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Artificial intelligent analyzer for mechanical properties of rolled steel bar by using neural networks

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ABSTRACT

In this paper, an artificial intelligent (AI) analyzer for mechanical properties of rolled steel bar by using neural networks was proposed. Based on the learning capability of neural network, the nonlinear and complex relationships among the steel bar's properties, the billet compositions and the control parameters of manufacture could be automatically developed. Such an AI analyzer could help the technician to precisely set the related control parameters on the bar rolling process. Not only the quality of steel bar could be improved, the production cost of the bar could also be greatly reduced.

1. Introduction

Steel bar plays a very important role in the materials of many engineering constructions, including building, bridge, road and so on. Its quality is highly related to the safeties of building and human's life. In fact, the degree of withstanding earthquake for each building is closely linked with the quality of steel bar. In year 1999, 921 Earthquake not only took away many people's life, but also caused a great economic loss to Taiwan. From then on, the government of Taiwan has reset the new policy for controlling the quality of steel bar. All disqualified steel bars must be melted and reproduced. However, any failed manufacturing process of bars will certainly increase the cost of steel company. Therefore, how to help the technician to make a good control on the manufacturing process of bars becomes a very important issue for the company.

Usually, in the complicated rolling process of steel bar, the relative control parameters, such as dimension, rolling speed, hydraulic pump and water's section, are mainly determined by the technician with full experiences in accordance with the compositions of billet (Hai-Kwang Corporation, 2001; The Handbook of CNS, 2000). Generally, in the compositions of billet, Carbon equivalent (C.E.), Carbon (C) and Manganese (Mn) are three main factors adopted for setting the values of control parameters by the technician who is full of experiences. The block diagram of manufacturing process of steel bars is simply shown in Fig. 1. However, except these three elements, the compositions of billet also include many other chemical elements. Some of them are even unknown and unspecified, especially when the sources of billet are from different countries. Undoubtedly, such conventional way for setting control parameters based on human's experiences easily makes the bar's quality be disqualified due to the less information of billet considered in the manufacturing process. It also means the cost of steel company will be increased with no doubt.

In last two decades, due to the powerful learning capability, neural network technique has been widely applied into many areas, such as control system, pattern recognition, system identification, decision making, and so on (Hwang, 1993; Khotanzad, Hwang, Abaye, & Maratukulam, 1995; Schiffman & Geffers, 1993; Shen, Huang, & Hwang, 2008). Through a simple training procedure, the neural network can automatically develop the complex and nonlinear relationships between input and output signals of training data. Such a well-trained neural model then can be used to perform a specific work expected by the user. Recently, the studies of steel bar's mechanical properties by using neural networks have been presented by several articles (Cetinel, Ozyigit, & Ozsoyeller, 2002; Li, Zhou, & Zheng, 2006; Ozerdem & Kolukisa, 2008; Toparli, Sahin, Ozkaya, & Sasaki, 2002; Zaid, Gaydecki, Quek, Miller, & Fernandes, 2004; Zhou, Zheng, Wang, & Ju, 2005). The research results have also shown the possibility and feasibility of neural network in this field successfully.

In this study, an AI mechanical properties analyzer for the rolled steel bars by using neural network was developed. The block diagram of the manufacturing process of steel bars with AI analyzer is presented in Fig. 2. Such an AI analyzer is designed for helping the technician to set the control parameters on rolling process before the bars are produced on-line. The information of proper control parameters could be generated by AI analyzer in

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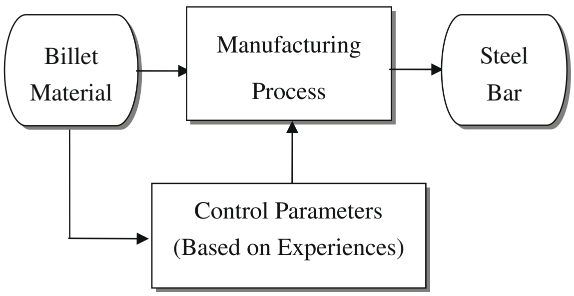

Fig. 1. The conventional manufacturing process of steel bars.

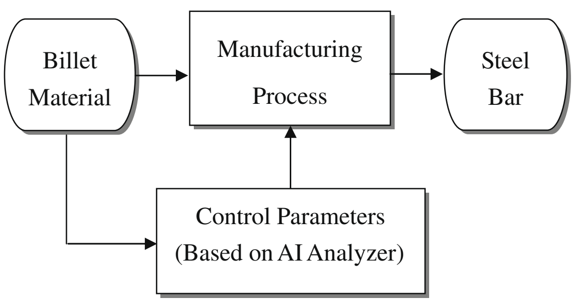

Fig. 2. The manufacturing process of steel bars with AI analyzer.

accordance with the chemical compositions of billet and desired mechanical properties in advance so that the junior technician could easily set the proper values of control parameters before the real-line manufacture. (Fig. 3) shows the flowchart of AI analyzer design and its function.

The organization of this paper is described as follows: Section 2 presents the backbone of the developed AI analyzer, i.e., neural networks. Some experiments performed by using AI analyzer are reported in Section 3. Section 4 gives the conclusion of this research and provides some recommendations for the future works.

2. AI analyzer and neural network model

A neural network structure commonly known as multi-layered feed-forward net was used as the main structure of the developed AI analyzer. Specially, a four-layered feed-forward neural network architecture as shown in Fig. 4 is the selected basic model in our study. AI analyzer is composed of three independent neural network models. Each model was constructed for individual mechanical property of steel bar, i.e., yield strength, tensile strength and percentage of elongation, respectively. The neural model consists of an input layer with twenty nodes, an output layer with one node and two hidden layers with twelve nodes in each. All neural networks' size is 20-12-12-1. The learning algorithm utilized in the neural models is "Back-Propagation Algorithm (BP)". The major steps of BP algorithm are listed as follows (Hwang, 1993; Khotanzad et al., 1995; Shen et al., 2008):

Step 1: Initial all weights (w_{ij}) to small random values (typically between -0.5 and 0.5).
Step 2: Present an input and specify the desired output.
Step 3: Calculate outputs using the present value of w_{ij} s.
Step 4: Find an error term, δ_j, for all the nodes. If d_j, O_j and X_j stand for desired value of the jth output node, the computed value of the jth output node, and the computed value for the jth hidden layer node, then the error terms are calculated as; for output node j: $\delta_j = (d_j - O_j)O_j(1 - O_j)$, for hidden layer node j: $\delta_j = X_j(1 - X_j)\sum_k \delta_k \omega_{jk}$, where k is over all nodes in the layer above node j.
Step 5: Adjust weights by $w_{ij}(k+1) = w_{ij}(k) + \alpha\delta_j X_i + \xi(w_{ij}(k) - w_{ij}(k-1))$, where $(k+1)$, (k), and $(k-1)$ index next, present, and previous iteration, respectively. α is the learning rate. ξ is the momentum which determines the effect of past weight changes on the current direction of movement in weight space. It is used to filter out the high-frequency variations of the error surface.

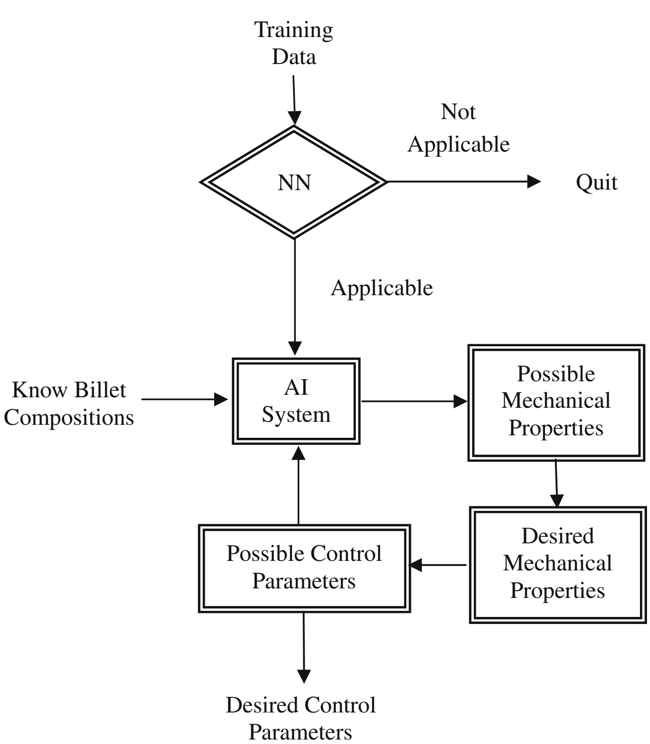

Fig. 3. The flowchart of AI analyzer design and its function.

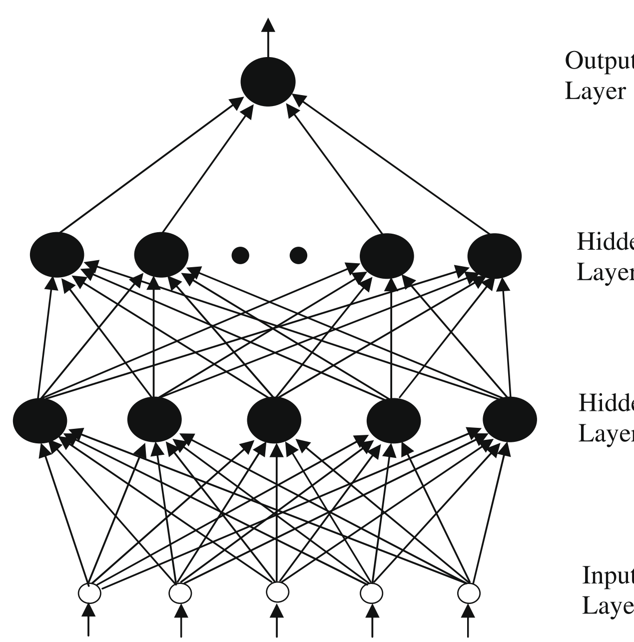

Fig. 4. Architecture of a four-layered neural network.

Step 6: Present another input and go back to step 2. All the training inputs are presented cyclically until weights stabilize.

3. Experiments

In our experiments, 1400 sets of data, including billet compositions, control parameters of rolling process and mechanical properties of rolled steel bars, provided by Hai-Kwang Corporation; Taiwan, were analyzed and simulated. The examples of data are listed in Table 1. The data includes, steel type, yield strength, tensile strength, Ts/Ys, percentage of elongation, Wt, Wt% C, Si, Mn, P, S, Cu, Sn, Ni, Cr, Mo, W, V, Al, Pb, Nb, CE, dimension, rolling speed, hydraulic pump and water section. The mechanical properties of rolled steel bars, including yield strength, tensile strength and percentage of elongation, were studied and estimated based on the corresponding billet compositions and relative influencing factors by AI analyzer. For demonstrating the feasibility of AI analyzer developed, the data was divided into two parts. The first part, 1000 sets of data, was used for training the neural models and the second part, 400 sets of data, was used for testing. The learning rate $\alpha = 0.2$ and momentum $\xi = 0.7$ were used for all three neural models. For each neural model, there are totally twenty inputs, including C, Si, Mn, P, S, Cu, Sn, Ni, Cr, Mo, W, V, Al, Pb, Nb, CE, dimension, rolling speed, hydraulic pump and water section. In article Ozerdem and Kolukisa (2008), only C.E., Si and Mn were considered as the inputs of neural model. Obviously, the information of inputs we collected is more complete. The mechanical properties of rolled steel bars, including yield strength, tensile strength and percentage of elongation, will be estimated by independent well-trained neural model, respectively.

Tables 2–4 list the testing error statistics of yield strength, tensile strength and percentage of elongation, respectively. The mean absolute error (MAE) and the mean absolute percentage error (MAPE) for overall testing data are used for the performance measures. In our experiments, the estimation errors of yield strength, tensile strength and percentage of elongation are 0.915%, 1.523% and 3.132%. Obviously, the estimation results performed by neural models are quiet well. The results also show that the AI analyzer developed is very promising. Figs. 5–7 show the neural models' performances in a graphical form.

From the experimental results, we can clearly find that AI analyzer developed do have the capability to capture the very complex relationships between mechanical property of steel bar and its influencing factors, including billet elements and control parameters of rolling process. Such a well-trained AI analyzer then can be used to help the technician to decide the related control parameters before the steel bar is on the real-line rolling process.

For instance, the qualified value of yield strength of thermo-processed deformed bar SD420 is in the range 42.9–55.1. The qualified values of its tensile strength and percentage of elongation are 63.3 and 12, respectively. Therefore, before the real-line bar's manufacture, if the billet compositions are known, the developed AI

Table 1
The examples of steel bar data.

Steel type	Yield strength	Tensile strength	Ts/Ys	Percentage of elongation
Wt	Wt%	C	Si	Mn
P	S	Cu	Sn	Ni
Cr	Mo	W	V	Al
Pb	Nb	C.E.	Dimension	Rolling speed
Hydraulic pump	Water section			
SD420	50.6	67.6	1.34	21.7
3.99	0.30	0.2778	0.0682	0.7091
0.0083	0.0159	0.0237	0.0018	0.0215
0.0237	0.0085	0.0080	0.0020	0.0013
0.0083	0.0012	0.3997	D25	8.9
3	4			
SD420	54.3	69.8	1.29	22.8
4.04	1.40	0.2613	0.0719	0.7203
0.0055	0.0123	0.0244	0.0018	0.0210
0.0237	0.0086	0.0073	0.0022	0.0000
0.0092	0.0014	0.3850	D25	8.9
3	4			
SD420	53.0	69.3	1.31	16.5
3.98	0.10	0.2930	0.0746	0.7199
0.0072	0.0198	0.0262	0.0018	0.0213
0.0236	0.0089	0.0080	0.0023	0.0013
0.0093	0.0015	0.4167	D25	8.9
3	4			
SD420	51.4	67.0	1.30	21.1
3.96	0.50	0.2604	0.0372	0.6219
0.0136	0.0184	0.0000	0.0090	0.0067
0.0028	0.0068	0.0058	0.0018	0.0000
0.0072	0.0008	0.3643	D25	8.9
3	4			
SD420	51.8	67.8	1.31	20.1
3.95	0.70	0.2862	0.1298	0.8570
0.0332	0.0294	0.4259	0.0288	0.0680
0.1719	0.0136	0.0160	0.0060	0.0000
0.0016	0.0022	0.4594	D25	9.6
2	3			

Table 2
The error statistics of yield strength.

MAE	MAPE
0.630	0.915%

Table 3
The error statistics of tensile strength.

MAE	MAPE
0.830	1.523%

Table 4
The error statistics of percentage of elongation.

MAE	MAPE
0.541	3.132%

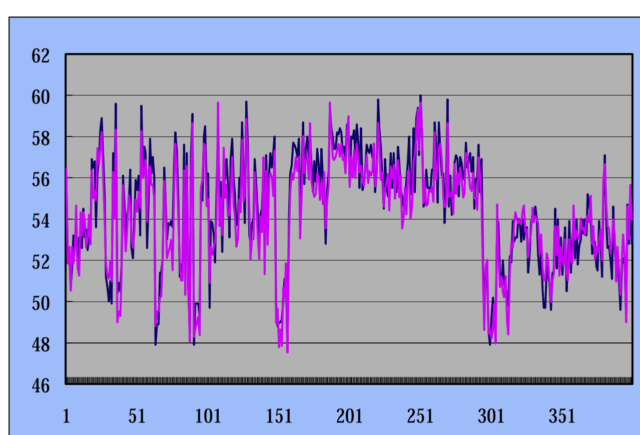

Fig. 5. The estimated results of yield strength. Dark line: actual values. Light line: estimated values.

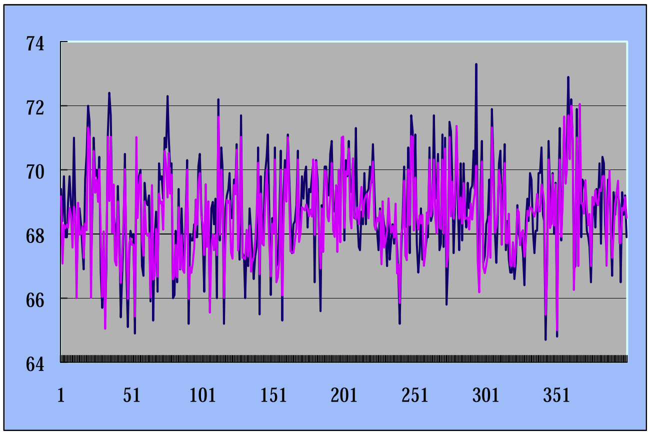

Fig. 6. The estimated results of tensile strength. Dark line: actual values. Light line: estimated values.

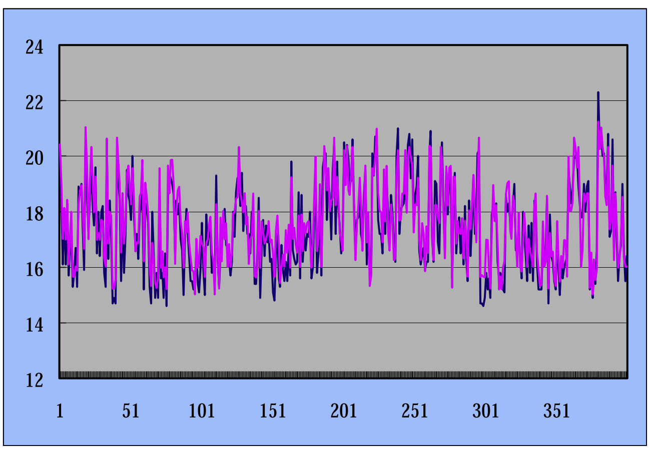

Fig. 7. The estimated results of percentage of elongation. Dark line: actual values. Light line: estimated values.

analyzer could generate a data base which consists of all possible mechanical properties based on different sets of control parameters. The technician could easily find the proper values of control parameters that make three mechanical properties be qualified from this data base.

Accurately, in order to avoid the effect caused by estimation error of AI analyzer, the proper values of control parameters should be selected to make the values of mechanical properties be in the confidence intervals that can cover the estimation error of AI analyzer due to some unknown factors or disturbances. For the example of SD420 bar, the best set of control parameters could be selected to make the value of yield strength be near 49, the value of tensile strength be larger than 63.3, and the value of percentage of elongation be also larger than 12, simultaneously.

4. Conclusion

In this paper, an AI analyzer for the mechanical properties of rolled steel bar based on three independent neural network models was developed and proposed. The nonlinear and very complex relationships among the mechanical properties of steel bar, billet elements and the control parameters of rolling process could be automatically developed by neural models. Then, such an AI analyzer could help the technician to set the proper control parameters before the bar is on the real-line manufacture. This AI analysis process not only can improve the quality of steel bar manufactured, buts also can reduce the running cost of steel company due to the failure of bar's manufacture.

However, in our studies, we certainly found that some bigger estimation errors do exist in the neural models. After the discussions with senior engineer of Hai-Kwang Corporation, the possible reasons are concluded as follows.

1. The lacks of information about water temperature and flow rate.
   In the manufacturing process of steel bar, the water temperature and its flow rate do affect the bar's mechanical properties. Unfortunately, there is no information about these two factors in the collected data. Therefore, if the water temperature and flow rate can be added, then the estimation accuracy of AI analyzer might be greatly improved.
2. The measurement error of billet compositions.
   In the measurement process of billet compositions, many man-made mistakes caused by careless operation will provide the incorrect information about billet. Such incorrect information indeed makes neural models do not have more accurate learning. For example, if the spectral analysis equipment does not have the check and adjustment regularly, or the surface of billet sample is shapeless; both these two mistakes will also provide the incorrect information about billet. So, if the man-made mistakes could be carefully eliminated in the measurement process, we do believe that the AI analyzer should perform much better.

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