An Integrated System Approach for Solving Multi-Objective Scheduling Problems and Advanced Control of an Experimental Hot-Rolling Mill

Sid-Ahmed Gaffour*, Mahdi Mahfouf*, George Panoutsos* and Jun Chen**

*Department of Automatic Control and System Engineering, Sheffield University, S1 3JD UK (Tel: 114-222-5613; s.gaffour@Sheffield.ac.uk, m.mahfouf@Sheffield.ac.uk).
**School of Engineering, Lincoln University, LN6 7TS UK (Tel: 1522 668901; juchen@Lincoln.ac.uk).

Abstract: Common to most industries, the metal industry is having to ‘rethink’ its short and long term strategies when it comes to producing metals to customers’ specifications. Indeed, metal producers are having to balance the requirements for more consistent and higher quality rolled products with those that are associated with greater efficiencies in energy costs and impact on environment. In the light of these considerations, the performance of key industrial systems such as hot-rolling mills must be carefully analysed in search of further improvements. Criteria for optimising hot-rolling of steel include system efficacy, advanced control strategies, optimal rolling schedule and product quality. This paper is the result of the authors’ extensive study on the use of advanced technologies and new integrated approaches in the field of optimal scheduling for the hot-rolling process. The proposed design is based on 1. a multi-objective optimisation-based Population Adaptive Immune Algorithm (PAIA); 2. physically-based models and Symbiotic data-driven modelling for the accurate prediction of mechanical properties of alloy steels; 3. advanced control, including Adaptive Fuzzy Generalised Predictive Control (AFGPC) to guarantee the optimal performance of the mill during the rolling process. Hence, the overarching aim of this research work is to integrate knowledge about both the stock and the rolling process to identify the optimal hot-deformation profiles in order to compute the most suitable rolling schedule and systematically ‘chart’ the optimal routes for processing and hence achieve ‘right-first-time’ production of these alloy steel via the desired final microstructure and mechanical properties.

Keywords: Hot-rolling mills, Adaptive Fuzzy Generalised Predictive Control, Multi-Objective Optimisation, Symbiotic Modelling Approach, Population Adaptive Immune Algorithm.

1. INTRODUCTION

Energy savings and higher production rates are two important objectives that today’s iron and steel industry is trying to achieve. One of the possible ways to reach these targets is through the optimal rolling schedule.

The quality of steel depends on the properties associated with its microstructure, including the arrangements, volume fraction, sizes and morphologies of the various phases of transformation with a given composition for a given processing route (Krauss, G 2004). It is well known that there exist a strong correlation between the hot-deformation of steel and its microstructure and the final properties and each type of microstructure and product is developed to characterize property ranges by specific processing routes that control and exploit microstructural changes. With this in mind, iron and steel production scheduling and control problems have been studied by many researchers and are no exceptions. However, many approaches are used in practice in order to find good and feasible solutions of best quantitative microstructural parameters and hot-deformation profiles in the scheduling problems and then set-up the process with effective parameters such as the rolling speed, temperature, amount of deformation, number of rolling passes, etc. Such approaches have been generally based on Genetic Algorithms (GA) in the problems sense and control theory principles and expert systems (Dixit and Dixit, 2000). These steps have for a long time been traditionally accomplished via trial-and-error operations which depend considerably on the designer’s intuition and experience. In this work, a new model-based design is used to optimise the scheduling and control of the hot-rolling mill hence enabling to achieve ‘right-first-time’ production of metals is proposed. Two main stages form the basis of this new strategy for the overall control design. In the first stage, the optimal rolling schedule is systematically calculated according to the desired final microstructure and properties. In this stage the design methodology is separated into a microstructure optimisation problem (module1) to obtain prescribed microstructural parameters such as final grain size and volume fraction recrystallised during deformation (Gaffour et al 2010a) and a rolling schedule optimisation problem (module2) to achieve the thermomechanical conditions required in the module1. The design approach requires four basic components for defining and setting-up the optimisation problem: 1. the stock model describing the microstructure evolution of the material during hot-rolling, 2. the optimal strategy based on symbiotic
modelling approach for the prediction of the mechanical properties of alloy steel (Gaffour et al 2010b), 3. the physical constraints present both in the stock and in the mill including the limitations of the forming process and the hot workability of the stock and 4. the optimality criterion.

In the second stage, the mill carries-out the rolling schedule using a new nonlinear Adaptive Fuzzy Generalised Predictive Control (AGFPC) to guarantee optimal process performance under load.

The remainder of this paper is organised as follows: Section 2 presents a general view of the proposed integrated framework design describing the optimisation methodology, the physically-based model for mild steel (C-Mn steel alloy), symbiotic modelling approach for predicting mechanical properties and nonlinear adaptive predictive controller implemented in the mill. Section 3 presents the results from real-time hot-rolling experiments. Finally, concluding remarks and further work are presented in Section 4.

2. STATE-OF-THE-ART MECHANISMS FOR SCHEDULING OPTIMISATION AND CONTROL

Extensive activity in materials research on steel and aluminium microstructures through rolling experiments within IMMPETUS: Institute for Microstructural and Mechanical Process Engineering: The University of Sheffield has inspired the authors to investigate the performance of a laboratory experimental mill, an experimental laboratory-scale hot-rolling mill as depicted in Figure 1. Because of the importance of the steel-making processes in modern industry, this experimental laboratory-scale mill has been subject of several other investigations concerning steel, aluminium, and titanium.

Figure 1.b depicts the block diagram of the model-based integrated system for microstructure optimisation, speed and gap control of the hot-rolling process.

2.1 Microstructure Optimisation

Using the above framework, one should first specify the desired mechanical properties and the initial conditions of rolling, then by using the symbiotic modelling technique which combines Non-Linear Iterative Partial Adaptive Least Square (NIPALS) model, Linear Regression Model (LR), Neural Network Model with double loop procedures (NNDLP), Neural-Fuzzy model (NF) and metallurgical knowledge, a microstructure optimisation-based Population Adaptive Immune Algorithm (PAIA) search to find near optimal quantitative microstructural parameters that will yield the above properties. For more details on this symbiotic modelling technique and PAIA algorithm refer to (Gaffour et al 2010a) and (Gaffour et al 2010b). To define the optimisation problem of this stage (Module1), it is necessary to establish an optimality criterion. This criterion is represented by the following objective function:

\[
\text{Min}(J_M) = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \end{bmatrix} \begin{bmatrix} \frac{P_1}{P_{\text{desired}}} \\ \frac{P_2}{P_{\text{desired}}} \\ \vdots \end{bmatrix} - \begin{bmatrix} P_1 \\ P_2 \\ \vdots \end{bmatrix} \begin{bmatrix} \frac{P_1}{P_{\text{desired}}} \\ \frac{P_2}{P_{\text{desired}}} \\ \vdots \end{bmatrix} \cdot i = 1,2,\ldots, N \tag{1}
\]

Subject to \( d_{\alpha \min} \leq d_{\alpha} \leq d_{\alpha \max} \) \hspace{1cm} \( V_p \leq V_{p \max} \), \hspace{1cm} \( M \)

The previous objective function assigns a cost to each objective of a solution, where \( P_i \) is the property considered in the optimisation problem and \( N \) is the number of properties contributing to the cost function; \( d_{\alpha} \) represents the ferrite grain size and \( V_p \) is the volume fraction of the pearlite colony in the final microstructure. In the study related to the Hille-mill, the number of properties considered...
is $N = 3$, which are the Tensile Strength TS, the Yield Strength YS and the Impact Transition Temperature ITT.

2.2 Rolling Schedule Optimisation

The scheduling problem is treated here as a multi-objective optimisation problem using the PAIA algorithm which minimises the error between the outcomes resulting from microstructure optimisation and the final microstructure in terms of its quantitative characteristics. The design approach requires three basic components: the stock model, the process or physical constraints, and the optimality criterion. Although this strategy attempts to be applied to a wide range of steel alloys, consider the case of the physically-based model of the C-Mn alloy, for which the microstructural state is defined mainly in terms of the grain size and the percentage of recrystallised material (Sellars, 1980).

In C-Mn steels, the recrystallisation curves generally follow an Avrami equation of the following form:

$$
\begin{align*}
X &= 1 - \exp\left[-0.639(t \div t_{50})^3 (\varepsilon \times \varepsilon_c^*) \right] \\
X &= 1 - \exp\left[-0.639(t \div t_{50})^3 (\varepsilon \times \varepsilon_c^*) \right]
\end{align*}
$$

where $t$ is time in seconds, $t_{50}$ is time for 50% static recrystallisation, $\varepsilon$ is the strain, $\varepsilon_c^*$ is the critical strain, $d_0$ is the initial grain size.

The grain size produced by complete recrystallisation without previous dynamic recrystallisation is described by the following system of equations:

$$
\begin{align*}
\begin{cases}
\frac{d_{rex}}{d_0} &= 0.5d_0^{0.67} \varepsilon^{-1} \\
\frac{d_{rex}}{d_0} &= 1.8 \times 10^3 Z^{-0.15} \\
\end{cases}
\end{align*}
$$

where $\varepsilon^* = 2.8 \times 10^{-4}d_0^{0.67}Z^{0.15}$ and $Z$ is the Zener-Hollomon parameter.

When recrystallisation is complete, further grain growth may take place even in the relatively short time available between passes. The time dependence of grain growth may be represented by the following equation:

$$
\frac{d_{sg}}{d_{sg}} = \frac{d_{rex}}{d_0} + 1.19 \times 10^{39} \exp\left(-567 \times 10^3 / RT \right)
$$

where $R$ is the gas constant and $T$ is the deformation temperature.

The evolution of the grain size through the different phases defines the final microstructure and properties. In this case ferrite grain is of paramount importance when defining mechanical properties. The transformation from austenite to ferrite can be expressed by the following formula (Pickering, 1978):

$$
d_{\alpha} = \left[a + b\left(dT / dt\right)^{0.5} + c\left[1 - \exp\left(-0.01d_{\gamma}\right)\right]\right] - 0.45\sqrt{\varepsilon}
$$

where $d_\alpha$ and $d_\gamma$ are the ferrite grain size and austenite grain size respectively, $dT / dt$ is the cooling rate during transformation, $\varepsilon$ is the strain in the austenite, $a$, $b$ and $c$ are material constants.

The above equations clearly show a high degree of sensitivity of microstructure to the operating conditions during rolling. Therefore, the optimality criterion $J$, which is to be minimized in order to determine during whole process the deformation temperature ($T$), strain $(\varepsilon)$, and strain rate $(\dot{\varepsilon})$ that is the deformation profile can incorporate a number of physically realistic requirements. For this specific problem of hot metal deformation the objectives are defined as follows:

$$
\text{objective}_1 = \frac{(d_{\gamma}(i) - d_{\gamma \text{target}}(i))^2}{d_{\max}(i)} \quad i = 1, 2, ..., n
$$

$$
\text{objective}_2 = \left[1 - X(i)\right]^2
$$

Subject to

$$
\begin{align*}
(i) & \quad \omega_{\min} \leq \omega(i) \leq \omega_{\max} \\
(ii) & \quad \%r_{\min} \leq \%r(i) \leq \%r_{\max} \\
(iii) & \quad T_{LOAD} \leq T_{LOAD \max}
\end{align*}
$$

The first objective function indicates that the ideal solutions should be close to the austenite grain size target $d_{\gamma}(i)$ value $d_{\gamma \text{target}}(i)$ required after each rolling pass $(i)$, and the second objective function that a full recrystallisation has to be achieved prior to either the next pass begins or the phase transformation. $\omega$ is the rolling speed, $\%r$ represents the percentage of reduction and $T_{LOAD}$ is the rolling torque, $n$ being the total number of rolling passes. For this bi-objective problem, an optimum design should ideally be a solution that achieves the austenite grain size target at a minimum cost without violating the constraints that define the Hille-mill limitations in order to create the feasible region for the optimal search.

Fig. 2 shows a flow chart indicating the process of searching for the optimal rolling schedule.

2.3 Optimising the Process Parameters

It is not physically possible to ensure that all the points in the deforming piece will undergo the strain, strain rate, and temperature trajectories obtained in the above optimisation. However, process parameters such the rolling speed, reduction, and rolling torque can be automatically calculated and will attempt to achieve the desired trajectories at predetermined points in the material piece. In this work an artificial neural network is used to model the rolling torque relationship (see Mahfouf, et al., 2005).

2.4 Rolling Mill Control

To achieve ‘right-first-time’ production of metal designs with specific microstructures and mechanical properties and to regulate the materials properties, different rolling schedules are designed with a precise reduction in metal thickness and a
The Adaptive Fuzzy Generalized Predictive Control (AFGPC) system consists of four components, namely the plant to be controlled, a reference model that specifies the desired performance of the plant, a neural network that models the plant, and the cost function minimization algorithm based on the gradient decent projection method that determines the input needed to produce the plant's desired performance. A neural-Fuzzy scheme based Radial Basis Function (RBF) has been designed to carry-out the on-line identification of the model parameters, with the aim of being used in an Adaptive Generalized Predictive Control of nonlinear systems and allow the mill to be used in a wide range of operating conditions. This scheme provides the ‘cost function minimization’ block with the nonlinear output predictions at each sample instant. A recurrent linear neuron with interpretable weights performs the on-line identification of the models by means of supervised learning which itself presents a challenging task.

In the case of predictive control, the minimization of the following criterion is carried out.

\[
J = \sum_{i=d+1}^{N_1} \left( P\left(z^{-1}\right)y(k+i) - w(k+i)\right)^2 + \sum_{i=1}^{N_2} \lambda(i)\Delta u(k+i-1)^2
\]

where \(N_1\) is the minimum costing horizon, \(N_2\) is the maximum costing horizon, \(u\) is the control horizon, \(w\) is the reference trajectory, \(\lambda(i)\) is the control weighting sequence and \(P(z^{-1})\) is the inverse model in the model following context with \(P(1) = 1\), \(d\) is the time delay of the system. The implementation of the Adaptive Fuzzy Predictive Control through RBF-based Neural-Fuzzy Model can be viewed as constrained nonlinear optimization when searching for an optimum and can be solved using the following iterative method:

\[
\begin{align*}
    u^{n+1}_{N_u} &= u^n_{N_u} - \eta P^n g^n \\
    g^n &= \frac{\partial J}{\partial u^n_{N_u}} \\
    g &= 2\frac{\partial u_{N_u}}{\partial u_{N_u}} \frac{\partial y}{\partial u_{N_u}} (\hat{y} - w) + 2\lambda \frac{\partial \Delta u}{\partial u_{N_u}} \Delta u
\end{align*}
\]

The gradient of \(J\) with respect to \(u_{N_u}\) can be calculated as follows:

\[
\frac{\partial J(n)}{u^{n}_{N_u}} = \begin{bmatrix}
    \frac{\partial J}{\partial u(k)} \\
    \frac{\partial J}{\partial u(k+1)} \\
    \vdots \\
    \frac{\partial J}{\partial u(k+N_u+1)}
\end{bmatrix}
\]

3. SIMULATION RESULTS
A total of 20 real-time hot-rolling experiments were carried out under different working conditions and design criteria. The experimental material used was a commercial type C-Mn Steel alloy (Bright Mild Steel) grade 080A15. After each rolling experiment, the metallography study of a materials microstructure was carried-out. The selected specimens were machined to be subjected to mechanical testing as well. The results from such laboratory tests were then compared to the desired metal design in order to evaluate the acceptable efficiency, accuracy and reliability of the proposed optimisation mechanism.

Consider the case in which the aim of the optimisation was to find the best rolling schedule to achieve a C-Mn steel alloy with the following mechanical properties: 452 MPa and 325 MPa of TS and YS respectively, with an ITT of -60°C.

In order to analyse the feasibility of the real-time implementation, as well as to set-up the design parameters for the controller, a series of computer simulations were carried out under different working conditions. The sample was preheated until the central temperature was 1050°C and the initial grain size was assumed to be 220µm. The initial stock geometry was 150 mm long, 50 mm wide and 25 mm thick.

In this experiment the Hille-mill working range was set in such a way that the electrical motor worked above the rated speed, which is between 30 rpm and 60 rpm.

For this reason, the capability of the motor to deliver electromagnetic torque was diminished, so that the constraints for the amount of reduction and rolling torque per pass had to be narrowed, the percentage of reduction per pass being between 10% and 30%, hence producing a rolling torque of as much as 2000 kNm. According to the desired value of the final properties of the metal design, the required ferrite grain size provided from the first stage “Module1” was found to be 15 µm with a pearlite fraction of 20.7%. It is nothing that these optimal solutions fall into the boundaries of the feasible solutions that required a ferrite grain size between 7 µm and 30 µm, with a pearlite fraction no larger than 30%. Using this information about the solutions given in the first stage, “Module2” searched for the optimal profile deformation of the stock being investigated leading to the best rolling parameters with three-pass rolling schedule. Table 11.5 shows the results provided by the scheduling mechanism.

A software called SLIMMER (Sheffield Leicester Integrated Model for Microstructural Evolution in Rolling) was used to simulate the microstructure evolution during hot-rolling experiments (Beynon and Sellars, 1992). Fig. 3 shows the computer simulation of the microstructure evolution during this experiment. The rolling passes were carried-out at 1, 20, and 40 seconds respectively. This figure revealed that the parameter given by the systematic rolling schedule mechanism led to a good control of the microstructure events at each rolling pass. It was observed that the amount of strain produced by the first pass was enough so that fraction in rolled metal have been recrystallised though the subsequent inter-pass static recrystallisation. In addition to the above rolling schedule, the developed optimisation mechanism gave the following information: cooling rate during the phase transformation = 2.03°C/s (air cooling); austenite grain size = 27.60µm (before transformation to ferrite); and final ferrite grain size = 14.11µm which is very close to the desired microstructure. Fig. 4 shows such a final microstructure. Fig. 5 shows also the results from the mechanical tests. The yield behaviour of the metal showed that the average starting point of deformation was 335.41 MPa. Similarly, the mean stress of fracture was 469.20 MPa.

Fig. 6 depicts the main variables recorded by the DAQ system during this real-time experiment using the nonlinear Adaptive Fuzzy Generalised Predictive Controller. It can be seen that no constraints violations occurred during all passes. In terms of the control performance, the closed-loop control properties under these rolling conditions where the system had operated above the rated speed were acceptable in terms of speed control and regulation with good load disturbance rejections. Furthermore, no overshoot was observed in any case, and very fast transient response was observed. Only nine rolling experiments have been presented showing the general trend in the results of this paper considering different scenarios of metal design and working conditions. Fig. 7 represents a summary of such results showing the user-defined requirements against the final products of tensile strength and yield strength.

4. CONCLUSIONS

This paper proposed a new optimisation framework to develop an integrated model-design strategy to optimise and control the hot-rolling mill. The use of ‘Symbiotic’ data-driven modelling and PAIA Algorithms provide such a framework which facilitates complex problems whose input-output relationships are not only highly nonlinear, but also belong to data distributions which are more often than not of a ‘sparse nature’. A series of hot-rolling real-time experiments and laboratory tests showed that the proposed systematic mechanism led to an ‘optimal’ rolling schedule under different criteria and achieved excellent performances in control of the process for different steel microstructure, hence suggesting that ‘right-first-time’ production of metal is possible.

REFERENCES


Fig. 3. Simulation of the microstructure evolution during the experiment.

Fig. 4. Photomicrograph of C-Mn steel for the experiment; (a) longitudinal and (b) transversal.

Fig. 5. Engineering stress-strain curve for testing material.

Fig. 6. Rolling mill real-time performance.

Fig. 7. Desired vs. final product (a) TS (b) YS.