DESIGN, IMPLEMENTATION AND TESTING OF AN INTELLIGENT KNOWLEDGE-BASED SYSTEM FOR THE SUPERVISORY CONTROL OF A HOT ROLLING MILL

L. Yao¹, I. Postlethwaite¹, W. Browne²,
D. Gu¹, M. Mar³ and S. Lowes³

¹. *Department of Engineering, University of Leicester, Leicester, UK*

². *Department of Cybernetics, University of Reading, Reading, UK*

³. *Alcoa, Europe, Flat Rolled Products, Kitts Green, Birmingham, UK*

Abstract: This paper describes the design, implementation and testing of an intelligent knowledge-based supervisory control (IKBSC) system for a hot rolling mill process. A novel architecture is used to integrate an expert system with an existing supervisory control system and a new optimization methodology for scheduling the soaking pits in which the material is heated prior to rolling. The resulting IKBSC system was applied to an aluminium hot rolling mill process to improve the shape quality of low-gauge plate and to optimise the use of the soaking pits to reduce energy consumption. The results from the trials demonstrate the advantages to be gained from the IKBSC system that integrates knowledge contained within data, plant and human resources with existing model-based systems.

Keywords: Expert System, Rolling Mill Control, Supervisory Control, Intelligent Knowledge-based Systems, Scheduling, Integrated Plant Control.

1. INTRODUCTION

In the metals production industry, the UK is considered a world leader in the design of low-level closed-loop controllers. However, for supervisory and plant wide control systems the UK has lost ground by failing to embrace new technologies. The motivation behind the work described here was to redress this situation and to deliver a competitive edge to producers and suppliers through the development of a knowledge-based system for supervisory control.

The control systems used for the production of aluminium plate can be normally divided into three levels: the level I control system directly communicates with the plant driven by set-points specified by the level II system. The level II supervisory control system is responsible for the production of set-points for several level I control systems, so that these sub-systems can co-operate together to produce quality products. Level III is the top-level control system of the whole plant including plant wide optimisation and scheduling. After many years of development, level I control techniques in rolling mill processes have reached a high standard of maturity. However, level II and III control systems still require a considerable amount of human involvement to fulfil supervisory and plant wide control tasks. As a consequence, plants are capable of producing prime quality products, but there is scope to improve yields and efficiency by implementing advanced systems. There are many developments using 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. This is because current supervisory control systems cannot quickly adjust to the wide variation of products required by a competitive market, and they are also unable to utilise fully all the human expertise and resources that are available. A technology capable of capturing human knowledge in a control system is required [1]. In recent years, attention has focused on the development of level II systems that work hand-in-hand with level I systems [1]. Several advanced level II rolling mill set-up systems have been developed [3,4]. In addition to using classical mill set-up models, some advanced model adaptation techniques have been adopted in level II control [5,6,7]. Expert systems and knowledge-based applications have grown, impacting many areas of decision making (especially in manufacturing) such as dynamic scheduling, production planning, quality management, plant layout, advanced manufacturing processes, process optimisation, purchasing and materials [8,9]. Integrated reasoning systems have been implemented to improve the quality control in a rolling mill [10]. Artificial Intelligence techniques have been used in mill set-up systems [11]. Combining an expert system with a conventional set-up system has been tested and proven using a prototype simulator. This approach makes use of existing and proven technology, whilst adding the flexibility and decision making capabilities of the expert system [12]. A hybrid modelling methodology was designed and implemented in the G2 real time expert system for rolling mills and was tested and found to be suitable using a simulated, laboratory scale rolling mill [13].

With EPSRC and industrial support an intelligent knowledge-based supervisory control system (IKBSC) is being developed in order to improve the shape of the product whilst increasing throughput and reducing cost on a real hot rolling mill. The IKBSC

system integrates an existing level II control system and an Expert system and cooperates with level I and level III systems. The existing supervisory control system, referred to as the Hot Mill Adaptation System (HMAS), (see the part A of Figure 3) was supplied by VAI technologies and has been recently commissioned to provide state of the art model-based adaptive control. HMAS was designed to provide on-line model adaptation and schedule generation functionality. The IKBSC system aims to produce schedules specifically for improved plate shape quality. Furthermore, it seeks to optimise the use of the soaking pits by augmenting human supervisory functionality using modern artificial intelligence technologies.

The development and implementation of the IKBSC system for an aluminium hot rolling mill process, is a joint project between Alcoa Europe Flat Rolled Products (Alcoa) and until recently VAI Industries (VAI). The overall aims of the project are to improve the shape quality of low-gauge plate and to optimise the use of the soaking pits to reduce energy consumption.

This paper describes the design, implementation and testing of the expert system so that it augments the existing system for improved supervisory control [3,14,15]. The expert system concentrates on utilising human knowledge, whilst HMAS provides the infrastructure for the overall system. The paper is organised as follows. Section 2 gives a brief overview of the aluminium soaking pit, the rolling plant and the relevant background. Section 3 describes the system architecture and the design method by which the expert system is integrated into the existing control structure. Section 4 explains the design of the IKBSC system, including details of the structure of the expert system, the scheduling and the optimisation of the soaking pits. The results of applying the IKBSC system to an aluminium rolling mill process are presented in Section 5. Section 6 provides the conclusions and discusses some possible directions for future extensions of the work.

2. THE ALUMINIUM SOAKING PITS AND ROLLING MILL PROCESS

2.1. Schematic Plant

The process under consideration consists of one scalper, nine soaking pits, one small furnace and one hot rolling mill. A layout of the process is shown in Figure 1.

Figure 1. The layout of the soaking pits and rolling mill process

Prepared slabs of aluminium, up to 525 mm thick, 1500 mm wide and 4.5 m long, are heated in pit furnaces for stress relief and homogenisation or are preheated up to the correct rolling temperature. A crane transfers a slab to the entry table, where an initial temperature measurement is taken. The recording of this value is used as a trigger for the level II supervisory control system to calculate the schedule. The schedule consists of the necessary number of passes, each containing the rolling mill set-points at that pass, in order to roll the slab down to the finished plate gauge. The most demanding dimensions are minimum thickness 5.70 mm, maximum width 3750 mm and maximum length 32 m.

The performance of the existing level II supervisory control system will be judged by the ability of the system to compute pass and mill parameters that result in the mill rolling on-gauge material. The mill will be deemed to be rolling on-gauge material if, after the workpiece enters the roll bite, any gauge error can be corrected by the optical gauge control system (OGC). A gauge setting error of ± 2.5 mm can be corrected by the OGC system if, after rolling, the workpiece is 15 mm thick. As the exit gauge of the workpiece is reduced the amount of correction is reduced. At a finished gauge of 10 mm or less the OGC system can correct a gauge setting of ± 0.85 mm. The existing level II supervisory control system will guarantee that the hot mill determines mill set points such that the probability of the head-end exit gauge falling within the operating window of the OGC system is 0.99. That is, on average ninety nine percent of plates will have a head-end gauge error that can be fully corrected by the action of the OGC system.

2.2. Existing Supervisory Control System (HMAS)

The National Instruments LabVIEW [16] is used to manage plant signals and co-ordinate stored plant information, plant models and human machine interfaces. The important plant information, such as roll dimensions, are held in a format which facilitates maintenance by engineers. The plant models, schedule generators and adaptation routines are written in C [5] because of the speed of operation required. Primary product data is down loaded from the level III system to the level II HMAS and stored in the product queue. The mill operator can change the components of the primary product data before generating a schedule if necessary. During the rolling of each pass the level I data acquisition package records parameters such as rolling load, mill motor currents, mill speed and roll spray cooling patterns. The short term (pass to pass) adaptation algorithm will be triggered during the rolling of the pass if under normal rolling conditions the temperature and gauge of the workpiece are not measured. Measurement of the temperature and thickness of the workpiece after the rolling of a pass will trigger model adaptation. In such circumstances both pass to pass and mill state adaptation coefficients will be adjusted to ensure that predictions of load, motor current, workpiece temperature and roll gap settings are accurate. The long term adaptation algorithm is triggered after the rolling of the last pass and the measurement of finished gauge and temperature. Long term (slab to slab) adaptation adjusts model parameters, such as alloy strength, roll bite friction and roll expansion.

2.3. Improvement of Existing System

An important aspect of plant control is its hybrid operation with a batch product being rolled continuously, either by multiple passes in a reversing mill or one pass through tandem mill stands. This restricts the amount of feedback / on-line adjustment and reliance on past cases that can be utilised by the control system. Despite this, there are some similarities in products, such as alloy type, initial dimensions and starting temperature that can form parts of general rules of thumb (heuristics). The action part of these heuristics relates to the product quality, which includes surface finish, flatness and gauge tolerance. Due to an anticipated increase in customer demands, flatness of the finished plate is viewed as a critical measure of quality.

The industrial considerations focus on how plant personnel want the expert system to function. On-line autonomous control is possible, but removes operator supervision; so is best suited to a proven system. On-line control with operator acceptance is useful to build confidence in any new system and to capture any system anomalies before they are implemented. Off-line use allows an engineer to interrogate the system about current performance, without affecting the control of the mill. The practical nature of the system means that it must exhibit industrial features including quasi-real-time performance and be fully switchable with existing systems in order to be developed without interrupting a plant's operation.

The existing control system has a number of features that may be improved upon to obtain *even* better control. Firstly, it is limited in scope with quality diagnosis and the soaking pit operation not being presented to the operators. Adaptation is used to adjust the mill models if any calculated parameter deviates from the equivalent measured plant parameter. Therefore, there is a need to obtain initially accurate predictions of plant parameters to minimise the adjustments made by adaptation and to maximise the amount of time with the correct adjustments.

3. IKBSC SYSTEM ARCHITECTURE

In industrial software development, the design of the system architecture is very important [17] and is especially so for the IKBSC system [18]. Figure 2 illustrates the overall architecture of an intelligent knowledge-based supervisory control system for the aluminium soaking pits and hot rolling mill process. There are three main parts in the architecture:

- Expert system (ES), which is a sub-system of HMAS;
- Hot Mill Adaptation System (HMAS), which is an existing level II system;
- Soaking Pits Optimisation (SPO), which is a scheduling of soaking pits and rolling mill operation utilising intelligent techniques.

The selected expert system shell was G2 from Gensym Corporation [19]. G2 is a real-time expert system, with a large installed user base that has proved its stability in industrial environments. As a sub-system of HMAS, the ES is directly connected to HMAS. The main ES computer has been used as an Engineer's workstation to generate on-line schedules via HMAS, and off-line development and maintenance for the ES. The plant models inside the ES can be accessed and modified.

The level I control system, AGC/OGC gauge control, all analogue and digital signals, and all serial communication data are connected to HMAS. It is presumed that HMAS passes all data gathered from and sent to these equipment and computers to ES, and that ES does not directly send any data to these equipment and computers. HMAS also communicates with the Level III Scheduling Manager system. The ES will directly communicate with the Planning System using TCP/IP for the purpose of Soaking Pit Optimisation. The plant models are directly linked to ES.

Figure 2. IKBSC System Architecture Schematic

An important aspect of system architecture design is to decide how the expert system links to other units of the complete system, and especially how it co-operates with the existing level II system to fulfil supervisory control tasks. As shown in Figure 2 and Figure 3, the expert system has been connected to a local area network (LAN) which allows the expert system to easily communicate with the existing level II supervisory control system, level I gauge controller and level III plant wide scheduling manager. Some plant devices have been indirectly connected via the existing level II system using the Direct Data Link (DDL). The existing level II system can trigger the expert system to provide a knowledge-based function to generate a schedule via the remote ActiveX link provided both in LabVIEW and G2. An important supervisory task is to detect any potential product errors from the measurements. Once the expert system has detected a serious product error in previous passes, it needs to inform the existing level II system to re-generate a new schedule so as to correct the error in the following passes. The expert system incorporates a number of physically based process models in conjunction with rules, in order to produce schedules. The process models have been implemented via a G2 Gateway link between the models and the expert system. Rules can be added to these models in order to adjust their output in given situations. The complete system maintains a database for various alloy-related metallic properties. This database is accessible to the expert system via the file sharing facility provided in Windows NT, so that engineers only need to maintain one copy of the database in the system [18].

The next stage was the identification of important processes that are not totally controlled by the current system. Soaking pit optimisation can add to the system, whilst shape optimisation focuses the functionality on an increasingly important area. Although improving just the model parameters and strategy selection would have been beneficial, this may not generate better product shape. Complete schedule generation may be justified by the difficulty in identifying the sources of schedule inaccuracies.

Integration with the existing system focused on distributing tasks to the programs and functions best suited to perform them. The shape prediction methods within the existing system will be used to trigger the expert system. Once triggered, a complete schedule generated by the expert system is passed back to the existing system for rolling. Having feedback of shape, even if only qualitative, is important to determine correct schedule generation practices. Measuring the benefit of the expert system is not straightforward as many factors are attempting to improve plant performance. Once knowledge has been described, set down or learnt, it becomes a commodity that everyone can, and should, use for improved plant performance. The accuracy of the shape prediction can be used to compare the existing system with the new expert system. Tracking yield, throughput, availability, operator's satisfaction and profitability over the course of implementing and using the expert system will give a quantitative indication of benefit.

The functionality of the existing level II control system has been incorporated as plant knowledge in the expert system and used to improve the schedule generation [20]. Consequently the overall system is improved through utilising plant knowledge, including soaking pit optimisation [21,22] and greater emphasis on shape.

4. DESIGN OF IKBSC SYSTEM

The design of the IKBSC system comprises of two main elements: an on-line system and an off-line system. The expert system itself consists of three main functions: shape optimisation, quality prediction and soaking pit optimisation. The core knowledge that provides the functionality must be the same in all elements to ensure system integrity. Therefore, the off-line system will not be able to operate unconstrained in parallel with the on-line system as changing knowledge during rolling could disrupt the rolling operation. However, the ability to test ‘what-if’ scenarios offline is important. During the scope of this project a copy of the knowledge base can be used with the system to test ‘what-if’ scenarios - eventually this feature can be integrated into a single package. The offline IKBSC system is operated such that the functionality of the expert system can be used without affecting the operation of the mill process. The online IKBSC system can directly or indirectly affect the control of the mill process.

4.1. Structure of Expert System and ES Manager

The knowledge base designed for the IKBSC system is based upon a combination of plant and process viewpoints. It is designed to have general application for various kinds of aluminium rolling mill processes, especially for hot rolling mills. It can be divided into two main sections, *specific* (to a particular plant) and *general* (to most plants), to make it flexible. The specific section is the top-level module. This module contains the operator experience, the plant dimensions and all the site information. In order to make the knowledge base reusable, maintainable and flexible, the general section is split into six modules: 1) the fault diagnosis, 2) the product, 3) the mill set-up, 4) the mill itself, 5) the operational models and 6) the interfacing. These modules consist of rule and knowledge bases that govern them.

Each module contains a set of related items that together comprise a knowledge base. An added advantage is that several developers can work on a single application by each working on a separate module. These modules can later be combined to form the entire application. Besides this, the class definitions and knowledge that are saved in a single module can be used across multiple applications.

The expert system requires a function to determine when it is to produce schedules for on-line implementation. This trigger could be one-way (HMAS to ES) or bi-directional with ES being capable of requesting that it supplies schedules. Initially, triggering will be one-way, from HMAS to ES.

The **Expert System Manager** co-ordinates the functioning of the ES and is defined as a global class-definition as shown in Figure 6. The ES Manager plays an important role in the ES and distributes relevant information and triggers to the main system functions and rules. The *Set-up module* governs the set-up ES manager and the mill set-up system.

There are five main elements in this global class-definition of ES Manager. **System Mode** has two options: *on-line mode* which links to HMAS and *off-line mode* which links to the ES for simulations. **System Generation** has three generation options: *case-based generation* which includes the case fixed and the case matched, *benchmark generation* which includes the HMAS benchmark and another benchmark, and *heuristics generation* which includes the *shape bounds* and the *maximum draft*. **Schedule Generation** has three options: *asleep* which means the rules are completed and the schedule is being rolled, *on-going* which starts the schedule or finishes the schedule, and *complete* which means the schedule is complete. **Model Data** has two options: *on-going* which starts the process model to get the data, and *complete* which means the process model is complete. **Debug Mode** has two options: *true* which shows the debug information on the message board, and *false* which does not show the debug information on the message board.

4.2. Production of Rules for IKBSC System

The generated schedule, which consists of mill set-points used to control the mill, is analysed to highlight the effect of the additional knowledge. Two different techniques are used to formulate the rules. The **first** is the conventional technique of Knowledge Elicitation, where the rules are obtained from plant experts. The **second** is Data Gathering, where the rules are obtained by multiple techniques including the modelling of the rolling process and the examination of logged data by statistical methods and data mining [23,24,25,26,27,28]. There are six stages of fusing elicited knowledge with mined knowledge:

1. Determine the scope of the knowledge base required to solve the problem.
2. Validate the scope by Data-Mining of the reduced data set.
3. Separate the domain into important sub-areas, as identified by Knowledge-Elicitation.
4. Critical rule identification through both Knowledge-Elicitation and Data-Mining.
5. Specific Rule Identification in Sub-domains via Data-Mining.
6. Off-line trials, on-line trials and commissioning.

Data mining became the main method to discover specific rules, with experts used to validate these rules - no rules formed were rejected outright for being factually incorrect. These rules often had less than five conditions, which could be manually separated to give five simple rules of differing subject. Experts were better at analysing chains of simple rules than sets of

complex rules. The data mining without the fusion needs thirty steps and the data mining with the fusion only needs fourteen steps to generate a rule which shows the simplifying effect on the output of data mining from fusing with knowledge-elicitation. An increase in rule quality was also observed [20, 29]. The knowledge base of the expert system was constructed using data mining and knowledge elicitation techniques.

Also the results of the knowledge elicitation proved more useful than data mining in the initial stages as experts had an overview of important and relevant information.

4.3. Communication between ES and HMAS

The ActiveX Toolbox within G2 is a powerful tool for creating a link between G2 and other applications, which support ActiveX communication. The ActiveX link turns G2 into an ActiveX link server. In HMAS the mill set-points are produced by the process models that are stored in an array of structures (clusters). The ES uses the same data interface to communicate with HMAS to provide mill set-points. In order to pass an array of clusters between LabVIEW and G2, a converter from array to cluster and a converter from cluster to array are used before and after the ActiveX link and LabVIEW.

• ES Interface within HMAS

HMAS can trigger the ES to provide a knowledge-based agent to generate the schedule via a generation schedule interface. The schedule generation data is selected by a schedule function in the level II system which includes the schedule generation data, the adaptation data, the mill data, the strategy data, the pit data, model data and the set point data. The data structure is in C functions and is shown in Table 1. These generated schedule data, as current plant knowledge, are used to improve the schedule generation by the ES.

The communication is based on the ActiveX link as shown on the right side of Figure 3. There are three link modes between HMAS and ES, but only one can elect to generate a schedule at any given time. A description of the link modes is given below:

- 1) **HMAS Only:** HMAS generates a schedule as normal.
- 2) **HMAS Use, Data to ES:** HMAS generates a schedule similar to **HMAS Only** and at the same time the schedule data is sent via the ActiveX link to ES through the G2 Gateway for decoding. At this stage, ES does not generate a schedule, but records the HMAS schedule data and monitors the level II system.
- 3) **ES Only:** HMAS elects **ES Only** to generate a schedule, using data generated by HMAS. The data are passed through the ActiveX link, decoded by G2 and sent to the expert system via G2 Gateway. The ES uses this data to generate a new schedule and sends it back to HMAS. HMAS uses this schedule generated by ES to roll a slab.

Table 1. Data Structure for Generation Schedule Interface

Generation Schedule Interface	
1	Initial temperature
2	Operation Number
3	1. <i>Number of passes in HMAS schedule</i> 2. <i>Number of passes in ES schedule</i>
4	Operation details
5	Alloy data
6	User strategy data
7	Slab model data
8	Process models data
9	Mill dimensions data
10	Process data
11	Pass to pass adaptation data
12	All slab to slab adapt data
13	1. <i>HMAS Set Points data</i> for all of passes; 2. <i>ES Set Points data</i> for all of passes;

Figure 3. ActiveX Link and DLL Link between HMAS and ES

The mode selection is made via a user switch included in HMAS so that an engineer can determine when to use the ES for schedule generation.

For example, when the user selects “*HMAS Only*”, the generation schedule interface sends the generation schedule data from HMAS to ES with *HMAS Set Point data*. Then the expert system generates a schedule and sends all of the data back, but changes *Number of passes in HMAS schedule* to *Number of passes in ES schedule*, and *HMAS Set Points data* to *ES Set Points data* in Table 1.

• Measuring Data

The IKBSC system is capable of obtaining feedback measurement data from the HMAS on-line system. This allows the expert system to check the schedule of the expert system to see whether it is within gauge tolerance when the predictions of plant properties are correct. This measurement data is very important and allows the expert system to reschedule if the gauge is over the tolerance level or, more likely, is predicted to be over the tolerance limit at the finishing pass. A soft link is used here to indirectly connect with the measuring devices, i.e. the DLL link between LabVIEW and G2. The communication is based on DLL link as shown on the left side of Figure 3. The data measuring function has been added to the original adaptation DLL without affecting the original system. For every pass of the rolling mill the measured data are saved to the workspace of the expert system. G2 Gateway waits to receive the measured data and decodes it to G2 format for the expert system to use. The measured data structure is shown in Table 2.

Table 2. Data Structure for Pass Measurement

Pass Measurement Data		
	Name	Unit
1	Mill speed	m/min
2	Initial roll gap setting	mm
3	Target exit gauge	mm
4	Level I: measured roll gap	mm
5	Level I: measured gauge	mm
6	Rolling load	MN
7	Motor current	Amps
8	Measured gauge	mm
9	Shear side temperature	⁰ C
10	Pit side temperature	⁰ C

- **Process Models**

The major process model components are incorporated in the knowledge-based agent to augment rules within the ES and to improve the hot mill scheduling and set-points. The mathematical models used to describe the rolling process are the rolling load, motor power and strip temperature. The model for the cooling of the strip includes the effects of heat transfer to air, the coolant wash and the work rolls. The rolling load model considers the effects 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 motor. Users and developers could include additional process models if necessary.

4.4. Expert System Scheduling

At this stage, the experts evaluated the complete schedule of set-points, not just the rules used in its formation. Data-mining would find this level of overview very difficult. Conversely, experts would find analysing the complex interaction of over 320 rules very difficult in the rules workspace (Figure 4). Experts proved intelligent in relating global phenomenon (the quality of the set-points schedule produced) to local causes (individual rules). The data-mining techniques used here were not capable of this level of abstraction.

Rules could be used to implement a basic mathematical schedule generation algorithm that considers a set draft reduction pattern, see Figure 5a. However, this does not include the rules generated to avoid shape problems, which have a significant effect (see Figure 5b). Important changes to the schedule include a more even pass reduction throughout the schedule, with most reductions during initial passes where shape is unlikely to occur and a smaller reduction during the later shape critical passes.

Figure 4. Rules Workspace

Figure 5. a. Schedule of set-points and b. Schedule after rules

The overall aim of the schedule is to prevent shape in the product. Three main methods are considered to generate an initial schedule: a) Top-down calculation; b) Bottom-up calculation and c) Fixed-schedule. Post-processing, iteration and on-line adjustment may still be required.

Top-down calculation is the simplest method to implement. The maximum pass reduction for a given gauge is used, until the end passes, which are adjusted for shape. In bottom-up generation the ideal end passes are determined and the schedule worked-out backwards until the start. This method tends to have larger gauges at the start of the schedule, which assists in keeping temperature in the plate. Finally, the fixed schedule relating to the given initial slab, alloy and finishing dimensions may be retrieved. Due to the combinatorially large amount of fixed schedules and complex matching algorithm needed to select an appropriate schedule, this method may not be appropriate for all products, especially as it would be hard to adjust.

Inside the ES there is a plant model which allows the system, in an off-line situation, to simulate rolling, from slab specification through schedule generation to final plate. The simulation will highlight any missing or conflicting rules. In practice, the transparent and modular design means that it is straightforward to scrutinise the rule operation and no gaps or conflicts are found. However, great care is needed with rule triggering as the ability to forward chain has to be tightly controlled otherwise unexpected scheduling may occur.

When the expert system has been setup and HMAS has not been run, the schedule generation of ES manager is in '*asleep*' mode, the model data of ES manager is in '*complete*' mode, G2 ActiveX link has been activated and is waiting for HMAS to call. When HMAS starts to setup (HMAS is calling), the schedule generation of ES manager is in '*on-going*' mode, the model data of ES manager is in '*on-going*' mode, HMAS data is passed to ES. ES generates a schedule and sends it back to HMAS, the schedule generation of ES manager changes back to '*complete*' mode, the model data of ES manager is also in '*complete*' mode, and HMAS finishes the call (see Figure 6).

Figure 6. ES Manager changes when ES generates a schedule

Operator experts evaluated the complete schedule of set-points and were successful in relating global phenomena (the quality of the schedule of set-points produced) to local causes (individual rules). The schedule generation diagram for the expert system is shown in Figure 7. This diagram shows how the expert system is triggered by the level II system, how schedule generation is monitored by the ES manager and how it is associated with the process model predictions, the rules and procedures.

Figure 7. Schedule Generation Diagram

4.5. Optimisation of the Soaking Pits

A soaking pit furnace is a key processing unit in the metals industry. Energy consumption by the soaking pits absorbs a significant part of the total operational costs, and the effectiveness of soaking pit operation has a pronounced effect on the downstream mill operation as well as on the quality of the final product. In the aluminium industry, processes upstream of rolling, which take place at room temperature, make the soaking pits a necessary part of the process.

The soaking pit optimisation (SPO) for this aluminium process, which involves sequential scheduling and resource allocation, has been considered in this project [21, 22]. SPO is an NP-Hard two-stage flow-shop problem. We presented an algorithm to synthesise a schedule which aims to increase the throughput and decrease energy consumption. The main components of the SPO are the estimation of processing times (which include the heating and rolling times), the resource allocation (which includes forming the processing sequence of the pit loads) and the allocation to the pits. The Johnson Algorithm (JA) is used to find the sequence in which the pit loads can be rolled most efficiently [30]. A Dynamic Programming algorithm (DP) by [31] is used to schedule pit loads into soaking pits in order to roll them in the sequence determined by the Johnson Algorithm (JA) and without any gaps in rolling. The schedule focuses on the process where groups of aluminium slabs are loaded into a number of soaking pits to be heated and after the content of a pit is soaked at the required temperature, the slabs are drawn out one by one and are rolled at the 4-high stand hot reversing mill. In order to produce a successful schedule, estimating the processing times of these two operations of heating and rolling is important. Our approach uses artificial neural network models to estimate these heating and rolling times. The aim of this work is to obtain better accuracy and resolution in calculation of these processing times, which are estimated manually at present.

The rolling sequence of the pit loads is currently determined manually and is essentially the sequence required by the horizontal heat treatment process (HHT) which follows rolling. It has been suggested that when the operation of the soaking pits and rolling mill system is restricted by the upstream and/or downstream processes, the JA sequence as proposed above can be changed or abandoned. One possibility is that the SPO system should use a sequence dictated by the HHT process or alternatively the HHT process should be scheduled with the SPO JA sequence. If there was a buffer of sufficient size between rolling and the HHT, then JA could be used for the SPO system and the usual HHT sequence used in the HHT process. The scheduling of the HHT process is left as future work at this stage. However, we have experimented with a modified SPO schedule. In this, we have used DP to schedule the pit loads into the soaking pits so as to facilitate the rolling of the slabs using the HHT sequence.

The principles of the SPO systems are demonstrated below by describing three schedules: first a manual schedule (MS) linked to the sequence required for HHT; then an SPO schedule using JA and DP; and finally a modified SPO schedule using the HHT sequence and DP.

The *first schedule*, the manually produced schedule, was used at Alcoa Europe FRP plant between 6th-9th December 2001. It was produced for 16 pit loads and 10 soaking pits were considered but pits 7 and 9 were kept empty because they were reserved for homogenising. The sequence used is that in which the pit loads are to be processed in the downstream HHT process. Data from this schedule has been tested on our simulated SPO system.

The *second schedule*, the SPO schedule using the JA sequence for the rolling mill. It took just two days and 21 hours, a reduction of 23 hours compared with the manually produced schedule. In addition, the total waiting time of pit loads for the rolling mill was reduced from 80 hours (MS) to zero (SPO) and the total waiting time of the rolling mill for pit loads was reduced from 24 hours (MS) to 14 hours (SPO). Furthermore, the total time for heating, rolling and waiting was reduced by 20%, which is equivalent to an energy reduction of 10% (see Table 3).

Table 3. Forward Plan of 6-9/12/2001 [Thursday – Sunday]

Time (hours)	MS	SPO	Reduced Time By SPO	MSPO (HHT)	Reduced Time By MSPO (HHT)
Heating	290	290		290	
Rolling	55	55		55	
Waiting (Rolling)	80	0	80 (100%)	0	80 (100%)
Waiting (Pit Loads)	34	14	20 (42%)	28	6 (17.6%)
Total Time	449	359	90 (20%)	373	76(16.9%)
Duration	92	69	23 (25%)	83	9 (9.8%)

The *third schedule*, the modified SPO schedule (MSPO) uses the HHT sequence for the rolling mill. It took three days and 11 hours, a reduction of 9 hours compared with the manually produced schedule. The total waiting time of pit loads for the rolling mill was also reduced from 80 hours (MS) to zero (MSPO) and the total waiting time of the rolling mill for pit loads

was reduced from 34 hours (MS) to 28 hours (MSPO). Furthermore, the total time for heating, rolling and waiting was reduced by 16.9%, which is equivalent to an energy reduction of 8.5%. The manual schedule has therefore been improved significantly by the MSPO schedule in this preliminary study (see Table 3).

These results are very promising and future work will expand the SPO system to include more practical constraints and consideration of the HHT process.

5. IMPLEMENTATION OF THE IKBSC SYSTEM FOR A HOT ROLLING MILL PROCESS

Three on-line trials have been successfully completed on the hot rolling mill process.

5.1. Trial Set-up

Before an off-line trial or an on-line trial the IKBSC system should be set up as below:

- 1) HMAS elects **ES Only** to generate a schedule by the Expert System (Figure 8a, Section 4.1 and 4.3);
- 2) System mode elects **On-line** (Figure 8b, Table 1 and Section 4.1);
- 3) System Generation elects **Heuristics** (Figure 8b and Section 4.1);
- 4) Basis elects **Shape-Bounds** (Figure 8b and Section 4.1).

Setting up the expert system for schedule generation, switching the operation of the level II control system to the Expert system and the procedure to link each system are detailed in Sections 4.1 and 4.3.

Figure 8a. GenSchedDll Interface

Figure 8b. Set-points Workspace

5.2. Off-line Schedule based on HMAS and ES

The aim of these off-line trials was to show the performance of the HMAS approach and to test the compliance of the expert system approach. There are two simulations in the off-line system: 1) the off-line simulation based on HMAS only; 2) the off-line simulation based on the expert system. Figure 9 shows the schedule generation by HMAS and ES.

Pass	S/D	Speed	Gauge	Load	Current
HC 1	76.43	28.1	76.56	924	395
HC 2	73.20	78.0	73.42	986	1108
MD 3	52.08	28.1	54.93	2395	2325
MD 4	38.49	28.1	41.14	2314	1855
MD 5	28.46	55.0	31.22	2385	3109
MD 6	22.44	78.0	24.67	2119	3200
MD 7	15.11	78.0	12.96	1902	2445
MD 8	15.11	78.0	16.53	1721	1895
MD 9	12.87	55.0	14.02	1596	1069
MD 10	11.27	55.0	12.17	1473	853

a. Off-line Schedule based on HMAS

Pass	S/D	Speed	Gauge	Load	Current
1	65.01	30.0	66.47	1586	1420
2	54.63	78.0	56.22	1655	3238
3	45.01	78.0	46.71	1719	3157
4	37.04	78.0	38.89	1795	2928
5	30.60	78.0	32.32	1724	2559
6	25.04	78.0	26.70	1698	2349
7	20.17	78.0	21.86	1709	2266
8	16.09	55.0	17.86	1755	1589
9	13.06	55.0	14.73	1699	1502
10	10.53	55.0	12.17	1683	1524

b. Off-line schedule based on ES

Figure 9. Off-line schedule

The initial specification of these off-line trials is shown in Table 4 and the results show the performance of the load profile and current profile, and that the expert system in Figure 9b was much smoother than HMAS system in Figure 9a. The speed of the expert system was more even and faster than HMAS. The finished temperature of the expert system was 34 °C above HMAS after the rolling. The off-line schedule of the expert system shows how much the knowledge base has affected and improved the schedule.

Table 4. Initial specification for the off-line schedule

Off-line schedule	NP	Entry Temp (°C)	Extry Temp (°C)	Entry Gauge (mm)	Exit Gauge (mm)	Exit Width (mm)	Exit Length (mm)
HMAS	10	450	326	80	12	2182	12653
ES	10	450	360	80	12	2182	12653

5.3. On-line Trials

The aim of these initial on-line trials was to show that the expert system approach was practical for supervisory control of aluminium plate rolling. The trials successfully tested the hardware linkage to plant, verified and validated the software links to the supervisory control system, communication over the links, switching to (and from) expert system operation, timely operation, schedules generation for different plates and conditions, the practicality of online rolling with expert system schedules and recorded the trial data. Three trials were used incrementally to test the practicality, performance and potential of this scheduling method.

The **First Trial** (which included 3 plates) had to be prudent, with many off-line tests, and an on-line ghost slab was checked to ensure safety of the mill and personnel. The specification was made to ensure that shape would be present if the schedule was incorrect, but the risk to the plant was minimised. This trial demonstrated schedule generation and subsequent shape performance at low gauges: 25 mm, 20 mm and 15 mm, and width at 1800 mm. The main conclusion drawn from the first trial was that the developed system is capable of obtaining flat plates. Successes included stable linking to the existing level II system -- HMAS, downloading the correct plate specification, generation of comprehensive schedules of set-points for challenging product specifications, returning to standard operation and producing flat plate for three different gauges. Apart from not recording some of the trial data, which will normally be handled outside the expert system, all aims and objectives for the trial were met. Issues existed about expanding the product range covered by the knowledge-base, obtaining further information from plant and ensuring gauge and profile tolerance, but these issues were outside the scope of this first trial. This gave encouragement for the further development and expansion of the expert system.

The **Second Trial** (which included 2 plates) focussed on plates of lower gauges: 12 mm and 10 mm, and greater width at 2800 mm as shown in Figure 10. Again flat plates were achieved with good shape. The main conclusion of the second trial was that the developed system is capable of obtaining flat plates within gauge tolerance when the predictions of plant properties are correct. Successes from the first trial were confirmed. This included rolling to lower gauge specifications than before, which were in the operating region where shape readily forms. Apart from not recording some of the trial data, all aims and objectives for the trial were met. Issues still existed about expanding the product range covered by the knowledge base, obtaining further information from plant and ensuring profile tolerance. Gauge performance through model prediction is to be improved at low temperatures. Further, the predictions are to be made more robust at all temperatures by the addition of adaptation and feedback of the overall mill-bounce.

In the **Third Trial** (which had one plate) the new system was shown to be capable of taking feedback measurement data from the low-level system, which could then be used to check the expert system's schedule and reschedule if the gauge was over

tolerance. The trial successfully saved the measurement data on the HMAS online system, and the rest of the output data was saved on the expert system. It utilised a manual schedule at the low gauge of 8 mm, with a width of 2800 mm. This was generated by a rolling expert to get the Knowledge-Elicitation information. The third trial also tested schedule generation and subsequent shape performance at the low gauge of 8 mm, with a width of 2800 mm.

These initial trials (first and second trials) were all conducted in open loop to determine the accuracy of the rules and models. Plant measurements will be fed back to improve gauge accuracy in future trials.

Issues still exist about expanding the product range covered by the knowledge-base, obtaining further information from plant and ensuring profile tolerance, but these issues were outside the scope of these trials. Gauge performance through model prediction is to be improved at low temperatures. Furthermore, the predictions are to be made more robust at all temperatures by the addition of adaptation and feedback of the overall mill-bounce. Increased confidence was gained for the development and expansion of the expert system, in order to increase the range and difficulty of the product scope; whilst satisfying customer tolerances on gauge and profile. This low-cost, flexible scheduling system offers many potential benefits in the production of quality aluminium plates.

In the trials the expert system used basic models for prediction without feedback from the mill. The level of accuracy can be seen from the results of the three trials in Table 5. The thickness tolerances of the plates were based on the thickness and the width of the plates as shown in Table 5 [32]. The gauge error for the plates of the first and second trials were very small and well within customer tolerances. The final plate in the third trial had a gauge error that would require further processing before meeting customer requirements. The temperature of this plate however had fallen to a low value, less than 180°C and this is much lower than previous operating experience for the expert system. However, the gauge errors were in the range that could be compensated by mill feedback when it is included.

Plate-1: gauge 12mm and width 2800mm

Plate-2: gauge 10mm and width 2800mm

Figure 10. Second Trial

The shape performance is critical when deciding to adopt the expert system approach. Figure 10 shows the flatness of the rolled plate. Visual inspection by operators, engineers and scheduling experts were extremely positive about shape performance. Slight wavy edge was seen to be starting on the last plate, which would need careful consideration if rolling this plate further to lower gauges.

Table 5. Gauge performance, gauge checks

Trail - Plate	Entry Temp °C	Exit Temp °C	Aim Gauge (mm)	Measured Gauge (mm)	Error AG – MG (mm)	Thickness Tolerances (mm)
1-1	465	385	15.00	14.75	+0.25	+/- 0.80
1-2	439	391	20.00	19.48	+0.52	+/- 0.90
1-3	416	381	25.35	24.40	+0.95	+/- 1.10
2-1	401	325	12.00	12.02	+0.02	+/- 0.95
2-2	370	233	10.00	10.84	+0.84	+/- 0.85
3-1	450	268	Manually Generated Schedule			
3-2	333	174	8.11	10.55	+2.44	+/- 0.75

6. CONCLUSION

A novel architecture was designed and implemented for integrating an expert system with an existing supervisory control system, a level I gauge controller and a level III plant wide scheduling manager for the rolling of aluminium plate. The design of the system emphasises the strengths of the expert system technique, i.e., reasoning about plant knowledge, by augmenting the existing system. A knowledge-base was designed, using data mining and knowledge-elicitation techniques, which was able to produce schedules of set-points for timely, safe and accurate rolling. The project illustrates the potential of using the expert system technique for supervisory control of modern industrial plant. Future work will expand the range of products that the IKBSC can handle.

Acknowledgements

This research was funded by the Engineering and Physical Sciences Research Council (EPSRC), UK. The help provided by VAI Industrials in the early stages of this work is acknowledged.

References:

- [1] Department of Trade and Industry, UK, <http://www.dti.gov.uk/>, 1999.
- [2] U. Rüttinger, Level 2 process control and automation – Set-up systems for aluminium rolling mills, *Metallurgical Plant and Technology International*, 21 (6) (1997) 64-67.
- [3] T. Watanabe, *et al*, A new mill-setup system for hot strip rolling mill that integrates a process model and expertise, *Proceedings of the IEEE International Conference on Systems, man and Cybernetics*, 3 (1997) 2818-2822.
- [4] R-M. Guo, Development of an optimal crown/shape Level-2 control model for rolling mills with multiple control devices, *IEEE Trans. Control Systems Technology*, 6 (2) (1998) 172-179.
- [5] P.A. Attack, I.S. Robinson, Adaptation of hot mill process models, *Journal of Materials Processing Technology*, 60 (1-4) (1996) 535-542.
- [6] R-M. Guo, Application of PC and LAN for a level 2 setup model of a single-stand reversing mill, *Iron and Steel Engineer*, 74 (8) (1997) 41-46.
- [7] R.I. Stephens, A. Randall, On-line adaptive control in the hot rolling of steel, *IEE proc. Control Theory Appl.*, 144 (1) (1997) 15-24.
- [8] P.A. Durkin, Expert systems, design and development, MacMillan, 1994.
- [9] S.S. Rao, A. Nahm, Z. Shi, X. Deng, A. Syamil, Artificial intelligence and expert systems application in new product development – a survey, *Journal of Intelligent Manufacturing*, 10 (1999) 231-244.
- [10] M. Gams, *et al.*: Integration of Multiple Reasoning Systems for Process Control, *Engineering Applications of Artificial Intelligence*, 10 (1) (1997) 41-46.
- [11] N. Pican, *et al*, Artificial neural networks for the presenting of a steel temper mill, *IEEE Expert*, (1996) 22-27.
- [12] Postlethwaite, P.A. Attack, I.S. Robinson, The improved control for an aluminium hot reversing mill using the combination of adaptive process models and an expert system, *J. of Mat. Proc. Tech.*, 60 (1996) 393-398.
- [13] D. A. Linkens, E. B. Tanyi, A G2-based hybrid modelling and simulation methodology and its application to a rolling mill, *Control Engineering Practice*, 7 (1999) 1101-1112.
- [14] D.A. Stirling, W.Y.D. Yuen, A combined expert system / modelling approach to the adaptive scheduling of stainless steel rolling, *ME*, 16 (1991) 135.
- [15] F. Sanfilippo, F. Martini, M. Oriati, Advanced integrated plant-product management system for rolling mills, *Iron and Steel Engineer*, (1996) 17-21.
- [16] National Instruments, LabVIEW User Manual, Version 5.0, 1998.
- [17] F. Buschmann, A. Geisler, T. Heimke, *et al.*, Framework-Based Software Architectures for Process Automation Systems, *Annual Reviews in Control*, 24 (2000) 163-175.

- [18] L. Yao, W.N.L. Browne, I. Postlethwaite, T. Ozen, P. Atack, M. Mar, S. Lowes: An Architecture for Intelligent Knowledge-based Supervisory Control of Rolling Mills, *IFAC Workshop on New Technologies for Automation of Metallurgical Industry*. Shanghai, China, October 2003, pp. 162-167.
- [19] Gensym Corporation, Inc., G2 Reference Manual, Version 7.1, 2004.
- [20] W.N.L. Browne, L. Yao, T. Ozen, I. Postlethwaite, P. Atack, C. Lane: Rule formulation for an expert system used to generate hot mill pass schedules, *International Conference on Thermomechanical Processing: Mechanics Microstructure & Control*, Sheffield UK. June 2002, pp. 263-269.
- [21] T. Ozen, L. Yao, D.W. Gu, I. Postlethwaite, J.M. Garibaldi, Hybrid Methods to Improve the Manual Schedules at an Aluminium Manufacturing Plant, Submitted (Under review) to *European Journal of Operational Research*, Oct. 2004.
- [22] T. Ozen, D.W. Gu, I. Postlethwaite, W. Browne, L. Yao. Optimization of Soaking Pit/Rolling Mill Process at British Aluminium Plate. *10th IFAC Symposium on Automation in Mining, Mineral and metal Processing*, Tokyo, Japan. Sep 2001.
- [23] J. R. Quinlan, C4.5: Programs for Machine Learning, Morgan Kaufmann, 1993.
- [24] K.D. Jong, M. Potter, W. Spears, Using Problem Generators to Explore the Effects of Epistasis, *International Conference on Genetic Algorithms*, 1997.
- [25] R.S. Sutton, A.G. Barto, Reinforcement Learning: An Introduction, MIT Press, Massachusetts, 1998.
- [26] H. Witten, and E. Frank, Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations, Morgan Kaufmann Series in Data Management Systems, 1999.
- [27] S.W. Wilson, *Mining Oblique Data with XCS*. In: Lanzi, P.L., Stolzmann, W., Wilson, S.W. (eds.): *Advances in Learning Classifier Systems*, Vol 1996 of LNAI, Springer-Verlag, Berlin, 2001.
- [28] Clementine SPSS Inc, *Data Mining System: Clementine 6.0*, SPSS Inc. 2000.
- [29] W.N.L. Browne, L. Yao, I. Postlethwaite, S. Lowes, M Mar: Knowledge-Elicitation and Data-Mining: Fusing Human and Industrial Plant Information, Submitted (Under review) to *Artificial Intelligence in Engineering*, Oct 2004.
- [30] S. Johnson, Optimal two- and three-stage production schedules with set-up times included, *Naval Research Logistics Quarterly*, 1 (1954) 61-68.
- [31] M. H. Rothkopf, Scheduling independent tasks on parallel process, *Management Science*, 12 (5) (1966) 437-447.
- [32] Data Base for Planning & Inspection, DB-TQ-321. Alcoa Controlled Document, 28, Oct 1992.