Modeling of a Winding Machine Using Genetic Programming

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Abstract- In this paper, we present a new method for modeling the dynamics of a winding process using genetic programming and compare it with traditional modeling approaches. Data sets collected from an actual industrial process was used throughout the experiments. Three models were developed to describe the dynamics of the winding process. Experimental results are presented and discussed.

1 Introduction

Modeling of physical systems is a complex task represents a challenge for both system theory and applications. A typical example of physical nonlinear systems is a winding processes. Winding systems are major components in a wide variety of industrial plans. For example, rolling mills in steel industry [1, 2], plants involving web conveyance [3, 4, 5] including coating, paper making and polymer film extrusion processes. In the last few decades, researcher have studied how to reduce the computational load associated with the design, analysis and implementation of control techniques in the web conveyance system [3], in sheet and film processes [5], in aluminum industries [6], and in steel industries [7].

Currently there is a growing interest of using Evolutionary Algorithms (EAs) to assist building a reasonable model structure for physical nonlinear systems. Few of these algorithms are Genetic Algorithms (GAs) [8, 9], Evolutionary Strategies (ESs) [10] and Genetic Programming (GP) [11, 12]. In [13, 14], Genetic Algorithms and Evolutionary strategies have been used in the parameter identification process of nonlinear systems with various degrees of complexity. In [15], GAs have been successfully used to provide an automatic methodology for generating model structure for nonlinear systems based the Volterra time-series and least-square estimation (LSE) was used to identify the model parameters. Using this methodology an efficient model structure was build to model the dynamics of the automotive engine.

Evolutionary Algorithms (EA) have been used to search complex spaces and exploit potential maxima/minima in a variety of industrial applications. In this paper, we develop various model structures for a winding machine using traditional model building techniques. We also explore the advantages of using GP to build a suitable model structure for a winding machine. A comparison between traditional techniques and the GP based approach using the error minimization criterion is provided.

2 Process Description

Industrial winding processes can be described by continuous differential equations with strong coupling between the winding components and the strip. The main role of a winding process is to control the web conveyance to avoid the effects of friction and sliding, as well as the problem of material distortion. Material distortion failure may slow down the production systems considerably, thus reducing the system productivity and damaging the quality of the final product.

The winding pilot plant introduced, in this study, represents a subsystem often met in several and different industrial processes as rolling mills in metallurgy and web conveyance system in paper industry. Its main function is to control the linear speed, the thickness or/and the tension of a strip.

The machine consists of three sections. The first section is the casting section, which casts the molten aluminum into a rod of square section area of $10 \times 10cm^2$. The second section is the rolling section which rolls the rod into a wire of a circular section area of $9mm$ diameter through six rolling mills driven by a DC motor via a gear reduction chain. The angular speed of the rolling mill motor is measured by a taco-generator. The third section is the winding section which winds the rolled wire into alternative two vertical spools located in a turret. Each spool is coupled with an AC induction motor via a gear reduction. The turret is coupled by AC induction motor and moves in two directions.

A Programmable Logic Controller (PLC) is used to control both tension and position of the wire. The PLC is used also to take measurements that helps in process identification with a sampling frequency of $10ms$.

3 System Equations

Several modeling studies have been proposed to describe tension behavior in different winding process [1, 3, 4]. Most of those theoretical models are based on the Hooke's equation given as follows:

$$\frac{dT}{dt} = \frac{EA}{l}(V_w - V_f) \quad (1)$$

where:

T	tension of the wire	(N)
V_w	winding spool linear speed	(m/s)
V_f	feeding linear speed	(m/s)
E	Young's modulus of the wire	(N/mm^2)
l	distance between feeding and winding sections	(m)
A	cross section of the wire	(mm^2)

In our winding system:

$$V_w = \frac{2\pi w_{sm}}{60 n_s} R_i \quad (2)$$

$$V_f = \frac{2\pi w_{fm}}{60 n_f} \frac{D_{ml}}{2} \quad (3)$$

where:

w_{fm}	feeding motor angular speed	(rad/min)
w_{sm}	spool motor angular speed	(rad/min)
D_{lm}	dim. of last rolling mill	(m)
R_i	rad. of spool at later i	(m)
n_f	feeding motor gear box ratio	
n_s	spool motor gear box ratio	

$$R_i = (\frac{D_{min}}{2} + id) \quad (4)$$

D_{min}	dim. of winding spool	(m)
d	wire dim.	(m)

An important characteristic of the winding system described above is the variation of the winding spool radius. The radius variations results in a corresponding variations in the moment of inertia of the winding spool as follows:

$$J_w = M_s \frac{{R_L}^2}{2} \quad (5)$$

J_w	winding spool inertia	(kgm^2)
M_s	mass of winding spool	(kg)

4 Experiments

In this section, we provide three types of models for a winding machine. For each model a set of 500 input values was generated and saved, the values of which were a pseudo random sequence. This input sequence was then applied to the winding system to obtain the corresponding system output values.

In system identification and parameter estimation we used to have a test sequence different from that one used for training. The test sequence is the sequence which the system will deal with after training. This statement is also true for different field of science. The difference in system identification is, we need to use a training sequence have more excitation than the testing sequence thus the values of the estimated system parameters be robust in certain domain of operation. The robustness is in the sense of accuracy.

Therefore, a second sequence of 500 input values is generated from values of another pseudo random sequence and is applied to the winding system as well as to the selected model to check the model performance. This new sequence is not part of the training data.

The developed model set for each example was employed based on some priori knowledge that engineer can gain from experiments. This knowledge may account for the model order or the number of system states.

4.1 MA-Linear Winding Machine Model

Traditional modeling and identification approaches provide us with models that help in solving system identification problems. One of the famous models is the Moving Average (MA) model. The MA model for a Two-Input Single-Output (MISO) system can be described in the following equation.

$$y(k) = \sum_{i=1}^{n} a_i u_1(k - \tau_i) + \sum_{i=1}^{n} b_i u_2(k - \tau_i) \quad (6)$$

The system inputs are u_1 and u_2 respectively. The value of n is referred to as the "truncation length" of the model. The criterion of evaluation (i.e. performance) was defined as the Mean Square Error (MSE) over the training and testing data.

In the problem under consideration we developed a moving average model with a truncation length of three for the winding machine. The selected model structure is given by the following equation:

$$\begin{aligned} \hat{y}(k) &= a_1 u_1(k) + a_2 u_1(k-1) + a_3 u_1(k-2) \\ &+ b_1 u_2(k) + b_2 u_2(k-1) + b_3 u_2(k-2) \end{aligned} \quad (7)$$

Figure 1(a) and 2(a) show the actual winding machine response compared to the developed MA model estimated response in both the training and testing cases. Figure 1(b) and 2(b) show the prediction error in both the training and testing cases. It can be seen that the error in training case is much better than the one in the testing case. The values of the model parameters computed using Least Square Estimation (LSE) are presented in Table 1. The values of the calculated MSE in both training and testing cases are given in Table 3.

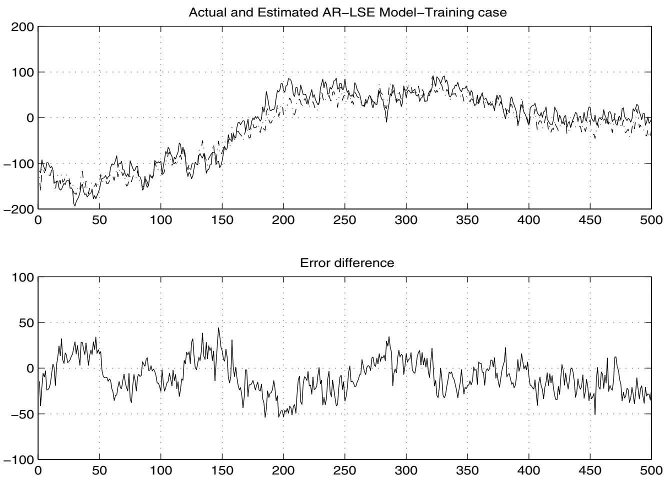

Figure 1: (a) Actual and estimated responses-Training Case; (b) Error difference between the actual and estimated responses

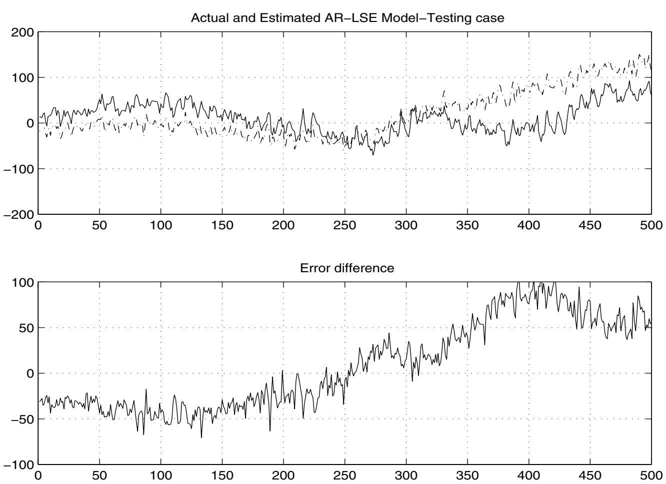

Figure 2: (a) Actual and estimated responses-Testing Case; (b) Error difference between the actual and estimated responses

a_1	-2.5169	a_2	-0.2371	a_3	0.9603
b_1	-0.3284	b_2	-0.5033	b_3	-0.3229

Table 1: Values of the a's and the b's parameters of the AR3 model

4.2 ARMA-Linear Winding Machine Model

In this section, we model the dynamics of the winding machine using the Auto-Regressive Moving Average (ARMA) model. The ARMA model for a Two-Input Single-Output (MISO) system can be described by the following equation:

$$\begin{aligned} y(k) &= \sum_{i=1}^{n} a_i u_1(k-\tau_i) + \sum_{i=1}^{n} b_i u_2(k-\tau_i) \\ &+ \sum_{i=1}^{n} c_i y(k-\tau_i) \end{aligned} \tag{8}$$

$y_1(k-\tau_i)$ represents system output response at instant τ_i. $i \in 1, 2, \ldots n$. The developed model structure is given by the following equation:

$$\begin{aligned} \hat{y}(k) &= a_1 u_1(k) + a_2 u_1(k-1) + a_3 u_1(k-2) \\ &+ b_1 u_2(k) + b_2 u_2(k-1) + b_3 u_2(k-2) \\ &+ c_1 y(k-1) + c_2 y(k-2) + c_3 y(k-3) \end{aligned} \tag{9}$$

Figure 3(a) and 4(a) show the actual winding machine response compared to the developed ARMA model estimated response in both training and testing cases. The prediction errors in the training and testing cases of the winding machine are shown in Figure 3(b) and 4(b). The error in both training and testing cases were significantly improved over the MA model. The values

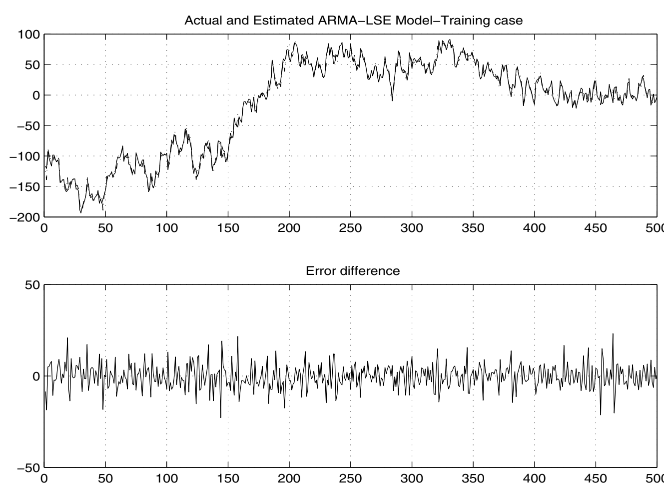

Figure 3: (a) Actual and Estimated responses-Training Case; (b) Error difference between the actual and estimated responses

of the model parameters computed using Least Square Estimation (LSE) are presented in Table 2. The values of the MSE in both training and testing cases are given in Table 3.

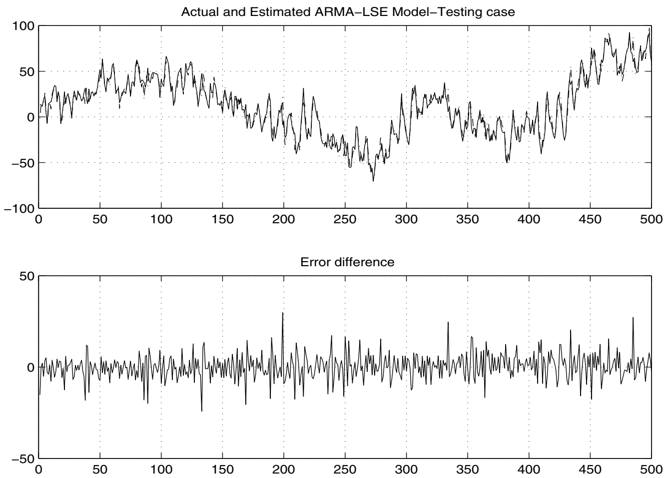

Figure 4: (a) Actual and Estimated responses-Testing Case; (b) Error difference between the actual and estimated responses

a_1	-2.8675	a_2	1.5076	a_3	1.3136
b_1	0.0012	b_2	-0.0140	b_3	-0.0142
c_1	0.6774	c_2	0.1703	c_3	0.1244

Table 2: Values of the a's, b's and the c's parameters of the ARMA3 model

4.3 GP Winding Machine Model

In this section, GP is used to build a suitable model structure of the winding machine. The terminal set used in our case consists of nine input variables and one ephemeral random constant

$$\begin{aligned} T &= \{u_1(k), u_1(k-1), u_1(k-2), \\ &\quad u_2(k), u_2(k-1), u_2(k-2), \\ &\quad y_1(k-1), y_1(k-2), y_1(k-3), R\} \end{aligned} \tag{10}$$

The ephemeral random constant range was defined as [-0.005,0.005]. The function set is defined as:

$$F = \{+, -, *\}$$

The initial population was generated using the ramped half-and-half method. The maximum depth of new individuals was set to be 6, while, the maximum depth of an individual after crossover was 17. We used the normal crossover and mutation operators. We ran GP for 50 generations with a population size of 15000 and crossover and mutation probabilities of 0.7, 0.3, respectively. The best model was found after 49 generation.

The best model that describes the dynamics of the winding machine using GP is presented below:

$$\hat{y}(k) = -3u_1(k) + 3u_2(k) + 0.9953y_1(k-1) + 0.00013 \tag{11}$$

In Figure 5(a) and 6(a), the actual winding machine output and the generated output from equation (10) in presented in training and testing cases. In Figure 5(b) and 6(b), the error differences between the actual and estimated responses are shown. The mean square error in both the training and testing cases is given in Table 3.

From the developed models, we can see, the ARMA model provided a less modeling error than other models. The GP based model is the simplest developed model structure. The modeling error in the case of GP is still acceptable. In this type of application, we are more likely to prefer simpler model structure to reduce the complexity and the cost of design.

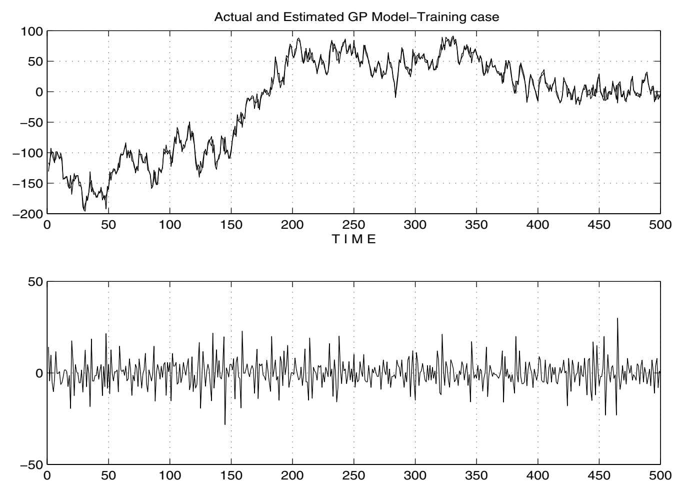

Figure 5: (a) Actual and Estimated responses-Training Case; (b) Error difference between the actual and estimated responses

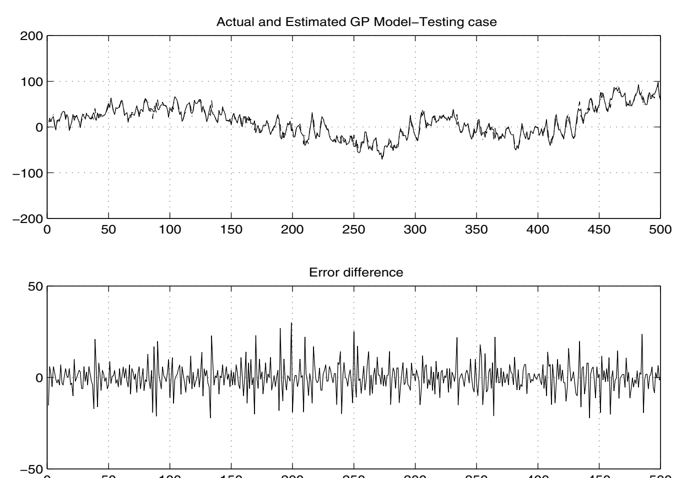

Figure 6: (a) Actual and Estimated responses-Testing Case; (b) Error difference between the actual and estimated responses

AR3	Case	MSE
	Training	436.3556
	Testing	2315.20
ARMA3	Case	MSE
	Training	44.8663
	Testing	48.2155
GP	Case	MSE
	Training	56.6132
	Testing	60.4261

Table 3: Mean square error using three different models

5 Discussion

In this paper, we have presented three methods for modeling a wire winding machine. These models include traditional statistical techniques like MA and ARMA models, and also an EA-based technique, GP. Based upon the training and testing results of these models, we can conclude the following:

- The ARMA model provided the least modeling error as compared to the other models. This is predictable since the ARMA technique uses both previous input and output values to predict new outputs. Thus, it has the capability of building a model that is likely to perform quite well.
- The GP based model is the simplest developed model structure with an acceptable performance. It should be noted that, in this type of applications, we are more interested in a simpler model structure with some acceptable error to reduce the complexity and the cost of the design.

Thus, our first observations about using GP for modeling nonlinear systems are very promising, and we feel that, with the proper evaluation function and tuning of the GP system, we can get better results.

6 Conclusions and Future Work

In this paper, we presented the results of applying three modeling techniques to the wire winding problem. The ARMA model produced the least MSE. GP was capable of discovering a simple model structure with acceptable MSE. From our point of view, GP has an advantage over ARMA since the evaluation function of the GP controls the features of the discovered models. Thus, simpler and accurate models can be discovered using GP by adapting the evaluation function to the needs of the application.

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