The Optimal Design for the Production of Hot Rolled Strip with “Tight Oxide Scale” by Using Multi-objective Optimization

Tao JIA,1) Zhenyu LIU,2) Hengfa HU3) and Guodong WANG2)

1) Formerly The State Key Laboratory of Rolling & Automation, Northeastern University, Shenyang, 110819 P R China. Now at The Centre for Metallurgical Process Engineering, The University of British Columbia, 309-6350 Stores Rd., Vancouver, BC, V6T1Z4 Canada. E-mail: tao.jia.81@gmail.com
2) The State Key Laboratory of Rolling & Automation, Northeastern University, Shenyang, 110819 P R China.
3) The Technical Research Institute, Meishan Steel Company, Nanjing, 210039 P R China.

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Recently, customers are demanding for hot rolled strip products to have tight oxide scales on the surfaces. Therefore, high finishing rolling temperature, low coiling temperature and fast finishing rolling speed have to be used to obtain tight oxide scale, which is different from conventional controlled rolling. In order to ensure the mechanical properties at the same time, a framework consisting of the Bayesian neural network and multi-objective particle swarm optimization has been established to determine the optimal hot strip rolling parameters. Due to excellent generalization ability, the Bayesian neural network was employed to develop the model for the prediction of mechanical properties of hot rolled automotive beam steels. The accuracy between the measured and predicted values was within ±30 MPa and ±4% for strength and elongation, respectively, providing a reliable model for the optimal process design. By applying multi-objective particle swarm optimization, the optimized hot rolling process was obtained for the production of hot rolled automotive beam steel with “Tight Oxide Scale”. Industrial trials have been carried out, which showed good agreement with the optimized hot strip rolling processes. It has been theoretically and practically proven that the optimal process design framework can effectively locate the optimal processing window for hot strip rolling.

KEY WORDS: process design; multi-objective optimization; particle swarm algorithm; Bayesian neural network; tight oxide scale.

1. Introduction

Hot rolled 510L steel is used as automotive beam with the required mechanical properties shown in Table 1. Conventionally, for the sake of avoiding damage to the stamping mold, the hot rolled steel is pickled to remove the oxide scale prior to stamping process. Unfortunately, this process results in environmental pollution and increased production cost. Alternatively, due to the decreased hardness, preferable ductility and adhesive ability, the Fe₃O₄ layer could be deformed with the steel matrix without cracking and even act as lubricant between the workpiece and tool. Therefore, hot rolled 510L steel with “Tight Oxide Scale” has been proposed recently by Chinese automobile manufacturers. The proposed oxide scale is composed by more than 75% Fe₃O₄ and residual FeO with a thickness of less than 15 μm. In order to produce the “Tight Oxide Scale”, finishing rolling temperature should be increased to avoid cracking of the oxide scale during finish rolling and coiling temperature should be decreased to promote the eutectoid reaction of FeO→Fe₃O₄+Fe after coiling. At the same time, the finishing rolling speed should be accelerated to minimize the thickness of oxide scale. Whilst, these modifications of process condition are motivated to obtain the desired oxide layer, it is critical that process parameters are selected that the required mechanical properties are achieved. Thus, process optimization is an urgent problem to be solved.

Traditionally, a large amount of pilot experimental work need to be done to simulate the variation of mechanical properties during hot strip rolling before the optimal process parameters can be determined. However, easy and complete access to the control and database system, which has been realized in modern and advanced steel plants, greatly promotes the development of data-driven intelligent models to facilitate the application of computer aided optimization and design (CAOD) technology, which is considered as an efficient way to resolve the aforementioned problem. Therefore, apart from the traditional, time-consuming pilot experiments, the optimal design of hot rolling process which is based on data-driven intelligent model and multi-objective

| Steel Grade | Tensile Test: L₀=5.65 \sqrt{S₀} | YS, MPa | TS, MPa | EL, % |
|-------------|--------------------------------|--------|--------|------|
| 510L        | ≥355                           | 510–610| ≥24    |

* L₀, S₀ are the gauge length and the cross-sectional area of working zone for tensile sample, respectively. YS, TS and EL represents yield strength, tensile strength and elongation, respectively.
optimization has been proposed to steel engineers and researchers. The concept of optimization has been widely applied in the field of hot processing for metallic materials. Based on the mathematical model between mechanical properties and heat treatment parameters, Ray et al.\textsuperscript{1) used the Steepest Ascent method to maximize the low-temperature impact property within the experimental region and Grid Search technique to obtain the optimum combination of the mechanical properties with a constraint of Re\textsuperscript{\geq}730 MPa. Steepest Descent Method has been employed by Saito\textsuperscript{2) to obtain the optimal cooling condition to achieve the predefined tensile strength. Malas III et al.\textsuperscript{3) adopted the control theory to optimize the microstructure evolution processes such as the variation of grain size during hot extrusion of AISI 1030 steel in order to design the optimum process parameters. Mahfouf et al.\textsuperscript{4) applied the particle swarm based multi-objective optimization mechanism for the optimal design of heat-treated alloy steels. However, due to the complexity and nonlinearity, the optimal process design with respect to customer demands has always been a challenging problem.

In the present paper, the optimal process design for hot rolling, consisting of a Bayesian neural network and multi-objective particle swarm optimization algorithm, has been applied to determine the optimal process parameters for the production of 510L steel with “Tight Oxide Scale”. Industrial trials have been carried out to verify the effectiveness of the optimized routes.

2. Modeling of Mechanical Properties

2.1. Database

According to the data analysis, the parameters which have strong effect on mechanical properties, including product thickness, chemical composition, total reduction rate in finish rolling stand F4–F6 (\(e_0\)), start finish rolling temperature (SFTC), finishing rolling temperature (FTC), coiling temperature (CTC) and average cooling rate (CR) on the run-out table, are selected as the inputs of Bayesian neural network. The mechanical properties are considered as the outputs. The average cooling rate is calculated as

\[
CR = \frac{FTC - CTC}{L/V_6} \quad \text{(1)}
\]

where \(L\) is the length of the continuous cooling line, and \(V_6\), the finishing rolling speed. The database consists of 400 cases, all of which were collected from a 1450 mm hot strip rolling line during a period of 3 month. The range, mean and standard deviation of the chemical compositions, process parameters and the measured mechanical properties are shown in Table 2.

| Variables                  | Range         | Mean         | Standard Deviation |
|----------------------------|---------------|--------------|--------------------|
| Product thickness, mm      | 2.51 - 7.93   | 6.41         | 1.74               |
| C, wt-%                    | 0.067 - 0.114 | 0.081        | 0.0094             |
| Si, wt-%                   | 0.03 - 0.252  | 0.212        | 0.0282             |
| Mn, wt-%                   | 1.161 - 1.482 | 1.228        | 0.0476             |
| P, wt-%                    | 0.011 - 0.022 | 0.017        | 0.0026             |
| S, wt-%                    | 0.0036 - 0.0099 | 0.0062 | 0.0014             |
| Nb, wt-%                   | 0.013 - 0.033 | 0.025        | 0.0044             |
| Ti, wt-%                   | 0.008 - 0.018 | 0.014        | 0.0015             |
| \(e_0\), %                 | 22 - 48       | 34           | 4.8                |
| SFTC, °C                   | 874 - 948     | 912          | 12.6               |
| FTC, °C                    | 827 - 876     | 859          | 6.5                |
| CTC, °C                    | 572 - 648     | 594          | 9.4                |
| CR, °C/s                   | 11.8 - 64.4   | 27.1         | 9.08               |
| YS, MPa                    | 430 - 520     | 476          | 15.8               |
| TS, MPa                    | 500 - 595     | 547          | 15.4               |
| EL, %                      | 20.5 - 36.5   | 28.1         | 2.79               |

2.2. Brief Description of Bayesian Neural Network

A neural network is capable of modeling highly nonlinear relationships. Because of the superiority in preventing overfitting and ability of providing quantified error bar on the network’s prediction, Bayesian neural network has been widely applied in modeling research in welding,\textsuperscript{5–7} hot torsion\textsuperscript{8} and heat treatment\textsuperscript{9,10} of steels. In the present work, due to the considerable complexity and nonlinearity of hot rolling pro-

\[
h_j = \text{Sigmoid}\left(\sum_{i} v_{ji}x_i + \theta_j\right) \quad \text{(2)}
\]

thereafter the output \(y\) can be calculated by

\[
y = \text{Sigmoid}\left(\sum_{j} u_{ij}h_j + \xi\right) \quad \text{(3)}
\]

where \(v\) and \(u\) are the weights, \(\theta\) and \(\xi\) are defined as the biases. The weights and biases are determined in such a way as to minimize the energy equation

\[
E(W) = \beta \cdot E_D + \sum_{g=1}^{G} \alpha_g E_{W(g)} \quad \text{(4)}
\]

where \(G\) is the number of regularizer, \(E_D\) the error function.
and $E_{W(g)}$ the regularizer are defined as:

$$
\begin{align*}
E_D &= \frac{1}{2} \sum_n (d_n - y_n(X_n, W))^2 \\
E_{W(g)} &= \frac{1}{2} \sum_i W_i^2
\end{align*}
$$

(5)

where $\{X_n, d_n\}$ is the data set, $X_n$ represents the input vector; $d_n$ is the desired output and $N$, the number of data set. The weights and biases in Eqs. (2) and (3) compose the vector $W$ and $W_g$ is the number of weights or biases in regularizer $E_{W(g)}$.

$\beta$ and $\alpha_g$, the regularizing constants, are updated before each back-propagation training process under a Bayesian framework. When $\alpha_g >> \beta$, the training of neural network is aimed to make the output of network smoother to minimize the fitting to noise in the data sets. Contrarily, when $\alpha_g << \beta$, the minimization of the error function is highlighted. The detailed information of Bayesian neural network can be found elsewhere.¹¹,¹²)

2.3. Prediction Model of Mechanical Properties

According to the “well-determined”¹¹ parameter, the number of hidden layer units is set to be 2, 2 and 3 for yield strength, tensile strength and elongation, respectively. Figure 2 shows the comparison between predicted and measured value. Dash lines represent the absolute error of ±30 MPa and ±4% for strength and elongation, respectively. Good prediction precision has been achieved.

3. The Multi-Objective Optimization Algorithm

For steels with given chemical composition, strength and ductility are competing objectives. To determine the optimal process design is a challenging multi-objective optimization problem which involves searching in a complex multi-dimensional space to achieve the pre-defined mechanical properties. Based on the particle swarm optimization (PSO) algorithm, developed by Kennedy and Eberhart in 1995, Mahfouf et al.⁴) proposed an extension of the PSO strategy, named Adaptive Weighted PSO (AWPSO), for solving the multi-objective problems. Using challenging benchmark functions, such as ZDT1-ZDT4, the proposed AWPSO algorithm was approved to achieve better convergence and diversity when compared to several widely recognized evolutionary algorithms, such as Non-dominated Sorting Genetic Algorithm (NSGA II) and Strength Pareto Evolutionary Algorithm (SPEA).⁵,¹³) The objective function of AWPSO algorithm is constructed by weighted aggregation approach as follows

$$
F = \sum_{i=1}^{m} \rho_i f_i ; \sum_{i=1}^{m} \rho_i = 1 
$$

(6)

Where $m$ is the number of objectives; $f_i$ represents the $i$th objective function. In order to achieve the “trade-off” solutions, i.e. Pareto solutions, the weights $\rho_i$ for each objective are changed and normalized at each iteration as follows

$$
\rho_i = \eta_i \left( \sum_{j=1}^{n} \eta_j \right) ; \eta_i = U(0, 1)
$$

(7)

where the function $U(0, 1)$ generates a uniformly distributed random number within $[0, 1]$.

By introducing the non-dominated sorting technology, the ability to solve the multi-objective problem has been realized in the AWPSO algorithm. In the present work, niching method⁶) is incorporated into the AWPSO algorithm to maintain the diversity along a front. It assigns each particle a parameter named Crowding Distance which is defined as the average distance of the two particles on either side of this particle along each of the objectives. The particle with larger Crowding Distance in a front would be selected first to the next generation. Meanwhile, the Controlled Elitist strategy⁷) is also applied in the AWPSO algorithm to achieve the lateral diversity. It tries to maintain a pre-defined distribution of number of particles in each front. The maximum number of particles allowed in the $k$-th ($k=1, 2… N_f$) front in the next generation is
Where \( r \) is a reduction rate within the range \([0, 1]\), \( N_f \) is the number of non-dominated fronts, and \( N_p \) is the number of particles. Therefore, each front is allowed to have an exponentially reducing number of particles. And the first front has the maximum allowable number of particles. Based on the above description, the flowchart of the improved AWPSO algorithm is shown in Fig. 3.

4. Optimal Design of Hot Rolling Process

4.1. Objective Function

As can be seen from Table 1, the lower limit of required mechanical properties should be guaranteed. Therefore, the objective function for each mechanical property is set as follows.

\[
f_i^{MP} = \begin{cases} 10^{10} & \text{if } MP_i < MP_i^t \\ MP_i - MP_i^t & \text{if } MP_i^t < MP_i \leq p \cdot MP_i^t \\ \mu \cdot |MP_i - MP_i^t| & \text{if } p \cdot MP_i^t < MP_i \end{cases} \tag{9}
\]

where \( MP_i \) and \( MP_i^t \) are the predicted and targeted value of the \( i \)th mechanical property, where \( i \) equals to 1, 2, 3 corresponding to yield strength, tensile strength and elongation, respectively. The coefficients \( \mu \) and \( p \), set as shown in Table 3, are designed to penalize the solutions with mechanical properties bigger than \( p \) times of targeted value.

The error bar \( \sigma_{\text{std}} \), calculated from the Bayesian neural network, acts as a quantified estimation of prediction error. It should be included in the optimization. The objective function in the AWPSO algorithm is stated as

\[
F = \rho_1 \cdot f_1 + \rho_2 \cdot f_2 + \rho_3 \cdot f_3 \tag{10}
\]

where,

\[
\begin{align*}
f_1 &= f_1^{MP} + 0.15 \cdot \sigma_{\text{std}}^1 \\
f_2 &= f_2^{MP} + 0.15 \cdot \sigma_{\text{std}}^2 \\
f_3 &= f_3^{MP} + \sigma_{\text{std}}^3
\end{align*}
\tag{11}
\]

4.2. Setting of Constraints during Optimization

Setting constraints for the parameters to reflect the capacity of the mill is a key issue that needs to be solved prior to the process optimization.

According the production plan, the 510L steel with 6 mm thickness is selected to conduct the optimal process design. Table 4 is the present implemented hot rolling process for the product with 6 mm thickness. In order to produce 510L steel with “Tight Oxide Scale”, the finishing rolling temperature should be controlled in the range of 870–880°C to avoid the cracking of the oxide scale. The process window for coiling temperature was set to be 540–600°C while lower coiling temperature being advantageous for eutectoid reaction of \( \text{FeO} \rightarrow \text{Fe}_3\text{O}_4 + \text{Fe} \). The thickness control of oxide layer requires increased finishing rolling speed which results in higher average cooling rate. Based on the analysis of production data, constraints for process parameters were set as shown in Table 5.

4.3. Hot Rolling Process Optimization

The chemical composition of the selected slab for production of 510L steel with “Tight Oxide Scale” is shown in Table 6. With the constraints given in Table 5, it is the objective to properly adjust the process parameters to make sure that the mechanical properties meet the requirements shown in Table 1. Therefore, the targeted value for yield strength, tensile strength and elongation was set to be 380 MPa, 550 MPa and 24% respectively, i.e. to maintain the tensile strength and to satisfy the lower limit of yield
strength and elongation. Conducting the optimal process design, the Pareto front shown in Fig. 4 suggests that the trade-off between strength and ductility has been found during the multi-objective optimization. It can be seen that the value of $f_1$ is bigger than those of $f_2$ and $f_3$. By employing the optimal process parameters, the yield strength of the final product could be far larger than targeted value, which is 380 MPa.

Table 7 shows the optimized solutions located in the Pareto front, which could be classified into two groups: ① “low coiling temperature, fast cooling rate”; ② “high coiling temperature, slow cooling rate”. Both of them can lead to the satisfactory mechanical properties.

The calculated results are analyzed by comparing to the predicted mechanical properties of 510L steel using traditional process route in Table 4. As can be seen from Tables 7 and 8, by applying the process route in group one which is more favorable for the production of 510L with “Tight Oxide Scale”, the strength and elongation is predicted to slightly increase and decrease, respectively. It can be understood as follows. The increased finishing rolling temperature decreases the accumulation of retained strain and favors the recrystallization in deformed austenite, both of which lead to the coarsening of ferrite grain size and thus the decrease of strength. However, this is overcompensated by increasing cooling rate and decreasing coiling temperature, which is known to refine the ferrite grain size and decrease the volume fraction of ferrite. In general, the currently developed framework of optimal design of hot rolling process provides effective guidance for the industrial trials of 510L steel with “Tight Oxide Scale”.

### 5. Industrial Trials

According to the optimized solutions shown in Table 7, the hot rolling process conditions for an industrial trial were selected as shown in Table 9. It was applied to two slabs with the chemical composition shown in Table 6. In addition, one slab with similar chemical composition was also employed to conduct the industrial trial.

The achieved process parameters and measured mechanical properties are shown in Table 10. The hot rolling process set in Table 9 was strictly followed and the achieved mechanical properties agree well with the predicted value in
Table 7. It is noticed that the achieved elongation, which is 2.5% lower than the predicted value, is almost on the edge of the required value in Table 1. Given this scenario, the model accuracy is recommended to be taken into consideration when conducting the optimal design of hot rolling process.

6. Conclusion

In combination with a Bayesian neural network to model mechanical properties, a multi-objective particle swarm optimization algorithm was employed to establish the optimal process design for hot rolling. It was aimed at finding the optimal process parameters in a constrained multi-dimensional space to achieve the pre-defined mechanical properties with respect to customer demands. Based on the Bayesian neural network, the strength and elongation of hot rolled 510L could be predicted with precision of ±30 MPa and ±4%, respectively. The error bar, as a quantified estimation of the reliability of each predicted value, has been brought into objective functions. By properly setting the constraints, the optimal process parameters for the production of 510L steel with “Tight Oxide Scale” was obtained to guide industrial trials. Compared with traditional process route, 510L steel with “Tight Oxide Scale” possesses an increased strength and a decreased elongation. Nevertheless, it still satisfies the required mechanical properties. It has been indicated that the optimal process design with respect to customer demands would make great contribution to reduce the development time for new processing path with computational tools.

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