Using Artificial Neural Networks to Predict Rolling Force and Real Exit Thickness of Steel Strips

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Abstract
There is a complicated relation between cold flat rolling parameters such as effective input parameters of cold rolling, output cold rolling force and exit thickness of strips. In many mathematical models, the effect of some cold rolling parameters has been ignored and the outputs have not a desirable accuracy. In the other hand, there is a special relation among input thickness of strips, the width of the strips, cold rolling speed, mandrill tensions, required exit thickness of strips with rolling force and the real exit thickness of the rolled strip. First of all in this study, the effective parameters of cold rolling process modeled using an artificial neural network according to the optimum network achieved by using a written program in MATLAB. It has been shown that the prediction of rolling stand parameters with different properties and new dimensions attained from prior rolled strips by an artificial neural network is applicable.

Keywords
Cold rolling, Artificial Neural Networks, Rolling force, real rolled, thickness of strips

1. Introduction
In the last years, Artificial Neural Networks (ANN) have been proposed as powerful computational tools due to the low time of processing that can be reached when the net is in operation. In 1998, Gunasekera investigated the flat cold rolling process with back propagation in neural network modeling. In his research, he expanded a nonlinear mathematical model for training and testing the problem [1].In 2001, Perzyk and Kochanski [2] predicted ductile cast iron quality by ANN using only the chemical composition of the melt. Shlang et al. proposed a hybrid neuron/analytical process model which is dependent on the considered mill which permits the calculation of the setup for the mill's actuators. Yang et al. presented a neural network model to predict roll load which was implemented to on-line roll-gap control. Guo and Sha [3] estimated the properties of Maraging steel using ANN. They used alloy composition, processing parameters and working temperature as input parameters. Ozerdem and Kolukisa [4] predicted mechanical properties of AISI10XX series carbon steel bars using only three chemical contents as inputs. Capdevila et al. [5] analyzed the influence of processing on the strength and ductility of automotive low carbon sheet steels, but they did not investigate the effects of Cooling Temperature (CT) because of lack of a database. Comparison with the indicated references showed that the authors of Ref. [6] used 16 input parameters. Thirteen of them represented the crystallographic texture, one for the carbon content, one for the carbide size and one for the rolling degree.

Reddy et al. [7] expanded an artificial neural network for investigating the torsional vibrations in cold rolling line [8].They modeled medium carbon steels with alloy compositions and heat treatment parameters as input, but they did not use cold rolling parameters in their model.

Cold rolling of steel is a very complex process. Knowledge of conditions in the rollingprocess is essential to achieve a good quality of final production. Some of its parameters may be exactly determined by measurement on the mill stand (geometrical dimensions, rolling force, front and back tensions, rolling velocity), some others can only be approximated by a suitable mathematical model (e.g. hardening of the processed material, friction coefficient between rolls and strip, strip temperature and flatness). There are some types of mathematical models for cold rolling. Off-line models are used for post processing analysis of rolling condition at a mill stand. The time for data processing is not critical in this case. Hence, more detailed models and complicated time consuming computational method can be used. On-line models are used for real-time control of rolling. The model issues have to be at disposal pending the current coil rolling. Therefore, the simplified but faster models are applied. The on-line models are also used for mill presetting. This type of model is often called torque-force model. The model computes friction coefficient, steel hardening and exit thickness of strips, roll force and torque according to real data measured on the mill. The friction coefficient depends on lubrication, rolling velocity and on the state of rolls abrasion. Steel hardening is affected by chemical composition and previous treatment of the material. Both variables strongly influence rolling force, torque and real exit thickness of the strip onthe mill stand. Incorrect mill presetting causes overloading or ineffective exploitation of mill drive. Unbalanced power distribution over the mill results in tandem or strip sliding in some mill stands. Hence, the optimal tandem presetting has been changed from coil to coil.

But in the mathematical models, authors often ignore the effect of rolling parameters on the rolling process.For example, in many rolling force models, the effect of rolling speed has been ignored. So, mathematical models are not very accurate methods to determine the rolling outputs. In this study, the neural network has been used for predicting the rolling force and exit thickness of strip.

2. Experimental procedure

All the data come from the experimental results in the two stands reversing cold mill system. (Mobarakeh Steel Company, Esfahan, Iran). Figure.1 presents the two stand reversing cold mill. In this tandem system, there are 3 passes each of which has 2 steps in two stands. At first, a coil is fed into the payoff reel and is passed among two stands and its end is clamped at the delivery reel. The first pass occurs between the payoff reel and the delivery reel and the second pass will be passed on the opposite direction between the delivery reel and the input reel. The third pass will be done in the opposite direction between the same reels.

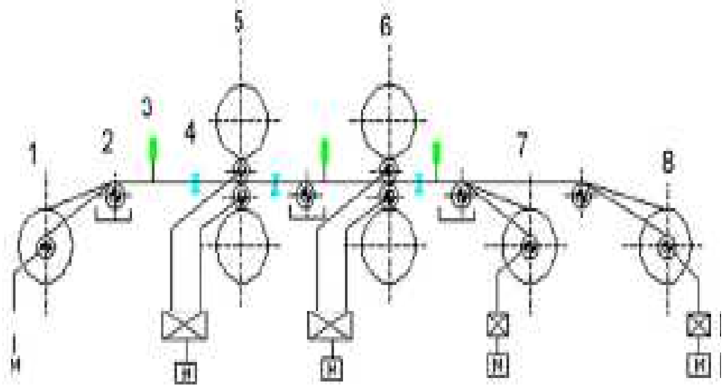

Figure 1.Two-stand tandem cold strip mill. (1) Coiling #2, (2) tension meter, (3) laser velocimetry, (4) thickness gauge, (5) stand #2, (6) stand #1, (7) coiling Machine #1 and (8) uncoiling machine [9]

3. ANN Modeling

Artificial neural network is a mathematical model that can learn and generalize the things learned. It makes a mapping function from input to output, giving information about practical phenomena. Because of the non-linear properties of neural networks, they are suitable for describing complex nonlinear phenomena which linear modeling techniques fail to describe. Basically, all the processes that have an adequate number of measured data can be modeled by ANN [10]. The ANN used in this study is a multilayer net which approaches the cognitive models that try to describe the operation of the human brain. The type of learning of that net is known as supervised learning based on the method of "back propagation". That neural network uses two or more layers with processing neurons. Input layer accepts the input information, and the last layer carries output information. The layers lying between the input and output layers are called the hidden layer. The basic unit (the neuron) acts as a processing element. An adjustable weight, representing the connecting strength, lies between the neurons in each layer. The basic function (net sum) of a neuron is to sum up its inputs and by means of the transfer function to produce an output. In our approach, in order to obtain a good generalization capability, the Levenberg-Marquardt and Bayesian Regularization algorithm are used to train the neural networks and the rolling force and the exit thickness of strip. They are predicted by feed-forward back propagate multilayer network in Cascade-Forward & Feed-forward Back propagation neural networks. The entry layer receives the external entries while the output layer is responsible by the generation of the output of the ANN. If there is a third layer, this receives the name of “hidden layer”. The definition of the net structure as the number of hidden layers and the number of neurons in those layers is still a problem without solution, although there are some approaches. In the case of the number of neurons for the hidden layer, it is suggested as 2N+1 neurons, where N is the number of inputs of the net. In this study, the Cascade-Forward Back propagation and Feed-Forward Back propagation have been used.The used algorithms for updating the weights among the neurons are such as:

Levenberg-Marquardt algorithm.

These algorithms are based on the hessian matrix and permit the network to learn the inputs more efficiently. The LM algorithm is the fastest method used in back propagation neural networks with medium dimensions [10].

Bayesian regularization algorithm

It is desirable to determine the optimal regularization parameters in an automated fashion. One approach to this process is the Bayesian framework. In this framework, the weights and biases of the network are assumed to be random variables with specified distributions. The regularization parameters are related to the unknown variances associated with these distributions. These parameters can be estimated using statistical techniques [10].

The schematic view of a multi-layer Artificial Neural Network (ANN) used in this study for modeling the cold rolling process is shown in Figure 2.The force and thickness models are developed using the experimental results that act as learning example. The five input variables used in the input layer are taken to be (1) input thickness, (micrometer), (2) the exit required thickness (micrometer), (3) the strip width, (mm), (4) the rolling speed, (rpm). The experimental results of the rolling force (ton) and the real exit thickness (micrometer) are two variables in the output layers

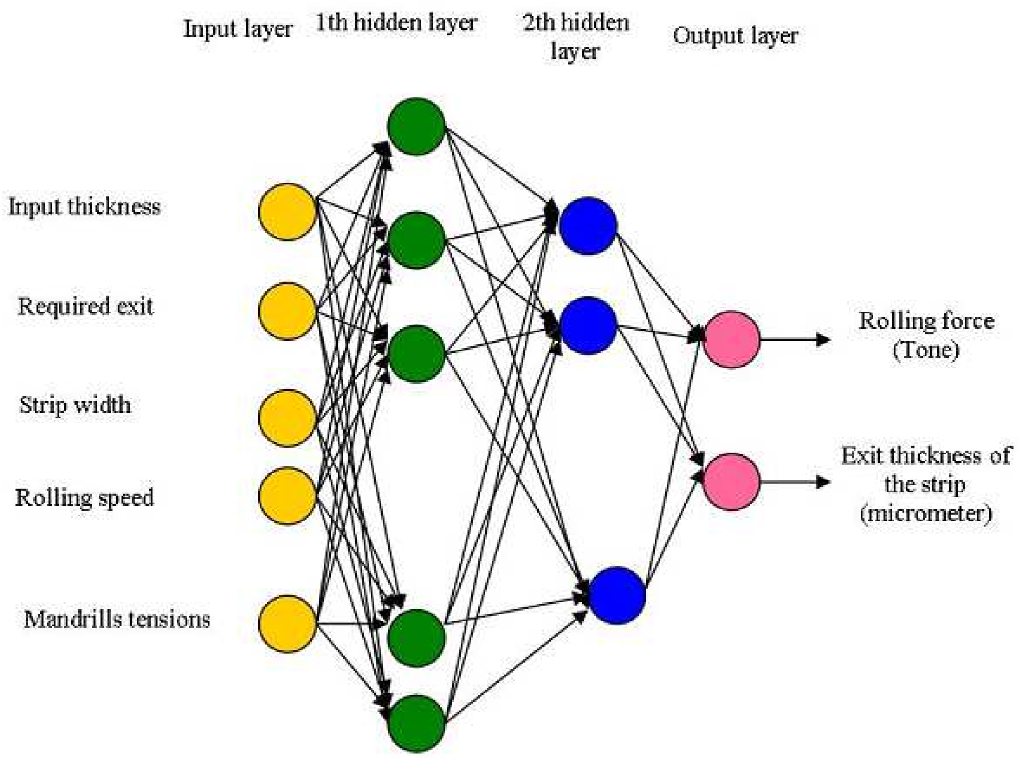

Figure 2.Configuration of the BP neural network model for cold rolling process

The activation functions for finding the optimum state of the learning process are:

1-sigmoid function

$$y_j = \frac{1}{1+2\exp(-x_j)} \qquad (1)$$

2-hyperbolic tangent

$$y_j = \frac{2}{1+\exp(-2x_j)-1} \qquad (2)$$

x_j is the sum of the inputs for each of the j^{th} layer neuron and is computed from equation 3.

$$x_j = \sum_{i=1}^{m} w_{ij\times y_i} + b_j \qquad (3)$$

For feed-forward back propagation multilayer network and Cascade-Forward Back propagation multilayer networks, m is the number of neurons in the output layer, w_{ij} is the weight between the i^th^ and j^th^ layers, y_j the output of j^th^ neuron and b_j is the bias for the neuron in the j^th^ layer [10].

For finding a network with a suitable topology and optimizing the cost function, the root mean square error criterion has been used which is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{T}}\sum_{\mathrm{k}=1}^{\mathrm{T}}(\mathrm{S_k} - \mathrm{T_k})^2} \tag{4}$$

Where RSME is the mean square error, $\mathrm{S_k}$ is the output of the network for the k^th^ pattern $\mathrm{T_k}$ is the real amount and m is the number of learning pattern. Also, in this study the absolute mean error has been used and that is:

$$E_{MA} = \frac{1}{\mathrm{T}}\sum_{\mathrm{k}=1}^{\mathrm{T}}|\mathrm{S_k} - \mathrm{T_k}| \tag{5}$$

First of all, for increasing the accuracy and the speed of the neural network, inputs have been normalized (Equation 6).

$$\mathrm{X_n} = \frac{X_i - \mathrm{X_{min}}}{\mathrm{X_{max}} - \mathrm{X_{min}}} \tag{6}$$

Where $\mathrm{X_n}$ is the normalized value, X_i is the value to normalize $\mathrm{X_{min}}$ and $\mathrm{X_{max}}$ are minimum and maximum variable values respectively. The average amount for feed-forward back propagation multilayer network and Cascade-Forward Back propagation multilayer networks with learning algorithms and different topologies have been investigated [10].

4. Results and discussion

In the Table1 the inputs are shown. There are two methods for optimizing in the neural network in this paper, FFBP and CFBP.

Table 1.The experimental rolling stand parameters (inputs for neural network)

	inputs				Out put	
layer	Input thickness of the strip (micrometer)	Required thicknesses of strips after rolling (micrometer)	Width of the strip (mm)	Tension at the both ends of the strip (ton)	Rolling force (ton)	exit thicknesses of strips (micrometer)
1	330	220	840	627	795	216
2	330	220	830	582	757	216
3	490	300	930	414	849	294
4	340	240	850	367	725	235
5	330	220	785	314	698	216
6	329	220	770	302	667	216
7	317	210	715	398	625	206
8	418	300	810	595	733	294
9	340	230	762	441	739	225
10	341	230	762	273	790	225
11	339	240	878	378	799	235
12	340	240	878	381	771	235.1
13	329	220	753	355	620	216
14	386	260	716	465	642	255

Table 2. The training errors for different layers, neurons with the same activation functions in the CFBP network

Training algorithm	E_{MA} %	The number of layers and neurons	Activation function	epochs
LM	0.045	5-10-18-2	LOGSIG	34
	0. 123			
	0.0905	5-18-2	TANSIG	26
	0.0439			
	0.077	5-10-25-18-2	LOGSIG	85
	-0.164			
BR	0.09	5-10-18-2	TANSIG	50
	0.05			
	0.181	5-18-2	TANSIG	28
	0.077			
	0.053	5-10-25-18-2	LOGSIG	108
	0.0780			

Table 3. The training errors for different layers, neurons and activation functions in the CFBP network

Training algorithm	E_{MA} %	The number of layers and neurons	Activation function	epochs
LM	0.08	5-20-2	TANSIG-LOGSIG	57
	-0.07			
	-0.07	5-15-18-10-2	LOGSIG-LOGSIG-TANSIG	62
	0.19			
	0.196	5-18-12-2	LOGSIG-TANSIG-	85
	-0.08			
BR	0.142	5-15-18-10-2	TANSIG-LOGSIG	45
	0.142			
	0.2	5-18-12-2	LOGSIG-TANSIG-	46
	0.044			
	.107	5-20-2	TANSIG-LOGSIG	57
	-0.63			

Table 4. The training errors for different layers, neurons with the same activation functions in the FFBP network

Training algorithm	E_{MA} %	The number of layers and neurons	Activation function	epochs
LM	0.038	5-10-18-2	LOGSIG	40
	-0.042			
	0.077	5-18-2	TANSIG	26
	-0.047			
	0.033	5-10-25-18-2	TANSIG	85
	0.050			
BR	0. 068	5-10-18-2	TANSIG	50
	-0.71			
	-0.07	5-18-2	LOGSIG	28
	0.083			
	0.051	5-10-25-18-2	TANSIG	47
	0.077			

Table 5. The training errors for different layers, neurons and activation functions in the FFBP network

Training algorithm	E_{MA} %	The number of layers and neurons	Activation function	epochs
LM	0.011 / -0.002	5-10-18-2	LOGSIG TANSIG	40
	0.09 / -0.06	5-18-2	LOGSIG-TANSIG	26
	-0.019 / -0.15	5-10-25-18-2	LOGSIG-TANSIG-	56
BR	0.09 / -0.028	5-10-18-2	LOGSIG TANSIG-	76
	0.107 / -0.37	5-18-2	LOGSIG-TANSIG-	56
	0.02 / -0.128	5-10-25-18-2	TANSIG-LOGSIG	47

A total of 14 examples for training the network and two examples for testing the network are adapted**.** The learning results were compared with the experimental results. They are listed in Tables 2- 5. As listed in these Tables, small values of percent error show that the neural network can realize for superior mapping relations between inputs and outputs. The implemented neural network algorithm is used to predict two testing examples. The testing results as compared to the experimental results are listed in Table 6.

Table 6. Evaluation of neural network for the new data

LAYER	ANN	Training algorithm	E_{MA}	The number of layers and neurons	Activation function	epochs
15	FFBP	LM	-0.07 / 0.05	5-10-18-2	LOGSIG-TANSIG	40
16	CFBP	BR	-0.09 / -0.07	5-10-18-2	LOGSIG TANSIG-	76

4. Conclusion

ANN is a suitable way to predict the rolling force and the exit thickness of strips. The best neural network for training the data is the feed-forward back propagation with Levenberg-Marquardt algorithm and LOGSIG-TANSIG-LOGSIG activation function for 5 neurons in the first hidden layer, 10 neurons in the second hidden layer, 18 neurons in the 3th hidden layer and 2 neurons in the last hidden layer (4^{th}).By using this method, we can predict the rolling force and the exit strip thickness in the actual rolling condition with an appropriate accuracy.

5. Nomenclature

x_j : Sum of the inputs

y_j : Activation functions

RSME : mean square error

S_k : Output of the network

T_k : Real amount
m: number of learning pattern
X_n : normalized value
X_i : Value to normalize
X_{min}, X_{max} : minimum and maximum variable values

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