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Neural Network Based Nonlinear Autoregressive Models for CNC Machine Process

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Abstract: ***Tool wear monitoring and control in the machining operations is necessary to enhance the productivity and decrease the operation cost. The identification of CNC machine process model and its control is so difficult due to its high non-linearity. Therefore, neural networks (NNs) one of the non-linear identification techniques, have been applied in addition to system identification field for the identification and control of nonlinear systems. In this paper, auto-regression recurrent neural network model structures NNARX and NNARMAX is proposed for CNC machine modeling with its cutting condition and vibration signals as input to obtain an accurate nonlinear system model for prediction of tool wear and surface roughness. Finally, the modeled neural network model structures for prediction of tool wear and surface roughness is validated with the observed tool wear and surface roughness for the accuracy analysis of modeled neural network model structures.***

Keywords: ***CNC machine, NNARMAX, NNARX, Error analysis.***

I. INTRODUCTION

The international research organization CIRP made a study of the situation considering the increase in demand for effectual industrial tool condition monitoring systems [1]. It provides the current comprehensive survey of sensor technologies, signal processing, and decision making strategies for process monitoring including tool condition monitoring. These days one of the most important machining processes in mechanized companies is turning. Turning is affected by many factors such as the speed, feed rate and depth of cut, which are the input parameters [2]. The desired product of dimensional accuracy and less surface roughness is influenced by the process variables which are the responses and the functions of these input parameters. In the cutting

region of turning process there are several process variables, such as cutting forces, vibrations, acoustic emission, noise,

temperature, surface finish, etc., that are influenced by the cutting tool state and the material removal process conditions. In recent years awareness has been paid to the acoustic emission and vibration problem in CNC machine tools that affects tool life and hard work have been made and still are made in several directions to hold back them to considerably low levels. The tool wear and surface roughness of work piece under dissimilar cutting conditions in machining by means of acoustic emission (AE) and vibration signature in turning are studied in [2, 3]. The modeling, identification and control of the CNC machine is highly complex as it is highly nonlinear and the vibrations produced by the machine tool itself affects accuracy of the CNC machine process. Many of the author's proposed neural networks based nonlinear auto regressive models such as NNARX, NNARMA, NNARMAX, NNOE...etc. for highly nonlinear process that includes pH process [4,5], essential oil extraction system [6-9], rainfall runoff modeling [10], tower bridge movements [11],thermal behavior prediction [12],pneumatic system [13], Servo-Hydraulic Vehicle Suspension System [14], Speech signal generating system [15]..Etc.

In this paper nonlinear identification of CNC machine process using auto regression recurrent neural network model structures NNARX (Neural Network Auto-Regressive model with eXogenous inputs) and NNARMAX (Neural Network Auto-Regressive Moving Average model with eXogenous inputs) for the cutting conditions and the results are discussed.

II. COMPUTER NUMERICAL CONTROL MACHINE

Computer Numerical Control (CNC) is one in which the functions and motions of a machine tool are controlled using prepared program containing coded alphanumeric data. The turning operation is done in CNC machine for various cutting conditions (speed, feed and depth of cut) to monitor tool condition.

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The tool condition can be monitored by means of two approaches – direct and indirect approach. The indirect measurement techniques such as vibration signals and acoustic emission signals generated during turning operation are measured by sensors and acquired through DAQ for further process.

The acquired signals are analyzed to extract features such as RMS, SD, Mean, Range, and Median…etc. The extracted features along with cutting conditions are hardened to predict tool wear. The predicted tool wear with its inputs predicts surface roughness. The amplitude of underdone vibration signal mechanism and corresponding tool wear, surface roughness at different cutting conditions is tabulated from reference [2] in table 1.

TABLE I. Experimented data

Cutting conditions			Vibration signal (v)	Tool wear (mm)	Surface roughness (µm)
Speed (m/min)	Feed (mm/rev)	Doc (mm)			
170	0.32	1	5.574	0.151	3.505
215	0.32	1	9.251	0.165	4.212
250	0.32	1	8.747	0.139	3.981
270	0.32	1	14.873	0.183	4.663
250	0.20	1	8.865	0.105	3.224
250	0.28	1	9.675	0.142	3.507
250	0.50	1	11.876	0.155	4.118
250	0.32	0.5	12.619	0.076	4.373
250	0.32	2	16.225	0.194	5.098

III. NONLINEAR MODEL STRUCTURES BASED ON NEURAL NETWORK

A linear dynamic system can be represented by

$$y(t) = G(q^{-1};\theta)u(t) + H(q^{-1};\theta)e(t) \qquad (1)$$

Where $y(t)$ refers to the ny dimensional output, u(t) refers to the nu dimensional input, e(t) refers to white noise, θ is the model parameter and q^{-1} refers to backward shift operator.

NNARX and NNARMAX MODEL STRUCTURE

The ARX model structure is given by,

$$y(t) = \frac{B(q^{-1})}{A(q^{-1})}u(t) + \frac{1}{A(q^{-1})}e(t) \qquad (2)$$

The ARMAX model structure is given by,

$$y(t) = \frac{B(q^{-1})}{A(q^{-1})}u(t) + \frac{C(q^{-1})}{A(q^{-1})}e(t) \qquad (3)$$

Where the polynomials $A(q^{-1})$ and $B(q^{-1})$ are given by

$$A(q^{-1}) = 1 + a_1(q^{-1}) + .. + a_{na}(q^{-na})$$
$$B(q^{-1}) = b_0 + b_1(q^{-1}) + .. + b_{nb}(q^{-nb})$$
$$C(q^{-1}) = 1 + c_1(q^{-1}) + .. + c_{nc}(q^{-nc})$$

To estimate nonlinear part of ARX and ARMAX structure, the neural network can be used. NNs based Modeling techniques have ensured to be quite useful for building excellence models from measured data. The Multilayer Perceptron (MLP) network is most likely considered as member of the neural network family. The neural network based ARX and ARMAX model structure is denoted as NNARX and NNARMAX. The general model structure of NNARX and NNARMAX is shown in Fig. 1(a) and 1(b) respectively.

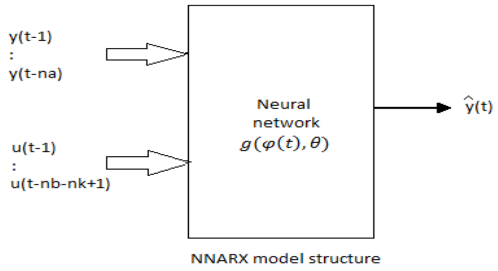

Fig. 1(a). General NNARX model structure

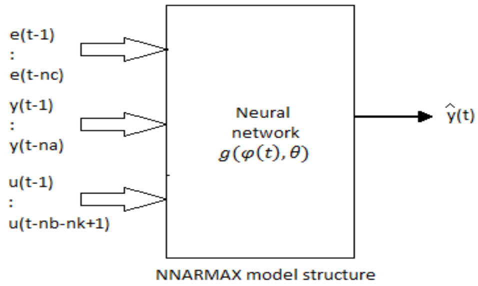

Fig. 1(b). General NNARMAX model structure

NNARX Regression vector is given by

$$\varphi(t) = [y(t-1) \ldots y(t-n_a) u(t-n_k) \ldots u(t-n_b-n_k+1)]^T \qquad (4)$$

NNARMAX Regression vector is given by

$$\varphi(t) = [y(t-1) \ldots y(t-n_a) u(t-n_k) \ldots u(t-n_b-n_k+1)\ \varepsilon(t-1) \ldots \varepsilon(t-n_c)]^T \qquad (5)$$

Where $\varepsilon(t)$ is the prediction error,

$$\varepsilon(t) = y(t) - \hat{y}(t|\theta) \qquad (6)$$

The predictor of NNARX and NNARMAX model structure is given by equation

$$\hat{y}(t|\theta) = g(\varphi(t),\theta) \qquad (7)$$

Where $\varphi(t)$ is a vector containing the regressors, θ is a vector containing the weights and g is the function realized by the neural network

The NNARX model structure predicts output by concerning the current output with the combination of past inputs and outputs while NNARMAX model structure predicts output by relating the current output with the combination of past inputs, outputs and residuals. A predictor without feedback is seen only in the NNARX model.

IV. NNARX AND NNARMAX MODEL FOR PREDICTION OF TOOL WEAR AND SURFACE ROUGHNESS

The nonlinear identification of CNC machine process consists of four steps- experimentation to obtain data set, model structure selection, model training and model validation.

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A. Experimentation

The experiment conducted in CNC machine for various cutting conditions produces a data set for prediction of tool wear and surface roughness. The data set consists of cutting conditions- speed, feed, and depth of cut, RMS value of vibration signals, manually observed tool wear and surface roughness. Then the obtained data set is divided into two for training and validation purposes.

The input-output sequences of the data set for tool wear prediction with speed, feed, and depth of cut, RMS value of vibration signals as input are displayed using MATLAB shown in Fig. 2.

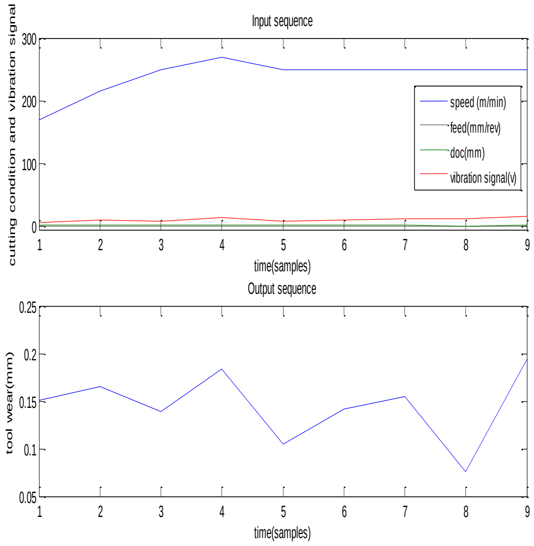

Fig. 2. Input-output sequence for tool wear.

The input-output sequences of the data set for surface roughness prediction with speed, feed, and depth of cut, RMS value of vibration signals and predicted tool wear as input are displayed using MATLAB shown in Fig. 3.

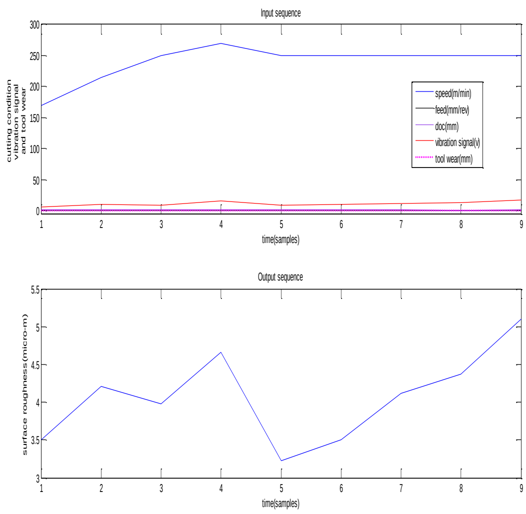

Fig. 3. Input-output sequence for surface roughness

The data set to be trained is scaled to zero mean and variance using dscale function before training to improve faster convergence and get better numerical stability

B. Selection of model structure

Once the data set is acquired, the next important step is model structure selection. Selection of model structure depends on the selection of a set of regressors and network architecture. The function lipschit is employed to determine the order of the system (regressors).

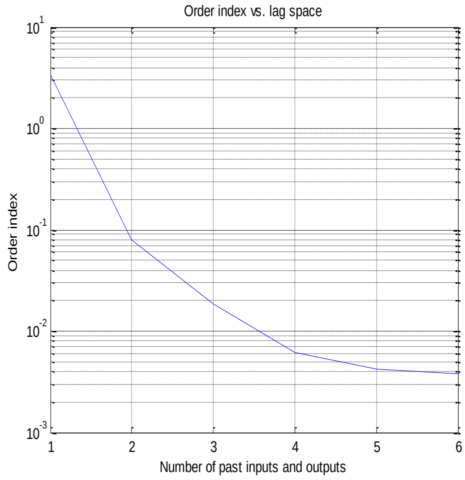

Fig. 4(a). Two Dimensional View of the Order of Index versus Lag Space for tool wear prediction

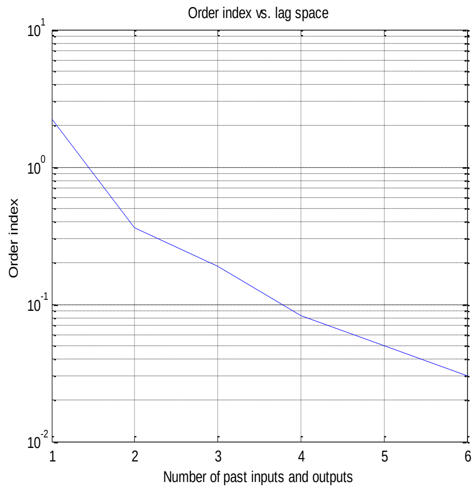

Fig. 4(b). Two Dimensional View of the Order of Index versus Lag Space for surface roughness prediction

The plots of the order index founded on the assessed Lipschit quotients for the input - output pair combinations adjacent to the lag space (number of past inputs and outputs) ranging from 1 to 6 is shown in Fig. 4(a) and 4(b). The plot shows that both the tool wear and surface prediction system can be modeled by a second order model in view of the fact that the slope of the curve is decreases for model orders >= 2.This implies that the suitable number of past inputs and outputs is 2.

The model order selected for training NNARX model structure for tool wear prediction is [2,2 2 2 2,1 1 1 1] and for surface roughness prediction is [2, 4 1 1 1 1, 1 1 1 1]. The model order selected for training NNARMAX model structure for tool wear prediction is [2 ,2 2 2 2, 2 , 1 1 1 1]and for surface roughness prediction is [2 ,4 1 1 1 1, 2, 1 1 1 1 1].The block diagram of NNARX and NNARMAX model structure for tool wear and surface roughness prediction is shown in Fig 5(a) and 5(b) respectively.

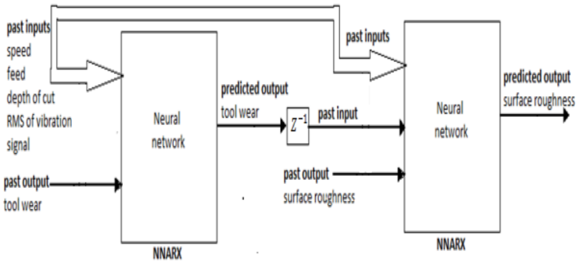

Fig. 5(a). Block diagram of NNARX model structure for tool wear and surface roughness prediction

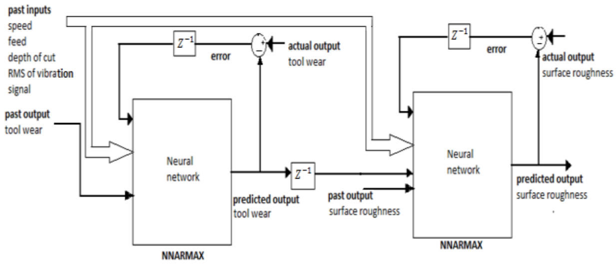

Fig. 5(a). Block diagram of NNARMAX model structure for tool wear and surface roughness prediction

The network architecture for all the selected regressors is constructed with 10 'tanh' units and one linear output unit. The network architecture of NNARX and NNARMAX model structure for tool wear and surface roughness prediction is shown in Fig. 6(a)-6(d).

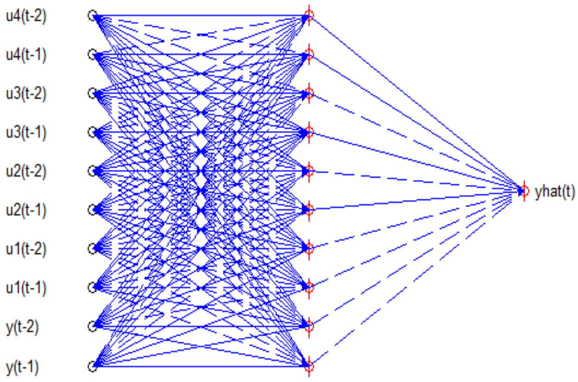

Fig. 6(a). Network architecture of NNARX model structure for tool wear prediction

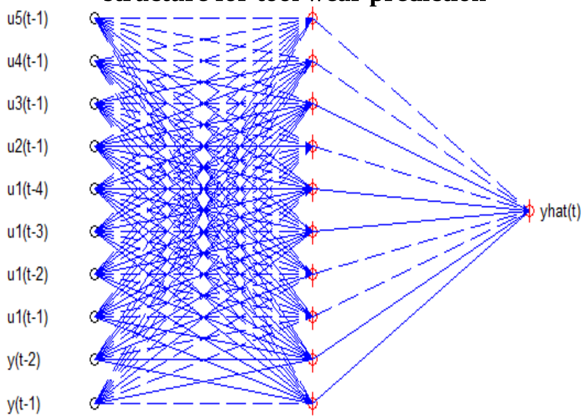

Fig. 6(b). Network architecture of NNARX model structure for surface roughness prediction

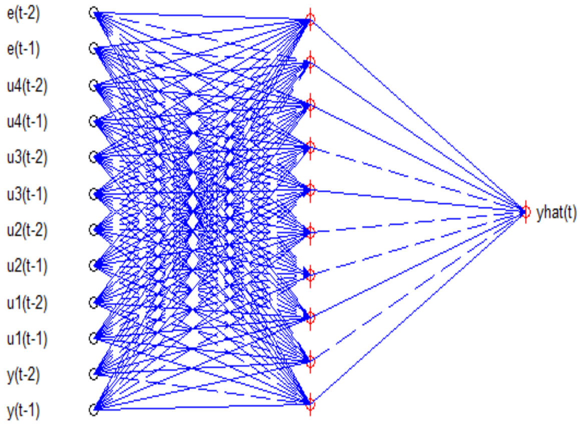

Fig. 6(c). Network architecture of NNARMAX model structure for tool wear prediction

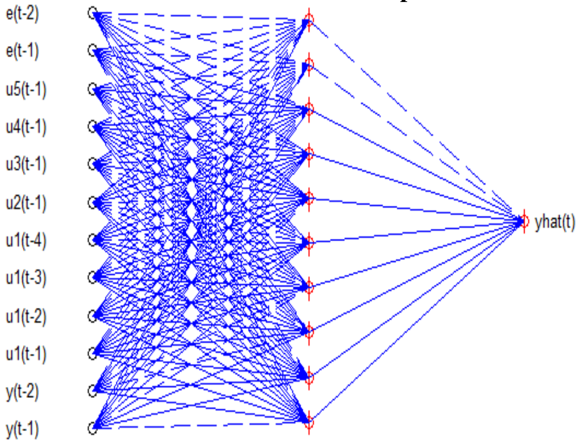

Fig. 6(b). Network architecture of NNARX model structure for surface roughness prediction

C. Model training

The selected model structures are trained using Levenberg-Marquardt algorithm for 200 iterations to generate NNARX models for prediction of tool wear and surface roughness. The fitness response for generated NNARX and NNARMAX models is shown in Fig. 7(a)-7(d).

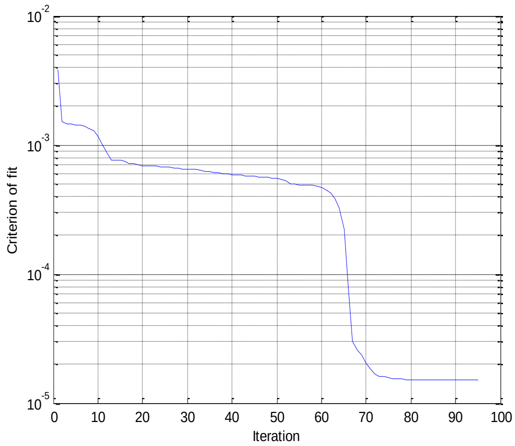

Fig. 7(a). Fitness plot of NNARX model structure for tool wear prediction

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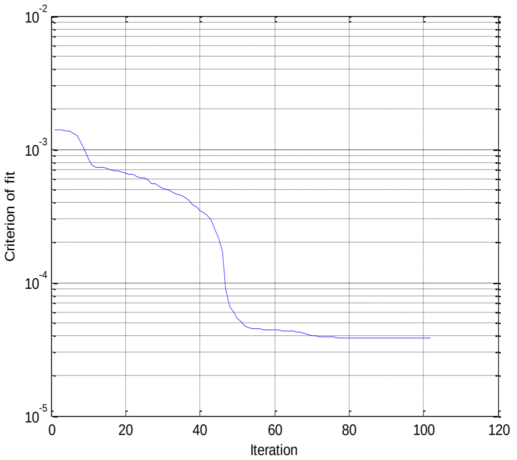

Fig. 7(b). Fitness plot of NNARMAX model structure for tool wear prediction

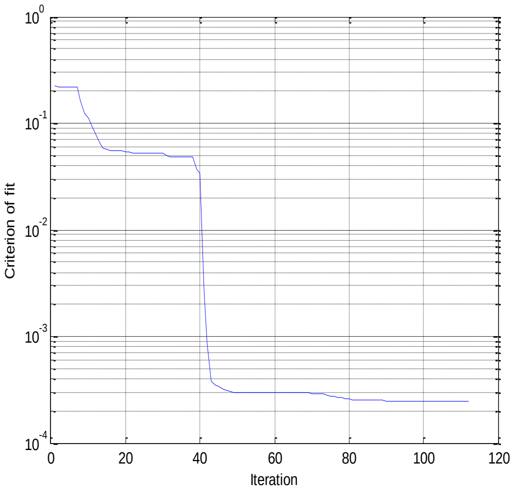

Fig. 7(c). Fitness plot of NNARX model structure for surface roughness prediction

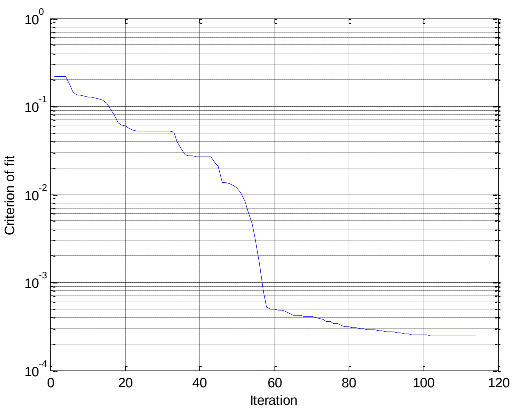

Fig. 7(d). Fitness plot of NNARX model structure for surface roughness prediction

The fitness of NNARX and NNARMAX for tool wear in Fig. 7(a&b) is converged between the 10e-4and 10e-5 orders and for surface roughness prediction Fig. 7(c&d) the fitness is converged between the 10e-3and 10e-4 orders.

D. Model validation

The network trained is validated with the model created with the fresh data set. The one-step ahead prediction, prediction Error, Auto correlation function of prediction error and cross-correlation between prediction error and input and a histogram plots are presented in Fig 8(a) – 11(c).

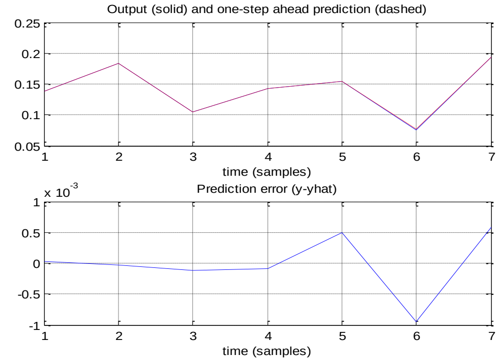

Fig. 8(a). one-step ahead prediction plot of NNARX model structure for tool wear prediction

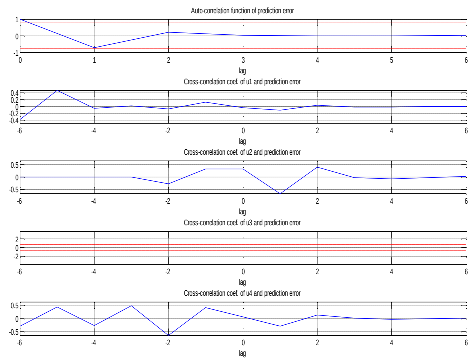

Fig. 8(b). auto and cross correlation plot of NNARX model structure for tool wear prediction

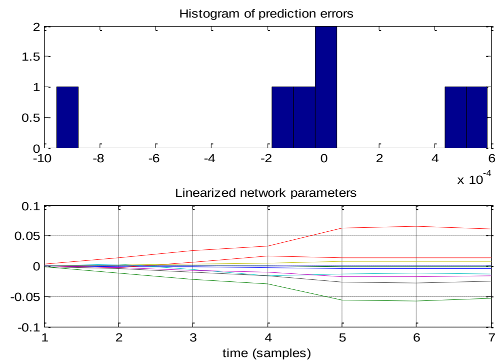

Fig. 8(c). Histogram plot of NNARX model structure for tool wear prediction

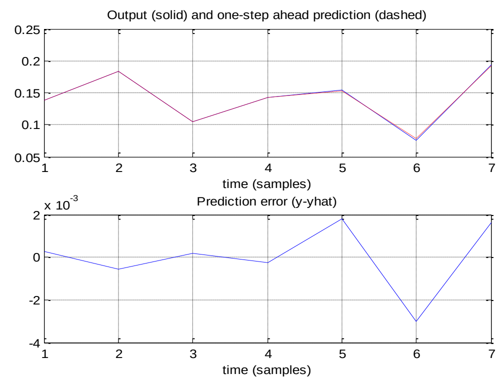

Fig. 9(a). one-step ahead prediction plot of NNARMAX model structure for tool wear prediction

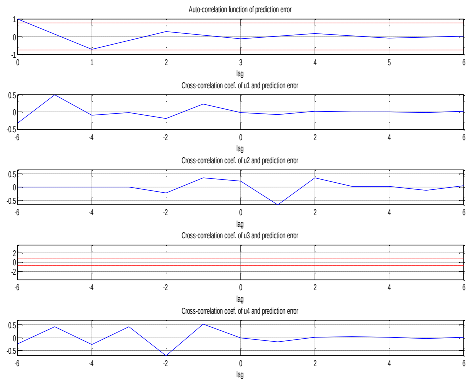

Fig. 9(b). auto and cross correlation plot of NNARMAX model structure for tool wear prediction

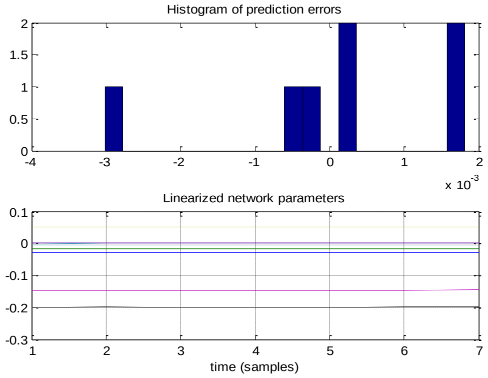

Fig. 9(c). Histogram plot of NNARMAX model structure for tool wear prediction

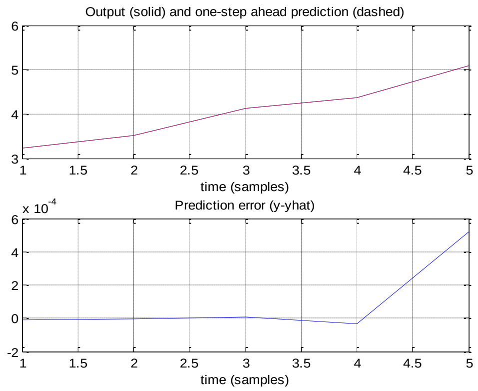

Fig. 10(a). one-step ahead prediction plot of NNARX model structure for surface prediction

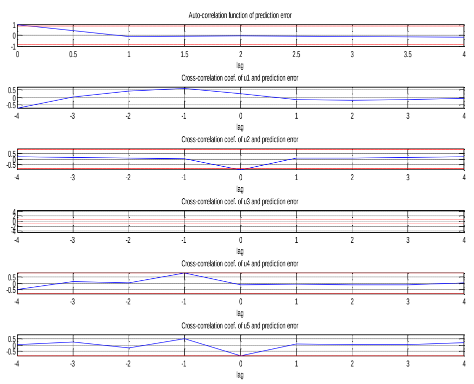

Fig. 10(b). Auto and cross correlation plot of NNARX model structure for surface roughness prediction

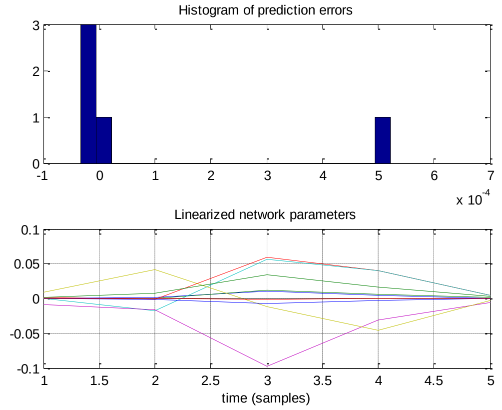

Fig. 10(c). Histogram plot of NNARMAX model structure for surface roughness prediction

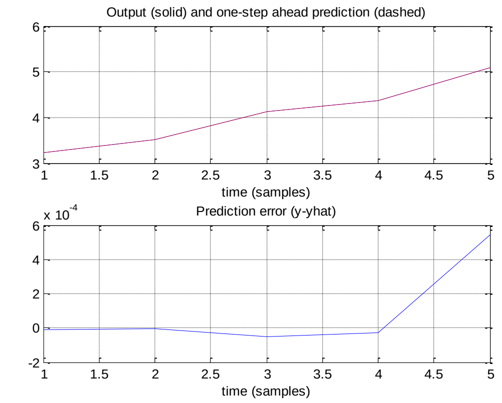

Fig. 11(a). one-step ahead prediction plot of NNARMAX model structure for surface prediction

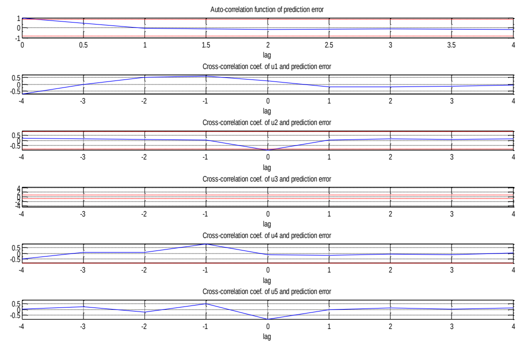

Fig. 11(b). auto and cross correlation plot of NNARMAX model structure for surface roughness prediction

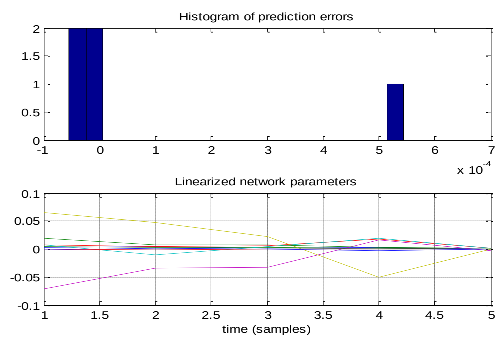

Fig. 11(c). Histogram plot of NNARMAX model structure for surface roughness prediction

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For all the NN based nonlinear autoregressive models, the one-step ahead prediction output overlapped the observed output almost perfectly shown in Fig. 8(a), 9(a), 10(a), 11(a).The Auto correlation function of prediction error and cross-correlation between prediction errors shown in Fig. 8(b), 9(b), 10(b), 11(b) and input delivers that the correlation coefficients almost lie within their standard deviations. A histogram plots in Fig. 8(c), 9(c), 10(c), 11(c) shows the distribution of the prediction errors. Although the prediction errors are distribute to the left and right, the magnitude is so smaller to make much impact.

V. RESULT ANALYSIS

The performance of extracted linear models is compared using comparison criteria Normalized Sum of Squared Error (NSSE) and Final Prediction Error (FPE). The model is said to be accurate when the network trained estimates smallest NSSE and FPE. The NSSE is defined by the following equation

$$NSSE = \frac{SSE}{2n} = \frac{\sum e^2}{2n} \quad (8)$$

Where, the error e is the difference between the observed output and the predicted output.

Akaike's Final Prediction Error (FPE) is defined by the following equation:

$$FPE = v\left(1 + {}^{2d}/_{n}\right) \quad (9)$$

Where, v is the loss function, d is the number of estimated parameters, n is the number of values in the estimated data set. Table 1shows the number of epochs, NSSE and FPE for the NN based nonlinear models.

TABLE II. Performance analysis

	Tool wear prediction		Surface roughness prediction	
	NNARX	NNARMAX	NNARX	NNARMAX
NSSE	1.0834e-07	1.1078e-6	2.7324e-08	3.0023e-08
FPE	0.0026	0.0079	10.8799	14.8974
EPOCHS	95	108	112	114

VI. CONCLUSION

In this paper, auto-regression recurrent neural network model structures NNARX and NNARMAX are trained using Levenberg-Marquardt algorithm to establish CNC machine model for prediction of tool wear and surface roughness. The modeled neural networks are validated with the testing data set. The results of validation is inspected both visually and statistically in order to obtain accurate model. The performance criteria's were used to compare the extracted linear models. Overall, results have shown that NNARX model structure generates accurate model with smallest NSSE and FPE while compared to NNARMAX model structure.

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