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EXPERIMENTAL DETERMINATION OF ELECTRICAL AND MECHANICAL PARAMETERS OF DC MOTOR USING GENETIC ELMAN NEURAL NETWORK

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Abstract

The most suitable and generalized neural network that represents the control system dynamics is the Elman Neural Network (ENN). This is due to its ability to memorize and emulate the system states. Moreover, ENNs learned by Genetic algorithms are found to be more representative to system order in terms of its structural complexity in comparison to those learned by back propagation algorithm. This facility is utilized efficiently to find the minimum ENN structure that represents the discrete-time state space model of the DC motor. Then by comparing the ENN weights with the well-known discrete-time state space equation in terms of the motor physical parameters (moment of inertia, torque constant, armature inductance, etc.), these parameters can be obtained.

Keywords: Elman Neural Networks, DC motor modelling, Genetic Algorithms, Parameters system identification.

1. Introduction

The neural networks can be used effectively in identification and control of linear and nonlinear systems [1-3]. Many neural network structures are suggested to map the input/output system dynamics such as feed-forward, recurrent and partially recurrent networks [3]. ENNs, as partially recurrent networks, attract many researchers due to their ability to memorize the system states and can be trained using the standard back propagation algorithm. However, it is found that the Genetic Algorithms (GAs) is more efficient in finding the minimum ENN structure that emulates suitably the unknown system dynamics [3].

Nomenclatures

A	Continuous-time state matrix
B	Viscous Friction, N.m/rad.s
b	Continuous-time input matrix
C	Continuous-time (or discrete time) output matrix
F	Discrete time state matrix
G	Discrete time input matrix
i_m	Armature current, A
J	Moment of inertia, kg.m^2
K_b	Back e.m.f constant, V/rad.s
K_T	Torque constant, N.m/A
L_m	Armature inductance, H
R_m	Armature resistance, Ω
T	Sampling time, s
U	System Input (armature voltage), V
W^{xc}	Hidden-context weights
W^{xu}	Hidden-input weights
W^{yx}	Hidden-output weights
$X(k)$	State vector of k^{th} sampling instant
$X^c(k)$	Context layer state vector
Y	System output
Greek Symbols	
ω_m	Angular speed, rad/s

Furthermore, physical parameters system identification is also an attractive branch in system modelling which is sometime called the Gray-box system identification. This branch deals with finding the physical system parameters rather than finding its input/output mapping as transfer function or state-space representation.

Isermann [4] suggested an estimation procedure for obtaining the physical parameters of a 6-axis industrial robot DC motor from nonlinear algebraic relations known from the theoretical modelling. Sandareswaran [5] used neural networks for computing the real time adaptive speed information of the induction motor without priori knowledge of the drive.

In this work, the weights of the genetic based ENN with minimum state realizable DC motor representation are used to find its physical unknowns such as moment of inertial, torque constant, armature inductance, etc. The learning procedure is accomplished using input (armature voltage) and output (angular velocity) data.

2. Utilizing GAs for ENN learning

The main structure of the ENN is given in Fig. 1, where it consists of modifiable feed-forward connections. The ENNs are able to approximate to any arbitrary precision a discrete time-state- space description [3].

In addition to input and output units, the Elman network has a hidden unit x_k and a context unit x^c. When linear hidden units are adopted and the biases of the hidden and output units are zero then the dynamic equations of the Elman Network are:

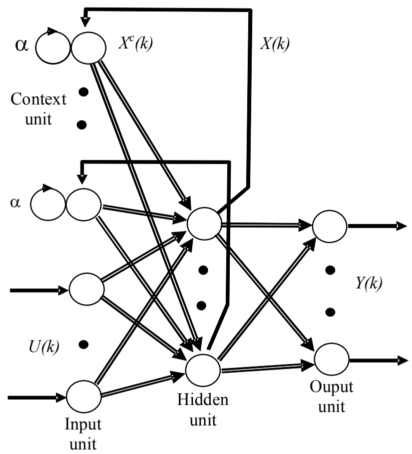


Fig. 1. The Modified Elman Network.

$$X(k)=W^{xc}X^{c}(k)+W^{xu}U(k-1) \tag{1a}$$

$$X^{c}(k)=X(k-1) \tag{1b}$$

$$Y(k)=W^{yx}X(k) \tag{1c}$$

where the matrices W^{xc}, W^{xu}, and W^{yx} define the interconnection for the context-hidden layer , the input-hidden layer, and the hidden-output layer, respectively. Eq. (1) is the standard state space description of dynamic systems where the order of the model depends on the number of states, which is also the number of hidden units.

In order to update the weight matrices W^{xc}, W^{xu}, and W^{yx}, the GAs is used as an optimization procedure to minimize the square of error between the Neural Network output and the actual output data (supervised learning). The standard GAs operations as selection, crossover and mutation are used.

3. Physical Parameter Evaluation of a DC Motor

The armature controlled DC motor with fixed excitation can be described by the following state space equations [8];

$$\dot{X}=FX+GU \tag{2a}$$

$$Y=CX \tag{2b}$$

where

$$F=\begin{bmatrix} \frac{-B}{J} & \frac{K_T}{J} \\ \frac{-K_b}{L_m} & \frac{-R_m}{L_m} \end{bmatrix} \tag{3}$$

$$G=\begin{bmatrix} 0 \\ \frac{1}{L_m} \end{bmatrix} \tag{4}$$

$$C=\begin{bmatrix} 1 & 0 \end{bmatrix} \tag{5}$$

are the state, input and output matrices.

In Eq. (3), B is viscous friction constant, J is the moment of inertia, K_T is the torque constant, K_b is the back e.m.f constant, R_m is the armature resistance, L_m is the armature inductance, $X = \begin{bmatrix} \omega_m \\ i_m \end{bmatrix}$, ω_m is the angular motor speed, i_m is the armature current, and U is the armature voltage.

The equivalent discrete-time state space equation is [7]

$$X_{k+1} = AX_k + bU_k \tag{6a}$$

$$Y_k = CX_k \tag{6b}$$

where the state and input matrices (A and b) are evaluated by:

$$A = I + FT + F^2 \frac{T^2}{2!} + ... + \frac{T^i}{i!} F^i \tag{7}$$

$$b = TG + \frac{T^2}{2!} FG + ... + \frac{T^i}{i!} F^{i-1} \tag{8}$$

Usually T (the sampling time) is chosen to be less than one, therefore Eqs. (7) and (8) can be truncated up to T, then

$$A = \begin{bmatrix} 1 - \dfrac{BT}{J} & \dfrac{K_T T}{J} \\ \dfrac{-K_b T}{L_m} & 1 - \dfrac{R_m T}{L_m} \end{bmatrix} \tag{9}$$

$$B = \begin{bmatrix} 0 \\ \dfrac{T}{L_m} \end{bmatrix} \tag{10}$$

and C as in Eq. (3).

Therefore, comparing Eqs. (1a) and (1c) with Eqs. (6a) and (6b), one can find that:

$$W^{xc} = \begin{bmatrix} w_{11}^{xc} & w_{12}^{xc} \\ w_{21}^{xc} & w_{22}^{xc} \end{bmatrix} = A = \begin{bmatrix} 1 - \dfrac{BT}{J} & \dfrac{K_T T}{J} \\ \dfrac{-K_b T}{L_m} & 1 - \dfrac{R_m T}{L_m} \end{bmatrix} \tag{11}$$

$$W^{xu} = \begin{bmatrix} w_{11}^{xu} \\ w_{21}^{xu} \end{bmatrix} = b = \begin{bmatrix} 0 \\ \dfrac{T}{L_m} \end{bmatrix} \tag{12}$$

$$W^{yx} = \begin{bmatrix} w_{11}^{yx} & w_{12}^{yx} \end{bmatrix} = C = \begin{bmatrix} 1 & 0 \end{bmatrix} \tag{13}$$

Indeed, a special ENN was suggested to match the state space equation of DC motor. The weights of this ENN are used in Eqs. (11) and (12) in order to obtain directly, using GAs, the unknown physical parameters. Notice that some ENN weights are forced to have constant values ($w_{11}^{xu} = 0, w_{11}^{yx} = 1, w_{12}^{yx} = 0$). However, in order to have consistency in solving Eqs. (11) and (12) by the GAs, it is assumed that the armature resistance is known as it can be directly measured using Volt-Ampere method while the other physical parameters (J, K_T, K_b, B, and L_m) can be suitably evaluated.

4. Experimental Results

The parameters of the separately excited DC motor under consideration are:
Rated armature voltage = 220 V, Rated current = 3.3 A,
Rated horse power = 0.75 hp, Moment of inertia, J = 0.052 kg.m^2,
Torque constant, K_T = 0.66 N.m/A, Back e.m.f constant, K_b = 0.64 V/rad.s
Armature resistance, R_m = 2.3 Ω, Armature inductance, L_m = 34.5x10^{-3} H,
Viscous friction control, B = 0.002 N.m/rad.s,

These parameters are obtained from the nameplate and the data sheet of the motor. In order to have a priori knowledge about the motor dynamic, a step armature voltage is applied and a motor speed is recorded. From this test it was found that the motor time constant is nearly equal to 0.4 s, therefore having 0.01 s as a sampling time is adequate.

An interface card was built to record 4000 samples of input-output where the learning input data are taken as follows:

$$U(k) = \begin{cases} 0 & \text{V} & 0 \le t < 3 & \text{s} \\ 3.8 & \text{V} & 3 \le t < 16 & \text{s} \\ 7 & \text{V} & 16 \le t < 28 & \text{s} \\ 9 & \text{V} & 28 \le t < 40 & \text{s} \end{cases} \tag{14}$$

The genetic algorithm of 20 population size with crossover probability (P_c= 0.75) and mutation probability (P_m= 0.04) is used to find the physical parameters of the DC motor using the ENN of Fig. 2.

The variations of each unknown parameter during 160 generations are shown in Figs. 3 (a) through (e). The actual and the mean values of the physical parameters during the last 60 generations are shown in Table 1.

Moreover, it is clearly illustrated from Fig. 4 that the responses of the motor and the trained ENN are comparable.

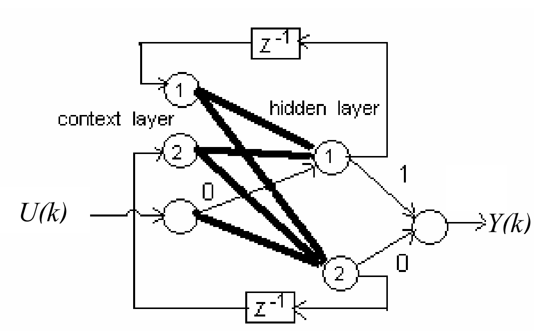
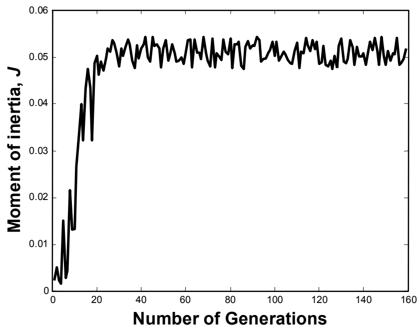


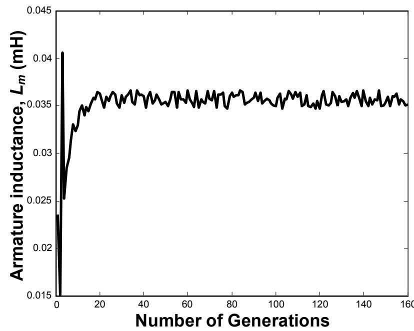
Fig. 2. The ENN for the DC Motor.

Table 1. The Actual and Estimated DC Motor Physical Parameters.

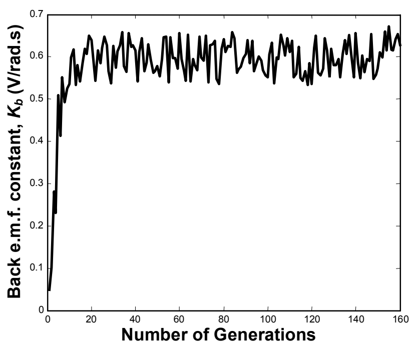
Physical parameters	The actual parameters	The estimated parameters
J (kg.m^2)	0.045	0.052
L_m (mH)	0.03	0.036
K_b (V/rad.s)	0.64	0.58
K_t (N.m/A)	0.62	0.65
B (N.m/rad/s)	7×10^{-3}	5.6×10^{-3}



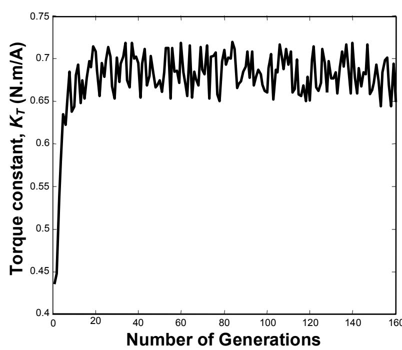
(a) Moment of Inertia.



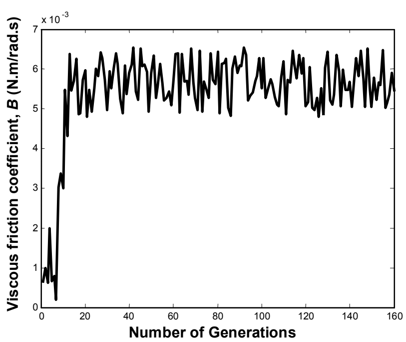
(b) Armature Inductance.



(c) Back e.m.f Constant.



(d) Torque Constant.



(e) Viscous Friction Coefficient.

Fig. 3. Variation of Physical Parameters against Number of Generations.

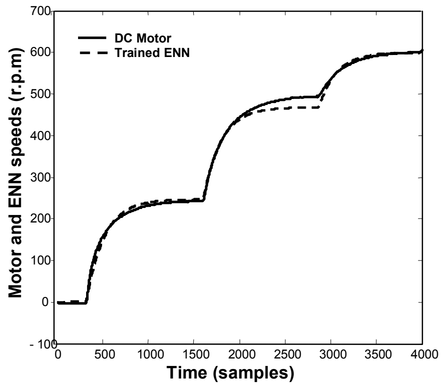


Fig. 4. The ENN and the DC Motor Speed Responses.

5. Conclusions

Linear ENN based Genetic algorithm is not only used to find the exact state-space order of the linear system, but also to identify its unknown physical parameters. Comparing the Elman neural network weights with discrete-time state space model representative does this by its physical parameters. As illustrates in the case of DC motor, the unknown parameters such as torque constant, armature inductance, viscous friction and the reflected moment of inertia on the motor shaft are very useful parameters for control engineers in servomechanism applications.

In contrast to the physical parameters identification by comparing the ENN with the symbolic representation of system state space, it is required during learning procedure that some weights should be fixed to certain values and update those which are symbolically related to the unknown physical parameters. This learning paradigm can cause problem of falling into local minimum if back propagation technique is used, while GA's can easily cooperate with such situation.

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