Modeling of a Winding Machine Using Non-Parametric Neural Network Model

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Abstract: - In this paper, we present a new methodology for modeling the dynamics of a winding process using a back-propagation neural network model. Herein, a neural network structure, model estimation, and model validation are developed to estimate a nominal linear model around the system operating point. The simulation results show that the estimated model response is satisfactory for industry applications.

Key Word:- Winding Machine, System Identification, Neural Networks, Modeling

1 Introduction

Winding processes are continuous-time systems often used in web conveyance systems, paper and textile making, plastic extrusion, steel rolling and food industries. Their main function is to make the conveyance of a continuous sheet of flexible material as regular as possible. The process can be represented as subsystem of complex industrial processes, known to be multivariable, nonlinear, and time variant. This type of processes is challenging in modeling, identification, and control. Moreover, most process variables (e.g. radius) are not measurable. For the last few decades, researchers have studied how to reduce the computational load associated with the design, analysis of multivariable web conveyance systems[3], sheet and film processes [5], Aluminum industries [7], and steel industries[6]. However, These Multi-Input Multi-output (MIMO) linear models are difficult to apply to a full scale and require complete knowledge of all process physical parameters. With the development of powerfull computational machines and statistical methods, new techniques for the analysis of data have emerged, these methods allow for more accurate and robust modeling of control systems. Neural networks are paticularly suited for modeling ill-defined, non-linear systems [13]. In this paper we use a neural network as a tool for system identification to estimate an ARMA (Auto regressive moving average) winding system model. The paper is organized as follows. Section 2 presents the winding process. The dynamical multivariable process model is formulated in section 3. Section 4 is concerned with the identification study including the experiment design, model estimation, and model validation. Finally, results and conclusion are outlined in section 5.

2 Process Description

Aluminum rod continuous casting and rolling plant at Egypt Alum in Naga Hammadi in Egypt has been in routine operation since 1974. It is designed for continuous aluminum casting with following crystallization and hot rolling of stock into rod (wire) of diameter from 9 to 14 mm. Ready wire is continuously wound onto two-spool winder. The maximum line speed is 10 m/sec. The line has a production capacity of 4.5 tones/hr. The main mechanisms used in this process are: Casting wheel units, shears, a rolling mill, a winder, lubricating and cooling systems. The majority of these mechanisms are equipped with DC electric drives that use thyristor converter cards. Auxiliary mechanisms are driven by induction motors. In 1999 a modernization plan for this line was implwmented to take advantage of new technology in drive systems and electrical controls, including tension control. Phase 1 of the modernization was concerned with the winder section of the plant. The winder is composed of spools, layer, and turret. Spool DC motors are replaced by AC induction motors equipped with frequency converters (FC). A hydraulic cylinder drives the layer movement with a proportional flow control valve instead of DC motor drive. The turret is driven by a bidirection AC induction motor to move the turret to threading, laying, and change positions of each spool. A progammable logic controller (PLC) is used to control the system. The PLC reads the feeding speed using a tachometer, the actual spool motors speed using a pulse encoders with 200p/rev, the actual spool motors current, and the position of the cylinder piston. The PLC sends a speed setpoints to the FC and the cylinder drive. The PLC is also used for the identification of the process with a sampling rate down to 10 ms.

3 Process Model

Several modeling studies have been proposed to describe tension behavior in different winding processes [1,3,4]. Most of those theoretical models are based on the Hoke's equation (1), which expresses the linear relationship between the traction force, δT and the elongation, δe, of an elastic stick.

$$\delta T = \frac{EA}{l}\delta e \tag{1}$$

where:

E Young's modulus (N/mm2)

L distance between feeding and winding sections(m)

A cross section area(mm2)

In winding systems the elastic wire moves from a feeding roll to the winding spool. Consequently, the elongation is time-variant, and can be expressed in terms of linear velocity, as defined by equation (2):

$$\frac{dT}{dt} = \frac{EA}{l}(V_w - V_f) \tag{2}$$

where:

T tension of the wire(N)

Vw winding spool linear speed(m/s)

Vf feeding linear speed(m/s)

The linear velocities of the feeding and winding can be obtained from their motors angular speeds as follows:

$$V_w = \frac{2\pi\omega_{sm}}{60 n_s}\left(\frac{D_{\min}}{2} + id\right)$$

$$V_f = \frac{2\pi\omega_{fm}}{60 n_f}\frac{D_{ml}}{2}$$

where:

ω_{fm} Feeding motor angular speed (rad/min)

ω_{sm} Spool motor angular speed (rad/min)

D_{im} Dim. of last rolling mill (m)

R_i Rad. of spool at layer i (m)

n_f Feeding motor gear box ratio

n_s Spool motor gear box ratio

$D_{\min}$ Dim. of winding spool (m)

d wire dim.(m)

An important characteristic of the winder system described above is the variation of the winding spool radius. The radius variation results in the corresponding variations in the moment of inertia of the winding spool as expressed in equation(3)

$$J_{sm} = M_s \frac{R_i^2}{2} \tag{3}$$

J_{sm} Winding spool inertia (kgm2)

M_s Mass of winding spool (kg)

$$td = J_{sm}\dot{\omega}_{sm} + \beta_{sm}\omega_{sm} + n_s R_i T \tag{4}$$

β_{sm} Friction coefficient of spool

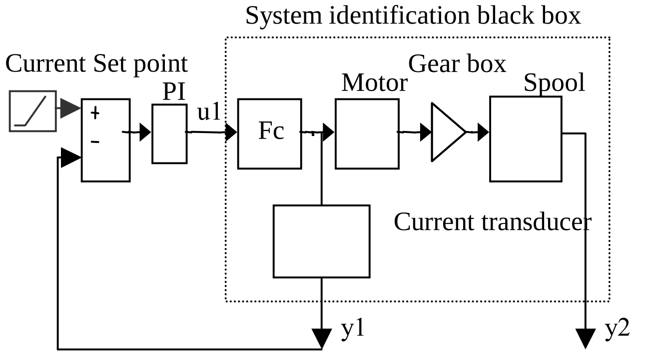


Figure (1) Block diagram of the control system

The theoretical equations, presented so far, show that angular speed ω_{sm} provide a degree of freedom which can be used as a control input. The associated control scheme is referred to as SS (speed speed) model configuration[11]. The drawback of this scheme is that any speed difference between feeding and winding affect the tension and can not be adjusted later due to the breakage of the Aluminum wire. Moreover, the resulting dataset does not contain sufficient sampled data to allow an accurate estimation of the model. This explains the use of spool motor current (I_m) as a system output variable instead of the motor angular speed.

This second strategy consists of using the system identification to find a linear model for the frequency converter and the motor with the load at normal operating conditions. Figure(1) shows the block diagram of the system and the black box for the system identification process.The system consists of single input, two output system. The input is the desired spool winding speed $u_1 = \omega_{sm}^*$ and the two ouputs are the motor current $y_1 = I_m$ and the actual speed $y_2 = \omega_{sm}$.

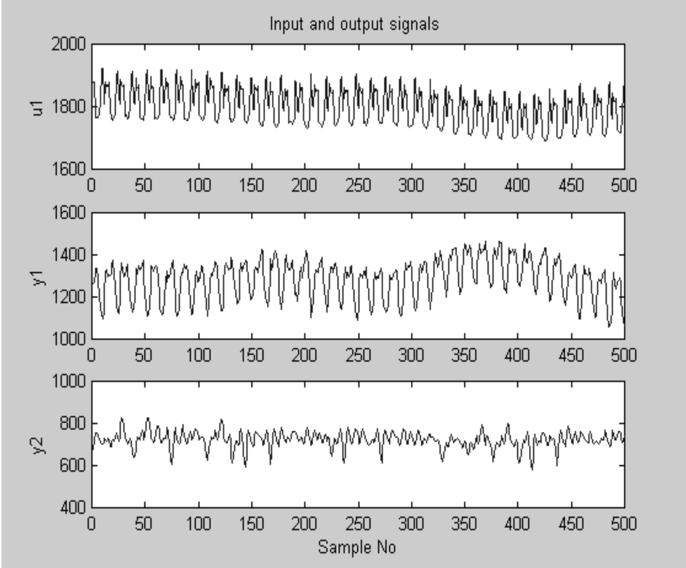


Figure (2) Input and output data

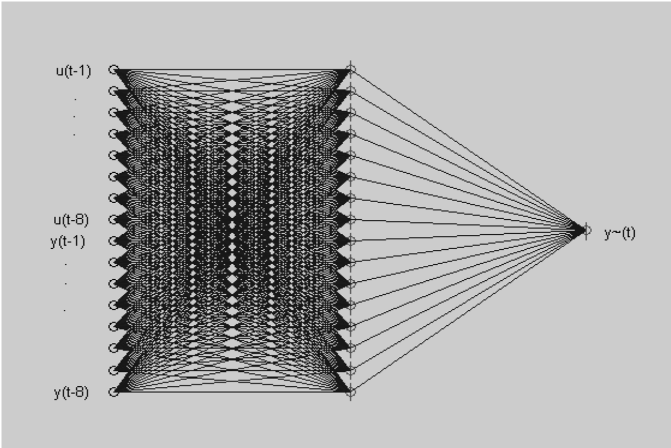


Figure (3) The network used

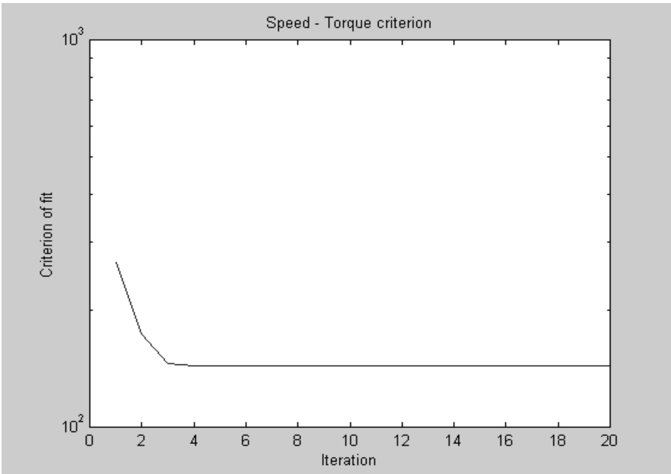


Figure (4) Criterion against iterations for y1

4 Neural Network in Modeling the Winding Machine

In this section, a multivariable online(on normal operating conditions) system identification of the winding process is given. A pseudo random binary sequence is superimposed to the speed set point at nominal operating conditions in order to overcome the problems of purely feedback systems[14].The sampling rate is set to (Ts = 40ms), and the data set size is 1000 sample. Figure(2) shows the data set of the experiment for 500 sample points.

After acquiring the data, the next step is to select a model structure. This issue is more difficult in the nonlinear compared to the linear systems. Not only it is necessary to choose the set of regressors but also a network architecture is required. The idea is to select the regressors based on inspiration from linear system identification and then determine the best posible network achitecture with the given regressors as inputs[12]. $\phi(t)$ is a vector containing the regressors, The regressor vector:

$$\phi(t) = [y(t-1) \ \ldots \ y(t-na) \ \ u(t-1) \ \ldots \ u(t-nb)]^T$$

After some trials the neural network ARMA model is used with nb=na=8 given as:

$$y(k) = \sum_{i=1}^{nb} b_i u_1(k-\tau_i) - \sum_{i=1}^{na} a_i y_i(k-\tau_i)$$

where nb, na are the number of regressors for input and output respectively.The input layer consists of 16 element. One hidden layer is used that consists of 16 neuron. The decision function is purly linear as shown in Figure (3).

Figures(4) and (5) show the fitting criterion ploted against the number of iterations. The Actual and estimated data for each output is ploted in Figures(6) and (7). The auto correlation and cross correlations of as compared to inputs is ploted in Figures(8) and (9).

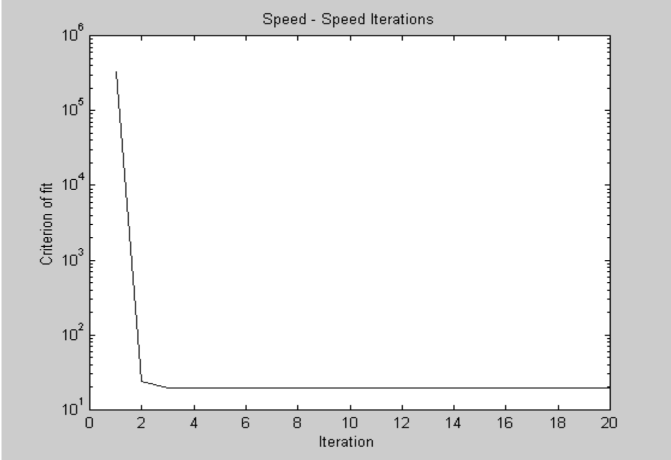


Figure (5) Criterion against iterations for y2

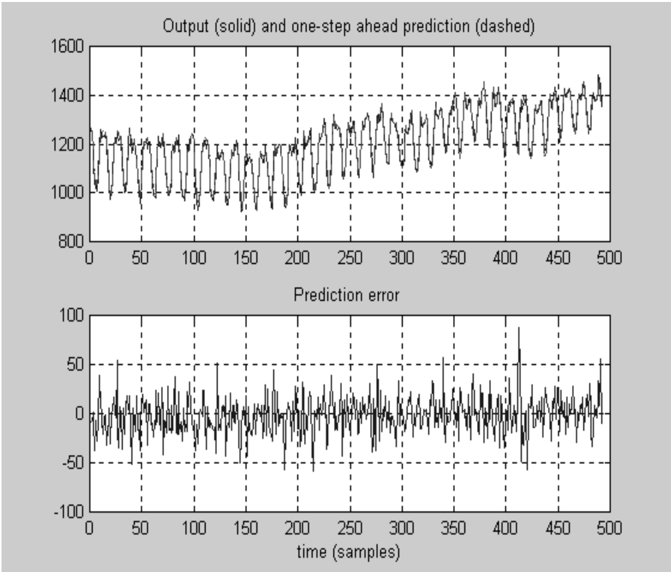
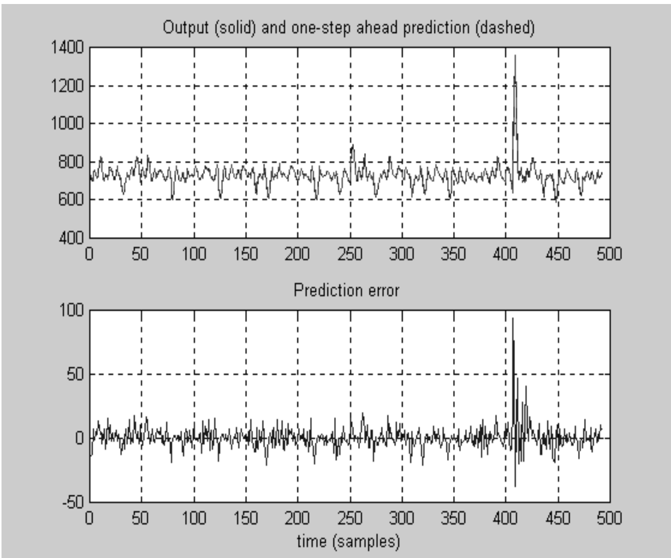


Fig (6) Actual versus estimated torque



Fig(7) Actual versus Estimated speed

5 Results and Conclusion

In this paper, we presented a neural network model for the winding machine. The presented results show that the obtained models are acceptable for industerial objectives. The auto corrlation of errors and the cross corrlation of error and input are within the confidence levels. Hence the Neural netwok back propagation method is an efficient apprcah for modeling the dynamics of winding machines when nonlinearlies are in presence.

Acknowledgemnet

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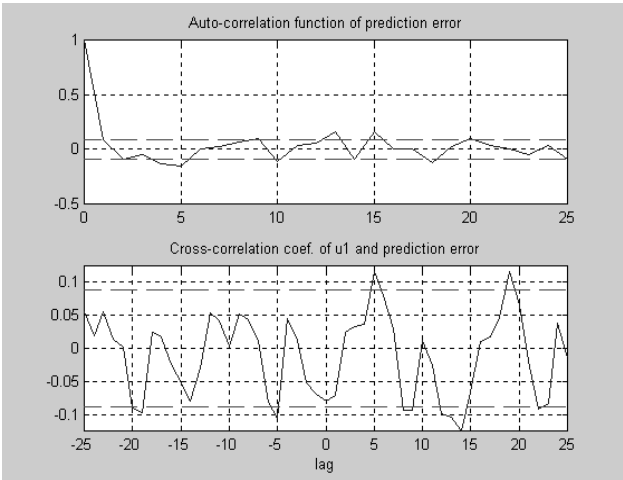

Fig. (8) Torque model validation

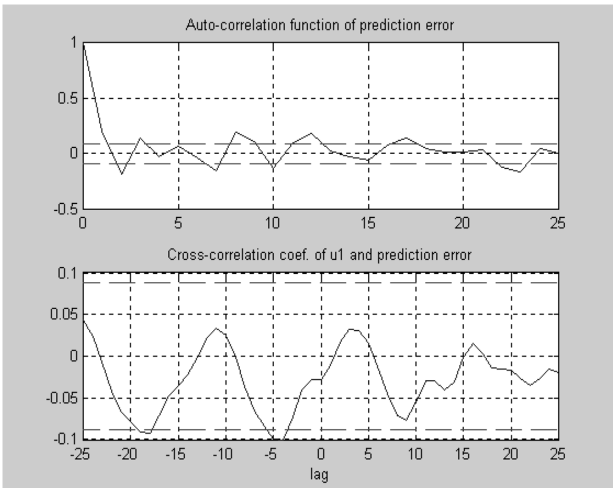

Fig (9) Speed model validation