Study of the Angular Positioning of a Rotating Object with Neural Model Reference Control

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Abstract - The study in the paper is placed in the broad context of research for increasing the efficiency of motion control. The purpose of the paper is to make a comparative analysis of the neural model reference control with the linear control for angular positioning of mechanical parts. The structure of the neural model reference control system and its design are presented. Transient characteristics obtained are compared from the point of view of their control efficiency criteria. The differences in performance criteria between the control methods studied are small.

Keywords: Motion control, linear control, deep learning, neural network model reference control, neural identification.
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1. Introduction

The paper presents the results of a research study in the field of motion control applied to positioning of an object with known moment of inertia, in the rotational motion around an axis. The purpose of the work is the analysis of methods for positioning based on neural network model reference control, compared with the conventional linear control method. The significance of the study is that it shows the efficiency of these methods, compared to each other. An example of position control of a vehicle subjected to unknown conditions using sliding mode and optimal control is presented in [1]. In [2] a study on the optimization of motion control in automatic machines, robots and multi-body systems is presented. In [3] some examples of the application of intelligent control techniques in motion control are presented. Conventional position control is done using as actuators electric machines, driven by cascade control systems, with internal current control loop, over which overlap a speed control loop and an external position control loop. This is the natural way for control. The current and speed control loops must respond as quickly as possible. And the control of the position must be done asymptotically, aperiodically with zero overshoot. In this paper, a heavy object is taken into consideration. The actuator inertia is not taken in consideration, because it has a very small time constant, compared to the moment of inertia of the object. Neural networks bring learning and training in control. The paper presents, in section 2, preliminary information related to the mathematical model of positioning process, the conventional linear position control, its transient characteristics and performance criteria. The third section presents the position control method based on neural network model reference control. A neural model of the process is developed based on neural identification of the motion model, testing and validation. The neural controller is also trained. The methods were modelled and simulated in Matlab/Simulink. The results that can be obtained with these method are presented in section 4. The characteristics obtained by simulations are compared, analyzed, and discussed. The main contribution of the paper can be summarized as a comparative analysis of two position control methods: conventional linear control and neural model reference control, with application in the particular case of a heavy object in rotational motion at variable angular positions. The behavior of the system with neural predictive control is analyzed. The results are compared with those obtained in the case of linear control. The analyzed methods ensure good performance criteria: zero control error, reduced response time, zero overshoot. The performance criteria differences between the control methods are small.

2. Preliminaries

2.1. Motion process

It is considered to adjust the position θ of the object with the moment of inertia J in the rotational motion with angular velocity ω. The rotational movement takes place in the presence of friction. The equations of motion are:

$$\begin{aligned} J\frac{d\omega}{dt} &= M - k_f\omega \\ \frac{d\theta}{dt} &= \omega \end{aligned} \tag{1}$$

where M is mechanical torque and k_f is coefficient of friction. A speed sensor is used, considered as a first-order delay element with a time constant $T_{T\omega}$. The values of the parameters considered are: J = 450 kg.m^2, k_f = 120 kg.m^2/s and $T_{T\omega}$ = 0.12 s, and maximum values: M_m = 1000 Nm, ω_m = 0.3 rad/s and θ_m = 180°.

2.2. Linear Control System

A closed-loop, cascading position control system is selected, as the reference control system. In this system, the speed in the inner loop and the position in the outer loop are adjusted. This mode of adjustment is a natural one. The internal speed control loop responds faster. The position control loop has an asymptotic aperiodic behavior. The process has a high mechanical time constant J/k_f and a low time constant $T_{T\omega}$ that of the sensor. Taking into account this model, the speed controller is dimensioned with the symmetric criterion in Kessler's variant [4], which recommends a PI speed controller, with the parameters: $K_{R\omega} = J/T_{T\omega}/2 = 1.875, T_{R\omega} = 4.T_{T\omega} = 0.48$.

Since the controlled process has a purely integrative character, a position regulator of proportional type is chosen, with gain coefficient $K_{R\theta} = 0.8$.

The block diagram of the position linear control system is shown in Fig. 1, where θ is denoted with *p*.

The step response of the position control system is shown in Fig. 2 and the speed characteristic is presented in Fig. 3.

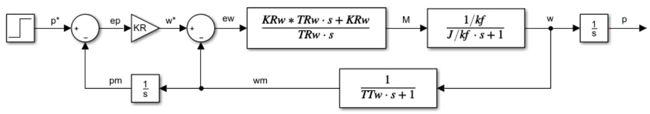

Fig. 1 Linear position control system.

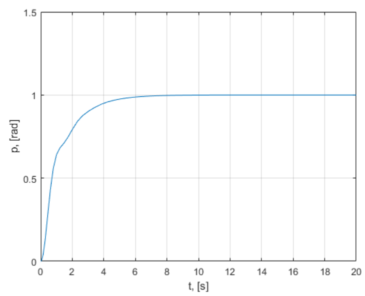

Fig. 2 The step response of the position control system.

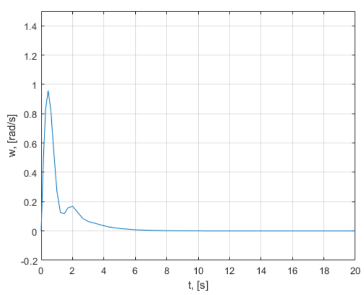

Fig. 3 Speed characteristic.

It is observed that the position response time is short, of the order of 6 seconds, compared to the high moment of inertia of object in motion. So, the object rotates at an angle of 57.2° in 6 seconds.

3. Neural model reference control system

3.1 Structure of the control system

According to the theory in [5, 6, 7, 8] the neural model reference control system can be used in control of mechanical parts. Physical variables of the process *M* and θ become variables of control system. The torque *M* is the control input of process and θ is the output variable of process. The reference variable is position reference θ*. The neural model reference control system is designed based on previous experiments [9, 10, 11].

The neural model reference control system architecture, presented in Fig. 4, uses two neural networks: a controller network and a motion process model network. The neural controller calculates the control input - the torque *M*. The motion process model is identified first, and then the controller is trained so that the position θ, denoted in figure with *p*, as process output, follows the reference model output.

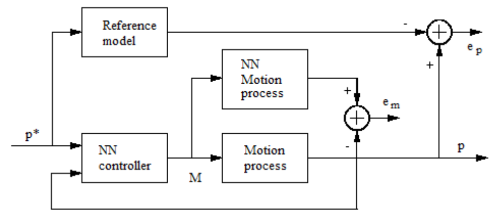

Fig. 4 Neural model reference control structure

There are three sets of controller inputs: delayed reference inputs (position reference θ*, denoted with *p**), delayed controller outputs (torque reference *M*) and delayed motion process outputs (position θ). For each of these inputs, the number of delayed values to use may be selected. Typically, the number of delays increases with the order of the process. In this case we may considered that the motion process is of the second order. And, if the sensor dynamic is taken in consideration, the process is of the third order. The first step in model predictive control is the object motion model identification, the determination of the neural network object motion model. In the second step the object motion model is used by the control system for developing the neural controller. Each network has two layers, and the number of neurons to use in the hidden layers may be selected.

3.2 Neural Identification

The neural identification of object motion model, or the system from toque *M* to measured position θ_m denoted with p_m, is made by training a neural network to represent the forward dynamics of the object motion model. The modelling error e_m between the object motion model output and the neural network model output is used as the neural network training variable. The structure of neural identification of the object motion model is presented in Fig. 5.

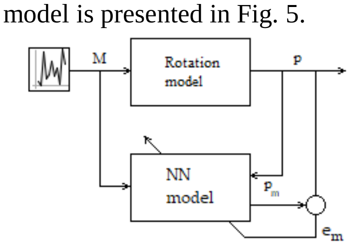

Fig. 5 The block diagram of neural identification

At identification, an uniformly distributed random signal, repeatable for a chosen period, with amplitude in the value range of the control input variable value *M* is used. The neural network object motion model uses previous inputs *M*(*t*) and previous position outputs θ(*t*) to predict future values of the object motion model output θ(*t*+1). The structure of the neural model of the object motion model is given in Fig. 6.

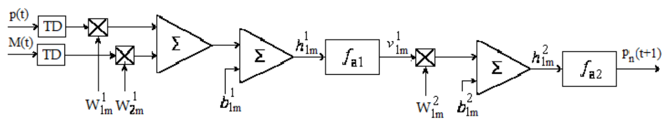

Fig. 6 The bloc diagram of the structure of the neural model

The neural network has two layers. The input variables are time delayed, with the blocks TD, to obtain values at previous times. It uses the position $\theta(t)$ and torque $M(t)$ values at moment t and gives the estimated value of the position $\theta(t+1)$ at moment $t+1$. The neural network has a hidden layer with weight matrices $W_{1m}{}^1$ and $W_{2m}{}^1$ and a bias vector $b_{1m}{}^1$ and an output layer with a weight matrix $W_{1m}{}^2$ and a bias vector $b_{1m}{}^2$. The activation function from the first layer is the hyperbolic tangent (sigmoid) function f_{a1} and for the second layer is the linear function f_{a2}. The relationship that describe the neural network is:

$$p_n(t+1) = f_{a2}(b^2_{1m} + W^2_{1m}.f_{a1}(b^1_{1m} + W^1_{1m}TD(p(t)) + W^1_{2m}TD(M^*(t))) \quad (8)$$

The neural network may be trained offline using data collected from the operation of the rotating process. The optimum structure of the neural network is chosen after some iterative trainings.

3.3 Neural Controller

A neural network is also used to implement the controller. The block diagram of the neural controller structure is presented in Fig. 7.

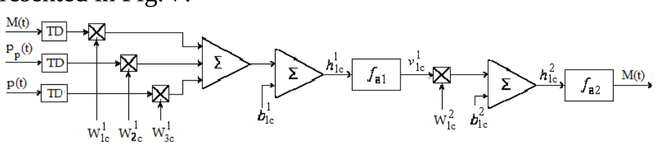

Fig. 7 The block diagram of the structure of the neural controller

The neural controller network has two layers. The input variables are time delayed, with the blocks TD, to obtain values at previous times. It uses the position $\theta(t)$, denoted $p(t)$, the prescribed position $\theta^*(t)$, denoted $p_p(t)$, and torque $M(t)$ values at moment t and gives the value of the torque reference $M(t+1)$ at moment $t+1$. The neural network of the controller has a hidden layer with weight matrices $W_{1c}{}^1$ and $W_{2c}{}^1$ and a bias vector $b_{1c}{}^1$ and an output layer with a weight matrix $W_{1c}{}^2$ and a bias vector $b_{1c}{}^2$. The activation function from the first layer is the hyperbolic tangent (sigmoid) function f_{a1} and for the second layer is the linear function f_{a2}. The relationship that describe the neural network is:

$$M(t+1) = f_{a2}(b^2_{1c} + W^2_{1c}.f_{a1}(b^1_{1c} + W^1_{3c}TD(p(t)) + W^1_{2c}TD(p_p(t)) + W^1_{1m}TD(M(t))) \quad (9)$$

The control structure contains the reference model which has the reference input $\theta^*(t)$ to obtain the position error e_p. The controller block determines the values of M that minimizes e_p, as the torque command. The desired response is given by the reference position characteristic.

The neural network model reference control structure was implemented in Simulink, using deep learning toolbox software.

4. Results

4.1 Neural Model Identification

The characteristics obtained for neural model training are presented bellow. The size of hidden layer is 10, the sampling interval is 0.05 s, number delayed process inputs 2, number delayed process output 2, training samples 10000, maximum process input of the random signal 120 Nm, minimum process input of the random signal -120 Nm, maximum interval value of the random signal 2 s, minimum interval value of the random signal 0.1 s, training epochs 300, training method Levenberg-Marquardt. The training is using input-output training data and it has a validation phase with validation data and a test phase with testing data. The neural network model training parameters are presented in Fig. 7.

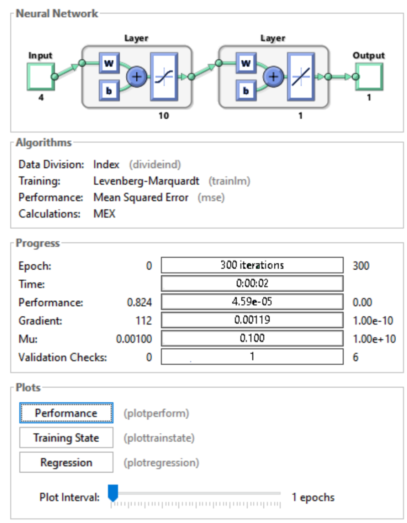

Fig. 7 Neural network parameters.

The generated data before training the neural model of the motion process, the training data of neural network model, the testing data of neural network model, the neural model validation, the performance of neural model identification, the training state of neural model identification data and the regression in neural model identication are presented respectively in Fig. 8, 9, 10, 11, 12, 13 and 14.

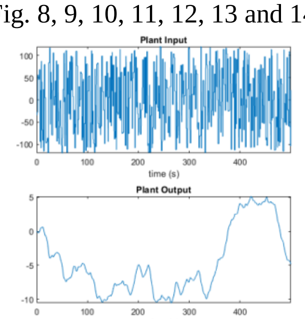

Fig. 8 The training data set of the motion process input and output

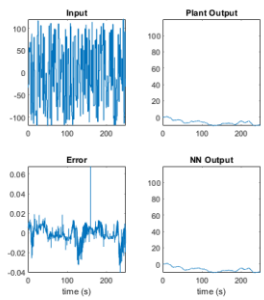

Fig. 9 The training data of neural network model

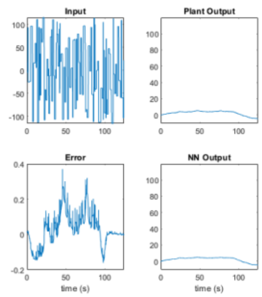

Fig. 10 The testing data

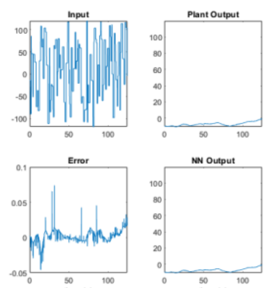

Fig. 11 The validation data

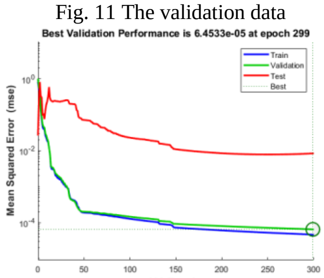

Fig. 12 The performance of neural model identification

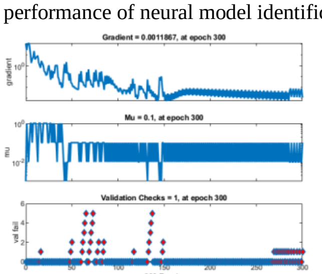

Fig. 13 The training state of neural model identification

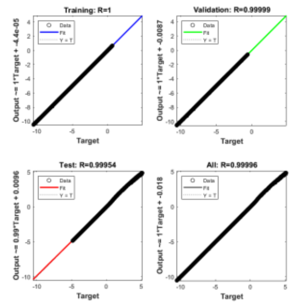

Fig. 14 Regression in neural model identification

4.2 Neural Controller Design

The characteristics obtained for neural controller training are presented bellow. The size of hidden layer is 13, the sampling interval is 0.05 s, number delayed reference inputs 2, number delayed controller outputs 1, number delayed process output 2, maximum reference value 3.14 rad, minimum reference value -3.14 rad, maximum interval value of random signal 2 s, minimum interval value 0.1 s, number of controller samples 6000, controller training epochs 10, controller training segments 30, training method Levenberg-Marquardt. The neural network controller training parameters are presented in Fig. 13.

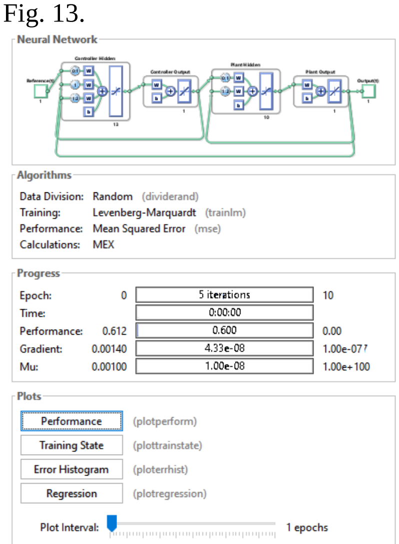

Fig. 13 Neural network controller training parameters.

The input-output data for neural network model reference controller, the neural network controller training performance, the neural network controller training state, the neural network controller training errors, and the neural network controller training are presented respectively in Fig. 14, 15, 16, 17 and 18.

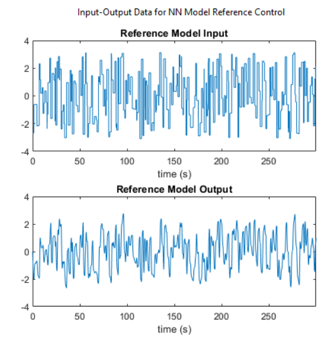

Fig. 14 Input-output data for neural network model reference controller

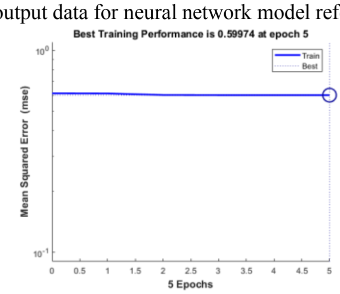

Fig. 15 Neural network controller training performance

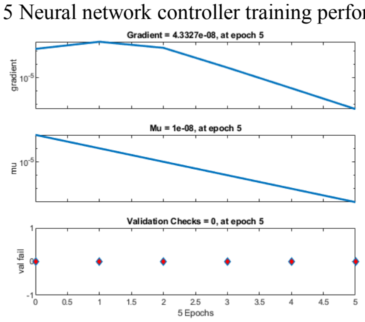

Fig. 16 Neural network controller training state

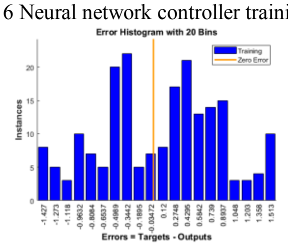

Fig. 17 Neural network controller errors

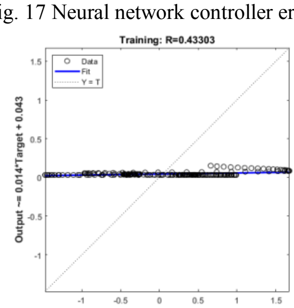

Fig. 18 Neural network controller training regression

The command torque, speed and position characteristics are presented in Fig. 19, 20, and 21, respectivelly.

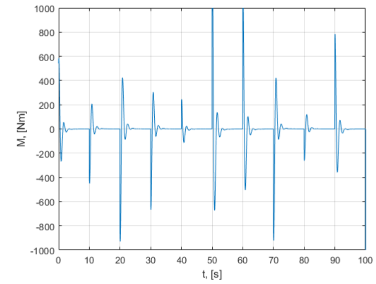

Fig. 19 Neural network controller training regression

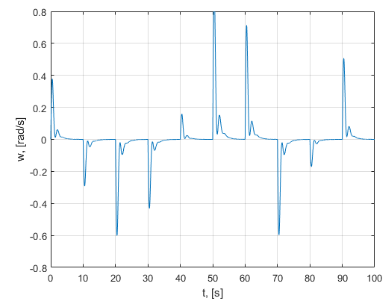

Fig. 20 Neural network controller training regression

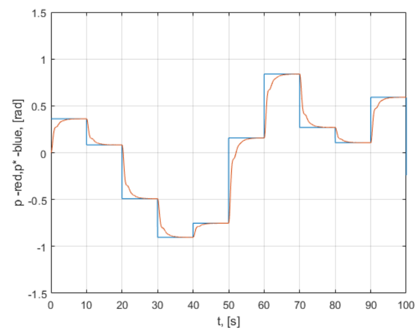

Fig. 21 Neural network controller training regression

Analyzing the obtained characteristics it can be said that with the help of a neural modfel reference control system a behavior similar to the linear state control system can be obtained: a zero error in steady state and an asymptotic aperiodic variation of position with zero overshoot.

5. Conclusions

The paper makes a presentation of results obtained with some angular position control structures: linear cascade control with error feedback and neural model reference control system. The design method of the neural model reference control system is presented. Their parameters and the performances of the neural trainings are presented. The transient responses at step input signal are presented, analyzed and compared. The control systems analyzed have good control performance criteria: zero error in steady-state, small response time compared to the high moment of inertia, zero overshoot, and an aperiodic, asimptotic position behavior. The differences between the efficiency criteria of two control structures are small.

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