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ORIGINAL PAPER

Optimal design of hot rolling process for C-Mn steel by combining industrial data-driven model and multi-objective optimization algorithm

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Abstract

A successful mechanical property data-driven prediction model is the core of the optimal design of hot rolling process for hot-rolled strips. However, the original industrial data, usually unbalanced, are inevitably mixed with fluctuant and abnormal values. Models established on the basis of the data without data processing can cause misleading results, which cannot be used for the optimal design of hot rolling process. Thus, a method of industrial data processing of C-Mn steel was proposed based on the data analysis. The Bayesian neural network was employed to establish the reliable mechanical property prediction models for the optimal design of hot rolling process. By using the multi-objective optimization algorithm and considering the individual requirements of costumers and the constraints of the equipment, the optimal design of hot rolling process was successfully applied to the rolling process design for Q345B steel with 0.017% Nb and 0.046% Ti content removed. The optimal process design results were in good agreement with the industrial trials results, which verify the effectiveness of the optimal design of hot rolling process.

Keywords Industrial data · Data processing · Mechanical property · Optimal design · Hot rolling process · C-Mn steel

1 Introduction

Traditionally, a large amount of pilot experimental works need to be done to obtain the optimal process parameters during hot strip rolling. With the development of computer technology, communication technology and automation technology, it is possible to establish data-driven models to cut down the workload of process optimization. Optimal design of process has been extensively investigated in many fields, such as welding process [1, 2], weld pool geometry [3], drilling process [4], grinding process [5], laser cladding process [6] and some other processes [7, 8]. In hot strip rolling field, Mohanty et al. [9] optimized the hot-rolled coil widths using a genetic algorithm to minimize the trim loss. Mahfouf et al. [10, 11] optimized the tensile strength (TS), reduction of area and cost of the investigated alloy steel by using fuzzy models and multi-objective optimization algorithm. Mohanty et al. [12] also correlated the mechanical properties (yield strength (YS), TS, elongation (EL) and plastic strain ratio) of the cold-rolled interstitial-free (IF) steel sheets with chemical composition and process parameters, then combined the genetic algorithm to design process parameters to achieve predefined properties. The researchers also optimized the process parameters of SPA-H steel to meet required mechanical properties before [13]. In order to ensure tight oxide scales on the surface and the mechanical properties simultaneously, the researchers optimized the process parameters of 510L steel by using the multi-objective particle swarm optimization algorithm [14].

However, as the amount of industrial data with low quality becomes large, modeling usually cannot achieve a predefined performance, which may lead to a failure in optimal design of hot rolling process. Therefore, a

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reasonable data processing method becomes essential to a successful data-driven model for reliable process optimization. Unfortunately, investigation about industrial data preprocessing is exiguous.

In this paper, the mechanical property prediction model of multi-grade C-Mn steel was established by using Bayesian neural network. With appropriate data processing, the mechanical property prediction models acquired good performances. Combined with the multi-objective optimization algorithm named Non-dominated Sorting Genetic Algorithm II (NSGAII), the models were employed for optimal design of hot rolling process. New rolling process was designed for reducing Q345B steel with 0.017% Nb and 0.046% Ti content removed. Industrial trials were extensively carried out, which showed good agreements with the optimized process.

2 Mechanical property modeling

2.1 Data processing

Industrial data for the production of hot-rolled strips are often redundant, abnormal and imbalanced, which may cause errors in mechanical property predictions. Figure 1 shows the fluctuation of YS for the same steel of C 0.156%, Si 0.24% and Mn 0.82% after the same rolling schedule with the finish rolling thickness (FDH) of 9.8 mm and coiling temperature (CT) of 552−560 °C. Due to the fluctuation in actual hot rolling process and testing of mechanical property, the acquired values have been measured to be fluctuant. The overfitting of fluctuant data caused by using neural network modeling would influence the effectiveness of optimal design of hot rolling process. It means that models should be established to predict average values under certain processes to ensure the stability of the prediction. Therefore, during the model development, the average values for certain rolling schedules have been used rather than all industrial data without data processing.

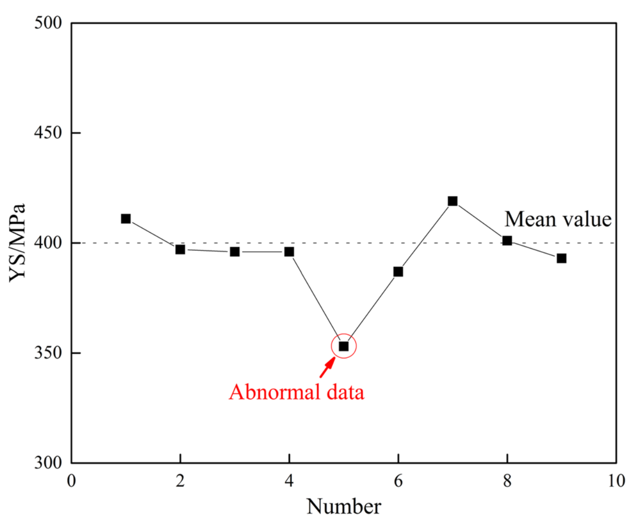

Fig. 1 Distribution of YS for same steel and same rolling schedule

Figure 2 shows the fitting results of YS data before and after data averaging. The YS increases as the dataset number increases according to physical metallurgy principle. Although data in each dataset have similar process parameters, the original YS values are fluctuant in a certain scale (Fig. 2a), which may cause misleading predictions because of the data overfitting by neural network. After data averaging (Fig. 2b), the regularity of the data becomes significant, which is beneficial for establishing a reasonable model.

The mechanical property prediction model based on Bayesian neural network model can be obtained by minimizing mean-square error between predicted values and training data through multiple iterative calculations. In this way, only the minimum mean-square error can be guaranteed, and the distribution of the error between the predicted value and training data is ignored. The distribution of industrial data is always imbalanced, which may cause the modeling to be accurate for some data but misleading for other data [10, 15]. To improve the imbalanced distribution of the training data, the data are sorted out by mechanical property and divided into n intervals. The number of data in each interval is expressed as D. Hence, all the intervals can be written in a vector $\boldsymbol{D} = \{D_1, D_2,\ldots, D_n\}$. $\boldsymbol{X} = \{X_1, X_2,\ldots, X_n\}$ are the number of balanced data after processed. The $\boldsymbol{\mu}$, which is integer, represents the replicating multiples of the unbalanced data number. The relationship between X_i, μ_i and D_i can be written as $X_i = \mu_i{\cdot}D_i$. Setting the maximum frequency as a constant, $D_{\max} = \max(\boldsymbol{D})$, then the objective function for obtaining the optimal $\boldsymbol{\mu}$ can be defined as follows:

$$\min F = \sum_{i=1}^{n} |X_i - D_{\max}| \tag{1}$$

where i is the interval of mechanical property. By substituting $\boldsymbol{X}$ into Eq. (1), the objective function can be written as $F = \sum_{i=1}^{n} |\mu_i \cdot D_i - D_{\max}|$. Therefore, $\boldsymbol{\mu}$ can be calculated by minimizing the objective function.

Figure 3 shows the distribution of YS data before and after data balancing. There are enough data at the high and low strength area for neural network training after data balancing. And the prediction accuracy at this area would be improved compared with data without balancing.

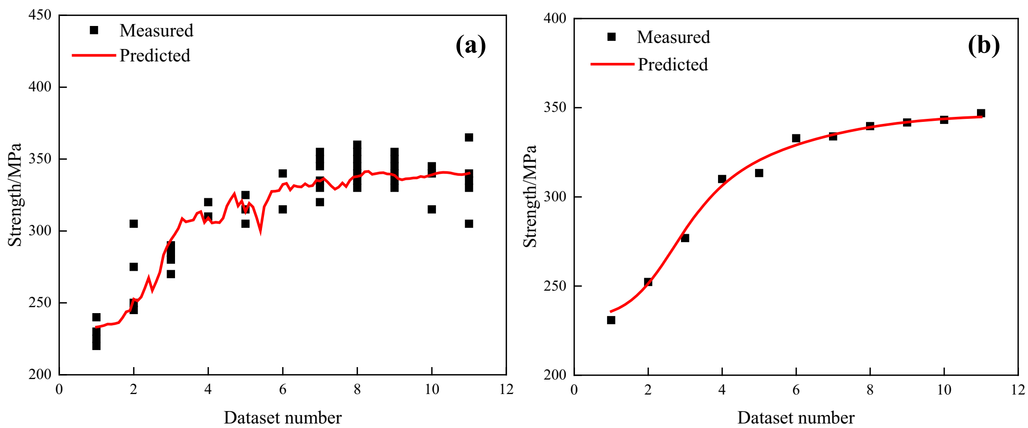

Fig. 2 Fitting results of YS data before (**a**) and after (**b**) data averaging

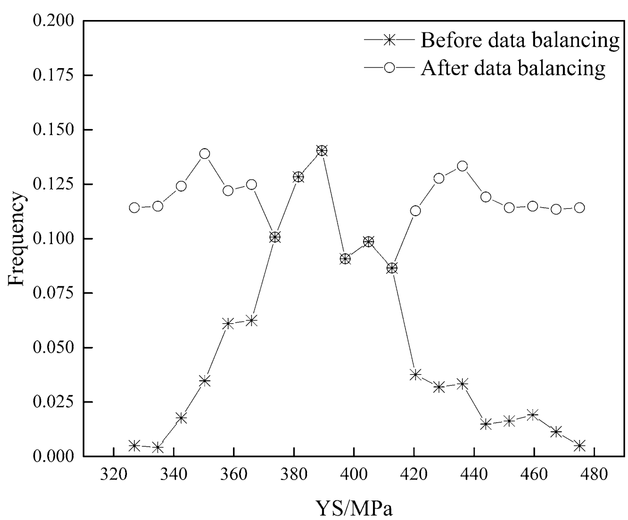

Fig. 3 Distribution of YS data before and after data balancing

2.2 Prediction model of mechanical property

Industrial data of C-Mn steel were used for the development of the mechanical property prediction models. Table 1 shows data scale before and after data processing. According to the data analysis, the process parameters which had strong effects on mechanical property, including chemical composition, furnace temperature (FT), intermediate slab thickness (FEH), rough rolling exit temperature (RDT), finish rolling temperature (FDT), FDH and CT, were selected as the inputs of the Bayesian neural network model. The mechanical properties, such as YS, TS and EL, were considered as the outputs, respectively. Based on the linear correlation among average cooling rate, FDT and CT, average cooling rate can be replaced by FDT and CT. In the same way, total reduction rate in finish rolling can be replaced by FEH and FDH.

Table 1 Data scale before and after data processing

Variable	Data before processing (7756 cases)				Data after processing (1090 cases)			
	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
YS/MPa	323	547	394.9	31.0529	354	443	393.5	14.9543
TS/MPa	449	640	531.5	20.4248	499	585	530.5	15.2935
EL/%	10.5	39	24.6	2.9837	20	31	24.3	2.6171
C/mass%	0.15	0.179	0.16	0.0073	0.15	0.179	0.16	0.0074
Si/mass%	0.21	0.27	0.24	0.0121	0.21	0.27	0.24	0.0121
Mn/mass%	0.8	0.87	0.83	0.0142	0.8	0.87	0.83	0.0144
FT/°C	1163	1265	1217.4	18.4067	1165	1256	1218.0	18.1226
FEH/mm	46	48	47.8	0.6097	46	48	47.8	0.6140
RDT/°C	974	1091	1038.1	21.9314	983	1091	1039.2	22.0856
FDT/°C	810	909	859.3	16.6787	812	909	860.2	16.1989
FDH/mm	9.45	12	10.6	0.9838	9.45	11.9	10.57	0.9796
CT/°C	492	623	556.8	22.3131	492	623	557.2	22.0540

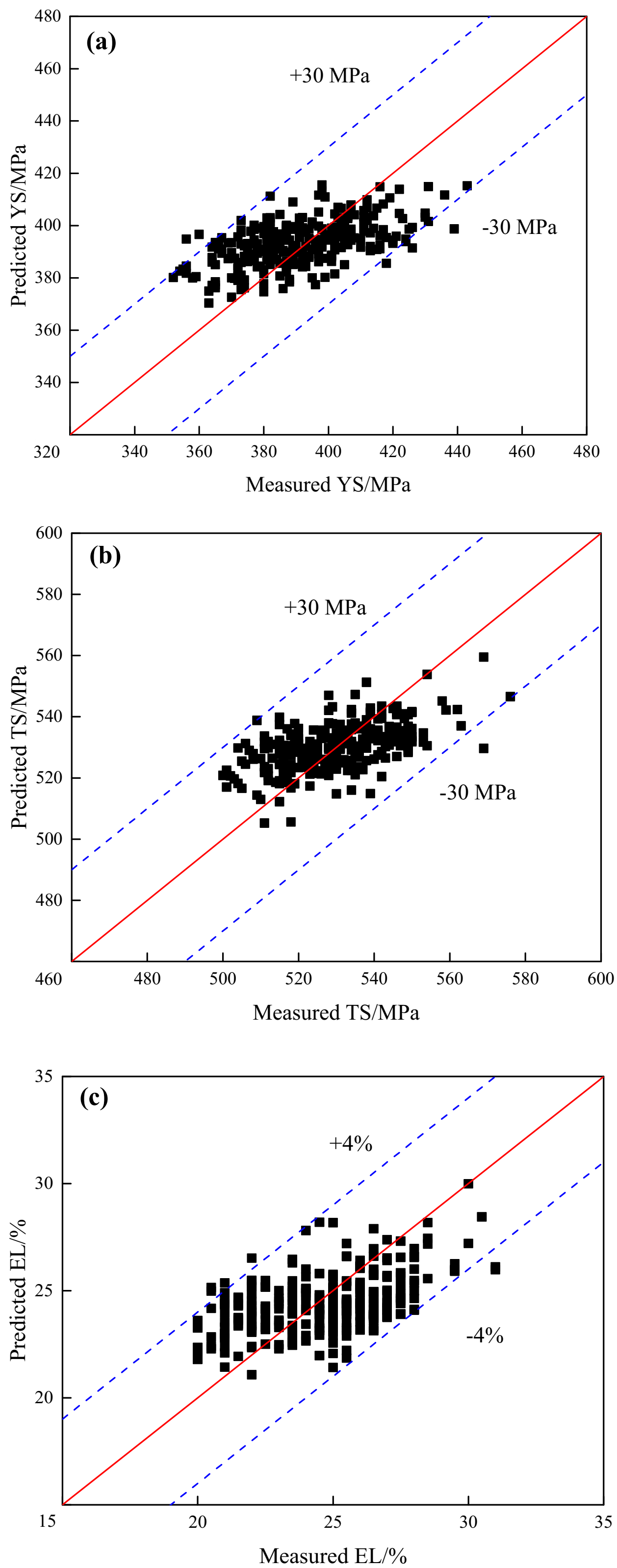

Fig. 4 Comparison between predicted and measured mechanical properties. **a** YS; **b** TS; **c** EL

The data were divided into training data and testing data according to approximately 1:1. These data were used for model development and accuracy testing. Another 299 cases data were used to test the final accuracy of the mechanical property prediction models. The modeling technology was applied according to Ref. [16]. The number of hidden layer units was set to be 9, 10 and 9 for YS, TS and EL, respectively.

Figure 4 shows the comparison between the predicted and measured mechanical properties. Dash lines represent the absolute error of ± 30 MPa and ± 4% for strength and EL, respectively, indicating that satisfactory precisions can be obtained.

3 Optimal design of hot rolling process and application

Minimization for the consumption of alloying elements is one of the most important directions for the production of steel products [17]. In current work, the optimal hot rolling process has been developed for Q345B steel by removing 0.017% Nb and 0.046% Ti content as compared with the conventional grade.

Table 2 shows the lowest limit for the required mechanical property of Q345B steel, and the objective function for each mechanical property is described by Eq. (2).

$$f_{\mathrm{MP}}^{i}=\begin{cases}1{,}000{,}000 & \text{if } \mathrm{MP}_i<\mathrm{MP}_i^{\mathrm{t}} \text{ or } \mathrm{MP}_i>\mathrm{MP}_i^{\mathrm{t}}+u\\ \mathrm{MP}_i-\mathrm{MP}_i^{\mathrm{t}} & \text{if } \mathrm{MP}_i^{\mathrm{t}}\le \mathrm{MP}_i\le \mathrm{MP}_i^{\mathrm{t}}+u\end{cases} \tag{2}$$

where MP_i and $\mathrm{MP}_i^{\mathrm{t}}$ are the predicted and targeted value of the ith mechanical property; i equals to 1, 2, and 3, corresponding to YS, TS and EL, respectively. The coefficient, u, is designed as the threshold value of the objective mechanical property range.

The chemical composition of the conventional Q345B steel contains about 0.017% Nb and 0.046% Ti, with C ranging from 0.06 to 0.08% and Mn ranging from 0.8 to 0.9%. Its typical hot rolling process parameters for the slab thickness of 9.75 mm include FEH of 46–48 mm, FT of 1150–1250 °C, RDT of 990–1090 °C, FDT of 840–880 °C

Table 2 Required mechanical property of Q345B steel with thickness smaller than 16 mm

Steel grade	YS/MPa	TS/MPa	EL/%
Q345B	≥ 345	470–630	≥ 20

Table 3 Constraint for process parameters in optimal design of Q345B steel

Limit	C/mass%	Si/mass%	Mn/mass%	FT/°C	FEH/mm	RDT/°C	FDT/°C	CT/°C
Upper limit	0.17	0.27	0.87	1250	48	1090	880	623
Lower limit	0.15	0.21	0.80	1165	46	990	812	500

Table 4 Parameters used in NSGAII

Parameter	Value
Population size	100
Maximum generation	200
Crossover fraction	0.8
Migration fraction	0.2
Pareto fraction	0.3

and CT of 580–620 °C. In current work, a new hot rolling process has been designed to remove Nb and Ti microalloying elements. In order to meet the predefined requirements for mechanical properties, the FDT and CT were set to be in the range of 812–880 and 500–623 °C, respectively, by using the ultra-fast cooling after hot rolling [18, 19]. Other process parameters were set according to the history data. Table 3 shows the constraints for process parameters in the optimal design of Q345B steel. The mechanical property prediction model of C-Mn steel was reversely optimized for acquiring the predefined mechanical property. The optimized solutions were the optimal chemical composition and rolling parameters. Therefore, taking the modeling errors and the equipment capability into account, the target values for YS, TS and EL were set to be 385 MPa, 510 MPa and 24% with the u of 60 MPa for YS and TS and 6% for EL, respectively. The hot rolling process of Q345B steel was optimized by NSGAII, with parameters shown in Table 4.

The optimized solutions in Table 5 show the diversity. It can be seen that the EL decreases as the strength increases.

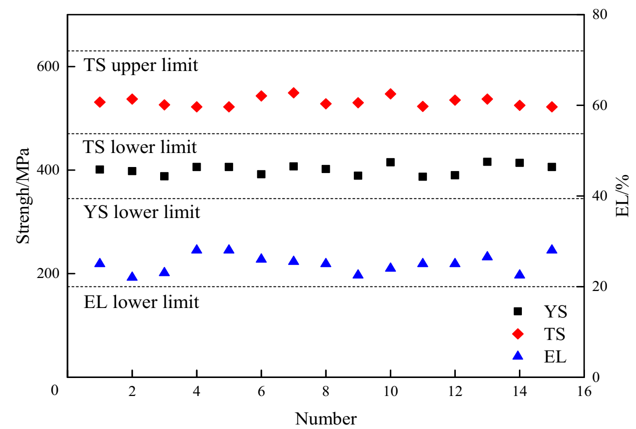

Fig. 5 Mechanical properties for industrial trials of reduced Q345B steel

The tendency of YS and TS is highly similar. According to the optimized solutions shown in Table 5, the first solution was selected as hot rolling process for industrial trials. The fluctuation of process parameters was controlled as C (0.1599 ± 0.05) mass%, Si (0.2555 ± 0.05) mass%, Mn (0.8356 ± 0.05) mass%, FT (1198 ± 30) °C, FEH (47.4 ± 0.5) mm, RDT (1043 ± 30) °C, FDT (853 ± 20) °C and CT (549 ± 20) °C. Figure 5 shows the mechanical properties for industrial trials of reduced Q345B steel. Although the Nb and Ti elements were removed in reduced Q345B steel, the mechanical properties could still meet the requirements of Q345B steel by decreasing the FDT and CT from 860 to 853 °C and from 600 to 549 °C, respectively.

Table 5 Optimized solutions and corresponding predicted mechanical properties

No.	C/mass%	Si/mass%	Mn/mass%	FT/°C	FEH/mm	RDT/°C	FDT/°C	CT/°C	YS/MPa	TS/MPa	EL/%
1	0.1599	0.2555	0.8356	1198	47.4	1043	853	549	401	537	24.8
2	0.1554	0.2537	0.8045	1226	47.7	1024	815	560	392	524	27.9
3	0.1684	0.2465	0.8106	1219	47.1	1032	876	566	405	539	25.7
4	0.1609	0.2489	0.8237	1221	47.8	1044	851	507	398	533	24.0
5	0.1577	0.2109	0.8202	1216	47.8	1033	875	547	387	526	25.2
6	0.1508	0.2265	0.8163	1245	47.7	1086	853	572	386	527	25.2
7	0.1578	0.2399	0.8247	1227	47.5	1064	862	517	403	534	24.1

4 Conclusions

1. Industrial data of hot-rolled strips collected from production line could not be used to establish models directly. Data processing including data averaging and data balancing is essential to develop a successful neural network model.
2. Based on the Bayesian neural network, the strength and EL of hot-rolled C-Mn steel could be predicted with the accuracy of ± 30 MPa and $\pm 4\%$, respectively.
3. By combining the data-driven models and multi-objective optimization algorithm, optimal design of hot rolling process for C-Mn steel could be carried out. New hot rolling process was designed for Q345B steel with 0.017% Nb and 0.046% Ti content removed. The optimal solutions and industrial trials results were compared, which were in good agreement to verify the feasibility of the optimal design of hot rolling process.

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