 and 4.4 the terms σ^2 and R each represent the measurement weighting matrix. The physical interpretation of this matrix is such that R or σ^2 is set to contain information concerning the confidence that is placed on a particular measurement. For this study R has been set as given below:

$$R = \mathrm{diag}\,(1\times10^{12},\, 5\times10^{10},\, 50) \tag{4.105}$$

where the first two terms for load and power respectively correspond to a measurement standard deviation of around 5% and for strip temperature of 7°C.

4.5.2 Starting point for algorithms

The choice of the initial values taken for the error covariance matrix P_0 and the adaptation coefficients θ_0 requires some consideration. Generally speaking the values taken for θ_0 are 1.0 for the cases where the coefficient is being used as an offset from the nominal conditions, for example the flow stress offset see Equation (4.4). For cases where θ is a true model parameter such as in Equation (4.78) then some initial values are determined from performing a least squares fit off-line on a sample set of data.

The initial values for the P matrix diagonal are large numbers typically 10^6, see Ljung [144].

4.5.3 Forgetting factor

The RLS algorithm presented in Section 4.3 assumes that the coefficients θ do not vary with time. As already discussed the rolling process does vary slowly and this variation must be tracked by the long term adaptation scheme. To allow this to occur the RLS algorithm is modified to include a forgetting factor β which allows the filter to exponentially forget data, see Ljung [145]. The smaller the value of β the quicker the data is forgotten. A value of 0.99 has been used throughout for β.

The forgetting factor can be used to improve the performance of the adaptation algorithm. By lowering its value from its nominal value of 0.99 to a value of 0.95 the speed of response of the algorithm is increased. Such a modification is made when it is anticipated that the operating point for the process models is about to change.

The effect of modifying the forgetting factor is described in Chapter 5.

4.5.4 Drift

Parameter drift is a long term phenomena which may typically occur over 20 or so slabs. The technique discussed in this section has therefore only been applied to the long term adaptation. As described in Section 4.3, long term adaptation is used to track variations in the mill characteristics over a typical time scale of a few hundred slabs. The algorithm, see Hang et al [146] and results presented here demonstrate how the performance of the adaptation algorithm can be enhanced.

For the process models applied to the rolling of aluminium, parameter drift can occur for two main reasons.

Case 1. The elements in the error covariance matrix P may become small indicating a high confidence in the coefficient states and hence a restriction to the movement of the adaptation coefficients. If the process operating point starts to move away from its current position then because the coefficients must move to follow this change. However, because the coefficients are restricted by the size of the error covariance matrix then the coefficients will appear to drift slowly towards the new operating point.

Case 2. If a fault occurs with one of the measuring instruments such that the measurement drifts away from a true reading then the coefficient will follow this drift. Such a fault can be detected and
rectified.

When the adaptation coefficient is close to its true value then due to the stochastic nature of the process the following equation is true:

$$P\{\Delta\theta_{k+1}^T\ \Delta\theta_k > 0\} \approx P\{\Delta\theta_{k+1}^T\ \Delta\theta_k < 0\} \qquad \textbf{(4.106)}$$

where $P\{\}$ denotes probability and

$$\Delta\theta_{k+1} = \theta_{k+1} - \theta_k \qquad \textbf{(4.107)}$$

When a fault occurs such that the coefficients begin to drift Equation (4.106) will no longer hold and the following will be true:

$$P\{\Delta\theta_{k+1}^T\ \Delta\theta_k > 0\} > P\{\Delta\theta_{k+1}^T\ \Delta\theta_k < 0\} \qquad \textbf{(4.108)}$$

The algorithm to detect a consistent movement of the coefficients in any one direction is given by:

$$\upsilon_{k+1} = \gamma_1 \upsilon_k + \Delta\theta_k \qquad 0<\gamma_1<1 \qquad \textbf{(4.109)}$$

$$s_{k+1} = sign\{\Delta\theta_{k+1}^T \upsilon_k\} \qquad \textbf{(4.110)}$$

$$r_{k+1} = \gamma_2 r_k + (1 - \gamma_2) s_{k+1} \qquad 0<\gamma_2<1 \qquad \textbf{(4.111)}$$

υ_k provides an indication of the trend in the movement of the coefficients and s_k shows the correlation between this trend and the instantaneous value of θ. The successive movement of r_k can be checked against a threshold value of r_0 and a fault is said to have occurred if r_k becomes greater than r_0. Following Hagglund [147], the detection algorithm parameters were set as follows: $\gamma_1 = 0.85$ $\gamma_2 = 0.95$ and $r_0 = 0.5$.

Once the fault is detected the following action is taken. If the diagonal elements of the P matrix are less than 10^{-2} then case 1 indicated above is assumed to have occurred. The action taken is to increase the diagonal elements of the P matrix by 100 times and to decrease the forgetting factor to 0.95. This has the effect of giving much larger corrections to the estimates and to give new measurements a much larger weighting.

If, however, the diagonal elements of the P matrix are greater than 10^{-2} then it is assumed that case 2 has occurred in which case the adaptation algorithm is halted and the measurement in question is monitored.

The results from the fault detection algorithm are described in Chapter 5.

4.5.5 Cautioning

There is a strong interrelationship between the parameters involved in the process model adaptation. Such interrelationships can introduce some oscillation of parameters when the adaptation algorithm is started up for the first time. A technique known as parameter cautioning MacAlister and Reeve [148] is used to introduce a cost onto each of the adaptation coefficients. This prevents the coefficients from moving too far away from a known safe set. The same technique can also be used to impose direct physical constraints onto the coefficients to prevent them moving into an undesired operating region.

The cautioning algorithm functions by firstly running the unconstrained RLS algorithm. If any coefficients stray outside the acceptable limits then cautioning is applied to that coefficient.

The cost function in Equation (4.51) is modified to include the cautious parameter set. The nature of the cost function is dependent upon the result from running the unconstrained RLS algorithm. Equation (4.51) is now modified to include the cautioning thus:

$$J = \left[\left(\frac{\Delta z_k}{\lambda (a_k - a_0)} \right) - \left(\frac{u_{k+1}}{\lambda} \right) a_k \right]^2 \tag{4.112}$$

where λ is a weighting function and a_0 is the constraint on the coefficient.

Figure 4.33 shows a simulation of the effect on the coolant wash HTC adaptation coefficient for the final coiling pass with and without cautioning being applied. In this case a lower limit of 0.6 was applied. Figure 4.34 shows the corresponding adjustment of the flow stress adaptation coefficient with and without the cautioning applied to the coolant wash HTC. The accuracy of the models is slightly better when the coefficients are unconstrained than when constrained.

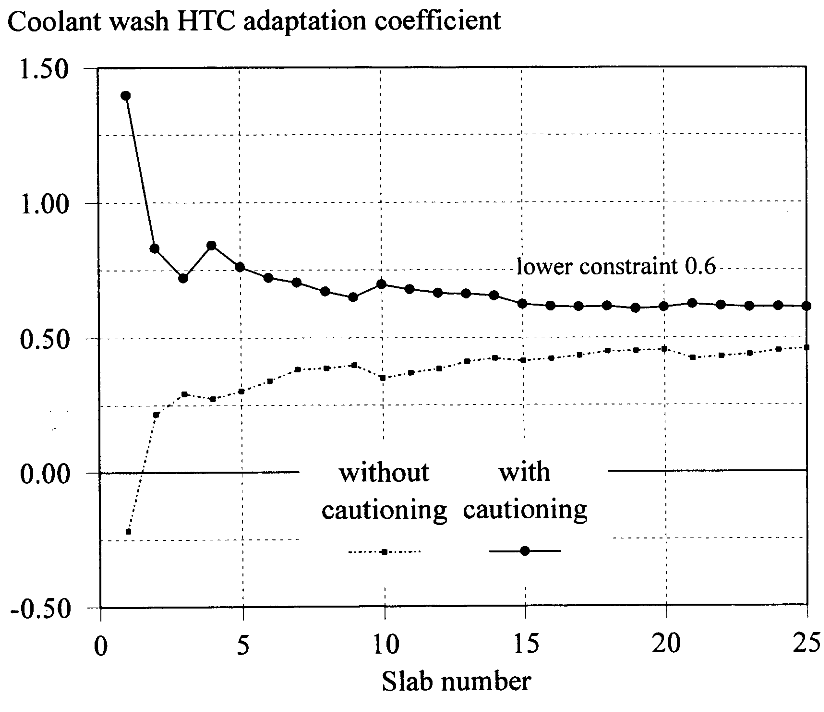


Figure 4.33 Effect on the coolant wash HTC coefficient when cautioning is applied

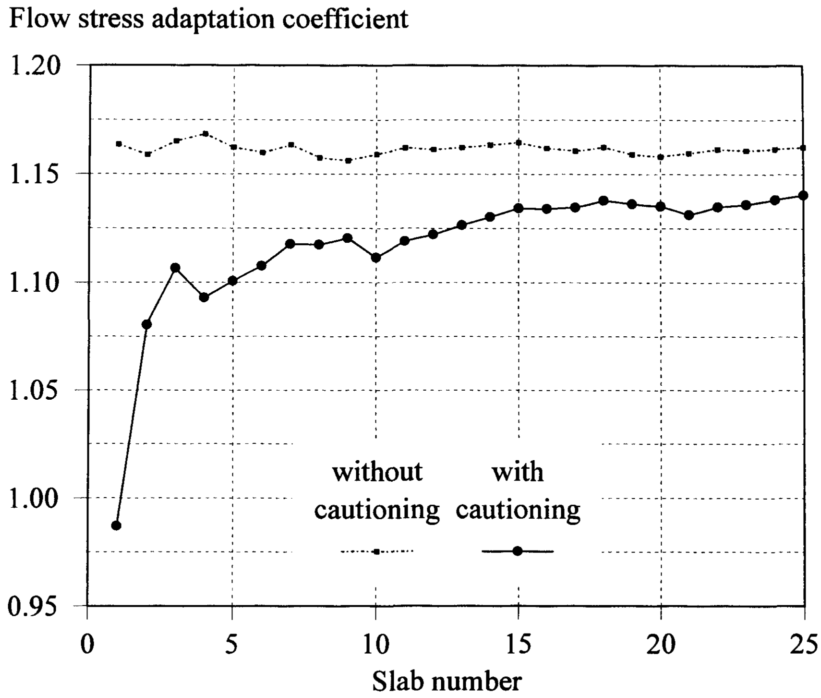


Figure 4.34 Effect on flow stress coefficient when cautioning is applied to coolant wash HTC coefficient

4.6 Conclusions

Its has been shown in this chapter how the process models described in Chapter 3 can be adapted with both long and short term schemes. The first section presented an original method for determining the partial derivatives required for adaptation using a perturbation analysis. The next sections presented for the first time a two level adaptation scheme for the aluminium hot reversing mill. The results presented show that the long term adaptation removes the model offset error, whilst the short term adaptation reduces the standard deviation of the model error. The improvements that are made to model accuracy using the two schemes have been illustrated both tabular and graph form. Accurate model predictions are possible for the load, power and strip temperature models and for the strip profile model.

The final section described the implementational considerations that should be made before the adaptation schemes are used on-line. It has also been demonstrated how using a set of relatively straightforward modifications to the basic adaptation algorithms it is possible to further enhance the performance of the process model adaptation. Such enhancements can then be used by an expert system to automatically monitor and control the execution of the adaptation schemes. Rules to perform this task are discussed in Chapter 5.

CHAPTER 5

Application of an Expert System

5.1 Introduction

This chapter describes the development of an expert system suitable for controlling the setup of an aluminium hot reversing mill. Setup is performed before the metal enters the mill, when suitable actuator set points are determined that will produce material as close to the desired quality as possible. Chapter 2 described the operation of mill setup systems and how they interface with the higher and lower level mill control systems. Traditionally mill operators have performed the tasks involved in setting up the mill. The operator's expertise and judgement will have been gained over many years. He or she will also be able to judge whether the mill's instrumentation and mechanical components are functioning normally. The supposition made in this thesis is that the tasks performed by the mill operators can be replicated using an expert system. To aid the expert system's judgements the process models described in Chapter 3 give estimates of important mill parameters used when mill setup is performed. The accuracy of these estimates is maintained using the adaptation schemes described in Chapter 4. The combination of the three components described in Chapter 3 to 5 when integrated together, produces an advanced mill setup system. This utilises the strengths of each of its components to give a more powerful hybrid control system. The idea of producing such a system has given rise to an original control architecture.

The task involved in this development was to construct a knowledge base containing the control strategies required to perform mill setup and supervisory control. Knowledge appropriate to this application was acquired and then defined in a syntax that could be stored within the expert system. This knowledge comprises a series of strategies that define a particular control aspect. Strategies maybe made up of several rules. Each rule is accessed in turn by the expert system, to perform the required control strategy. The sequence in which the rules are activated is determined by the configuration of the inferencing technique used within the expert system.

In Section 5.2 the basic concepts of expert systems are introduced. The overall architecture of the expert system is presented. Structures used for storing knowledge are described along with methods used to elicit the knowledge. A technique used to access the knowledge, called inferencing, is explained.

Section 5.3 then describes how an expert system can be structured for the rolling mill application. The expert system has been split into three main knowledge bases each containing a set of rules. Strategies are defined to perform diagnostics on both the mill measurements and the process quality and these are described in Section 5.4. A set of strategies are concerned with the control, scheduling and setup of the rolling mill and these are detailed in Section 5.5. The final group monitor the performance of the process models and the adaptation, presented in Section 5.6. As the system was tested off-line, simulations were performed to test the system's response to various scenarios that occur on the mill. For each strategy, results are given which demonstrate its operation and where appropriate a comparison is made without the expert system.

In Section 5.7, an original architecture is developed which integrates the expert system, process models and the adaptation into a single system. The components of this system which have not been described in any previous chapter are explained at this point. The implementation of the various components of the system are also discussed in this section.

The chapter ends with conclusions given in Section 5.8.

The detailed descriptions of the implementation of the mill setup control strategies presented in this chapter will demonstrate that the expert system is an appropriate technique for control of the rolling process.

5.2 Expert system structure and components

This chapter defines what constitutes an expert system and each of the constituent parts is described in detail.

5.2.1 A definition of artificial intelligence and an expert system

Durkin [149] defines artificial intelligence as 'the goal of making a computer reason in a manner similar to a human being'. The primary task is to construct a program that attempts to mimic the problem solving ability of a human, see Sardis and Valavanis [150]. Advantages to be gained by using such technology include the fact that less dependency is placed upon having a costly human expert. Table 5.1 summarises the advantages that a machine has over a human.

Factor	Human operator	Expert system
Time availability	Work day	Always
Geographic	Local	Anywhere availability
Safety	Irreplaceable	Replaceable
Perishable	Yes	No
Performance	Variable	Consistent
Speed	Variable	Consistent
Cost	High	Affordable

Table 5.1 Comparison of a human operator and an expert system

One subjective measure of the success of AI programs is given by applying the Turing test, Frenzel [151]. Briefly, the test involves having two identical terminals in a room, one linked to a human operator and the other to a computer. If the operator is unable to decide which terminal is connected to the human and which is connected to the computer, then the computer can be credited with intelligence. From an objective point of view one can imagine testing, for example, a rolling mill AI control system against a human operator by subjecting the plant to a series of scenarios. Each scenario would require some complex decision making process to be undertaken to control the process. By comparing the two performances one would have a measure of the intelligence of the system to control this application, see Vaithyanathan [152] for a review of machine learning in the metals industry.

To construct such an intelligent program, one must first establish what mechanisms are used by humans when problem solving. At present we do not have a complete understanding of how the human brain operates. In spite of this incomplete understanding Albus [153] identifies the following:

i) A mechanism for obtaining and processing the data related to a new problem.

ii) Storing or learning the knowledge and information gained from experience in a way that can be quickly accessed.

iii) Retrieving the relevant knowledge from the data store.

iv) Making a decision based upon experience for a given problem.

v) Making a decision for an unseen problem by either adapting previously leant data or learning from trial and error, as reviewed in Vepa [154].

Research in AI has several directions each one of which addresses some of the above elements. The particular branch of interest in this thesis is *expert systems.* An expert system attempts to solve (ii), (iii) and (iv) in the above list. Other branches include neural networks, genetic algorithms and fuzzy logic which address different combinations of items in the above list, see White [155] and Portmann [156]. These have learning mechanisms by which unseen data is automatically learnt and stored. Such algorithms are beyond the scope of this present study, but some ideas are discussed in the conclusions and further work presented in Chapter 6.

An expert system is designed to model the problem-solving ability of a human expert, see Durkin [150] and Mockler [157]. Conventional expert systems have no direct learning mechanism, which means that they can only be applied to the application for which they were designed. All the knowledge stored within them must be preprogrammed. Guidelines for performing this task are given by DTI [158] and Cohen [159].

The fundamental qualities of the expert system are its ability to:

i) Deal with complex information that would normally require a considerable amount of human expertise.

ii) Explain or justify the reasons for the solutions and recommendations attained for a given problem, which is done by attaching an appropriate explanation to each rule.

iii) Provide a high degree of performance in terms of speed and reliability in order to be a useful tool.

5.2.2 Expert system architecture

This section will describe the typical architecture of an expert system. It can be seen in the simplified block diagram shown in Figure 5.1 that an expert system consists of five main components as described below:

i) A *knowledge base* containing all the preprogrammed facts, rules and knowledge appropriate to the expert system's application field. This is analogous to the long term memory of the human brain.

ii) A *working memory* that contains all the data relevant to the current problem being solved. The data stored here may have come as input data or have been inferred from rules contained within the knowledge base. This is analogous to the short term memory of the human brain.

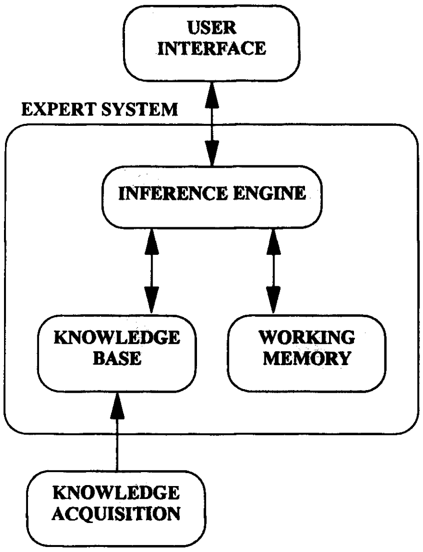


Figure 5.1 Expert system architecture

iii) An *inference engine* that processes data held within the working memory, drawing conclusions about the problem by accessing the relevant parts of the knowledge base.

iv) A *knowledge acquisition* phase, when the accumulated process rules are structured and programmed in to the knowledge base.

v) A *user interface* which provides a means of entering data into the expert system and then presenting the conclusions or recommended actions for the given problem.

For the work involved in this project a proprietary expert system shell has been used, see Vesey [160] and Laffey [161]. The work required to construct the expert system suitable for the hot rolling of aluminium addressed the areas of determining suitable rules via knowledge acquisition, constructing the knowledge base, sequencing the order in which the inferencing takes place, testing and creating a suitable user interface.

The following sections describe in more detail the main components of an expert system.

5.2.3 Knowledge elicitation or acquisition

The process of acquiring expertise, the rules and strategies suitable for storing within the knowledge base is known as knowledge acquisition or elicitation, see Diaper [162]. There are several methods which can be used to acquire the knowledge suitable for developing a rolling mill setup and supervisory control expert system. These include:

i) Interviewing operators or engineers closely connected with the operation of the rolling mill, as described in Bainbridge [163]

ii) Analysing measurements logged when an operator is setting up the mill.

iii) Published literature on the subject which outline possible control strategies, see literature survey in Chapter 2.

iv) Performing off-line simulations with a model to develop new strategies.

In this thesis a combination of all these methods has been adopted in developing the knowledge base. Some typical examples include:

i) The strategy established to maintain good shape whilst rolling was first developed experimentally by Shoet and Townsend [118].

ii) Literature on quality control describes methods of detecting when the manufacture of a product is out of control, see for example Bissell [164].

iii) Distinct patterns were found in the variation of the roll speed.

An important consideration is to determine how good the data or information is, that has been acquired. For example each mill operator will use a slightly different operating practice to control the mill. Only good operating practice should be stored, based on knowledge acquired from the operators. Another dilemma which faces the knowledge engineer is should the expert system be designed to operate exactly as an operator would behave, by capturing the operator's knowledge precisely, or should he or she attempt to improve the knowledge, and how should this be done.

The resulting expert system may perform better than its human counter part if one uses knowledge which has been improved in some way. In such a scenario the Turing test described in Section 5.2.1 would fail because now the computer may perform the tasks more accurately than its human counter part.

5.2.4 Knowledge base

The knowledge base within the expert system contains all the facts, strategies and rules which are necessary to encapsulate the domain knowledge. The problem to be solved by the software engineer is how to construct the knowledge base from the information given to him or her by the knowledge engineer. Fortunately a number of tools are available which make the task easier. The first decision to be made is what are the important parameters in the problem. For each type of parameter a structure can be setup to enable information about that parameter to be stored within the system. The next task to be performed is to construct the rules which are to be held within the knowledge base. At this stage in the design, rules which are related must be grouped together into sets in order to reduce the processing time during the expert system's execution.

A proprietary expert system shell called LPA *flex* was used for the development, see Vesey [160]. This meant that the primary goal of the work was the creation of a knowledge base. During the development of the knowledge base it was found that the rules fell into one of three categories. Each category is in turn subdivided into the individual rules and strategies. The three main categories of rules are:

i) *Diagnostic rules*. A variety of measurements are made during the rolling of each pass. The rules in this part of the knowledge base check for normal mill operation. Decisions are largely based on whether or not sets of measurement are reliable and consistent.

ii) *Scheduling and production rules* define the strategies adopted to find the actuator set points that result in finished coils with the desired quality parameters as specified in the furnace queue. Information drawn upon to perform this task is taken from the schedule databases, model predictions and measurements. The production rules mainly consist of actuator constraints and simple *if then* combinations of schedule parameters.

iii) *Process models and adaptation rules* systematically check the accuracy of model predictions and monitor the behaviour of the adaptation algorithms. The rules look for long term drift in the adaptation coefficients, check for instability and adjust weighting and forgetting factors accordingly.

5.2.5 Data representation

The object-orientated method for defining and storing data within an expert system is to use data structures known as frames, see Winston [165]. These frames are constructed for each different type of object, so for example, a frame can be defined for an object to represent a measurement, see Figure 5.2. For every instance of a measuring device this frame is replicated so that each measurement is represented by an identical structure.

The syntax for constructing a frame is as follows:

frame *frame_name*
default *attributes_name*

Instances of such a frame are created as follows:

instance *instance_name* is a *frame_name*

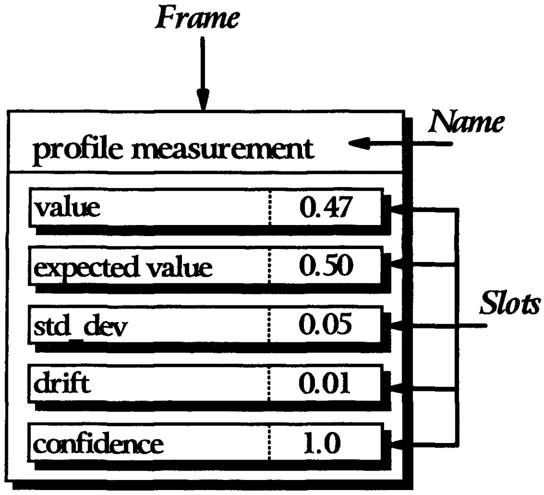


Figure 5.2 Typical frame structure for a measurement

5.2.6 Knowledge representation

Having established the data to be represented within the system, the knowledge acquired at the acquisition phase must be defined. Several tools are available to make this task easier and allow the construction of the rules in an English like syntax. Some illustrations of this syntax are given below.

i) A *rule* is a knowledge structure that relates some information to other information that can be concluded or inferred to be known. It consists of two parts a 'premise' and a 'conclusion'. Each time the rule is fired by a forward chaining type inference engine the premise is checked before the conclusion can be activated. Additional information may be supplied within the rule to provide an explanation of the actions taken. Finally a score may be associated with the rule which helps in situations where rule conflicts occur. A high score associated with the rule would indicate to the inference engine that the rule was more important than a rule with a low score.

Rules are constructed as follows:

rule *rule_name*

if *premises* then *conclusion*

ii) A *ruleset* is made up of several rules which are grouped together to form a strategy. For example:

ruleset *ruleset_name*

rule_names

iii) An *action* consists of one or more directives. A directive is simply an assignment which replaces the variant on the left hand side of the expression with the value on the right hand side. The operation is most commonly used for sequencing several operations. For example:

action *action_name*

directives

iv) *Relations* are constructed to simplify the syntax of the rules. They consist of a premise which may contain a directive returning a value to the rule. For example:

relation *relation_name*(*variables*)

if *premises* and

directive(variables)

v) *Synonyms* are used to replace frequently occurring terms or expressions within the rulebase with a usually shorter and more readable syntax. For example:

synonym *longname1*

shortname1

Using the above constructs, the knowledge base for the aluminium hot mill expert system was created to have an English like syntax.

5.2.7 Working memory

The working memory holds data and conclusions inferred from the current run of the inference engine. The working memory is often termed the short term memory. During each run of the inference engine information about the current problem will be entered into the working memory. The system matches this information with knowledge contained in the knowledge base to infer new facts. The system then enters these facts into the working memory and the matching process continues until some conclusion is reached.

5.2.8 Inference engine

The expert system models the process of human reasoning with a module known as the inference engine. It works with the facts contained within the working memory and the knowledge domain contained within the knowledge base to derive new information. There are two main types of inference technique, *forward chaining* and *backward chaining.*

Forward chaining works from a given set of data and a predefined sequence for firing the rules held in the knowledge base. It searches the rules for a match between their premises and the information contained in the working memory. When the inference engine finds a match, it adds the rule's conclusion to the working memory and continues to scan the rules for new matches. Backward chaining works in the opposite sense in that the data stored in the working memory is used to scan the THEN parts of the rules. The conditions that must have been met to achieve this conclusion are then added to the working memory. The inferencing continues until a solution is achieved.

The work carried out in this thesis used the forward chaining type of inferencing technique.

5.2.9 User interface

The user interface provides a means of communication between the expert system and the outside world, which may either be a human or another computer. The basic requirement for such an interface is that the expert system will be triggered and given a set of input data. The expert system will then start to fire the sequence of rules which are appropriate for the task it is required to perform. The expert system may require further information to be given before a complete solution can be obtained. The solution or a list of possible solutions, will be provide to the operator together with an explanation.

5.2.10 Design procedure for an expert system

The previous sections have described the main components which make up an expert system. There are a number of phases in the development of a typical expert system, as illustrated in Figure 5.3. Phase 1, should be an assessment of the problem area, including a feasibility study and a cost/benefit analysis to establish that the chosen field is suitable for the application of an expert system. Phase 2 consists of collecting the knowledge which will be needed to construct the expert system, as indicated in Section 5.2.3. Several techniques are available to perform this task. Having gathered the data, it must be structured into a suitable form so that it can be represented in the chosen expert system software tool and this occurs at phase 3. The design of the knowledge base and the sequencing of the inferencing to access the rules must also be considered at this stage. Phase 4 is concerned with testing the expert system to ensure that it is producing results consistent with the data used in its programming. Any gaps in the knowledge can also be established and modifications made by either acquiring new data or by restructuring the existing knowledge. The expert system becomes a useful tool for an operator with the attachment of a user interface at phase 5. Finally the finished product must be documented and have suitable maintenance facilities so that the knowledge base can be developed or modified if required.

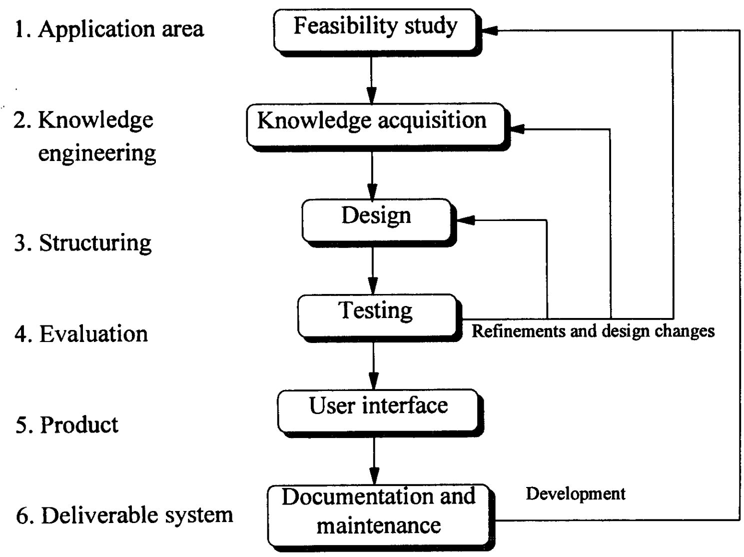


Figure 5.3 Expert system development phases

5.3 Development of the knowledge base for a rolling mill application

This section describes the structure of the expert system which has been designed to perform the task of supervisory control and setup for a rolling mill. The idea of using an expert system to perform mill setup on a hot aluminium rolling mill is an original idea. Section 5.3.1 describes the frames that have been created in order to represent the parameters involved in controlling the rolling process. Then Section 5.3.2 presents the architecture of the knowledge base constructed for this application.

The approach that has been adopted is to divide the knowledge base into three main sections. This simplifies the construction of the expert system and speeds up its execution because only the relevant rules are consulted when a given task is performed. The three groups of rules are:

i) **Diagnostics.** The rules in this section of the knowledge base are concerned with diagnosing any problems with the measurements or with the quality of the rolled product.

ii) **Scheduling.** The scheduling strategies adjust the actuator set points prior to the slab being rolled to counteract any variability in the process.

iii) **Process models and adaptation.** Rules check the model accuracy, adjust adaptation parameters, determine the state of the slab and assemble a schedule from measured data.

There is considerable novelty in the work described in the following sections, as this is the first time that the strategies involved in setting up an aluminium mill have been described in a single publication. Additionally new strategies have been developed for all three sections of the knowledge base. The approach of constructing an expert system to implement the strategies is completely novel. Finally the idea of combining the expert system with process models and adaptation has a considerable advantage over just using a single technology.

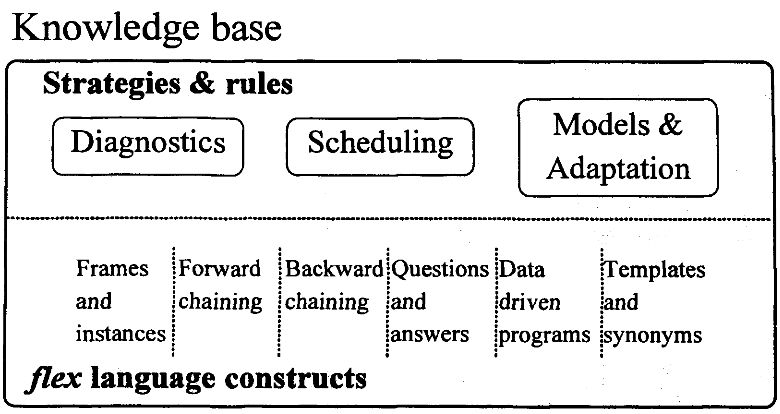


Figure 5.4 Knowledge base components

Figure 5.4 shows a block diagram of the three main elements within the knowledge base. Also shown are the language constructs, some of which were described in the previous section which are used to create the knowledge base within the *flex* expert system shell.

Section 5.2 described how frames are used to describe objects which are used to store data about the process. This section describes the frames which have been constructed to represent the objects required for the rolling process. Each object is then replicated to represent all the instances that occur within the process and the automation system.

Frames are used to define the process measurement, model predictions, adaptation coefficients, actuator values, the slab state, process targets and schedule information.

The expert system has been designed so that it consists of several small partitioned rule sets. Each of these rule sets contains a control strategy for a particular component of the control system. Three main types of rules have been identified within the knowledge base as described above. Figure 5.5 shows how these three sections within the knowledge base have been split into smaller elements. Each individual element may in turn be made up of several rules to define its control function. Sections 5.4 to 5.6 now describe the strategies contained within each of the main three sections of the knowledge base.

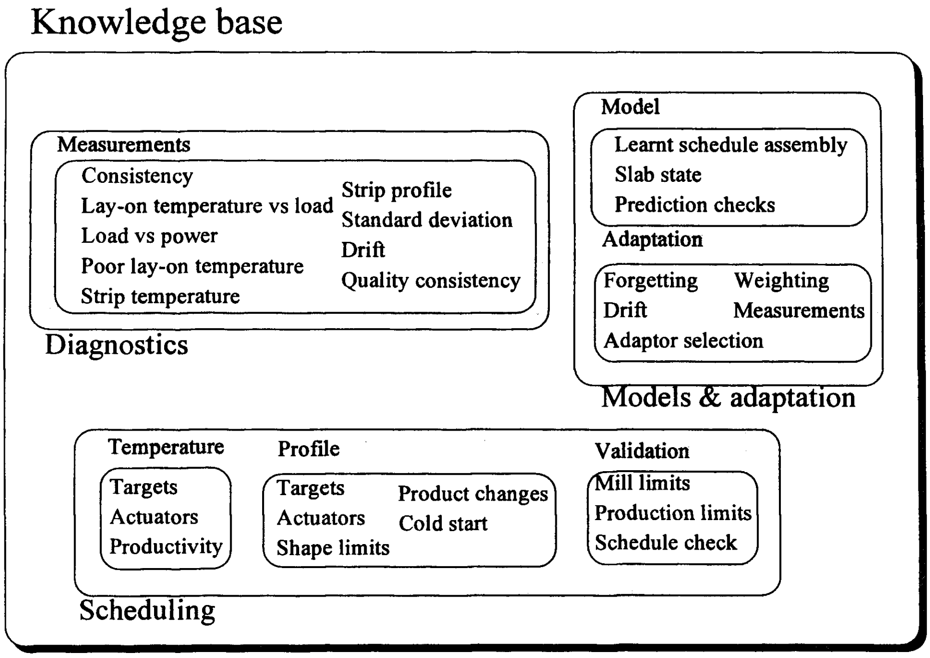


Figure 5.5 Structure of knowledge base

Appendix 1 gives samples of the expert system code which was constructed for the application described in this chapter.

5.4 Diagnostics

This section describes the set of rules stored in the knowledge base concerned with identifying faults that may occur during rolling, see Pokkunuri [166] and Kumar [167]. These rules are divided into two main groups; one set is used to ensure that the process measurements are consistent both with each other and with previous experience, the other set is used for monitoring the quality of the rolled product. The first set of rules makes use of fault detection and fault diagnosis, see Sohlberg [168], Tzafestas [169] and Isermann [170]. The design of rules for fault diagnosis, involves four main steps:

i) Deciding which parameters to monitor in order to identify when a fault is occurring.
ii) Processing the chosen parameters in order to decide when a fault has occurred.
iii) Determining the most likely reason for the fault.
iv) Providing a suitable remedy or advice to remove the fault.

The set of rules used for checking the quality of the rolled product makes use of ideas from statistical process control.

The next sections describe the rules implemented within the knowledge base used for performing the hot mill diagnostics.

5.4.1 Measurement consistency with past experience

During the rolling of each pass of the schedule a set of process measurements is made, both of the slab state and the mill state. The slab state measurements are the strip temperature on later passes of the schedule and the gauge and profile on the final pass. The mill state measurements are the rolling load and main motor power. After the pass has been rolled and the measurements are made available to the system, their consistency with past experience can be established. This is achieved by comparing the measurements with the learnt schedule, which is described in detail later in this chapter. In summary, the learnt schedule contains a snap shot of measurements for a particular type of product which the expert system has deemed to be a good representation of how the slab is rolled.

Each measurement is allowed to deviate from the average operating point by a predefined amount. Figure 5.6 shows a typical set of measurements and clearly identifiable is a measurement that has strayed away from the nominal expected value. As soon as the deviation becomes larger than would normally be expected, the confidence of the measurement is reduced. Confidence in the measurement may be re-established if it is found that the measurement set is consistent. These consistency rules are described below.

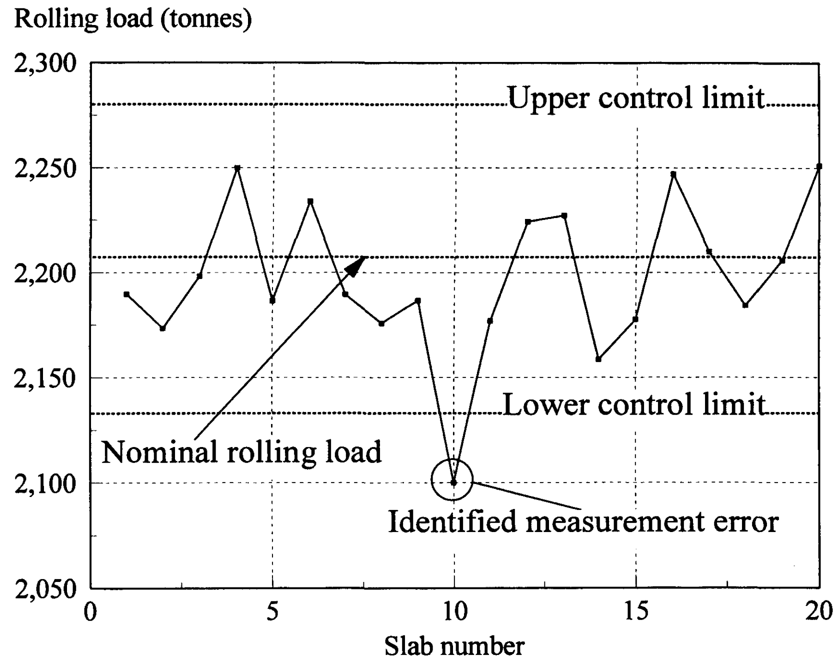


Figure 5.6 Measurement consistency with past experience

5.4.2 Relationship between lay-on temperature and rolling load

The sequence of events that occur before the slab is rolled are that the slab will be removed from the furnace and is transported to the mill roller table. At some stage before the first pass is rolled the temperature of the slab is measured using a contact thermocouple. Such a measurement is usually termed the lay-on temperature. Such a measurement allows the process models to take into account any variation in the slab's lay-on temperature when a prediction of the rolling load is made. Under some circumstances the measurement of this lay-on temperature may be inaccurate. The reasons for this may be:

i) The thermocouple did not make good contact with the surface of the slab due to the presence of oxide.

ii) The thermocouple is no longer correctly calibrated correctly.

iii) The surface temperature of the slab is not a good representation of the overall slab temperature. During a delay the surface cools differentially compared to the inside of the slab.

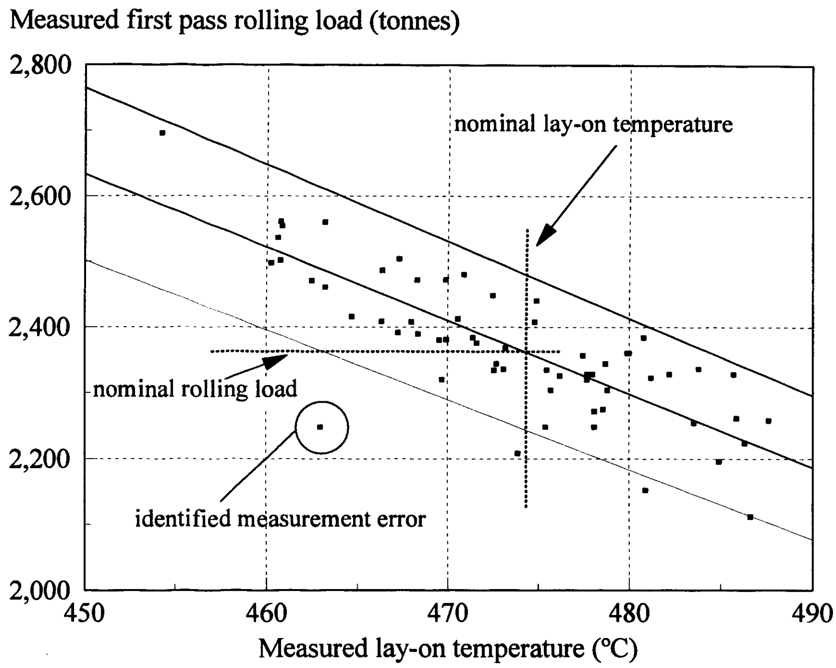


Figure 5.7 Relationship between lay-on temperature and rolling load

Diagnosing that a poor measurement of the lay-on temperature or rolling load has been made, is achieved by comparing the measurements with the nominal operating point stored in the learnt schedule, see Figure 5.7. The learnt schedule is described in Section 5.6.1. This operating point is extrapolated using the model prediction of the slope, to take into account variations in schedule parameters such as the reduction and mill speed. Any discrepancy between the load and lay-on temperature can then be identified and the confidences set accordingly. At this stage, however it is impossible to tell whether it is the load or the lay-on temperature that is at fault.

5.4.3 Relationship between rolling load and main motor power

Figure 5.8 shows a plot of the rolling load against main motor power. It can be seen that there is a linear relationship between the load and power. Also shown is the differential of the power with respect to the load obtained from the process models. It can be seen that there is good agreement between the model predicted slope and the measurements.

Diagnosing that there is an error in either the load or power measurement is achieved by comparing the measurements with the stored nominal load and power for a given pass. Any discrepancy between the load and power is identifiable. This rule will establish whether the load and power measurements are consistent, if an error is identified, however, it is impossible to tell with which measurement the error lies.

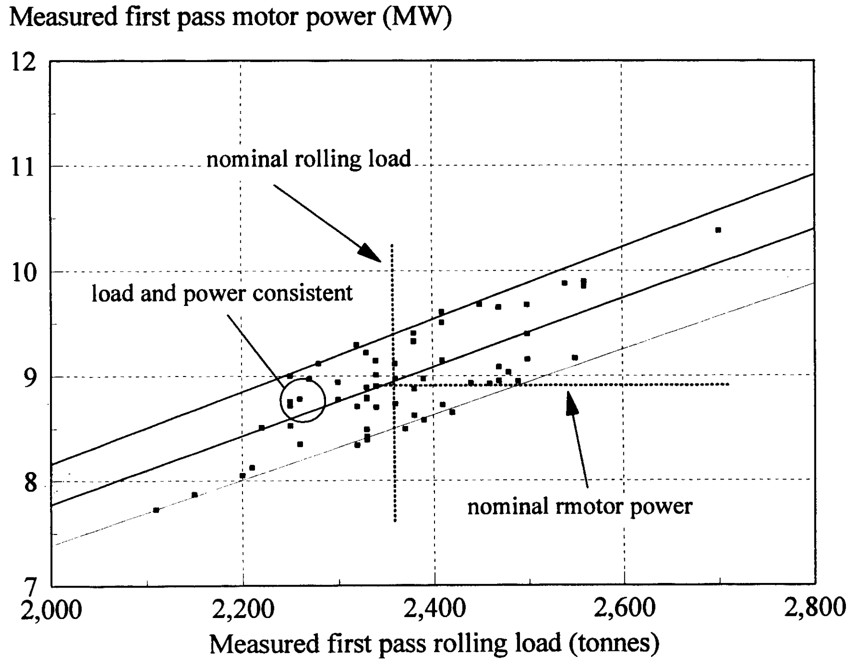


Figure 5.8 Relationship between rolling load and motor power

5.4.4 Diagnosing a poor lay-on temperature measurement

For the first pass of the rolling schedule the information from the previous two sections is used to diagnose where the most likely measurement error lies. By cross checking the confidences of the lay-on temperature, rolling load and motor power it is possible to establish which, if any, are likely to be in error. Looking at the encircled points in Figures 5.7 and 5.8, which are for the same slab, it is possible to see that the most likely conclusion to be drawn is that the measured lay-on temperature is incorrect. The true measurement should have been approximately 20°C higher.

Once the confidence of each measurement has been set, other parts of the knowledge base can use the information. In the case of a lay-on temperature measurement being found to be inaccurate, a strategy in the adaptation section of the knowledge base, configures the pass to pass adaptation scheme to identify the true temperature of the slab.

5.4.5 Diagnosing a poor measurement of strip temperature

A measurement of the temperature of the strip is usually taken on later passes of the schedule when control of temperature becomes important to achieve the correct microstructure. Inaccuracies in measuring the temperature of the strip can occur for a number of reasons as described in Section 5.4.2.

On later passes of the schedule, the relationship between the rolling load and strip temperature becomes highly nonlinear due to the temperature dependency of both the material flow stress and the roll bite friction. Checking a measurement of the strip temperature is achieved by comparison with the nominal value stored in the learnt schedule as described in Section 5.4.1.

5.4.6 Relationship between strip profile, roll bend, thermal camber and rolling load

When a measurement of the strip profile is available on the final pass of the schedule. The process model used to predict the strip profile is nonlinear and involves many parameters. Performing a check on the accuracy of the strip profile measurement with every independent variable is therefore difficult. However, using just three parameters has proved to be successful. Confidence in the measured profile is accomplished by examining its consistency with the work roll bend, the thermal state of the work rolls and the rolling load. Generally speaking it is known that an increase in the work roll bend leads to a decrease in the strip profile. An increase in the rolling load results in an increase in the strip profile, whilst cold work rolls produce a large strip profile. Using these generalisations and the nominal operating point stored within the learnt schedule, the accuracy and consistency of the strip profile measurements is established. Figure 5.9 shows the effect of work roll bend and thermal camber on the strip profile. The x-axis shows the relative state of the thermal camber of the work rolls, whilst the y-axis shows the strip profile of the strip. Also shown is the relative effect of work roll bend on the strip profile. The figure demonstrates the generalisations made earlier and allows the consistency of any profile measurement to be checked with what one would expect.

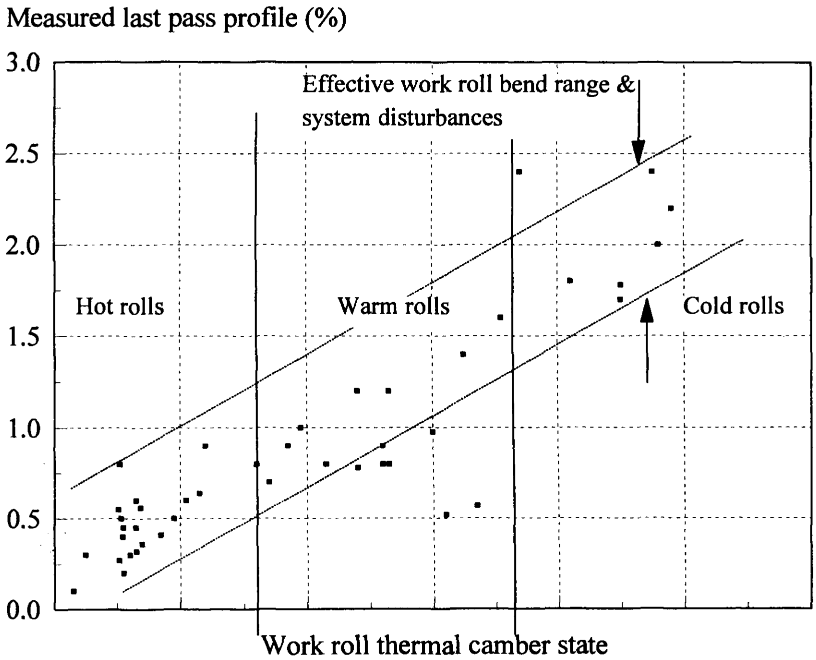


Figure 5.9 Relationship between thermal state and strip profile

5.4.7 Sample standard deviation

When measurements of the process are made, a number of samples are taken over a defined logging interval. The mean measurement value is then calculated by averaging all the samples. At the same time the standard deviation of this data set is also calculated. This provides information about the accuracy of the measurement, a large deviation indicating that the process is noisy or that the measurement device is faulty. Once the standard deviation has been checked and is found to be large, the measurement confidence is set to uncertain as an indication to other parts of the knowledge base that less reliance should be placed on that particular measurement. For example the adaptation will take into account the standard deviation of the measurement as described in Section 4.5. Figure 5.10 shows the effect on the standard deviation when a signal has a high and low noise associated with it.

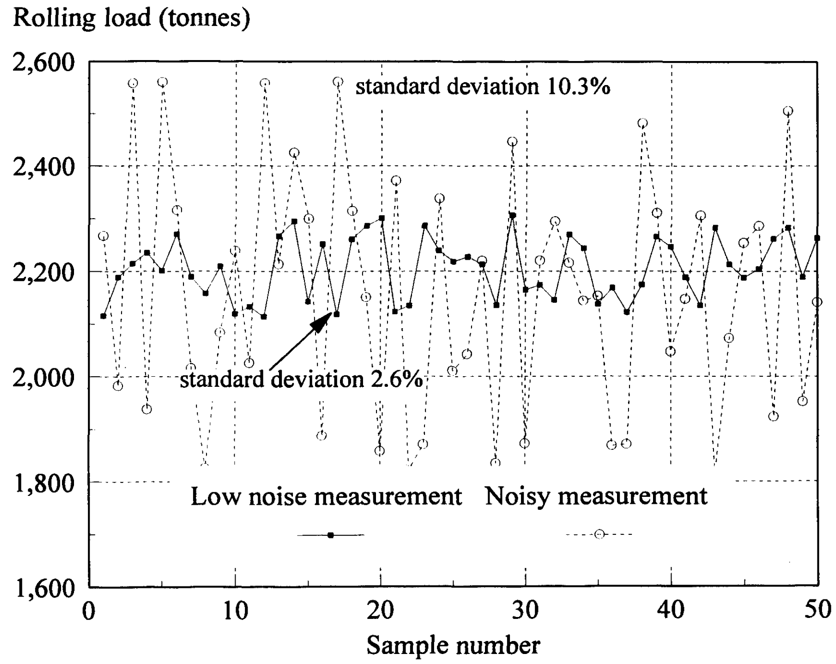


Figure 5.10 Rolling load measured for 50 samples with a low noise and high noise signals

5.4.8 Drift

Measurement drift can occur whereby the measuring instrument slowly moves away from a true reading. Any distinct drift can be determined by filtering the measurements to establish the trend of the movement. Once the trend crosses a control limit this strategy sets the measurement confidence to low to indicate that the measurement is probably inaccurate. At the same time any consistency in the observed drift between the measurements may, however, indicate a movement of the process operating point. For example Figure 5.11 shows such a change in the process operating point is identified and the information is passed on to other parts of the knowledge base.

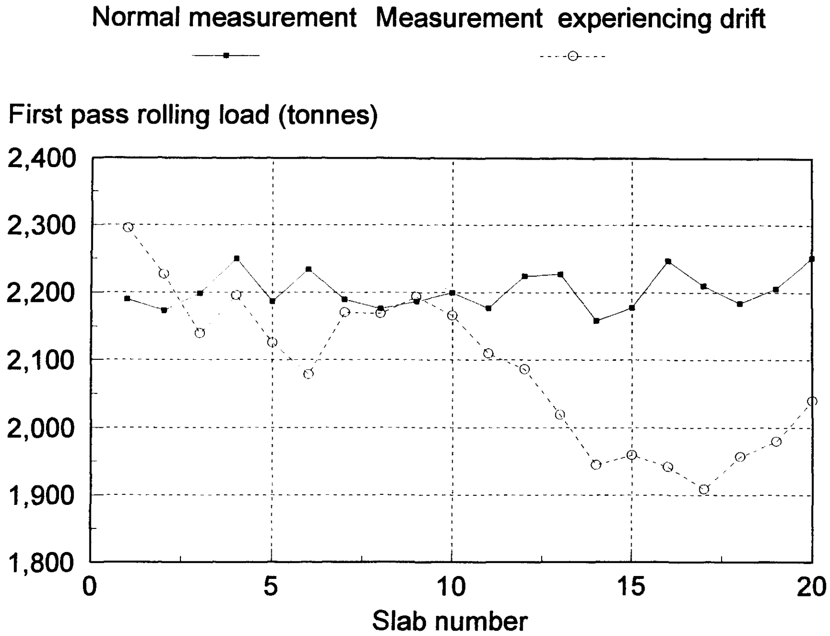


Figure 5.11 Effect of measurement drift

5.4.9 Quality consistency

The quality of the rolled product is governed by the strip's coiling temperature, finish profile and flatness. The consistency of the quality is measured by recording the number of consecutive slabs which meet the quality parameters. If a number of slabs do not meet these quality parameters then a diagnostic strategy is run to attempt to correct the problem. Figure 5.12 shows the strip temperature of a number of slabs, at first the temperature is within the acceptable boundaries, however at the fifth slab the temperature falls outside of the acceptable boundaries. Further increase is strip temperature is not possible without the intervention of a suitable strategy. At present this strategy assumes that the actuators used to setup the mill must be saturated. If the mill speed is saturated on a particular pass or passes then the expert system advises that the amount of strip cooling should be modified if this cannot be performed automatically.

If the work roll bend is saturated this indicates that the thermal state of the work rolls is incorrect. The expert system modifies the target thermal camber to attempt to solve this problem.

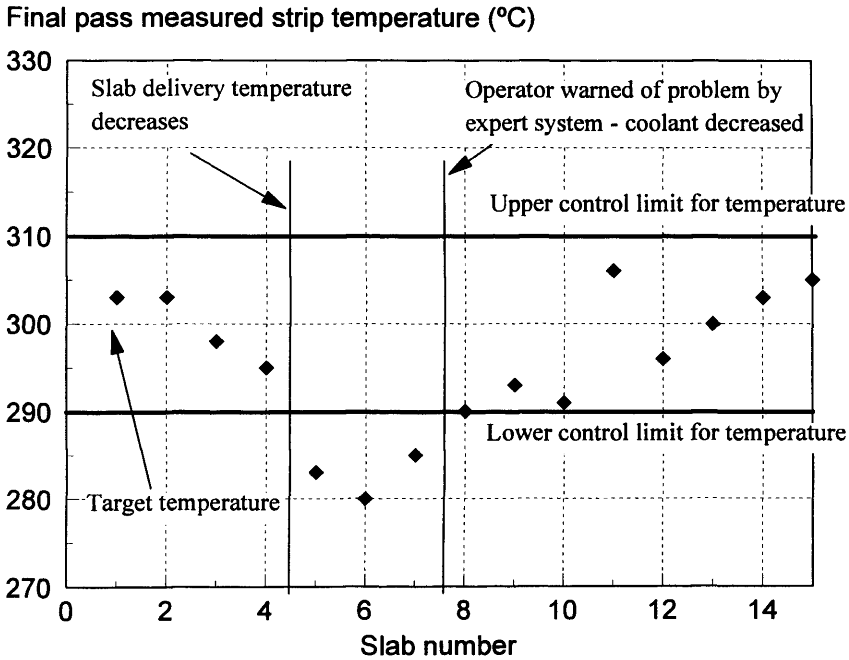


Figure 5.12 Tracking quality of rolled product

5.5 Scheduling

The next set of rules consists of strategies to perform the scheduling functions to set each actuator prior to the rolling of a pass. When setting the actuators some consideration must be made to future slabs in the rolling queue so that the operation can be optimised.

5.5.1 Target setting for temperature

The temperature of each slab must be controlled in such a way that the strip is coiled at the desired target temperature, see Ditzhuijzen [171]. This is required so that the aluminium has the correct microstructure. To achieve this, temperature scheduling takes place from pass to pass to ensure that the strip is neither too hot nor too cold. Additionally the mill should ideally be rolled as fast as possible in order to maintain a high level of productivity. Information about the past evolution of the temperature is obtained from the learnt schedule. The target temperature for each pass is taken from the learnt schedule which only stores results from slabs that have been rolled with ideal finish quality. A forward prediction of the strip temperature is available from the process models and the actual temperature state can be measured on certain passes. The estimated deviation away from the pass target temperature is determined by comparing the target with the estimated slab exit temperature state. Figure 5.13 shows three sets of data concerning the temperature of the strip. Plotted on this graph is the predicted temperature from the process models, the measured temperature and the target temperature, which has only been specified for the last flat pass and the final pass of the schedule.

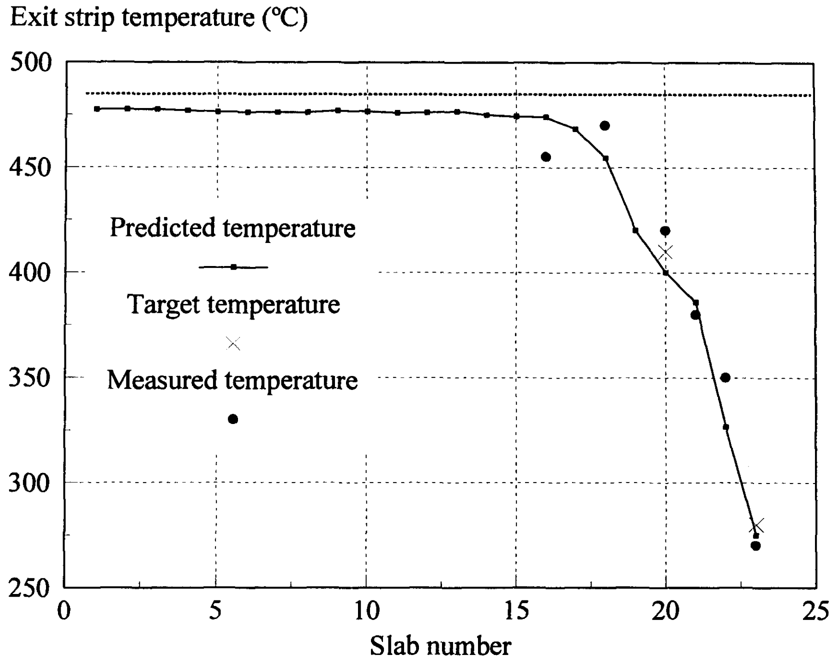


Figure 5.13 Information regarding strip temperature target

5.5.2 Determining the rolling speed

Before each pass of the schedule is rolled the main mill motor controller must be provided with a target run speed so that the mill can be threaded and then accelerated up to the steady state speed. The setup value for the run speed of the mill is adjusted to ensure that the pass target temperature is achieved. The required correction to the run speed is determined using the process model partial derivative and the temperature error. Any modification to the mill speed is checked, (see Section 5.5.9), to ensure the change is realistic. In addition three main strategies are applied:

i) A dead band is applied about the target temperature to allow for small discrepancies in the exit strip temperature.

ii) On early passes the speed is only adjusted by small amounts in response to any temperature error. This is because the slab temperature is very insensitive to speed changes.

iii) On later passes the speed is increased within the temperature dead band, wherever possible, so that the productivity is increased.

Figure 2.7 and 2.8 show two simulations showing the effect on the head end strip temperature when a good and bad target mill speed is given to the main motors. Figure 2.7 shows the bad mill setup with a mill speed set point some distance away from the actual value required to produce strip at the target temperature. Once the mill has ramped up to the run speed closed loop temperature control adjusts the mill speed until the temperature target is achieved. Comparing Figure 2.7 with Figure 2.8 it can be seen that the quality of the latter coil is more consistent than the former due to the correct set point being provided to the controller.

5.5.3 Target setting for profile

The control of profile and flatness of the strip is highly interactive. To ensure the strip is coiled at the desired target profile and with good shape properties, profile scheduling takes place from pass to pass, see Shaw [172]. Information about the profile is available from the various data sources (learnt schedule, measurements and model predictions). The target profile for a particular pass is taken from the learnt schedule which only contains profile data for slabs that have been rolled with ideal finish quality. Forward prediction of the strip profile is available from the process models. The estimated deviation away from the pass target profile is determined by comparing the target with the estimated slab exit profile state. The desired change in profile for a pass is checked to ensure that it is not greater than the shape change limit. Figure 5.14 shows the target profile for the last six passes of twenty three pass schedule. Also shown are the limits imposed on the profile change from one pass to the next by the buckling criteria.

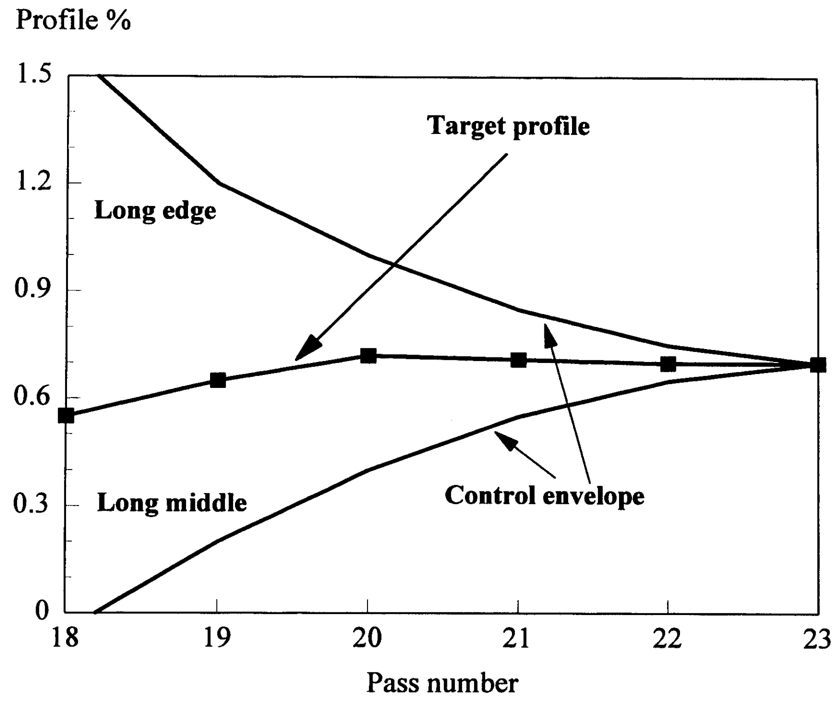


Figure 5.14 Target profile from pass to pass

5.5.4 Spray selection after a roll change

After a work roll change or after a long delay between slabs the thermal camber on the rolls will be lower than the ideal steady state value. The amount of thermal camber present on the work rolls directly influences the value of the strip profile. In order to achieve the desired strip profile, there is an optimum value for the thermal camber. This camber can only be built up after the rolling of a number of slabs, typically 3 or 4, and the strip profile of these slabs is unlikely to be within the desired profile quality limits.

The work roll spray strategy developed adjusts the level of the sprays depending upon the state of the thermal camber. To determine the thermal state of the work rolls the current predicted thermal camber at the edge of the strip is compared to a target value. This target value is initially entered as a value gained from experience by the running the process models for the particular schedule.

The comparison between the predicted and target thermal camber is categorised into one of five sets:

i) The camber is very small.
ii) There is some thermal camber, but it is still some way from the steady state value.
iii) The camber is at steady state.
iv) The camber is slightly larger than the steady state value.
v) The camber is very much larger than that required at steady state.

For each possible state of the work roll thermal camber a predefined spray pattern is stored which will result in the reduction of the error between the target and predicted thermal camber. The steady state spray pattern is defined and stored in the learnt schedule or if this is still to be defined, the fixed schedule is used. The patterns for the small camber and very large camber cases are calculated from the known limits on the spray level. Finally patterns ii and iv are calculated by taking the average of the patterns defined for i and iii, and the average of the patterns defined for iii and v respectively. So in fact only one spray pattern is actually defined.

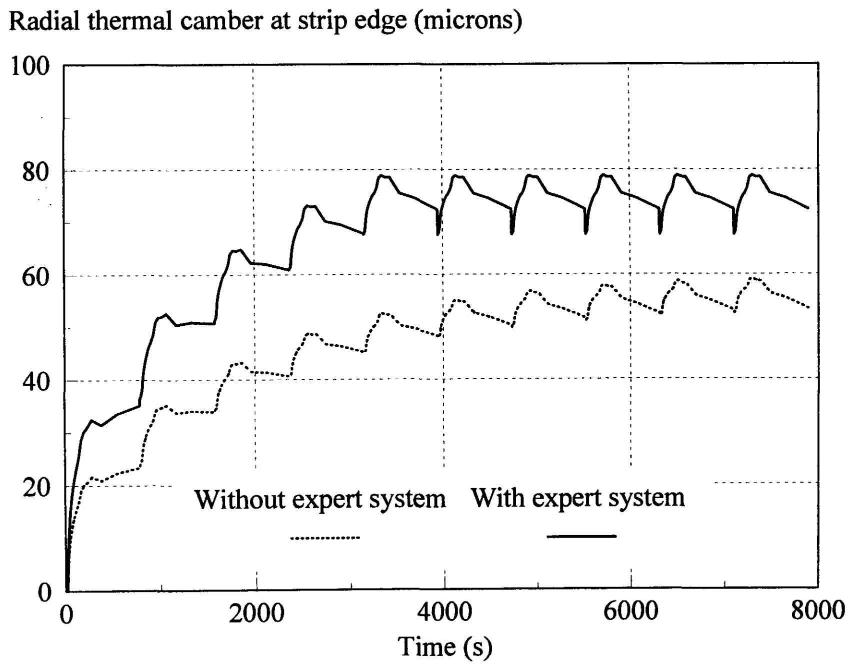


Figure 5.15 Thermal camber from a cold start

When the strategy is run, the sprays are adjusted before each pass is rolled and the new spray pattern is determined. Figure 5.15 shows the predicted work roll thermal camber with and without expert system control. Figure 5.16 shows the strip profile which results from this thermal camber. Finally Figure 5.17 to 5.19 show the spray patterns which are used for each pass for the cold, warm and steady-state rolling conditions. It can be seen that the expert system strategy is able to produce strip profile within the defined target limits quicker than if a fixed spray pattern is used.

The process knowledge stored within this strategy is a defined work roll coolant pattern associated with different levels of work roll thermal camber.

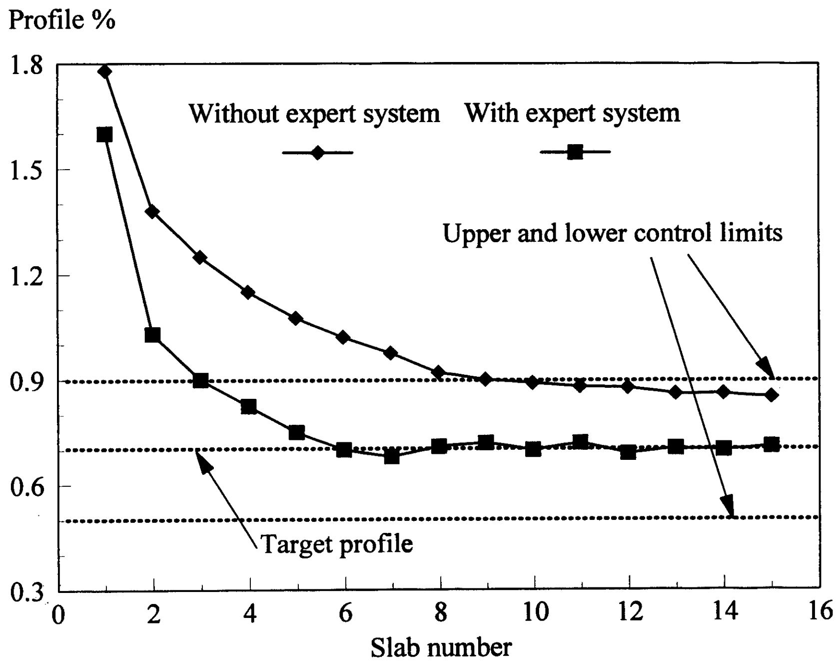


Figure 5.16 Profile after a cold start

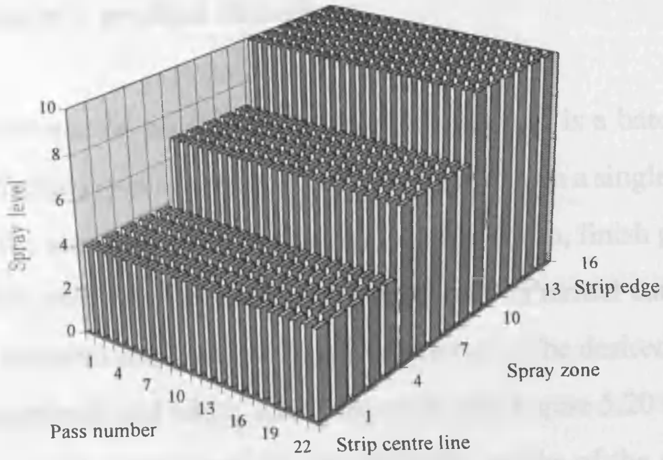


Figure 5.17 Work roll spray used for cold rolls

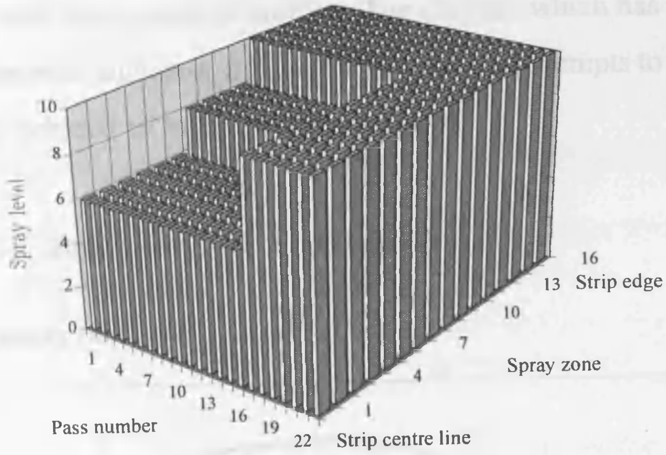


Figure 5.18 Work roll sprays used for warm rolls

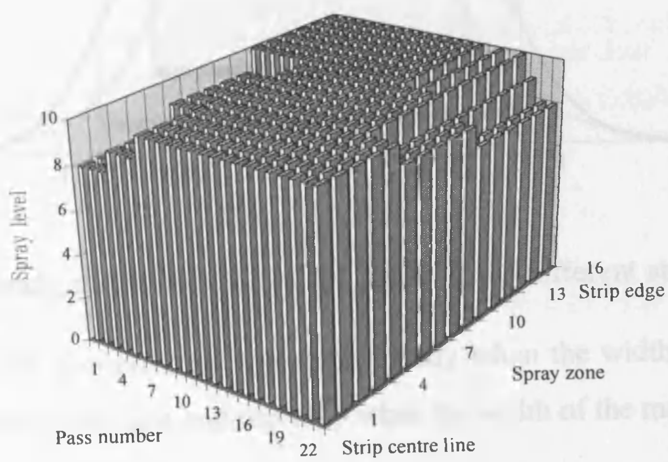


Figure 5.19 Work roll sprays used for hot rolls

5.5.5 Spray selection at a product change

The rolling of aluminium slabs on a single stand reversing mill is a batch process. This means that several different types of products will have to rolled on a single mill. A product is usually defined by the aluminium alloy composition, slab width, finish gauge and target finish temperature. For each product the desired steady state thermal camber which will result in good quality material being produced is likely to vary. The desired thermal camber can vary in both its magnitude and width across the work roll. Figure 5.20 shows the steady state thermal camber which is required for two different widths of the same aluminium alloy. At a product change it takes 2 or 3 slabs for the thermal camber to completely transform itself from one steady state to another. The strategy which has been developed varies the work roll sprays to anticipate the product change and attempts to begin to modify the thermal camber to achieve an improved performance.

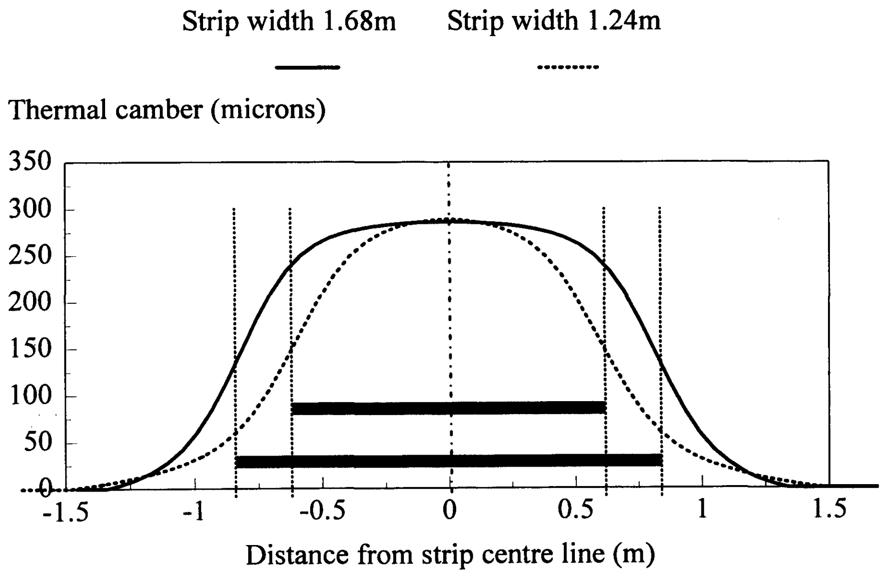


Figure 5.20 Steady state thermal camber required for different strip widths

The strategy deals with two possible situations. Firstly when the width of the material increases from one slab to the next and secondly when the width of the material decreases from one slab to the next.

i) Increase in strip width

In these circumstances as can be observed from Figure 5.20 the camber which is seen at the edge of the wider strip immediately after the product change is larger than is actually required. The effect on the slab is to roll out the centre of the material leaving the edge shorter. Such a defect is usually termed a tight edge. To reduce the effect on the strip profile, immediately before the slab is rolled the work roll sprays are left on for a defined period of time which has the effect of removing heat from the roll and reducing the variation in roll expansion across the barrel width. Figure 5.21 shows profile results from a simulation with and without the expert system controlling the sprays. The process model is configured so that the work roll sprays can be left on or off in the delay between slabs. It can be seen that the error in the strip profile immediately after the product change has been reduced.

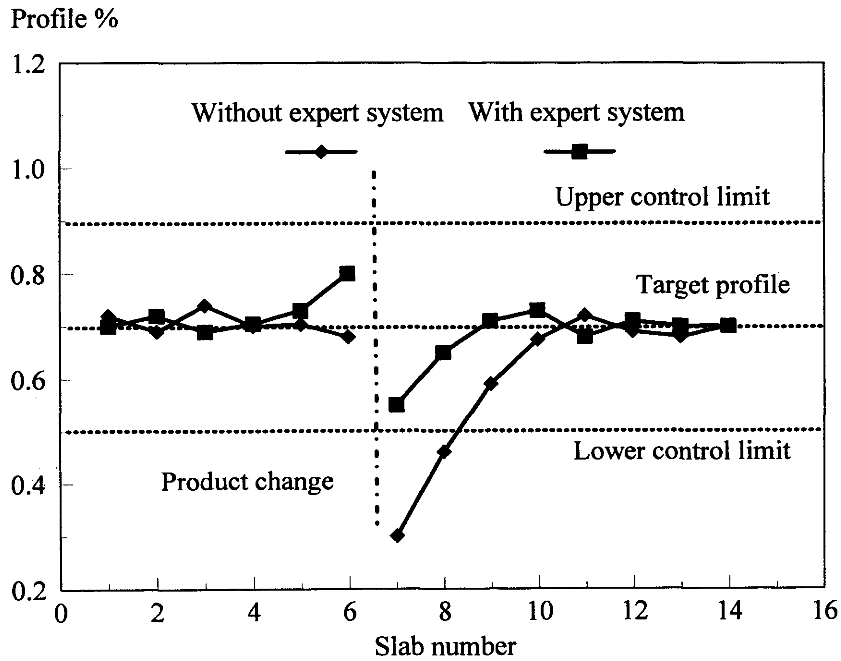


Figure 5.21 Strip profile before and after an increase in strip width

ii) Decrease in strip width

In these circumstances, again referring to Figure 5.20 the camber seen at the edge of the narrow strip immediately after the product change is less than is actually required. The effect on the strip profile can be seen from Figure 5.22. The strip sees virtually no thermal camber and hence a larger strip profile will be produced than is desirable. The situation is very similar to that at a cold start. The method adopted to reduce the effect at the product change is to reduce the spray level in the centre of the strip and increase the spray coolant at the edge of the strip. This has the result of increasing the overall thermal camber and results in a larger camber being seen by the narrower strip. Figure 5.22 shows the results of using the expert system control strategy. In the simulation the spray pattern of the two slabs prior to the product change were set to the warm spray pattern.

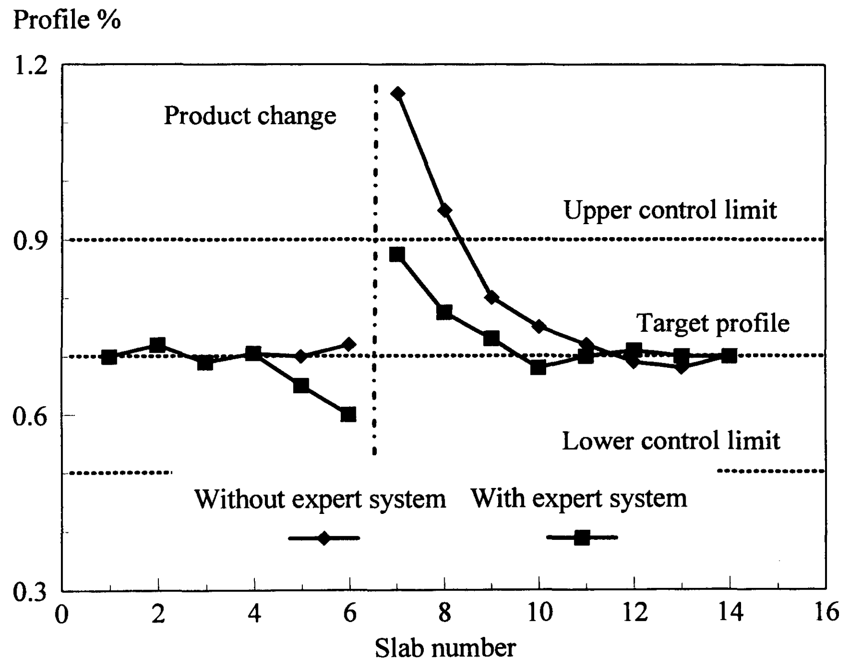


Figure 5.22 Strip profile before and after a decrease in strip width

The two strategies discussed in this section store process knowledge about work roll coolant spray control at a product change.

A conflict occurs between these two strategies and the strategy setting the sprays during steady state rolling. This conflict is resolved by giving the product change strategies a higher priority provided that the last slab rolled met the profile performance.

5.5.6 Work roll bend for good shape

A common method of controlling strip profile is to use work roll bend, see Fapiano [173], Fujimoto [174] and Tellman [175]. Associated with each product is a target final pass profile. As the slab is rolled and the profile is developed, the roll bend is adjusted to yield a coil with the desired profile. Once the thickness of the workpiece drops below a critical level (20 to 30 mm) adjusting the roll bend based solely on the profile error is no longer possible. Maintaining good strip shape becomes an important issue. Bad shape is developed if the profile change from the entry to exit sides of the mill is greater than the shape change limit for the pass in question, Shoet [118] and Konishi [176]. Establishing the profile trajectory that results in acceptable shape is therefore important. The rule-based strategy uses model predictions of profile and shape change limits to determine how to set the roll bend. Figure 5.23 compares the profile on the last six passes of a twenty three pass schedule using the fixed schedule set points and that from using the adjusted set points.

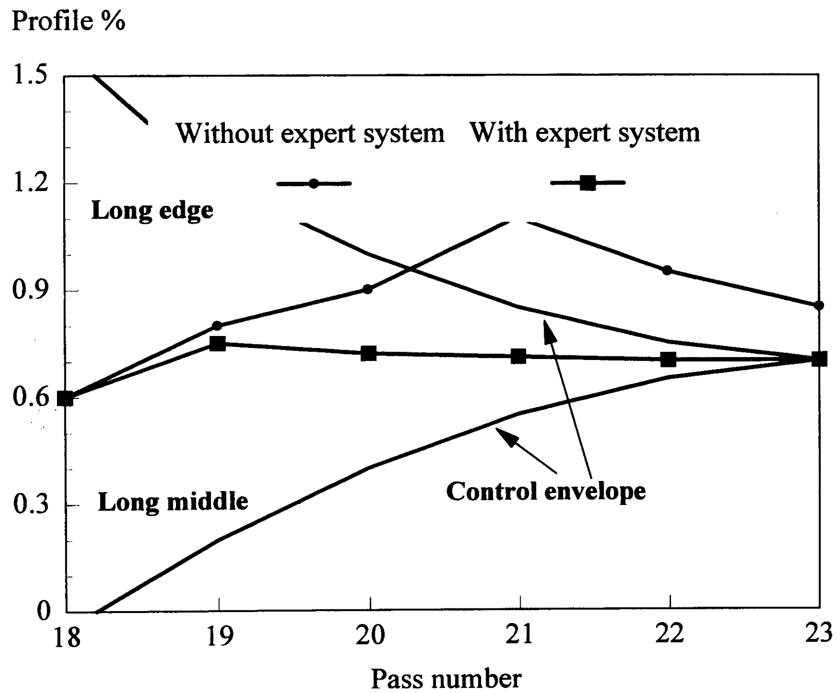


Figure 5.23 Effect on strip profile of controlling the work roll bend setting

5.5.7 Production rules

Process limits are split into two main groups. Firstly, there is a set that defines the actual physical limits that apply to the mill all of the time, such as the maximum motor power or the actuators ranges. A second set is used to store limits that are only applicable to certain passes of the schedule or to certain products. For example, the minimum allowable work roll coolant spray level must be limited for certain products to avoid large roll temperatures that can cause surface marking of the strip. The second type of production limit is tailored specifically to the mill to which the expert system is being applied.

5.5.8 Delays in production

The mill is subject to delays from time to time, for example due to equipment failure. During such a delay cooling occurs within the mill and heat is lost by the slab currently being processed. Loss of the work roll thermal camber is remedied using the strategy described above for a cold start. Heat lost from the work rolls is tracked by the thermal camber model and hence the spray setting strategy is able to correct the spray pattern according to the calculated camber error. Any reduction in the temperature of the slab results in higher rolling loads due to the hardening of the material. If the temperature drops below a critical threshold the expert system displays a warning to the operator that the slab is likely to produce inferior quality material and he or she may then decide to scrap the slab.

5.5.9 Checking the revised schedule.

Any revisions to the rolling schedule must be checked against the learnt schedule to ensure that realistic changes are made. Such a check avoids large fluctuations in the operation of the process. If the mill is subject to a change in its operating point, then this is accommodated in two or three smaller changes. Figure 5.24 shows a plot of the work roll bend for the last six passes of a schedule. The simulation shows the effect of a delay in production during which time both the slab and work roll temperature drops. The result of the decrease in the strip temperature is to increase the rolling load due to the interrelationship between the material flows tress and temperature. Consequently the deflection of the mill stack increases and there is a larger roll gap profile. The result of the decrease in the work roll temperature is a lower thermal camber and again an increase in the roll gap profile. The value of the work roll bend set point can be seen to increase following this delay. The strategy limits the work roll bend change away from the nominal value stored in the learnt schedule. It can be seen that after three passes have been rolled the work roll bend setting has returned closer to the nominal value. This strategy avoids large deviations away from nominal operating practice and the associated risks with doing so.

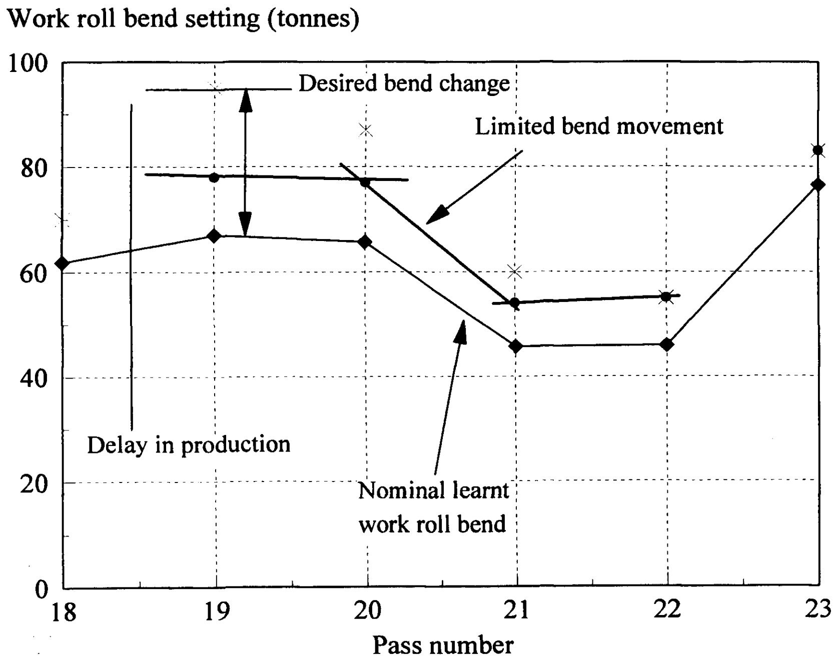


Figure 5.24 Effect of limiting the actuator movement following a delay in production

5.6 Model and adaptation control

The third and final set of rules are concerned with ensuring good performance of the process models, the adaptation algorithms and other components within the mill setup and supervisory control system.

5.6.1 Learnt schedule assembly

The rule set in Sections 5.4 and 5.5 make reference to the learnt schedule data for checking the accuracy of the measurements. The learnt schedule is updated after each slab has been rolled if the slab was deemed to be of good quality. This then provides a means of checking the measurements, the process model predictions and the generated actuator set points.

The data stored within the learnt schedule consists of a schedule which when applied to the mill at steady state, results in optimum quality material being produced. The schedule not only consists of optimum actuator settings but also a set of reference measurements. In the case where a measurement is not available, for example a profile measurement on a particular pass, then the appropriate model prediction is used. The learnt schedule is an invaluable tool for enabling the system to make consistency checks. The learnt schedule is updated after a slab has been rolled with superior quality.

The learnt schedule is updated using a simple filter algorithm. A weighting function allows more or less forgetting to take place. The nominal value for this weighting function is 0.5. In the case of the spray patterns the result must be adjusted to firstly ensure that only integers are to be stored and secondly to ensure that at least one of the spray levels is at the maximum level.

5.6.2 Determining the slab state

A number of sources of information are available to the system to determine the most likely state of the slab before and after each pass is rolled. The information available comes from the model predictions, measurements and the database of learnt schedule information. The confidence of each source is examined to establish which is the best. The state of the slab is therefore made up of a combination of measurements and predictions. Wherever appropriate, a measurement is always to be preferred to a prediction provided it satisfies the diagnostic checks described earlier.

5.6.3 Checking predictions

The model predictions can become inaccurate for a number of reasons. For example, if inaccurate data is applied to the model then the model predictions are also likely to be inaccurate. The models are checked against the learnt schedule to ensure that they lie within an acceptable tolerance and then the confidence of each prediction is set appropriately. The models may be inaccurate for the following reasons:

i) The data related to the slab's state, namely the slab temperature, width, thickness or profile is not a true reflection of the true slab state. In such a case if inaccurate data is applied to the model then the prediction made by the model will also be inaccurate.

ii) Insufficient measurements have been applied to the adaptation algorithm to alow the models to be accurately calibrated.

iii) Conditions are applied to the models which are outside the models' normal operating conditions.

In Section 4.5 a number of techniques were discussed which can be used to improve the performance of the process model adaptation algorithms. The following sections discuss suitable rules which can be used to monitor and control these parameters.

5.6.4 Control of forgetting

The model adaptation algorithm contains a forgetting factor, which when adjusted, increases the response of the algorithm to a change in the process operating point. This strategy identifies any distinct changes in the process operating point, for example changes in the width of the material. The forgetting factor is then reduced from its nominal value of 0.99 to a value of 0.75, which greatly improves the response of the adaptation algorithm. The justification for using such a low value is that the models must adjust to the new operating point within one or two slabs. Traditionally the forgetting factor is only normally allowed to drop as low as 0.95. This however is for cases where very many more samples of data are being input into the filter during the interval when the operating point change occurs.

Once the models have adjusted to the new operating point, the forgetting factor is reset to its nominal value. Figure 5.25 shows the effect on the last pass rolling load prediction compared to the predicted value with and without the expert system strategy running.

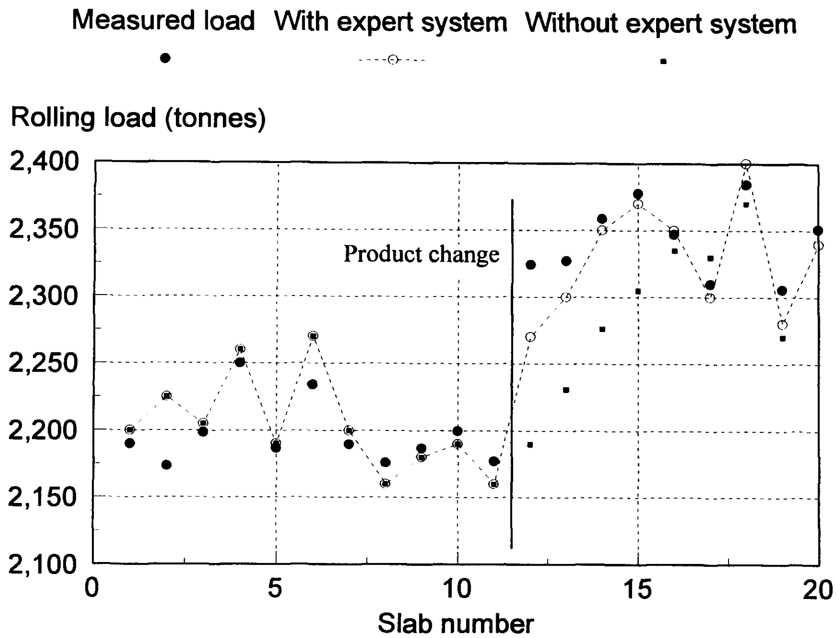


Figure 5.25 Effect on the load prediction at product change with and without control of adaptation forgetting factor

5.6.5 Control of error covariance matrix within the recursive least squares algorithm for correcting parameter drift

The error covariance matrix represents the memory of the adaptation algorithm. If the value of the diagonal of the matrix is increased, then the filter can be made to respond quicker to changes in the operating point of the process in a similar way to that described in Section 5.6.4. The drift of the adaptation parameters is monitored using the algorithm described in Section 4.5.4. The reasons given for parameter drift were firstly that the error covariance matrix has become small and secondly because the measuring instruments themselves are drifting or have become faulty. The expert system monitors the diagonal values in the error covariance matrix which correspond to the confidence placed upon the parameter. To ensure that the models continue to track variations in the process the fault detection algorithm described in Section 4.5.4 will identify if a parameter is consistently moving in a one direction. If it found that the corresponding diagonal term in the error covariance matrix is less than 10^{-2} then action is taken by multiplying he diagonal elements of the error covariance matrix by 100 and decreasing the forgetting factor to 0.95. Figure 5.26 shows the results from the operation of this strategy on the flows tress adaptation coefficient. Initially it can be seen that the coefficient is slowly decreasing because it is attempting track the variation in the rolling load. At the point indicated the fault detection algorithm detects that the parameter is slowly moving and increases the error covariance matrix. The movement of the coefficient is now observed to increase and settle down after 2 slabs. Thus the expert system has detected a fault within the adaptation algorithm and corrected it.

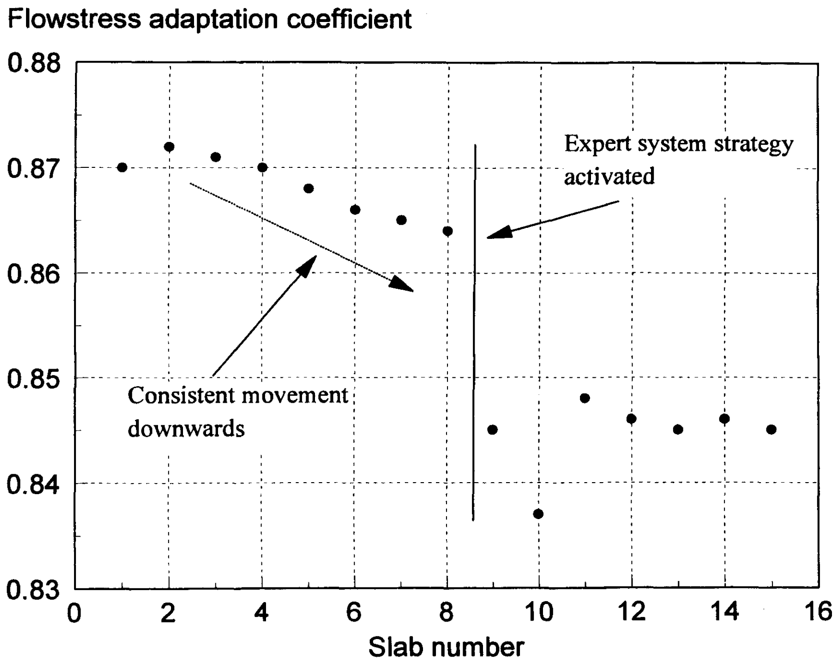


Figure 5.26 Detecting drift in the flow stress adaptation coefficient

5.6.6 Selection of adaptor

In Section 4.1, a technique was described for identifying whether the lay-on temperature of the slab is accurate or not. The result from this strategy allows the expert system to configure the adaptation algorithm. The short term (pass to pass) adaptation is modified so that a temperature observer identifies the true slab temperature state. Otherwise, a flow stress offset is used as the pass to pass adaptation parameter. The results from using the temperature observer and the flows tress offset was discussed in Section 4.3 together with graphs showing the performance of such a strategy.

5.6.7 Removing measurements from adaptation

The diagnostics described in Section 5.4 set the confidence of each measurement depending upon how accurate it is deemed to be. Additionally by observing the drift of the adaptation coefficients as described in Section 4.5.4 the measuring may b identified as defective. In situations where a measurement has been found not to be reliable, then both the long term and short term process model adaptation schemes must be configured to neglect that measurement. This avoids applying defective measurements to the adaptation which may be detrimental to the performance of the process models. The expert system examines the information gathered from the diagnostics and outputs the configuration to the adaptation schemes.

5.6.8 Setting measurement weighting

The long term and the short term adaptation algorithms allow the measurements to be weighted according to the confidence placed upon them. This weighting is provided by the standard deviation that was obtained when the measurement was sampled from the process. The larger this standard deviation is, the less confidence the system has in its accuracy. In some circumstances the diagnostics are unable to decide, with any degree of certainty, if a measurement is definitely correct or incorrect. In such cases the measurement can still provide useful information. This strategy assigns such a measurement with a higher standard deviation (weighting) than was actually measured.

5.7 Overall system integration

This section will describe the overall system architecture which integrates the process models described in Chapter 3, the adaptation described in Chapter 4 and the expert system described earlier in this chapter. There is, in addition to these three main components, some further modules which will be described in this section. The architecture for a mill setup system based on an expert system is shown in Figure 5.27. The figure has the same levels as that shown in Figure 2.5. The levels are the rolling mill at the lowest level, the closed loop controllers at level I, the setup system at level II and finally the plant wide control at level III. The figure illustrates level II expanded into its fundamental components. The main components which make up this level II system have already been described in this thesis in detail, namely the process models, adaptation, derivatives and the expert system. The remaining components are described below:

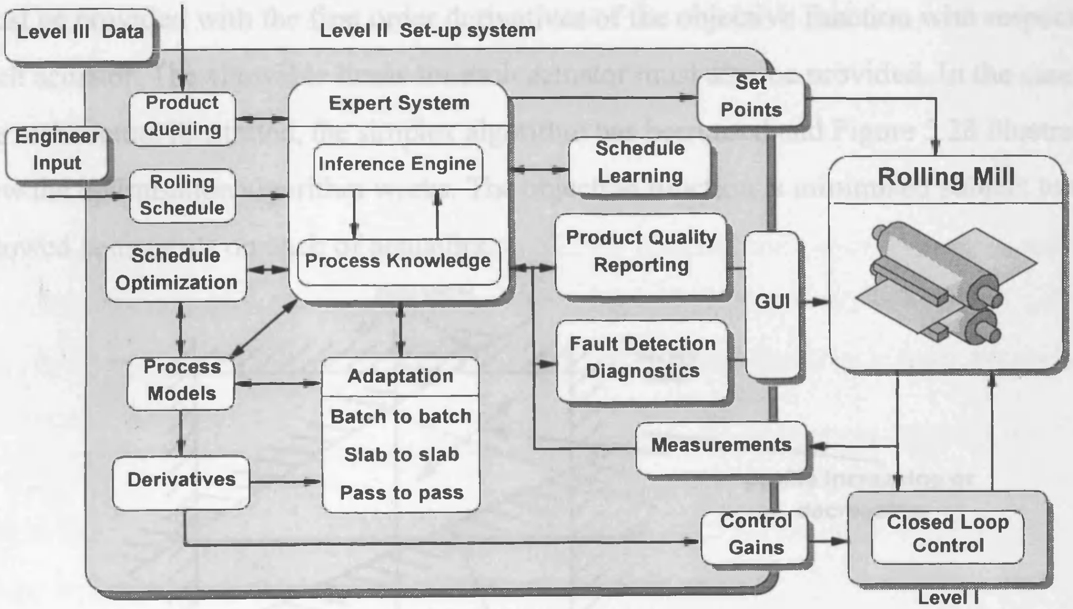


Figure 5.27 Overall level II system architecture

Three distinct types of user input can be identified:

i) *The product queue* defines the order in which slabs are rolled. Linked to each slab are its initial and desired final states.

ii) *Two databases containing pass schedules*. Pass schedules hold the set point data needed to ready the mill to roll. What set point data is stored varies from mill to mill, depending upon the available control actuators. A typical pass schedule includes drafting and spray patterns along with mill speed and roll bend set points. Plant schedules are based on operator knowledge or are generated by a scheduling algorithm. Learnt schedules are assembled by the expert system as slabs are rolled.

iii) *Measurements made when rolling* allow the system to compare the expected performance of the mill against its actual performance.

The schedule optimisation block shown is used when more than one actuator is available to control a particular quality parameter. For example, strip temperature may be controlled using the mill speed or some external strip cooling. Where this occurs the expert system must call upon an optimisation routine to determine the set points. The optimisation routine must be provided with the first order derivatives of the objective function with respect to each actuator. The allowable limits for each actuator must also be provided. In the case of the architecture illustrated, the simplex algorithm has been used and Figure 5.28 illustrates how the optimisation algorithm works. The objective function is minimised subject to the allowed constraints on each of actuators.

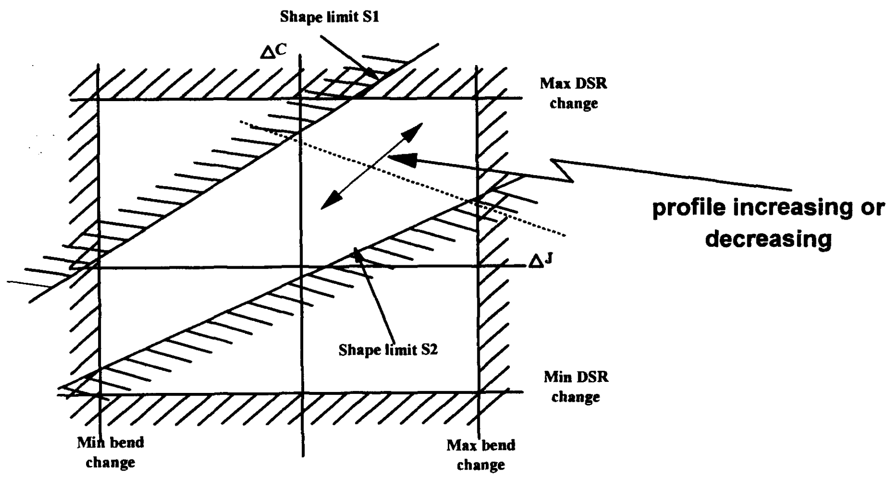


Figure 5.28 Optimisation of strip profile with two available actuators

Using this input data the expert system adjusts the actuator set points such that the mill rolls a prime quality product. The inference engine processes the data using the knowledge base.

The typical sequence of operations that would occur is as follows:

i) The rolling queue for the next twenty slabs would be passed down from level III computer. The information contained within the rolling queue will be used to determine whether a product change is imminent and to activate the appropriate rules within the expert system.

ii) The rolling schedule for the next slab to be rolled is retrieved from the schedule database and the learnt schedule database will be searched for a matching schedule. This provides the expert system with a record of how the slab has been previously rolled.

iii) The slab's temperature may be measured and the expert system will determine the entry state of the slab.

iv) The actuator set points will be determined by running the process models and the scheduling rules within the expert system. The model performance will be checked and the suggested set points checked with past experience. The predicted exit state can then be determined.

v) The mill will then be rolled and measurements will be collected to establish the quality of the rolled product and to use to adapt the process models.

vi) The measurements made will be passed through the diagnostics to ensure a consistent set and then adaptation will be run with any advice presented to it by the adaptation rules within the knowledge base. The new exit state can then be determined.

vii) The slab is ready for the next pass when the procedure is repeated starting from item iii. The process is repeated until the final gauge is achieved, when the quality rules are run to establish if the process is producing a satisfactory product.

The expert system was implemented using a proprietary expert system shell called flex which has been constructed on top of the programming language Prolog. The shell consists of three main components. A knowledge specification language (KSL), a support predicate and an engine for integration into Prolog. The KSL at the top level enables the expert system rules to be written in English-like form which may be easily read by non-programmers. Sentences may be developed using the construct illustrated in Section 5.2. Appendix 1 gives samples of the expert system code developed. The adaptation and process models were implemented in C and the interface between the expert system and the model was built using dynamic data exchange (DDE) under Windows 3.1. Figure 5.29 shows how the expert system and process models were interfaced together via a Lotus 123 spreadsheet which held the databases used for the simulations.

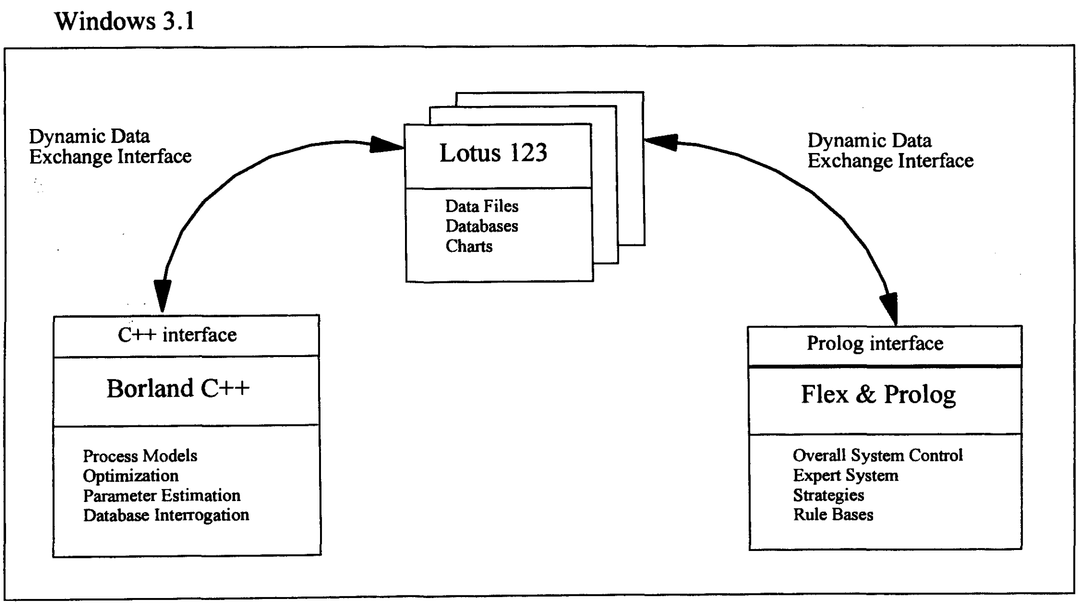


Figure 5.29 System integration

Figures 5.30 to 5.32 show sample screen displays from each of the three software programs used in the implementation of the prototype expert system.

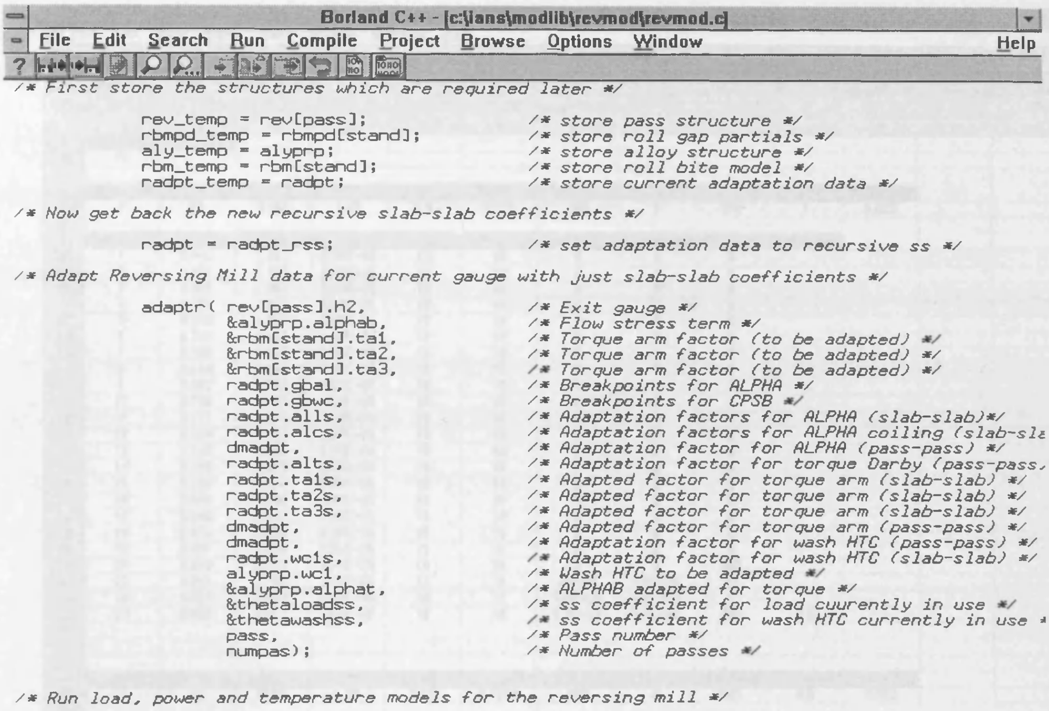


Figure 5.30 Sample screen from process model code

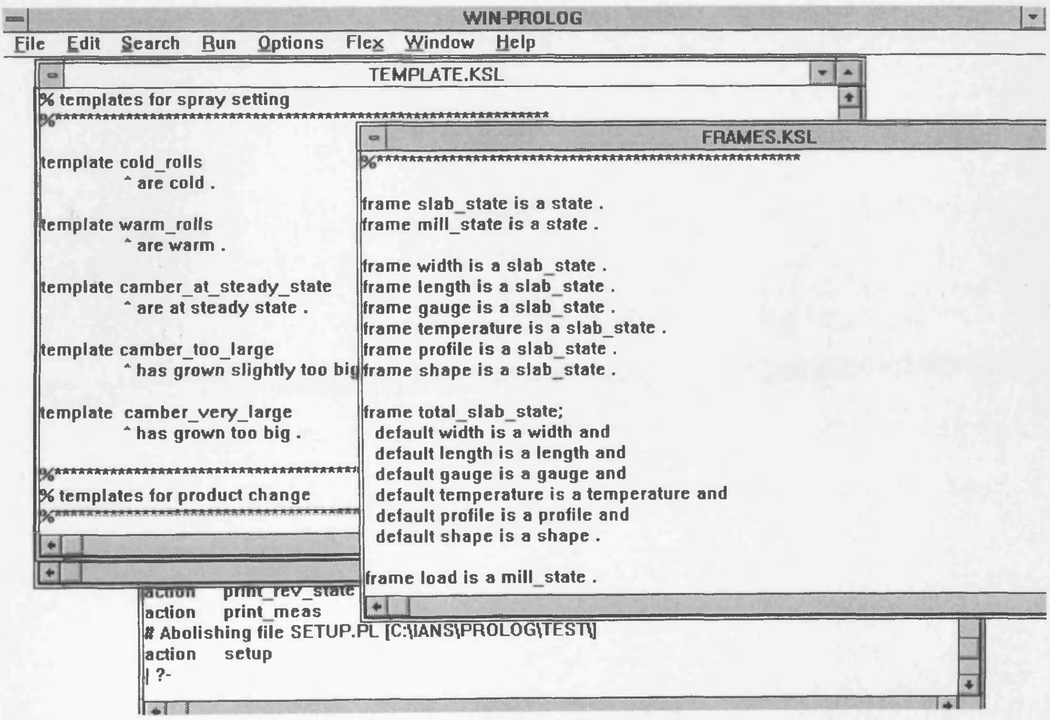
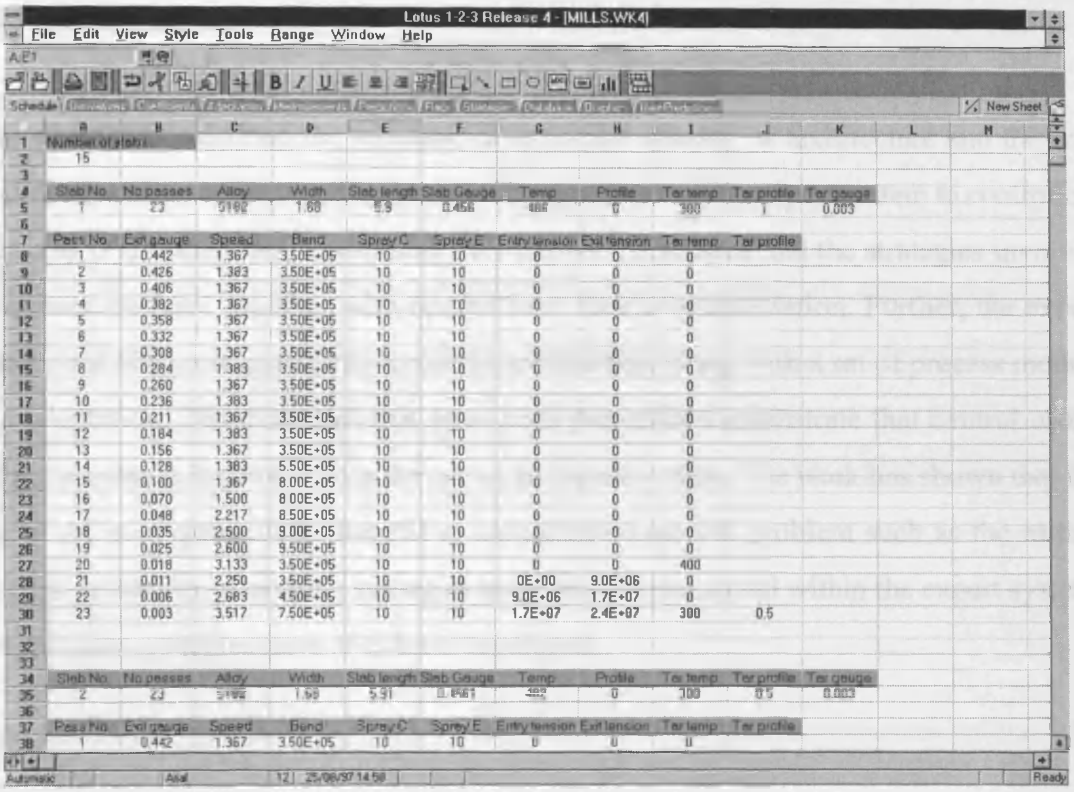


Figure 5.31 Sample screen from expert system code



Lotus 1-2-3 Release 4 - [MILLS.WK4]

File Edit View Style Tools Range Window Help

	A	B	C	D	E	F	G	H	I	J	K
1	Number of slabs										
2	15										
3											
4	Slab No	No passes	Alloy	Width	Slab length	Slab Gauge	Temp	Profile	Tar temp	Tar profile	Tar gauge
5	1	23	5182	1.60	5.9	0.456	[illegible]	0	300	1	0.003
6											
7	Pass No	Exit gauge	Speed	Bend	Spray C	Spray E	Entry tension	Exit tension	Tar temp	Tar profile	
8	1	0.442	1.367	3.50E+05	10	10	0	0	0		
9	2	0.426	1.383	3.50E+05	10	10	0	0	0		
10	3	0.406	1.367	3.50E+05	10	10	0	0	0		
11	4	0.382	1.367	3.50E+05	10	10	0	0	0		
12	5	0.358	1.367	3.50E+05	10	10	0	0	0		
13	6	0.332	1.367	3.50E+05	10	10	0	0	0		
14	7	0.308	1.367	3.50E+05	10	10	0	0	0		
15	8	0.284	1.383	3.50E+05	10	10	0	0	0		
16	9	0.260	1.367	3.50E+05	10	10	0	0	0		
17	10	0.236	1.383	3.50E+05	10	10	0	0	0		
18	11	0.211	1.367	3.50E+05	10	10	0	0	0		
19	12	0.184	1.383	3.50E+05	10	10	0	0	0		
20	13	0.156	1.367	3.50E+05	10	10	0	0	0		
21	14	0.128	1.383	5.50E+05	10	10	0	0	0		
22	15	0.100	1.367	8.00E+05	10	10	0	0	0		
23	16	0.070	1.500	8.00E+05	10	10	0	0	0		
24	17	0.048	2.217	8.50E+05	10	10	0	0	0		
25	18	0.035	2.500	9.00E+05	10	10	0	0	0		
26	19	0.025	2.600	9.50E+05	10	10	0	0	0		
27	20	0.018	3.133	3.50E+05	10	10	0	0	400		
28	21	0.011	2.250	3.50E+05	10	10	0E+00	9.0E+06	0		
29	22	0.006	2.683	4.50E+05	10	10	9.0E+06	1.7E+07	0		
30	23	0.003	3.517	7.50E+05	10	10	1.7E+07	2.4E+07	300	0.5	
31											
32											
33											
34	Slab No	No passes	Alloy	Width	Slab length	Slab Gauge	Temp	Profile	Tar temp	Tar profile	Tar gauge
35	2	23	[illegible]	1.60	5.91	0.4561	[illegible]	0	300	0.5	0.003
36											
37	Pass No	Exit gauge	Speed	Bend	Spray C	Spray E	Entry tension	Exit tension	Tar temp	Tar profile	
38	1	0.442	1.367	3.50E+05	10	10	0	0	0		

Automatic Arial 12 25/06/97 14:58 Ready

Figure 5.32 Sample screen of Lotus 123 simulation data

5.8 Conclusions

This chapter has defined the structure of an expert system, its architecture and the way knowledge can be constructed into rules. The application of an expert system to controlling the setup of aluminium hot reversing mill has been discussed and the strategies involved have been outlined together with results from their implementation. Further, the expert system has been integrated into a control architecture along with a set of process models and adaptation. The examples that have been presented demonstrate that control of the rolling process is improved with the use of an expert system. The work has shown that the use of AI is of quantifiable benefit to an industrial control problem such as the rolling process. A number of existing strategies have been implemented within the expert system. Several new strategies have also been developed.

CHAPTER 6

Conclusions and recommendations for further work

This chapter will summarise the work presented in this thesis, draw conclusions and offer some recommendations for further work. The thesis has presented the results of a study into setup and supervisory control for a hot aluminium rolling mill. The primary goal was to build upon and improve existing technology, namely the process model and adaptation, and to integrate this into a new architecture which would enhance the performance of the setup system. The literature survey revealed that the majority of present setup systems were based solely around process models and adaptation. This has the limitation that not every part of the process can be modelled accurately enough for the systems to perform well under all possible operating conditions. There was clearly a requirement for new techniques to be incorporated into these setup systems which would have some form of intelligence to assist the level 2 setup system. A novel contribution of this thesis has been the introduction of an expert system and its integration into the new level 2 system architecture.

The thesis firstly described the rolling process, how it is controlled and why there is the need for good initial actuator set points. The illustrative example clearly showed the improvements in product quality made when accurate set points are used. The literature survey revealed that expert systems have been used within the rolling industry but have tended to be applied to level 3 systems. The question that this thesis has posed and answered is: 'can artificial intelligence be built into the setup system so that it can replicate strategies adopted by the mill operator?'.

Chapter 3 presented a detailed description of each process model. Novel and interesting aspects within this chapter included the presentation of a unified rolling load model for both thick and thin stock material, the solution to the roll bite heat conduction problem and the formulation for strip profile and shape. Chapter 4 presented an original method for determining the partial derivatives required for adaptation using a perturbation analysis. The next sections presented for the first time a two level adaptation scheme for the aluminium hot reversing mill. The results presented show that the long term adaptation removes the model offset error, whilst the short term adaptation reduces the standard deviation of the model error. Significant improvement in the accuracy of the process models was shown in both tabular and graphical form. The final section described the implementational considerations that should be made before implementing the adaptation schemes on-line. It was also stated that some of the techniques provided a mechanism whereby the expert system can be used to control the performance of the adaptation schemes.

Finally Chapter 5 discussed and presented an expert system for hot mill setup. It was demonstrated that a large variety of different strategies can be implemented in such an expert system. The idea of using an expert system to perform the aluminium hot mill setup is completely original. It was shown that the expert system's knowledge base can be divided into three main sections. Firstly, a section of the knowledge base diagnoses and cross checks measurements to ensure consistency. It also contains some strategies to perform checks on product quality from slab to slab. Secondly, a section of the knowledge base stores the strategies used to set the actuators prior to the rolling of each pass. The final section stores rules which are used to control the adaptation and further enhance the accuracy of the model predictions. Within all the sections of the knowledge base new and original strategies have been developed, implemented and tested. The results presented clearly show that improvements can be made at level 2 with the introduction of an expert system. The thesis has proved that strategies can be implemented within a knowledge base of an expert system which encapsulate or replicate the actions of a mill operator. The programming of the knowledge base is performed in an English-like syntax which is easier to understand than a lower level language such as C. The knowledge is also distinctly separated from the main system code.

In conclusion, the thesis has demonstrated that artificial intelligence may be incorporated in a level 2 setup system with improvements in the system performance. The artificial intelligence has been introduced via an expert system which has been incorporated into a novel level 2 architecture. The thesis has produced new work worthy of publication in technical journals and conferences (see author's list of publications at the end of the thesis).

There are several areas where the work can be extended:

i) The knowledge base is split into three main blocks. There is clearly work that can be done to add additional rules to each of the sections within the knowledge base. Additional rules could be added to the diagnostic, the scheduling or the model and adaptation parts of the knowledge base.

ii) The interface between the level 2 and the level 1 systems could be examined to answer questions such as what information needs to pass between the two levels and what is the optimal form for this data? Another consideration is the split between the two levels. Bearing in mind the sampling rates and complexity of the two levels, at what level the functions should be divided?

iii) The interface between the level 2 and the level 3 systems could also be investigated. As for ii above, the information and how the functions are split between the two levels could be examined.

iv) The expert system work could be extended to look at the level 3 system. For example, determining the optimum route for a slab around a plant involving a large number of possible processing routes. This would have to take into account the plant's current order book, the capacity of each mill and furnace and the space within the various holding bays.

v) The expert system work could be extended to look at the level 1 system. For example to include rules for controller selection, strategies for threading the mill, tuning the controllers and gain scheduling.

vi) The final possible area of expansion is to examine techniques for automatic rule adaptation or generation. One limitation of the expert system is that all the rules are fixed. This will obviously limit the performance of the system when rules are approximated, contain expressions which may vary with time or when a rule has not been constructed at all. Clearly there is the need for rule adaptation or creation. There are several branches of artificial intelligence that offer the potential to perform this task, in particular neural networks and genetic algorithms.

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Title: The improved control for an aluminium hot reversing mill using the combination of adaptive process models and an expert system.
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Conference: 1st International Conference on Modelling of Metal Rolling Processes 21-23 September 1993, London

Title: Optimisation of hot rolling tandem mill schedules

Authors: P.A.Atack and I.S.Robinson

Conference: Modelling of Metal Rolling Processes Symposium No 5 10 December 1992 London

APPENDIX 1

This appendix contains sample listing from the expert system source code for reference.

This appendix contains:

A. Frames.ksl Definition of frames used in the expert system

B. Consts.ksl Definition of instances and constants used in the expert system

C. Relations.ksl Definition of relations used in the expert system

D. Templates.ksl Definition of templates used in the expert system

E. Ruleset6.ksl Definition of ruleset used in the expert system

A. Frames.ksl Definition of frames used in the expert system

```
%*****************************************************************
% File name:  FRAMES.KSL
% This file contains all the frames
% used in the main expert system
%
%  Created: 3 March 1995
%*****************************************************************

%*******************************************************
% Define frames and their associated slots
%*******************************************************

%*******************************************************
%          Measurement frame
%*******************************************************

frame measurement;                          % standard frame for measurements
  default value is 0 and
  default standard_deviation is 0 and
  default expected_value is 0 and
  default drift is 0 and
  default confidence is 0 .

%*******************************************************
%          Model predictions frame
%*******************************************************

frame prediction;                           % standard frame to hold predictions
  default value is 0 and
  default standard_deviation is 0 and
  default average_deviation is 0 and
  default confidence is 1 and
  default learnt_flag is 1 .

%*******************************************************
%          Derivatives frame
%*******************************************************

frame derivative;                           % standard frame to hold derivative
  default value is 0 and
  default confidence is 1 .

%*******************************************************
```

```
%        Adaptation frame
%*******************************************************

frame coefficient;                              % standard frame to for coefficient information
  default value is 0 and
  default err_cov is 0 .

%*******************************************************
%        Actuator frame
%*******************************************************

frame actuator;                                 % define a frame for actuator data
  default value is 0 and
  default max_value is 0 and
  default min_value is 0 and
  default learnt_flag is 1 .

%*******************************************************
%        Slab state frame
%*******************************************************

frame state;                                    % define a frame for the slab state
  default value is 0 and
  default confidence is 0 and
  default learnt_flag is 1 .

%*******************************************************
%        Slab identity
%*******************************************************

frame slab_id;                                  % standard frame for slab id details
  default alloy is 0 and
  default slab_number is 0 and
  default numpas is 0 .

%*******************************************************
%        Process targets
%*******************************************************

frame process_targets;                          % standard frame for slab targets
  default target_profile is 0 and
  default target_temperature is 0 and
  default target_gauge is 0 and
  default target_camber is 0 .

%*******************************************************
%        Create individual types of predictions
%*******************************************************

frame temperature_prediction is a prediction .
frame load_prediction is a prediction .
frame power_prediction is a prediction .
frame profile_prediction is a prediction .
frame shape_prediction is a prediction .
frame thermal_camber_prediction is a prediction .
frame gauge_prediction is a prediction .
frame width_prediction is a prediction .
frame length_prediction is a prediction .
frame long_middle_prediction is a prediction .
frame long_edge_prediction is a prediction .

frame predicted_mill_state;
  default load_prediction is a load_prediction and
  default power_prediction is a power_prediction and
  default thermal_camber_prediction is a thermal_camber_prediction .

frame predicted_slab_state;
  default temperature_prediction is a temperature_prediction and
  default profile_prediction is a profile_prediction and
  default gauge_prediction is a gauge_prediction and
```

```
  default width_prediction is a width_prediction and
  default length_prediction is a length_prediction and
  default shape_prediction is a shape_prediction and
  default long_middle_prediction is a long_middle_prediction and
  default long_edge_prediction is a long_edge_prediction .


frame predictions is a predicted_mill_state,
                       predicted_slab_state .

%*******************************************************
%       Create individual types of slab state
%*******************************************************

frame slab_state is a state .
frame mill_state is a state .

frame width is a slab_state .
frame length is a slab_state .
frame gauge is a slab_state .
frame temperature is a slab_state .
frame profile is a slab_state .
frame shape is a slab_state .

frame total_slab_state;
  default width is a width and
  default length is a length and
  default gauge is a gauge and
  default temperature is a temperature and
  default profile is a profile and
  default shape is a shape .

frame load is a mill_state .
frame power is a mill_state .
frame thermal_camber is a mill_state .

%*******************************************************
%       Create individual types of actuator
%*******************************************************

frame exit_gauge is an actuator .             % create instances of actuators, this is done so that
frame speed is an actuator .                  % all instances of an actuator can be accessed with a
frame spray_cooling is an actuator .          % single rule
frame roll_bend is an actuator .
frame pc_angle is an actuator .
frame centre_spray_level is an actuator .
frame edge_spray_level is an actuator .

frame spray_pattern;                          % spray pattern made up of edge and centre levels
  default centre_spray_level is a centre_spray_level and
  default edge_spray_level is an edge_spray_level .

frame actuator_data;                          % standard frame for actuator set-points
  default exit_gauge is an exit_gauge and
  default speed is a speed and
  default roll_bend is a roll_bend and
  default centre_spray_level is a centre_spray_level and
  default edge_spray_level is an edge_spray_level and
  default spray_cooling is a spray_cooling and
  default pc_angle is a pc_angle and
  default exit_tension is 0 .

%*******************************************************
%       Create frames for the temperature measurement
%*******************************************************

frame temperature_measurement is a measurement .

%*******************************************************
%       Create a frame for the slab pdi
```

```
%*******************************************************

frame slab_pdi is a total_slab_state,
                    process_targets,              % pdi is made up of slab state, targets and id .
                    slab_id ;
 default inter_slab_spray is 0 .

%*******************************************************
%        Frame to represent pass schedule data
%*******************************************************

frame pass_schedule_data is an actuator_data,    % standard frame for schedule data
                              process_targets ;
 default pass_no is 0 .

%*******************************************************
%        Frame to represent learnt schedule data
%*******************************************************

frame learnt_schedule is an actuator_data,        % learnt schedule data
                            total_slab_state,
                            process_targets ,
                            predicted_mill_state ;
 default pass_no is 0 .

%*******************************************************
%        Frame to represent a flag (used to allow data
%         to be passed to and from C)
%*******************************************************

frame flag;
 default value is 0 .
```

B. Consts.ksl Definition of instances and constants used in the expert system

```
%****************************************************************
% File name:  CONSTANTS.KSL
% This file contains all the constants
% used in the main expert system.
%
%  Created: 3 March 1995
%****************************************************************

%************************************************
% Adaptation coefficients
%
%************************************************

instance load_coeff is a coefficient                    % Load coefficient
 value is 1.0 and
 err_cov is 0.01 .

instance washhtc_coeff is a coefficient                 % Wash HTC coefficient
 value is 1.0 and
 err_cov is 0.01 .

instance torque_coeff is a coefficient                  % Torque coefficient
 value is 1.0 and
 err_cov is 0.01 .

instance profile_coeff is a coefficient                 % Profile coefficient
 value is 1.0 and
 err_cov is 0.01 .

instance select_temp_or_flowstress is a flag            % Select flowstress or temperature coefficient
 value is 0 .                                           % (pass-pass)

instance forgetting_factor is a flag                    % Forgetting factor (slab-slab)
 value is 1.0 .

instance increase_p is a flag                           % Increase the P matrix (slab-slab)
```

```
 value is 1 .

%*************************************************
% PDI for this slab and next slab
%
%*************************************************

instance this_slab_pdi is a slab_pdi .            % define the current slab's pdi

instance next_slab_pdi is a slab_pdi .            % define the next slab's pdi

instance learnt_schedule_pdi is a slab_pdi .

%*************************************************
% Schedule data types:-
% Fixed schedule
% Learnt schedule
% Revised schedule
%
%*************************************************

instance this_pass is a pass_schedule_data .            % The revised pass schedule
instance previous_pass is a pass_schedule_data .

instance fixed_schedule is a pass_schedule_data .       % The fixed schedule

instance this_pass_of_learnt_schedule is a learnt_schedule .          % The learnt schedule
instance previous_pass_of_learnt_schedule is a learnt_schedule .      % The learnt schedule

%*************************************************
% Slab entry and exit states
%
%*************************************************

instance entry_state is a total_slab_state .            % The estimated entry state of the slab

instance exit_state is a total_slab_state .             % The estimated exit state of the slab

%*************************************************
% Define some commonly used predictions from
% the process models
%*************************************************

instance entry_slab_prediction is a predicted_slab_state .
instance exit_slab_prediction is a predicted_slab_state .
instance mill_state_prediction is a predicted_mill_state .

%*************************************************
% Define derivatives used
%
%*************************************************

instance temp_speed_derivative is a derivative .
instance profile_bend_derivative is a derivative .

%*************************************************
% Define some commonly made measurements
% made during rolling
%*************************************************

instance layon_temperature_measurement is a measurement;
 value is value of temperature of this_slab_pdi and
 standard_deviation is 0.819 and
 drift is 1.0 and
 expected_value is value of temperature of learnt_schedule_pdi .

instance entry_temperature_measurement is a measurement ;       % Measured entry temperature
 standard_deviation is 0.819 and
 drift is 1.0 and
 expected_value is value of temperature of previous_pass_of_learnt_schedule .
```

```
instance entry_profile_measurement is a measurement ;          % Measured exit profile
 standard_deviation is 0.119 and
 drift is 0.1 and
 expected_value is value of profile of previous_pass_of_learnt_schedule .

instance exit_temperature_measurement is a measurement ;       % Measured exit temperature
 standard_deviation is 0.819 and
 drift is 1.0 and
 expected_value is value of temperature of this_pass_of_learnt_schedule .

instance exit_profile_measurement is a measurement ;           % Measured exit profile
 standard_deviation is 0.119 and
 drift is 0.1 and
 expected_value is value of profile of this_pass_of_learnt_schedule .

instance exit_shape_measurement is a measurement ;             % Measured exit shape
 standard_deviation is 0.05 and
 drift is 0.05 and
 expected_value is value of shape of this_pass_of_learnt_schedule .

instance load_measurement is a measurement ;                   % Measured load
 standard_deviation is 0.819 and
 drift is 5.0 and
 expected_value is value of load_prediction of this_pass_of_learnt_schedule .

instance power_measurement is a measurement ;          % Measured power
 standard_deviation is 0.819 and
 drift is 5.0 and
 expected_value is value of power_prediction of this_pass_of_learnt_schedule .

% Create dummy measurements which are set to schedule parameters

instance entry_gauge_measurement is a measurement ;    % Measured entry gauge
 value is value of exit_gauge of previous_pass .

instance exit_gauge_measurement is a measurement ;     % Measured exit gauge
 value is value of exit_gauge of this_pass and
 confidence is 2 .

instance entry_width_measurement is a measurement ;    % Measured entry width
 value is value of width of this_slab_pdi .

instance exit_width_measurement is a measurement ;     % Measured exit width
 value is value of width of this_slab_pdi .

instance entry_length_measurement is a measurement ;   % Measured entry width
 value is value of length of this_slab_pdi .

instance exit_length_measurement is a measurement ;    % Measured exit width
 value is value of length of this_slab_pdi .

instance entry_shape_measurement is a measurement ;    % Measured exit width
 value is 0 .


%**************************************************
% Spray patterns:
% The spray patterns are determined using the
% max and min values for a particular pass
%**************************************************

instance ss_spray_pattern is a spray_pattern .           % set the ss spray pattern equal to fixed schedule

instance cold_spray_pattern is a spray_pattern .         % set the ss spray pattern equal to fixed schedule

instance warm_spray_pattern is a spray_pattern .       % set the ss spray pattern equal to fixed schedule

instance hot_spray_pattern is a spray_pattern .          % set the ss spray pattern equal to fixed schedule

instance very_hot_spray_pattern is a spray_pattern .     % set the ss spray pattern equal to fixed schedule
```

```
%*************************************************
% Global frame to define parameters
%*************************************************
frame global
 default first_slab is 1 and
 default learnt_schedule_exists is 0 and
 default learnt_schedule_exists_profile is 0 and
 default this_starting_point is 1 and
 default next_starting_point is 1 and
 default halt_updating is 0 and
 default fault is 1 and
 default dt_dv is 25.0 and
 default dt_ds is 25.0 and
 default dk_dj is 0.02 and
 default dk_dt is 2.0 and
 default product_change is 0 and
 default beta is 0.5 and
 default uncertain is 0.5 and
 default correct is 1.0 and
 default incorrect is 0.0 and
 default first_pass is 1 and

% target setting model constants
 default breakdown_pass_breakpoint is 0.100 and
 default temp_gauge_breakpoint is 0.100 and
 default profile_gauge_breakpoint is 0.100 and

% Acceptable standard deviations and drifts for different types of measurements

 default max_temperature_sd is 10 and
 default max_profile_sd is 0.2 and
 default max_shape_sd is 0.1 and
 default max_other_sd is 10 and
 default max_temperature_drift is 5 and
 default max_profile_drift is 0.1 and
 default max_shape_drift is 1 and
 default max_other_drift is 10 and
 default unexpected_measurements is 0 and
 default temp_control_limit is 20 and
 default profile_control_limit is 0.5 and
 default shape_control_limit is 0.3 and
 default other_control_limit is 15 and

% Acceptable deviation from targets

 default profile_target_limit is 0.2 and
 default temperature_target_limit is 10 and

% Actuator limits

 default max_roll_bend is 1000000 and
 default min_roll_bend is -1000000 .

% Action to store actuator limits in slots

action set_limits;
do
max_value of exit_gauge := 0.5 and
min_value of exit_gauge := 0 and
max_value of speed := 5 and
min_value of speed := 1.2 and
max_value of roll_bend := max_roll_bend and
min_value of roll_bend := min_roll_bend and
max_value of pc_angle := 1 and
min_value of pc_angle := 0 and
max_value of centre_spray_level := 10 and
min_value of centre_spray_level := 0 and
max_value of edge_spray_level := 10 and
min_value of edge_spray_level := 0 .
```

```
action set_patterns;
do
 value of centre_spray_level of  ss_spray_pattern := 10 and
 value of edge_spray_level of ss_spray_pattern := 10 and
 value of centre_spray_level of cold_spray_pattern := 4 and
 value of edge_spray_level of cold_spray_pattern := 10 and
 value of centre_spray_level of warm_spray_pattern := 7 and
 value of edge_spray_level of warm_spray_pattern := 10 and
 value of centre_spray_level of  hot_spray_pattern := 10 and
 value of edge_spray_level of hot_spray_pattern := 7 and
 value of centre_spray_level of very_hot_spray_pattern := 10 and
 value of edge_spray_level of very_hot_spray_pattern := 4 .
```

C. Relations.ksl Definition of relations used in the expert system

```
%**************************************************************
% File name:  RELATION.KSL
% This file contains all the relations
% used in the main expert system also refer to TEMPLATE.KSL
%
%  Created: 3 March 1995
%**************************************************************

synonym temp_target
        target_temperature of this_pass .

synonym temp_error
        value of temperature of exit_state - temp_target  .

synonym profile_target
        target_profile of this_pass .

synonym profile_error
        value of profile of exit_state - profile_target  .

synonym camber_target
        target_camber of this_pass .

synonym camber_error
        value of thermal_camber_prediction of the mill_state_prediction - camber_target .

%******************************************************
%        Measurement relations
%******************************************************

% Acceptable standard deviations for different types of measurement

relation Measurement has a large_standard_deviation
        if  [ Measurement = exit_temperature_measurement or
        Measurement = layon_temperature_measurement or
        Measurement = entry_temperature_measurement ] and
        standard_deviation of Measurement > max_temperature_sd

        or  [ Measurement = entry_profile_measurement or
        Measurement = exit_profile_measurement ] and
        standard_deviation of Measurement > max_profile_sd

        or  [ Measurement = entry_shape_measurement or
        Measurement = exit_shape_measurement ] and
        standard_deviation of Measurement > max_shape_sd

        or [ Measurement = load_measurement or
        Measurement = power_measurement ] and
        standard_deviation of Measurement > max_other_sd  .

relation SD is a small_standard_deviation
        if SD < 10.0 .

% Acceptable drift for different types of measurement

relation Measurement has a large_drift
```

```
        if [ Measurement = exit_temperature_measurement or
        Measurement = layon_temperature_measurement or
        Measurement = entry_temperature_measurement ] and
        drift of Measurement > max_temperature_drift

        or [ Measurement = entry_profile_measurement or
        Measurement = exit_profile_measurement ] and
        drift of Measurement > max_profile_drift

        or [ Measurement = exit_shape_measurement or
        Measurement = entry_shape_measurement ] and
        drift of Measurement > max_shape_drift

        or [ Measurement = load_measurement or
        Measurement = power_measurement ] and
        drift of Measurement > max_other_drift  .


relation X disagrees with Y
        if Y=0 .

% Acceptable control limits for different types of measurement

relation Measurement above control limit
        if [Measurement = exit_temperature_measurement or Measurement = entry_temperature_measurement
        or Measurement = layon_temperature_measurement ] and
        [ value of Measurement > expected_value of Measurement + temp_control_limit ]

        or [Measurement = exit_profile_measurement or Measurement = entry_profile_measurement] and
        [ value of Measurement > expected_value of Measurement + profile_control_limit ]

        or [Measurement = exit_shape_measurement or Measurement = entry_shape_measurement] and
        [ value of Measurement > expected_value of Measurement + shape_control_limit ]

        or [ Measurement = load_measurement or
        Measurement = power_measurement ] and
        [ (value of Measurement - expected_value of Measurement) *100 / expected_value of Measurement
                        > other_control_limit ] .

relation Measurement below control limit
        if [Measurement = exit_temperature_measurement or Measurement = entry_temperature_measurement
        or Measurement = layon_temperature_measurement ] and
        [ value of Measurement < expected_value of Measurement - temp_control_limit ]

        or [Measurement = exit_profile_measurement or Measurement = entry_profile_measurement] and
        [value of Measurement < expected_value of Measurement - profile_control_limit ]

        or [Measurement = exit_shape_measurement or Measurement = entry_shape_measurement] and
        [ value of Measurement < expected_value of Measurement - shape_control_limit ]

        or [ Measurement = load_measurement or
        Measurement = power_measurement ] and
        [  (expected_value of Measurement - value of Measurement) *100 /  expected_value of Measurement
                        > other_control_limit ] .

relation X is the_same_as Y
        if X = Y .

%********************************************************
%       Prediction relations
%********************************************************

relation Parameter agrees with Schedule
        if  [ Parameter is not equal to 0 and (Parameter - Schedule) *100 / Parameter
                        <  30 and
         (Schedule - Parameter) *100 /  Parameter
                        < 30 ] .

%********************************************************
%       Speed setting relations
```

```
%********************************************************

relation Pass is a breakdown pass
        if value of exit_gauge of Pass is greater than or equal to breakdown_pass_breakpoint .

relation Pass is an intermediate pass
        if value of exit_gauge of Pass is less than breakdown_pass_breakpoint
        and exit_tension of Pass is equal to 0 .

relation Pass is a coiling pass
        if exit_tension of Pass is greater than 0 .

relation Temperature is about the right temperature
        if temp_error =< 5.0
        and temp_error >= -5.0 .

relation Temperature is too hot
        if temp_error > 5.0 .                    % and temp_error < 20.0 .

relation Temperature is too cold
        if temp_error < -5.0 .           % and temp_error > -20.0 .

relation Temperature is very hot
        if temp_error >= 20.0 .

relation Temperature is very cold
        if temp_error =< -20.0 .

%********************************************************
%       Profile setting relations
%********************************************************

relation Profile is too large
        if profile_error > 0.2 .         %and profile_error < 0.5 .

relation Profile is too small
        if profile_error < -0.2 .        % and profile_error > -0.5.

relation Profile is very large
        if profile_error >= 0.5 .

relation Profile is very small
        if profile_error =< -0.5 .

relation Profile is about the right profile
        if profile_error =< 0.2
        and profile_error >= -0.2 .

%********************************************************
%       Thermal camber setting relations
%********************************************************

relation Rolls are cold
        if camber_error =< -15.0 .

relation Rolls are warm
        if camber_error < -5.0 and camber_error > -15.0 .

relation Rolls are at steady state
        if camber_error >= -5.0 and camber_error =< 5.0 .

relation Roll_Camber has grown slightly too big
        if camber_error > 5.0 and camber_error < 15.0 .

relation Roll_Camber has grown too big
        if camber_error >= 15.0 .

%********************************************************
%       Product change
%********************************************************
```

```
relation Width_X increases width from Width_Y
        if (Width_X - Width_Y) > 0.25 .

relation Width_X decreases width from Width_Y
        if (Width_X - Width_Y) < -0.25 .

relation Width_X changes width from Width_Y
        if Width_X  increases width from Width_Y or
        Width_X decreases width from Width_Y .

relation Temperature_X changes temperature from Temperature_Y
        if (Temperature_X - Temperature_Y) > 15 or
        (Temperature_X - Temperature_Y) < -15 .

relation Gauge_X changes gauge from Gauge_Y
        if (Gauge_X - Gauge_Y) > 0.001 or
        (Gauge_X - Gauge_Y) < -0.001 .

%*******************************************************
%       Slab state
%*******************************************************

relation Confidence is a high confidence
        if Confidence > 0.5 .

relation Confidence is a low confidence
        if Confidence < 0.5 .

%*******************************************************
%       Checking targets
%*******************************************************

relation State is on target
        if [ State = value of temperature of exit_state and
        [ State > target_temperature of this_pass  -  temperature_target_limit and
        State < target_temperature of this_pass + temperature_target_limit ] ]
        or [ State = value of profile of exit_state and
        [ State >  target_profile of this_pass -  profile_target_limit and
        State < target_profile of this_pass + profile_target_limit ] ] .


%*******************************************************
%       Functions
%*******************************************************

function update(X, Y) = (1 - beta)*X + beta *Y .
```

D. Templates.ksl Definition of templates used in the expert system

```
%*****************************************************************
% File name:  TEMPLATE.KSL
% This file contains all the templates required
% used in the main expert system for the rules and relations
%
%  Created: 3 March 1995
%*****************************************************************

%*****************************************************************
% templates for adaptation and measurement checking
%*****************************************************************

template large_standard_deviation
        ^ has a large_standard_deviation .

template small_standard_deviation
        ^ is a small_standard_deviation .

template large_drift
        ^ has a large_drift .

template disagrees_with
```

```
        ^ disagrees with ^ .

template above_control_limit
        ^ above control limit .

template below_control_limit
        ^ below control limit .

template is_same_as
        ^ is the_same_as ^ .

%****************************************************************
% templates for prediction checking
%****************************************************************

template agrees_with
        ^ agrees with ^ .

%****************************************************************
% templates for speed setting
%****************************************************************

template breakdown
        ^ is a breakdown pass .

template intermediate
        ^ is an intermediate pass .

template coiling
        ^ is a coiling pass .

template too_hot
        ^ is too hot .

template too_cold
        ^ is too cold .

template about_right_temperature
        ^ is about the right temperature .

template very_cold
        ^ is very cold .

template very_hot
        ^ is very hot .

%****************************************************************
% templates for profile actuator setting
%****************************************************************

template too_large
        ^ is too large .

template too_small
        ^ is too small .

template very_small
        ^ is very small .

template very_large
        ^ is very large .

template about_right_profile
        ^ is about the right profile .

%****************************************************************
% templates for spray setting
%****************************************************************

template cold_rolls
```

```
        ^ are cold .

template warm_rolls
        ^ are warm .

template camber_at_steady_state
        ^ are at steady state .

template camber_too_large
        ^ has grown slightly too big .

template  camber_very_large
        ^ has grown too big .

%****************************************************************
% templates for product change
%****************************************************************

template temperature_change
        ^ changes temperature from ^ .

template width_change
        ^ changes width from ^ .

template width_increase
        ^ increases width from ^ .

template width_decreases
        ^ decreases width from ^ .

template gauge_change
        ^ changes gauge from ^ .

%****************************************************************
% templates for slab state
%****************************************************************

template high_confidence
        ^ is a high confidence .

template low_confidence
        ^ is a low confidence .

%****************************************************************
% templates for checking targets
%****************************************************************

template is_on_target
        ^ is on target .
```

E. Ruleset6.ksl Definition of ruleset used in the expert system

```
%****************************************************************
% File name:  RULESET6.KSL
% This file contains rules relating to
% determining the entry and exit state of the slab
% and  for checking measurement accuracy
%
%  Created: 6 March 1995
%****************************************************************
%
% Confidence values
%        correct    Measurement Ok
%        uncertain Indicates that value is unexpected but may still be correct
%        incorrect  Measurement is not reliable

% Rules which process the measurements

action check_measurements

forward_chain(fcfs,true,fail,fixed,check_meas1) .
```

```
forward_chain(fcfs,true,fail,once,check_meas2) .

group check_meas1
        recalibrate,                                   % Check for large standard deviation or drift
        check_measurement_against_expected .           % Check measurements with learnt schedule

group check_meas2
        cross_check_layon_load_1,
        cross_check_layon_load_2,
        cross_check_layon_load_3,
        cross_check_layon_load_4 ,
        cross_check_power_load_1,
        cross_check_power_load_2,
        cross_check_power_load_3,
        cross_check_power_load_4,
         cross_check_profile_load .

%
% Check the measurement against the expected measurement value
%

rule check_measurement_against_expected
        if Measurement is some instance of a measurement
        and learnt_schedule_exists is 1
        and confidence of Measurement is correct
        and [Measurement below control limit or
        Measurement above control limit ]
        then confidence of Measurement becomes uncertain
        and write('Unexpected ') and write(Measurement) and write(' Pass ') and
        write(pass_no of this_pass) and nl .

%
% Determine from the sampled information whether the measurement is valid
%

rule recalibrate
        if Measurement is some instance of a measurement
        and confidence of Measurement is correct
        and [Measurement has a large_standard_deviation
        or Measurement has a large_drift]
        then confidence of Measurement becomes incorrect and
        write('Unreliable ') and write(Measurement) and nl.

% Use the results from check_measurement_against_expected
%
% Perform a cross check if layon temp & load lie outside the control limits
% Case 1 layon is uncertain but load OK then layon is probably incorrect
% Case 2 layon is OK but load is uncertain then load is probably incorrect
% Case 3 layon and load are both uncertain the check for any consistency
%        using the fact that load and layon are are linearly dependent
% Case 4 layon an load incorrect

rule cross_check_layon_load_1
        if pass_no of this_pass is 1 and
        confidence of layon_temperature_measurement is uncertain and          % case 1
          confidence of load_measurement is correct then
            confidence of layon_temperature_measurement becomes incorrect and
            write('Layon temperature measurement is incorrect') and nl .

rule cross_check_layon_load_2
         if pass_no of this_pass is 1 and
        confidence of load_measurement is uncertain and          % case 2
                confidence of layon_temperaturer_measurement is correct then
                confidence of load_measurement becomes incorrect and
                 write('Load measurement is incorrect') and nl .

rule cross_check_layon_load_3
         if  pass_no of this_pass is 1and
        [layon_temperature_measurement above control limit and                % case 3
                load_measurement  below control limit] or
```

```
                [layon_temperature_measurement below control limit and
                load_measurement  above control limit] then
                confidence of load_measurement becomes correct and
                confidence of layon_temperature_measurement becomes correct and
                write('Load and layon temperature measurements consistent') and nl .

rule cross_check_layon_load_4
        if  pass_no of this_pass is 1 and
        confidence of load_measurement is uncertain and            % case 4
                confidence of layon_temperature_measurement is uncertain then
                confidence of load_measurement becomes incorrect and
                confidence of layon_temperature_measurement becomes incorrect and
                write('Load and layon temperature measurements incorrect') and nl .

% Use the results from check_measurement_against_expected
%
% Perform a cross check if power & load lie outside the control limits for any pass
% Case 1 power is uncertain but load OK then power is probably incorrect
% Case 2 power is OK but load is uncertain then load is probably incorrect
% Case 3 power and load are both uncertain the check for any consistency
%        using the fact that load and power are are linearly dependent
% Case 4 power an load incorrect

rule cross_check_power_load_1
        if confidence of power_measurement is uncertain and                 % case 1
          confidence of load_measurement is correct then
            confidence of power_measurement becomes incorrect and
            write('Power measurement is incorrect') and nl .

rule cross_check_power_load_2
        if confidence of load_measurement is uncertain and                  % case 2
                confidence of power_measurement is correct then
                confidence of load_measurement becomes incorrect and
                 write('Load measurement is incorrect') and nl .

rule cross_check_power_load_3
        if  [power_measurement above control limit and                      % case 3
                load_measurement  above control limit] or
                [power_measurement above control limit and
                load_measurement  above control limit] then
                confidence of load_measurement becomes correct and
                confidence of power_measurement becomes correct and
                write('Load and power measurements consistent') and nl .

rule cross_check_power_load_4
        if  confidence of load_measurement is uncertain and                 % case 4
                confidence of power_measurement is uncertain then
                confidence of load_measurement becomes incorrect and
                confidence of power_measurement becomes incorrect and
                write('Load and power measurements incorrect') and nl .


%
% Perform a cross check if profile & load lie outside the control limits for any pass
%

rule cross_check_profile_load
        if  [exit_profile_measurement above control limit and
                load_measurement  above control limit] or
                [exit_profile_measurement above control limit and
                load_measurement  above control limit] then
                confidence of load_measurement becomes correct and
                confidence of exit_profile_measurement becomes correct and
                write('Load and profile measurements consistent') and nl .


group determine_entry_state
        set_entry_state_to_pdi,
        set_entry_state_to_exit_state ,
        set_entry_state_to_schedule,
```

```
        update_entry_state_to_measured .

% Always set the entry state to the pdi for the first pass

rule set_entry_state_to_pdi
        if State is some instance of a slab_state and
        confidence of State of entry_state is 0 and
        pass_no of this_pass is 1 then
          value of State of entry_state := value of State of this_slab_pdi and
          confidence of State of entry_state := 1
        score 3 .

% Set the entry state to the exit state

rule set_entry_state_to_exit_state
        if State is some instance of a slab_state and
        confidence of State of entry_state is 0 then
           value of State of entry_state := value of State of exit_state and
           confidence of State of entry_state := 1
        score 1 .

% Unless a good measurement is made

rule update_entry_state_to_measured
        if State is some instance of a slab_state and
        confidence of State of entry_state is 0 and
        join2('entry_',State,Measurement,'_measurement') and
        confidence of Measurement is 1 then
           value of State of entry_state := value of Measurement and
           confidence of State of entry_state := 1 ;
        score 2 .

% Set the entry state to the exit state

rule set_entry_state_to_schedule
        if State is some instance of a slab_state and
        confidence of State of entry_state is 0 then
           value of State of entry_state := value of State of exit_state and
           confidence of State of entry_state := 1
        score 1 .

group determine_exit_state
        set_exit_state_to_predicted,
        update_exit_state_to_measured .

% Set the exit state to the predicted state

rule set_exit_state_to_predicted
        if State is some instance of a slab_state and
        confidence of State of exit_state is 0 then
        join(State,Prediction,'_prediction') and
        value of State of exit_state := value of Prediction of exit_slab_prediction and
        confidence of State of exit_state := 0.5 ;
        score 1 .

% Unless a good measurement is made

rule update_exit_state_to_measured
        if State is some instance of a slab_state and
        join2('exit_',State,Measurement,'_measurement') and
        confidence of Measurement is 1 and
        confidence of State of exit_state is not equal to 1 then
           value of State of exit_state := value of Measurement and
           confidence of State of exit_state := 1 ;
        score 2 .
```