Predicting Strip Tearing in Cold Rolling Tandem Mill using Neural Network

A. Haghani *
Department of Mechanics, Faculty of Engineering,
Shahrekord Branch, Islamic Azad University, Shahrekord, Iran
E-mail: ahmad.eng82@gmail.com
*Corresponding author

A. R. Khoogar
Department of Mechanical Engineering,
Maleke-Ashtar University of Technology, Lavizan, Tehran, Iran
E-mail: khoogar@yahoo.com

F. Kumarci
Department of Computers, Faculty of Engineering,
Shahrekord Branch, Islamic Azad University, Shahrekord, Iran
E-mail: kumarci_farshad@yahoo.com

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Abstract: Strip tearing during cold rolling process has always been considered among the main concerns for steel companies, while several works have been done so far regarding the examination of this issue. In this paper, experimental data from cold rolling tandem mill is used for detecting strip tearing. Sensors are placed across the cold rolling tandem mill, to collect information on parameters (such as angular velocity of the rolls, voltage and the electrical current of electrical motors driving rolls, roll gap, and strip tension force between rolls) directly from the cold rolling tandem mill. The information includes two modes: perfect rolling and ruptured rolling. A neural network is designed by means of MATLAB software and, then, trained using the information from the related data files. Finally, the neural network is examined by new data. It is concluded that the neural network has good accuracy in distinguishing between perfect and defected rolling.

Keywords: Cold Rolling Tandem Mill, Strip Tearing, Neural Network, Multi-layer Perceptron

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Biographical notes: A. Haghani is a PhD student in Mechanical Engineering at IAU University, Science and Research Branch, Tehran, Iran. **A. R. Khoogar** is Assistant Professor of Mechanical engineering at Maleke-Ashtar University, Lavizan,Tehran, Iran. **F. Kumarci** is Assistant Professor of Computer engineering at IAU Shahrekord branch, Shahrekord, Iran.

1 INTRODUCTION

The cold rolling process is among the major processes of metal forming with a relatively long history. Figure 1 illustrates an example of a five stand cold rolling tandem mill. As seen in this figure, a continuous cold rolling tandem mill is composed of five main parts: coils opening part, welding machine which welds the end of the opened coil to the new coil to make the cold rolling line continuous, loop car which stores strip in rolling line like a condenser in electrical circuits, stands of cold rolling which reduce strip thickness, and strip cutting machine and coil collector which collects the rolled strips. Since coils open in a rate faster than strip rolling speed, extra strip is stored by loop car in line till the beginning of the new coil is welded to the end of the opened coil. At this moment, the rate of coil opening reaches zero. The strip required for rolling line is provided by loop car.

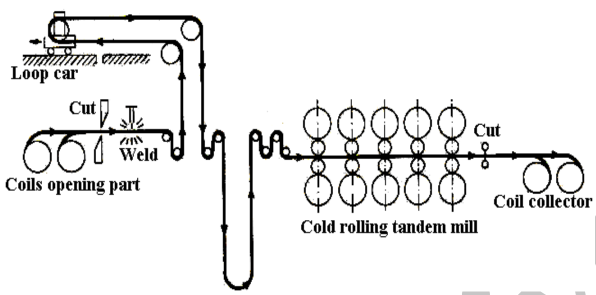

Fig. 1 An example of a five stand cold rolling tandem mill [1]

Making the cold rolling process continuous also accompanies strip tearing, where this brings about damages for steel strip manufacturers. Many attempts have been directed toward the neural network in the rolling process; a number of studies are implied below.
Bagheripoor et al., applied neural network in the hot rolling process [2]. Numerical results that obtained from FEM, were used for training the neural network. They optimized rolling force and torque which are function of various parameters like rolling speed, thickness reduction percentage, friction coefficient, and temperature. Ghaisari et al., designed a neural network that using this network, they were able to optimize the mechanical properties of cold rolling line products [3]. They intended to prevent costly experiments regarding the enhancement of the products quality.
The input parameters to neural network are rolling mill parameters and the outputs are yield strength, ultimate tensile strength and elongation. The results demonstrated that the reduction in skin pass, thickness after tandem and the ratio of Nitrogen to Aluminium are effective parameters on the mechanical properties of rolling productions.
Chen et al., examined the deformation and closure of void in flat sheet during cold rolling process [4]. Then, they compared simulation results with laboratory results, where the outcome was very satisfactory. In the end, they designed and trained a back propagation neural network for different parameters gained from simulation including the principal stress distribution and plastic strain around the void. Finally, it was concluded that the network predicts void behaviour during cold rolling process with acceptable accuracy. Rath et al., designed a feed-forward artificial neural network for prediction of the roll force [5]. The network was trained with the data obtained from hot rolling mill including the roll gap, rolling temperature, rolling speed, and plate width.
A Backpropagation algorithm with variable learning rate was used in the network training. Comparing the results obtained from the network and rolling mill data, demonstrated a high accuracy of the network in prediction of the hot rolling force. Mohanty et al., used an artificial neural network to express the mechanical properties of cold-rolled sheets as a function of chemical composition of steel, rolling and batch annealing parameters [6]. The designed network has the capability to establish an acceptable relationship between the variable of the problem.
Shahani et al., presented a FE model of hot rolling process for AA5083 Aluminium alloy [7]. During the process, temperature distribution, stress, strain and strain rate fields were extracted. For the convergence of results the experimental and theoretical data were used. Since the FE simulation of rolling process is time-consuming, a BP neural network was used, where the outputs of the FE simulation were applied for training of the neural network. Then the network was used for prediction of slab behaviour during the rolling process. Peng et al., extracted a new method for controlling the shape of the strip [8]. This method is composed of two parts: the first recognizes various patterns of sheet geometry, and the second uses one or a combination of several controls on sheet geometry to optimize it.
This new method was validated on an 800 KN HC mill. The results demonstrated that the new method reduces the strip shape error. Gudur et al., presented a rigid-plastic FE code for cold rolling process and then used the output results for the training of a neural network [9]. Then, they applied it to predict velocity field and location of neutral point. In order predict the tensile strength of hot-rolled alloy strip, Kim et al., designed a neural network [10]. The data for tensile strength of alloy are obtained from a POSCO hot strip mill. This network had a high predictive accuracy and computation power. Since the rolling force has a non-linear nature, the conventional methods with simple

mathematical models are not proper prediction of rolling force. Thus Xie et al., introduced a combination of mathematical model of rolling force and the adaptive neural network, where there was a good agreement between the calculated results and the measured values [11].

Liang et al., designed a progressive neural network to predict the rolling force in the cold rolling process [12]. Bayesian method was used for training the network and the numerical method of Gauss - Newton was used for solving the Hessian matrix. The designed neural network was more accurate and had a faster convergence rate compared with the prediction model based on Backpropagation neural network. Zhang et al., designed an innovations feedback neural network (IFNN) based on the idea of Kalman prediction and used for prediction of roll force in hot strip mill [13]. The theoretical results and the offline simulation demonstrated that the IFNN prediction of roll force compared with normal BP network was more accurate. Yang et al., presented two optimization schedules [14]. Schedule1 was energy-saving performance and schedule2 was making power distribution balanced as well as good flatness. These two schedules were used in a BP neural network to predict the rolling force. These two schedules had a suitable effect on rolling force and strip shape.

Hence, the designed neural network is more promising than the traditional BP neural network. Surface inspection is of great importance to improve quality of steel strip. Kang and Liu studied the local defects of steel strips in the rolling process [15]. They designed a feed-forward neural network that inspects the surface of steel strips and recognizes the local defects. The experiments demonstrated that this network is effective. Son et al., developed an online learning neural network to predict the rolling force in hot rolling mill [16]. The predicted rolling force by this network compared with the conventional mathematical method and the neural network with offline learning method, was more accurate.

In order to increase the accuracy of rolling force in hot rolling mill, Lee et al., designed and trained a corrective neural network with long term learning method [17]. The long-term learning method, one of the neural network learning method, compared with the short-term learning method, further reduces the thickness error.

Frayman et al., designed a direct model-reference adaptive control scheme with a cascade-correlation neural network (CCNN) to control the thickness [18]. The results demonstrated that this model improves the precision of thickness compared with the PID control system. Lin simulated the three-dimensional rolling process using the finite element method and neural network; subsequently he predicted the rolling force [19]. The results of rolling force and surface deformation obtained from FE simulation, were given to the neural network to obtain a model for the rolling process variables. Comparing with experimental data, this network gave acceptable results.

Quanfeng et al., used the Levenberg-Marquardt optimized in the improved backpropagation network to predict the rolling force in five-stand cold rolling mill [20]. Compared with the normal neural network, the rate of convergence and the accuracy of this network were higher. Gunasekera et al., presented a BP neural network for rolling process [21]. In order to guide and supervise the learning procedures, a nonlinear mathematical model based on the slab method was used. Using this model, the learning errors, prediction errors and training times were improved.

Larkiola et al., developed a neural network and used it to predict the mechanical properties of steel strips and rolling force [22]. The results of this network were used for adjusting the control parameters of rolling process, where 1.8% improvement in efficiency was obtained. Korczak et al., developed a neural network to predict the mechanical properties of hot rolled plates [23]. They gained good results regarding the prediction of nonlinear relationship between the chemical composition of steel, cooling rate, and final mechanical properties of the hot rolling product by means of this neural network.

Cho et al., presented a suboptimal mathematical model in order to model the rolling process [24]. They trained two multi-layer perceptron neural networks for this purpose. One of them directly predicts the rolling force and the other one calculates a correction factor which should be multiplied to the prediction made by a mathematical model. Both of neural networks improved the accuracy by 30-50%. Aistletner et al., designed a neural network to predict the eccentricity in the rolling process [25].

The results of this neural network compared with other method for calculating the roll eccentricity demonstrated a better accuracy.

According to the mentioned studies, it is found that these studies are about using neural network for optimization of control parameters such as rolling force. In previous research, prediction of strip tearing in cold rolling process using neural network has not been investigated, where in this research it will be examined. In this paper, first, the experimental parameters of the cold rolling tandem mill are examined.

Then, effective parameters on the strip tearing will be extracted. A neural network is taught using experimental data from cold rolling tandem mill regarding both perfect and defected rolling modes of strip. In the end, the neural network is applied to predict perfect rolling or defected rolling in the cold rolling tandem mill.

2 BASIC PARAMETERS IN COLD ROLLING PROCESS

The cold rolling process is a complex process whose analysis and control require examination, adjustment, as well as controlling many parameters. Parameters that play a central role in regulating and controlling the rolling line are described in the following [26].

1. **Gap between the rolls:** it is the space between two working rolls in the rolling process. During the rolling process, this gap changes in short courses with rolling control systems. Regardless of the negligible elastic return of the sheet, thickness of the sheet leaving each stand is equal to the value which is considered for the gap between the rolls.
2. **Rolling force:** it is the radial force applied to the rolls. It should be noticed that the bending value of rolls which is done by hydraulic jacks also affects this force. During the rolling process, this force may change a lot which is due to exercising the command of control equipment and fixing the thickness of the sheet leaving each stand. As the temperature increases, the deformation resistance of material decreases. Therefore, work hardening of hot rolling is greater than that of cold rolling. This is why the rolling force of cold rolling is greater than the hot rolling.
3. **Tension force between rolls:** It is exerted on the stretching sheet to reduce the rolling force in cold rolling process. The tension force created before each roll is called back tension force and the tension force created after each roll is called front tension force.
4. **Rolling torque:** It is the torque exerted by the drives on the working rolls for performing the rolling process. This is one of the most important rolling parameters which is taken into consideration in the analytic relations and the practical issues. Due to the changes in engine speed and friction coefficients, the rolling torque varies over time practically.
5. **The speed of strip:** The speed of strip when entering or leaving the stands, which is due to the rotation of the rolls, is one of the basic parameters both in practice and in theoretical relations. Due to the rolling process, the speed when entering the stands is always less than the speed when leaving the stands. In practice, it is tried to keep the speed constant over time. However, in practical terms, it is necessary in some cases that the speeds of five stands simultaneously decrease or increase at the same rate. To increase the production speed, it is always tried to carry out the rolling process with maximum speed as much as possible. It should be noticed that strip speed and linear speed of the rolls are not equal in practice and they have negligible differences which is due to slip.
6. **Friction coefficient:** Friction coefficient in cold rolling process is less than its value in hot rolling. This value changes depending on the type of emulsion used between the roll and the strip, the angular speed of the roll, and the speed of the strip. The exact calculation of friction coefficient is not possible due to the inability of direct measurement. Therefore, the estimated values are used in simulation and analytical calculations. The friction in cold rolling process is different from the friction in hot rolling process, because the first one is considered as sliding friction and the second one is considered as adhesive friction.

3 INTRODUCTION TO DAS (DATA ACQUISITION SYSTEM) SOFTWARE

DAS is the most comprehensive system of data storage and data display for continuous cold rolling line. This software, which is produced by Italian AISIRobicon Company, has a system of graphical representation of information. Using this system, users can view the history of a number of their desired signals at the same time.

Data related to continuous cold rolling line is stored in DAS at 50 ms intervals. Due to the high volume, the data is stored online in DAS-specific files by date, hour, and second. Therefore, they can be operated or interpreted offline if needed. Currently more than 200 signals on rolling lines are stored online in DAS. Of course new signals can be added to the software according to user's requirements.

4 IDENTIFICATION OF DATA SIGNAL IN DAS SOFTWARE

The information contained in DAS includes data on key parameters of the cold rolling process. Before referring to the details of this information, it is necessary to introduce some of the terminologies [26].

1. **Reference signal:** In control systems (whose signals are available in many rolling lines), the optimum value of a quantity (such as the optimum value of force or tension) is called reference value. These signals are usually named with *Ref* suffix. The reference value of a signal may change over time, due to circumstances.
2. **Feedback signal:** The aim of a closed circuit monitoring system is to deliver the real value of a quantity to its optimal value. For example, the purpose of inter- shelf tension control system is to

deliver the actual amount of inter- shelf tension to the determined optimum tension and to save it. The actual values of quantities are the signals which are measured by the sensors that are called feedback signals. These signals are usually named with *Fbk* suffix in DAS.

3. **Deviation signal:** In some quantities, such as thickness of sheet entering the shelves, fluctuations of a quantity is of particular importance. In this case, an independent signal, named deviation signal, has been created in DAS to evaluate this quantity. In fact, this signal is the derived values of the original signal over time.
4. **Difference signal:** Since the rolls in gap adjustment systems uses separate operators in their two ends, the signals corresponding to each operator must be examined separately. On the other hand, signals corresponding to the two ends of the rolls must be adjusted in order that they don't have much difference. Big difference between the two signals will be followed by asymmetry of the exerted force and consequently the system will be locked and the sheets will tear. According to this, signals with the suffix of *Diff* are created in DAS. These signals show the difference between the signals of operator side and the signals of drive side.
5. **Set signal:** in some cases, it is necessary to show the maximum possible value of a signal. Signals with the suffix of *set* are used in these quantities. The maximum value of a signal is calculated according to the limitations in the performance of mechanical and control equipment in the production program. There is a large difference between the feedback of a signal and the set value.

5 THE EFFECTIVE PARAMETERS ON STRIP TEARING

As mentioned earlier, the experimental data of five stand cold rolling tandem mill is related to the Mobarakeh Steel Company, Isfahan. Data is collected by sensors located across the rolling tandem mill and saved as files by DAS software. The data include both perfect and tearing modes. These files contain signals received from rolling tandem mill. Each signal is considered to be an experimental parameter. These signals are in the form of diagrams showing each parameter change based on time. For instance, Figure 2 illustrates the angular velocity of first stand based on time. Figure 3 shows feedback signal diagram for the tension force between first and second stand based on time. Over 200 parameters were collected from cold rolling tandem mill. First, they were examined based on cold rolling tandem mill experts. And, then, the number was reduced to 122 regarding the way they affect strip tearing. Some of these parameters are: the location of roll, tension force between rolls, angular velocity of rolls, strip thickness change after each stand, strip linear velocity after each stand, and so on.

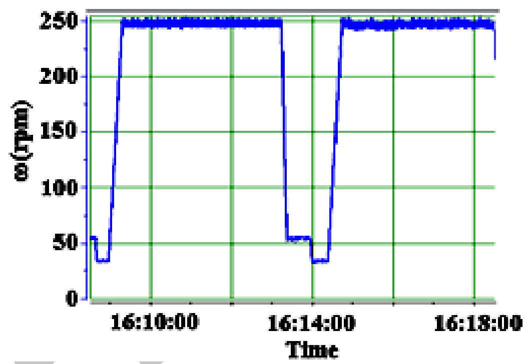

Fig. 2 The angular velocity of first stand based on time

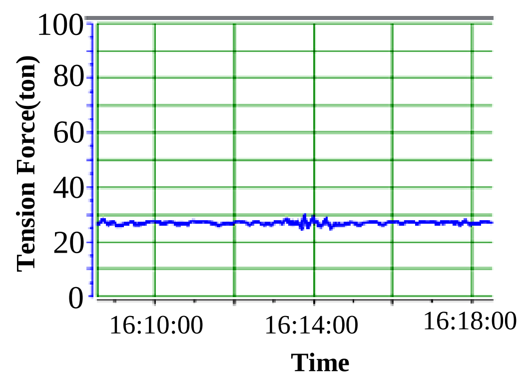

Fig. 3 The tension force between first and second stand based on time

Upon storing these 122 parameters by DAS software for both perfect and tearing modes and examining them again, it was perceived that merely mean parameter for five stands was needed for some of them. Hence, respective parameters were omitted. No significant difference was observed in the values of some other parameters for perfect and tearing modes. In addition, there was a significant difference between reference and feedback modes regarding some signals. These signals were again omitted from examinations. Finally, the number of parameters was reduced from 122 to 3.

These three parameters include [26]:

1. Parameter 1: Mean error of location of rolls (micrometer)
2. Parameter 2: Mean error of tension force between rolls (ton)
3. Parameter 3: Mean error of angular velocity of rolls (rpm)

6 NEURAL NETWORK MODEL

The neural network model used for predicting strip tearing in cold rolling tandem mill is perceptron neural network with three hidden layers, because this number of layers is the minimum number of layers that the neural network gives the correct answer. Properties of the network are listed in Table 1.

Table 1 Properties of the neural network used in this study

Input layer neurons (n_0)	First hidden layer neurons (n_1)	Second hidden layer neurons (n_2)	Third hidden layer neurons (n_3)	Output layer neurons (n_4)
3	10	20	20	1

Perceptron neural network model is taken to be among the most widely used neural network models regarding the prediction and detection of patterns. Figure 4 shows a schematic view of the designed neural network, where the operator function for hidden layers and output layer is "tansig".

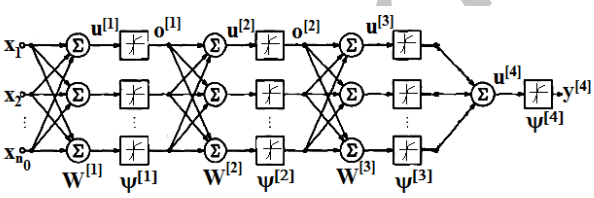

Fig. 4 Schematic view of perceptron neural network with three hidden layers [27]

7 NEURAL NETWORK TRAINING

To train neural network, generalized delta law was applied. Network training means the synoptic weight of different layers so that the mean square error of external layer neurons is the least. The error of J^{th} neuron (e_j) from an external layer means that the difference is between network output values and desirable values expected as network output. This error is presented based on Eq. (1). In this equation, d_j stands for desirable output value and y_j is the network output value [27].

$$e_j = d_j - y_j \tag{1}$$

The operator used for this network is a bipolar sigmoid function. Criterion function E_j which must be minimized by mean square error is presented based on Eq. (2) [27].

$$E_j = \frac{1}{2}(d_j - y_j)^2 = \frac{1}{2}e_j^{\ 2} \tag{2}$$

Training is carried out in terms of pattern-by-pattern. Changes in synoptic weight w_{ij} are implemented based on Eq. (3) where η is a positive coefficient [27].

$$\Delta w_{ji}^{\ [s]} = -\eta \ \frac{\partial E_p}{\partial w_{ji}^{\ [s]}}, \eta > 0 \tag{3}$$

If η is small enough, this algorithm can gain the general minimum of criterion function. Training multilayer perceptron neural networks begin from the last layer. Data is back propagated toward earlier layers. The weight coefficients of external layer are corrected based on following equations. In these equations, x_i is an input parameters vector, $u_j^{[s]}$ is the stimulating signal of j^{th} neuron of s^{th} layer, $o_j^{[s]}$ is the output signal of j^{th} neuron of s^{th} layer, and $\psi_j^{[s]}$ is the operator function of j^{th} neuron of s^{th} layer [27].

$$\Delta w_{ji}^{[4]} = -\eta \frac{\partial E_p}{\partial w_{ji}^{[4]}} = -\eta \frac{\partial E_p}{\partial u_j^{[4]}} \frac{\partial u_j^{[4]}}{\partial w_{ji}^{[4]}} \tag{4}$$

$$u_j^{[4]} = \sum_{i=1}^{n_4} w_{ji}^{[4]} x_i^{[4]} = \sum_{i=1}^{n_4} w_{ji}^{[4]} o_i^{[3]} \tag{5}$$

$$\delta_j^{[4]} = -\frac{\partial E_p}{\partial w_j^{[4]}} = -\frac{\partial E_p}{\partial e_{jp}} \frac{\partial e_{jp}}{\partial u_j^{[4]}} = e_{jp} \frac{\partial \psi_j^{[4]}}{\partial u_j^{[4]}} \tag{6}$$

$$\Delta w_{ji}^{[4]} = \eta \delta_j^{[4]} x_i^{[4]} = \eta \delta_j^{[4]} o_i^{[3]} \tag{7}$$

The modification of coefficients in the hidden layers is also calculated based on following equations [27].

$$\Delta w_{ji}^{[3]} = \eta \delta_j^{[3]} o_i^{[2]} \tag{8}$$

$$\delta_j^{[3]} = \frac{\partial \psi_j^{[3]}}{\partial u_j^{[3]}} \sum_{i=1}^{n_4} w_{ji}^{[4]} \delta_i^{[4]} \tag{9}$$

$$\Delta w_{ji}^{[2]} = \eta \delta_j^{[2]} o_i^{[1]} \tag{10}$$

$$\delta_j^{[2]} = \frac{\partial \psi_j^{[2]}}{\partial u_j^{[2]}} \sum_{i=1}^{n_3} w_{ji}^{[3]} \delta_i^{[3]} \tag{11}$$

$$\Delta w_{ji}^{[1]} = \eta \delta_j^{[1]} x_i \tag{12}$$

$$\delta_j^{[1]} = \frac{\partial \psi_j^{[1]}}{\partial u_j^{[1]}} \sum_{i=1}^{n_2} \delta_i^{[2]} w_{ij}^{[2]} \tag{13}$$

Neural network is trained for 10 perfect rolling modes and 10 tearing rolling modes. Then, it is capable of distinguishing between the perfect and tearing rolling modes by the entrance of similar patterns. Tearing rolling modes are because of both control and physical defects and this neural network must consider both of them. Table 2 shows an example of values of parameters affecting strip tearing for both perfect rolling and tearing rolling modes. It is based on experimental data from the cold rolling tandem mill of Mobarakeh Steel Company, Isfahan [26].

Table 2 An example of values of parameters affecting strip tearing

Rolling status	Parameter 1	Parameter 2	Parameter 3
Tearing rolling mode	165.93	27.49	202
Perfect rolling mode	27.152	2.299	136.8

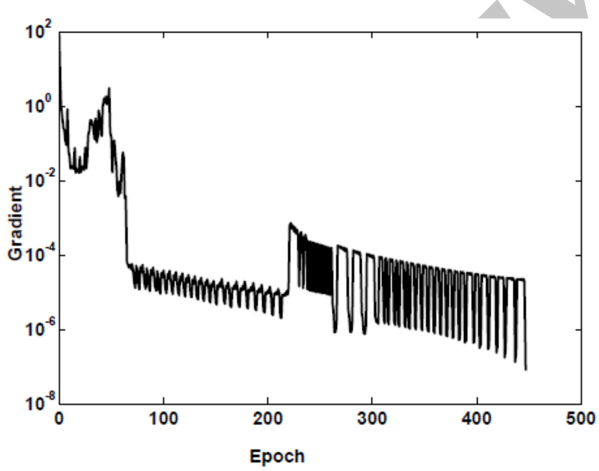

Fig. 5 Criterion function gradient based on the number of solution steps

Since the operator functions of layers are bipolar sigmoid functions, then, network output interval is (-1, 1). Further, as the output approaches 1, the more probable the perfect rolling mode will be. Reversely, as the output approaches -1, the more probable the tearing rolling mode will be.

Figure 5 shows criterion function gradient based on the number of solution steps related to network training. As seen in the diagram, the gradient is descending. It reaches its minimum value (7.71×10^{-7}) in step 447. Figure 6 illustrates the criterion function mean square error based on the number of solution steps related to network training. As seen in the diagram, the mean square error is descending. It reaches its minimum value (0.462) in step 447.

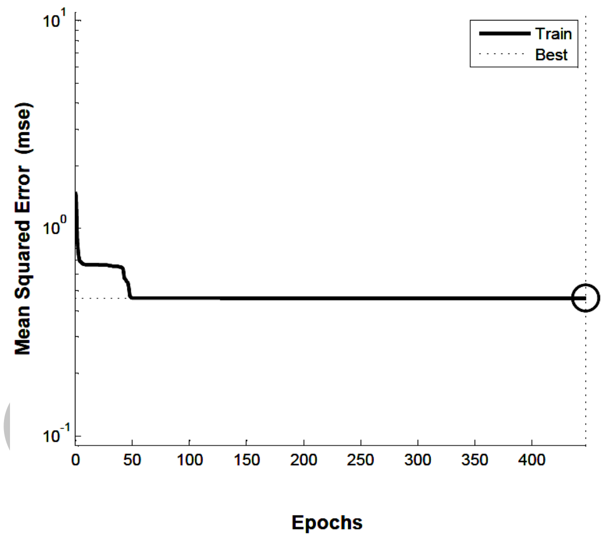

Fig. 6 Criterion function mean square error based on the number of solution steps

8 EXAMINING NEURAL NETWORK BY NEW PATTERNS

Neural network was examined for 8 perfect rolling mode patterns and 8 tearing rolling mode patterns. Results are listed in Table 3.

Table 3 Results of neural network examination for new input patterns

Rolling status	Tearing (-1)	Perfect (1)	Accuracy percentage
8 Tearing rolling mode	7	1	87.5
8 Perfect rolling mode	0	8	100
Final accuracy percentage			93.75

As seen from the table 3, the designed neural network has good accuracy in detecting rolling status (perfect or tearing).

9 CONCLUSION

A perceptron neural network with three hidden layers are designed after the examination of signals collected from cold rolling tandem mill of Mobarakeh Steel Company and the extraction of parameters affecting strip tearing. Then, it is trained for both perfect and tearing rolling modes by experimental data regarding parameters affecting strip tearing. Finally, the network is tested using new data.

In network training, the criterion function gradient reaches its minimum value (7.71×10^{-7}) in a descending trend (in step 447). The mean square error of criterion function has a descending trend, where it reaches its minimum value (0.462) in step 447. In examining network by new data, it is seen that the designed neural network has good accuracy in distinguishing rolling status (perfect or tearing).

Since the experimental values of parameters affecting strip tearing are registered every moment, the designed neural network can be mounted on cold rolling tandem mill and predict strip tearing before it happens. This is crucial because it prevents sheet rupture and cold rolling tandem mill stoppage in long term, and as a result, it reduces damages.

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