Neural Networks - Based Quality Control of Cutting in Road Rolling Machine

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Abstract -**The cutting machine in road rolling mill has a particular importance because it definite the quality of the head and tail of the obtained product. The possible failures in the shear such as the wear gives a bad cutting results. We consider in this work an application of fault detection and diagnosis (FDD) to define the necessary corrective actions (maintenance planning). The diagnosis is carried out by an analysis of residual obtained between an optimal cutting model output and the model output according to actual cutting sequence. The cutting model is a dynamic relationship (NARMA) of the motor cutting current signal.**
A feed forward neural network is used, after several trials a neural network structure and parameters have been selected. Cutting quality via new series of production data including road bar cutting quality has been evaluated. Application of this approach reduces the quality cost management and improves the quality inspection conditions in road rolling machine.

I. INTRODUCTION

New methodologies are being investigated, not only to increase production, but also to increase the quality of the final products. Under this perspective, new interest has arisen in on FDD mechanisms. Generally, an FDD system is composed by a model used for comparison with the system's response. Faults are detected if the residual generated from the difference between real measurements and their estimates using the model, exceeds a predefined threshold. If this happens, then the residual is analysed and the proper measures taken in order to stabilise the parameters values and, consequently, reduce the anomalies. However , this is not an easy task as the dynamics of the process seem to be rather complex.
Because of their capability of learning from examples without needing the process analytical description, neural networks are an attractive approach not only in process modelling but also in fault diagnosis. Furthermore, it is believed that it is possible to increase the final product quality by reducing the anomalies and by acting, whenever necessary, in the whole process behaviour by predicting its future state using an Artificial Neural Network (ANN) model [1,2,3].
We consider in this work an application of neural network modelling and simulation to cutting quality evaluation in road rolling mill. Fault detection and diagnosis is realised in two stages. In the first step process modelling is carried out by process data acquired from normal operating conditions and neural network training based on the back propagation algorithm. In the second step, model obtained during the learning process is used in on line simulation to predict the process output which is compared to its real values. Residual is then applied to fault detection and diagnosis.

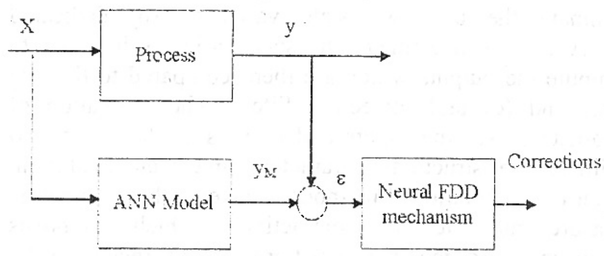


Fig.1. Principle of Neural Networks Fault Detection and Diagnosis

II. PROCESS DESCRIPTION

Figure.2 gives the principle of cutting in road rolling mill. The road bar is engaged between rolls of different rolling cages. The head of the considered rolling bar must be cut. The first time change of the signal u(t) (as a switch on off) is used to activate the cutting process characterized by its signal y(t). Dynamic of the signal y(t) defines the quality of cutting process. Data acquired from a good cutting sequence are used for neural network modelling and identification.

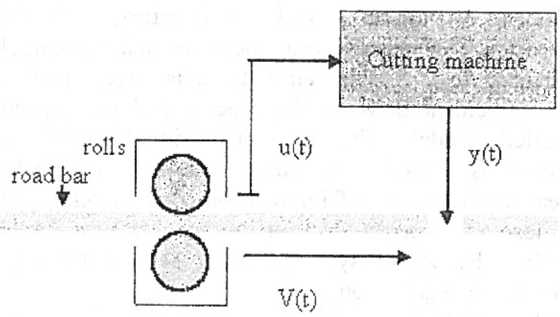


Fig.2. Cutting machine in road rolling mill

Quality control was performed off-line in some kind of quality control laboratory, as shown in Figure3. Obviously, a time delay is incurred in analysing the test samples, which can be in the range of some minutes to some hours. This could be too late to make the necessary adjustment. Poor quality parts are usually associated with some deviation in variable values. If the system could predict in advance the process behaviour, it would be able to identify future deviations and proceed with the necessary actions.

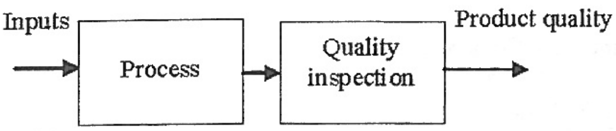


Fig.3. Conventional quality control procedure

III. FAULT DIAGNOSIS METHODS

Model-based techniques can be further classified into estimation methods (either of state variables or of parameters. Estimation of state variables is based on the generation of residuals in one of several ways (a) parity space, which generates the residual by projecting the mathematical relationships linking process variables to eliminate the unknown state variables, (b) dedicated observers, which estimate the state variables in order to compute the outputs which are then compared to the real ones, and (c) fault detection filters. The estimation of parameters uses the inputs and outputs of the process to estimate the structural parameters and their evolution. Pattern recognition methods cover three phases: measurement, feature extraction, which removes redundancy and generates a pattern strictly related to the actual mode of operation of the system. Pattern recognition techniques are applied when dynamics are negligible[]. Model –based methods require, however, an exact model of the system which is not always possible as the process dynamics is, in most cases unknown pr partially known. A possible solution would be linear approximation. However , this means that some dynamic characteristics would be left out, leading to an unsuitable model. A more plausible solution is to use artificial intelligence techniques, such as knowledge-based systems, fuzzy logic sets or neural networks, since they do not need mathematical models. The choice of the correct method depends , in great extent, on the desired accuracy and on the complexity of the problem. It is well known that in complex processes, like those found in the cutting machine of road rolling mill, it is extremely difficult to develop an accurate mathematical model du to the existence of process non–linearities and the complex mechanical low. In this sense, there is almost never an exact agreement between the process and its respective estimated model. The necessary simplifications and assumptions leave out some relevant information, increasing the degree of imprecision of the model, which may lead to incorrect decision by the FDD mechanism, affecting the whole system's response and leading to performance degradation.

Neural networks have remarkable advantages for heuristic modelling due to their capability to generalise by inductive learning from examples. Neural networks require little or no a priori knowledge of systems, and provide an effective tool for dealing with non linearity.

IV. PRINCIPA COMPONENT ANALYSIS (PCA)

In order to identify the relationships between variables and to detect the possible causes of faulty situations, some statistics have been used. PCA allows clusters of linked variables to be derived. One way think on PCA as a technique to find the directions in which a cloud of data points is most stretched. In this way, it is possible to extract the main relations in data as well as to detect its abnormal behaviour. PCA is a linear dimensionality reduction technique, optimal in term of capturing the variability of the data. It determines a set orthogonal vectors, called loading vectors, ordered by the amount of variance explained in the loading vector direction. Given a training set of n observations and m process variables stacked into a matrix S. The loading vectors are calculated by solving the stationary points of the optimisation problem. The loading vectors are orthogonal column vectors in the matrix V, and the variance of the training set projected along the i[th] column of V is equal to σ_i^2. We solve an eigenvalue decomposition of the sample covariance matrix X [3].

$$S = \frac{1}{n-1} X^T X = V \Lambda V^T \qquad (1)$$

Where the diagonal matrix

$$\Lambda = \Sigma^T \Sigma \qquad (2)$$

$\Sigma \; \Xi \; R^{mxm}$ Contains the negative real eigenvalues of decreasing magnitude and the i[th] eigenvalue equals the square of the i[th] singular value (i.e, $\lambda_i = \sigma_i^2$).
X is defined as:

$$X = \begin{bmatrix} x_{11}, x_{12}, \ldots\ldots x_{1m} \\ x_{21}, x_{22}, \ldots\ldots x_{2m} \\ . \\ x_{n1}, x_{n2}, \ldots\ldots x_{nm} \end{bmatrix} \qquad (3)$$

In order to optimally capture the variations of the data while minimising the effect of random noise corrupting the PCA representation, the loading vectors corresponding to the a largest singular values are typically retained. The projections of the observation X into lower-dimensional space are contained in the score matrix.

$$T = XP \qquad (4)$$

And the projection of T back into the m-dimensional observation space.

$$\hat{X} = TP^T \qquad (5)$$

$$E = X - \hat{X} \qquad (6)$$

The residual matrix E captures the variations in the observation space spanned by the loading vectors associated with the m-a smallest singular values. The

subspaces spanned $\hat{X}$ by and E are called the score space and residual space, respectively.
In this way, PCA technique ca n be used as a filter that reject noise via the projection of the observation X into the lower-dimensional space. Application to modelling of cutting sequence defined by the y(t).

$$X = \begin{bmatrix} y(t), y(t-1), \ldots\ldots\ldots\ldots y(t-n) \\ y(t-1), y(t-2), \ldots\ldots\ldots\ldots y(t-n-1) \\ . \\ y(t-m), y(t-m-1), \ldots\ldots y(t-m-n) \end{bmatrix} \quad (7)$$

V. THE NEURAL NETWORKS PROCESS MONITORING APPROACH

In this paper, a method for process monitoring of cutting machine in road rolling mill. The main objective is to predict the cutting quality of rolling bar as well as the defect classification.
Principle of filtering data and modelling using PCA and neural networks is given by the following scheme.

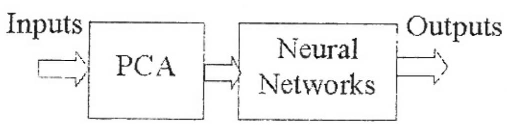


Fig.4. Principle of PCA-Neural networks modelling

The modelling using PCA aWe consider that the cutting machine is a dynamic system which is governed by the following non-linear relationship (NARMA), y(t) is the cutting signal acquired from the cutting motor mechanism using a computerised data acquisition system.

$$y(t) = f(y(t-1), \ldots, y(t-n)) \quad (8)$$

The identification and modelling principle is shown in Fig.3. The Back-propagation (BP) algorithm is explained in detail by different works [4-10]. We will briefly explain here. The network to be trained consists of L layers of nodes. The k^{th} layer contains N_k nodes, and for L=k, one "bias" node where the activation is always 1. Adjacent layers are exhaustively interconnected by weighted branches. The weight W_{ijk} refers to the branch from node i in layer k to node j in layer k+1. The first layer contains the network input x and the last layer the network output y.

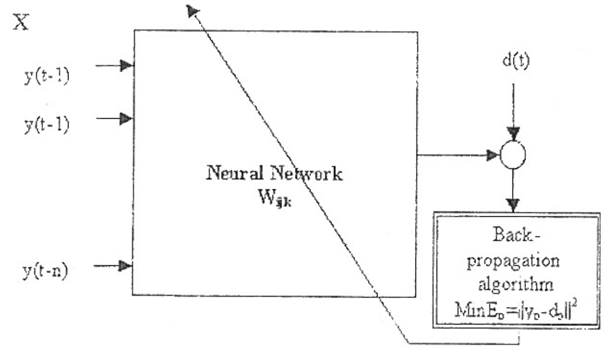


Fig.5. Principle of neural network learning process

z as an exponential function of the weight sums of its inputs in the form.

$$z_{jk} = \frac{1}{1+e^{-u_{jk}}} \quad (9)$$

where

$$u_{jk} = \sum_{i=1}^{N_{k-1}+1} z_{i,k-1} W_{i,j,k-1} \quad (10)$$

The network outputs are the activation of the last column z_L.
In the learning mode, a set of training examples consisting of p input/output vector pairs (x_p, d_p) is given. The objective is to select weights that minimize the sum of squared errors between the net predictions y_p and the desired outputs specified by the training examples d_p over all training examples:

$$\min_{w} J = \sum_{p=1}^{P} E_p \quad (11)$$

where E_p is the sum of squared errors associated with a single training example and expressed as follows:

$$E_p = \|y_p - d_p\|^2 \quad (12)$$

To be learning, the network is initialized with small random weights on each branch. A training example is selected randomly, and the input vector x_p is propagated through the network to get the predicted output y_p. A gradient in the space of network weights is then calculated using the Generalized Delta Rule (GDR) that gives the steepest descent direction m_p associated with the training example p [1,2, 4 -11].
Using the gradient m_p, the weight changes on step q, $\Delta_q W$, are calculated according to the formula:

$$\Delta_q W = \eta m_p + \alpha \Delta_{q-1} W \quad (13)$$

In this expression two constants (α, η) appear, called the learning rates which are equivalent to a step size, and which acts as a momentum term to keep the direction of descent from changing too rapidly from step to step. When the weights are updated, a new training example is selected, and the procedure is repeated until satisfactory reduction of the objective function is achieved.
Using the cutting data according to a good cutting quality sequence, we obtain the following results in Figure.6.

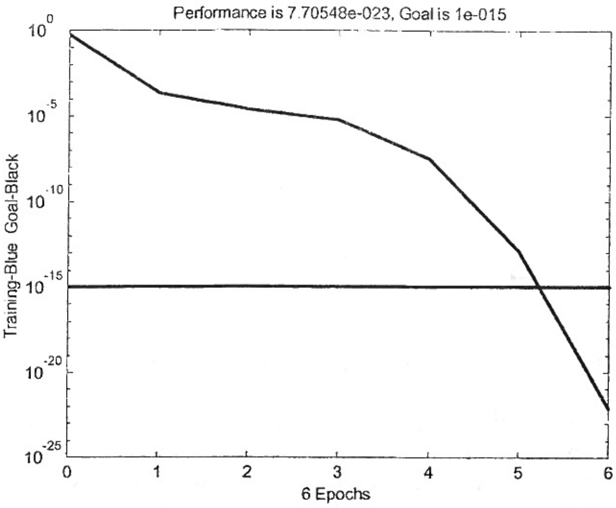


Fig.6a. Learning convergence

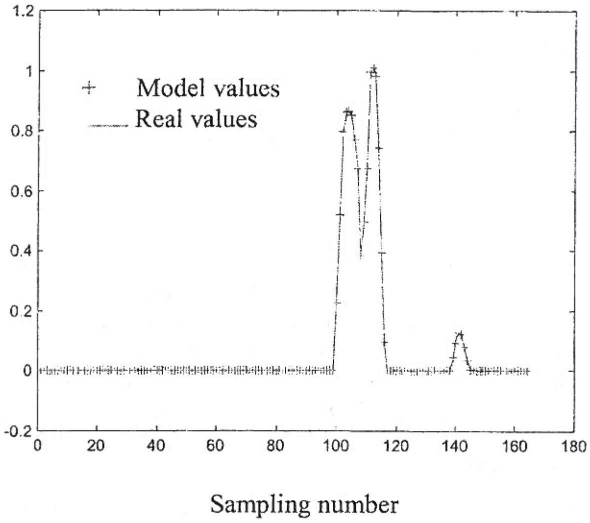


Fig.6b. Real and model outputs

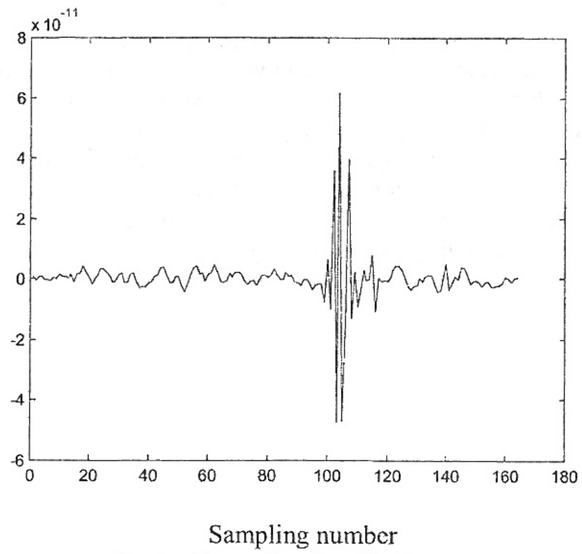


Fig.6c. Dynamic of residual

VI. APPLICATION

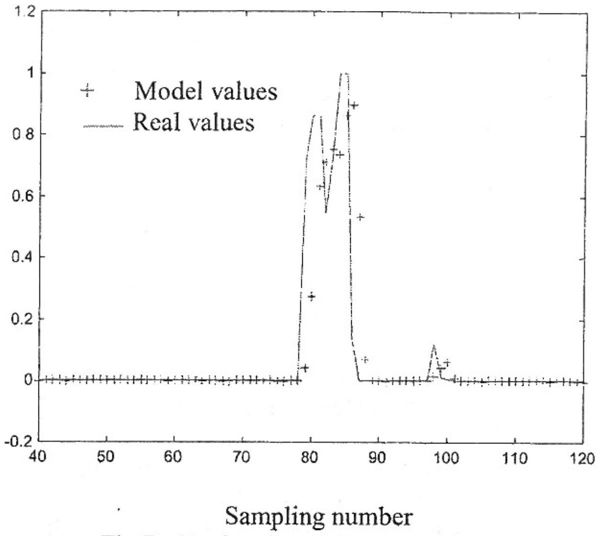


Fig.7a. Real and model outputs

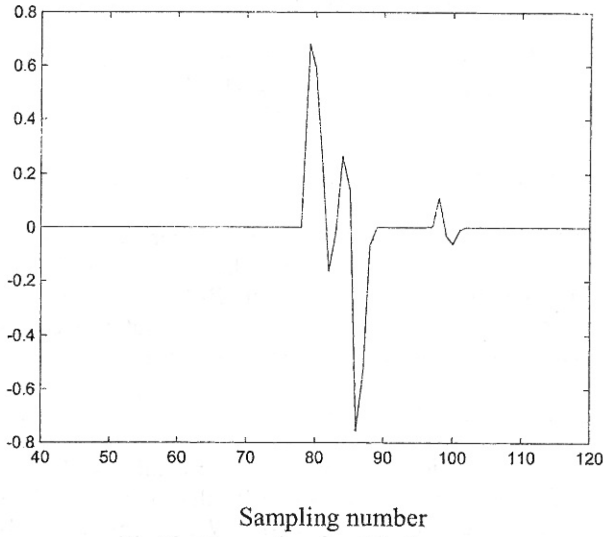


Fig.7b. Dynamic of residual

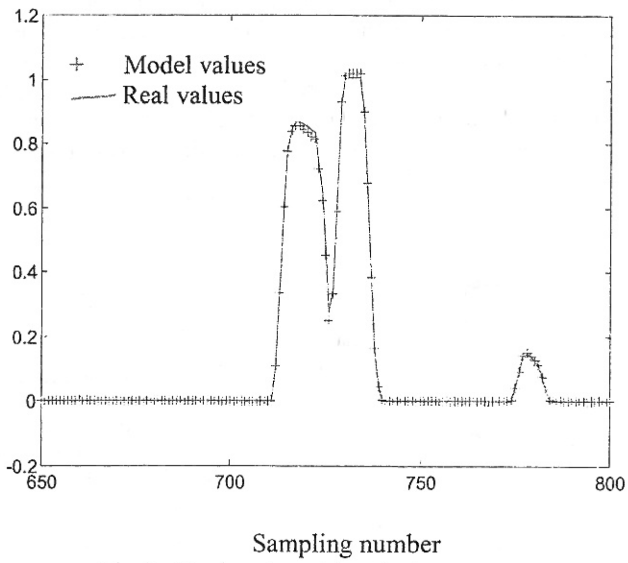
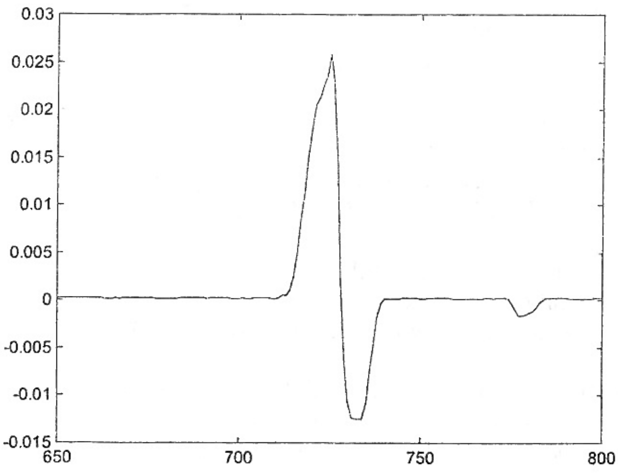
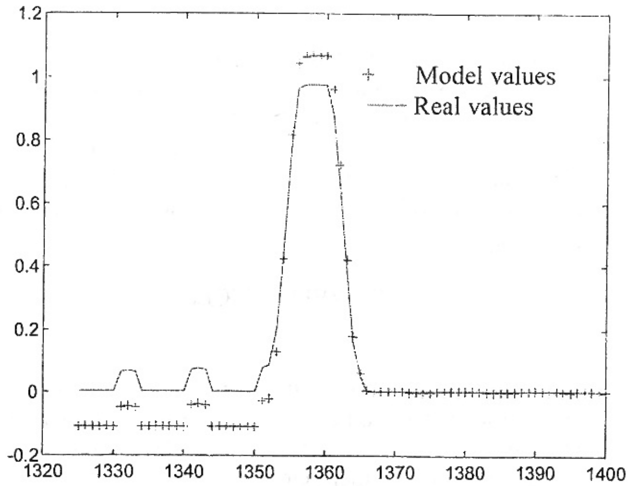


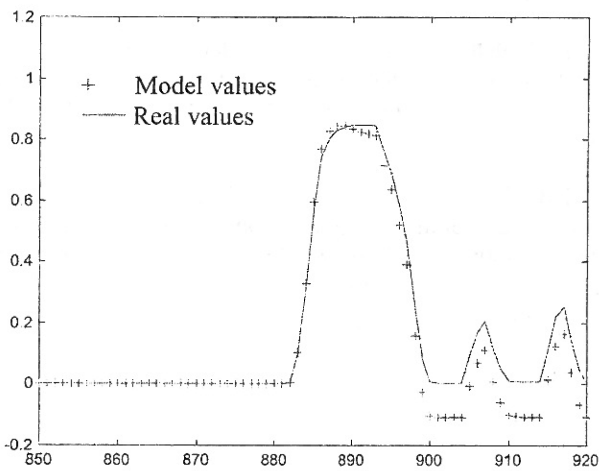
Fig.8a. Real and model outputs



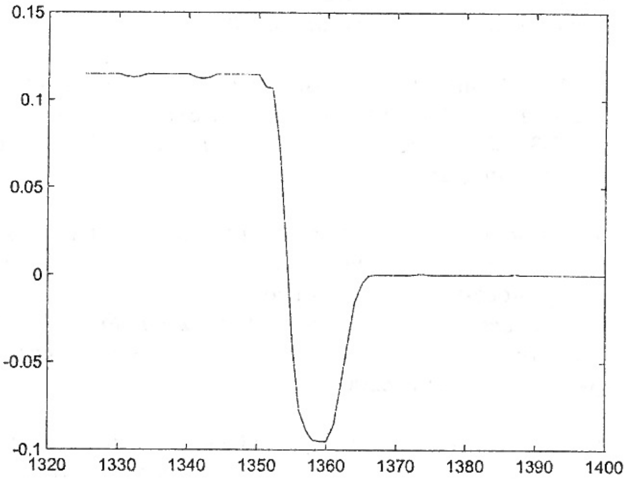
Sampling number
Fig.8b. Dynamic of residual



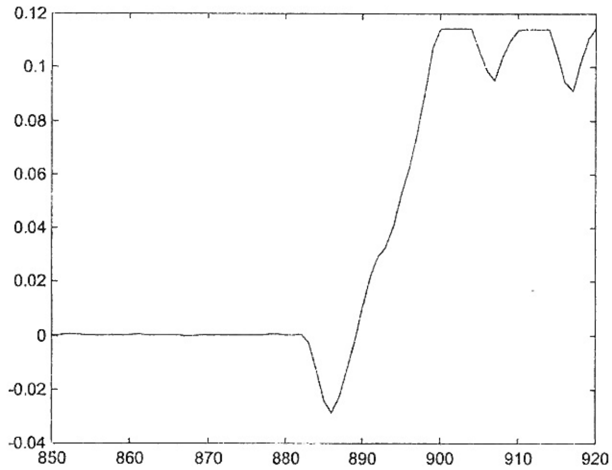
Sampling number
Fig.10a. Real and model outputs



Sampling time
Fig.9a. Real and model outputs



Sampling number
Fig.10b. Dynamic of residual



Sampling number
Fig.9b. Dynamic of residual

Application results are summarised in table1, The quality of cutting depends on the prediction error dynamic. The quality of cutting of each sequence presented in Figure 6 to Figure 10 is evaluated by its Mean Sum Squared Error (MSSE). After inspection the quality of cutting were classified in good medium, poor etc according to the MSSE values.

TABLE I

QUALITY CONTROL AND CLASSIFICATION USING MSSE

Cutting sequence	**MSSE**	**Quality classification**
Sequence 1 (Fig.6)	$2.5425\ 10^{-18}$	Optimal
Sequence 2 (Fig.7)	0.0067	Good
Sequence 3 (Fig.8)	0.0131	Good
Sequence 4 (Fig.9)	214.2667	Medium
Sequence 5 (Fig.10)	$2.3133\ 10^{3}$	Poor

VII. CONCLUSION

An application of neural network modelling and simulation in cutting process of road rolling mill has been developpcd. This model permit to evaluate the quality of cutting process and it will be integrated in a software package for on line cutting quality evaluation. The integration of this approach reduces the cost of quality inspection and management in road rolling mill.

VIII. REFERENCES

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