Engineering Applications of Artificial Intelligence 45 (2015) 152–167

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Adaptive neural speed controllers applied for a drive system with an elastic mechanical coupling – A comparative study

Marcin Kaminski, Teresa Orlowska-Kowalska *

Department of Electrical Machines, Drives and Measurements, Wroclaw University of Technology Wroclaw, Wybrzeze Wyspianskiego, 27, 50-370 Wroclaw, Poland

ARTICLE INFO

Article history:
Received 18 December 2014
Received in revised form
24 April 2015
Accepted 11 June 2015
Available online 16 July 2015

Keywords:
Neural networks
On-line adaptation algorithms
Speed control
Electrical drive
Two-mass system
Vibration damping

ABSTRACT

This paper presents an analysis and comparison of neural-adaptive controllers applied in a control structure of an electrical drive with an elastic mechanical coupling between the driving motor and a load machine, using only one state variable used in the feedback loop (a motor speed). However, the presented considerations can be assumed as a general neural speed control of the drive with a fast enough electromagnetic torque control loop of an electrical machine. This is justified by analogy with a design process independent of the parameters of a specific drive system and its electromagnetic torque control loop. Four types of neuro-controllers and training methods are analyzed: Adaptive Linear Neuron with Delta Rule, Multi-Layer Perceptrons Neural Network with the Backpropagation method, Feedforward Network with Adaptive Interaction adaptation and Radial Basis Function Neural Network with gradient algorithm, applied as speed controllers. Two main problematic issues related to neural controllers trained on-line are discussed: initial parameters selection for a neural network and determination of learning factors used in adaptation algorithms. Simulations are confirmed in experiment tests, using dSPACE1103 card. All the tested neurocontrollers are compared to a classical PI solution with one state variable used in the feedback loop of the analyzed drive system.

1. Introduction

A vast majority of real objects are nonlinear and have parameters which are hard to identify. In many cases, values of these parameters are time-varying during work of the system. Moreover, mathematical equations describing the systems are simplified and do not ideally represent the behavior of the system. The achievement of high control quality of such objects is very difficult. However, in control theory, there are algorithms that can ensure precise control despite the presence of the above mentioned problems. The main feature of these methods could be on-line adaptation to object changes. Variable gains of such controllers can help to find optimal control even for uncertainties and parameter changes. Therefore adaptive controllers are often applied also in real objects (Tao, 2003; Spooner et al., 2001; Ding, 2013).

The object of interest in this article is an electrical drive with a complex mechanical part, such as elasticity of the connection between a driving machine and a loading mechanism. Such a drive is considered a two-mass system, where in a speed control loop the main state variables: motor speed, load speed and shaft torque should be taken into account (Muszynski and Deskur, 2010; Szabat and Orlowska-Kowalska, 2007; Harnefors et al., 2013).

The elasticity of the shaft could be significant and leads to oscillations of the state variables in the drive system. Therefore precise control of speed or position in such drives is difficult. In order to damp the torsional vibrations of drive systems with an elastic joint, in the optimal solution all signals (motor speed, shaft torque and load speed) are directly controlled (e.g. additional feedbacks are applied in classical solutions (Szabat and Orlowska-Kowalska, 2007)). However these are only theoretical considerations. In real drives, the measurement of shaft torque or load speed in practice can be hard. Reduction of the number of sensors in electrical drive is also advantageous, because the costs of construction are lower and drive reliability increases. Therefore, the authors have assumed only one feedback from an easy to measure state variable – motor speed ω_1. Such assumption is not new, there are a lot of papers presenting control structures of the two-mass system based on one state variable only. It is possible to achieve proper system performance, but dynamics is obviously not so high as in the case of e.g. a state space controller, where all state variables of the drive are controlled in proper feedback loops. It is

* Corresponding author. Tel.: +48 71 320 34 67.
E-mail addresses: marcin.kaminski@pwr.edu.pl (M. Kaminski), teresa.orlowska-kowalska@pwr.edu.pl (T. Orlowska-Kowalska).

http://dx.doi.org/10.1016/j.engappai.2015.06.011
0952-1976/

Notation and symbols

NN	neural network
ADALINE-DR	Adaptive Linear Neuron with Delta Rule
MLP-BP	Multi-Layer Perceptrons Neural Network with the Backpropagation method
NN-AI	Feedforward Network with Adaptive Interaction adaptation
RBF-GD	Radial Basis Function Neural Network with gradient algorithm
ω_1	motor speed
ω_2	load speed
m_e	electromagnetic torque
m_s	shaft torque
m_L	load torque
u	control signal
T_1	mechanical time constant of the motor
T_2	mechanical time constant of the load machine
T_c	stiffness time constant
T_{me}	total delay of torque control loop
IAE	Integral Absolute Error
φ	activation function
w	weight coefficient
x	input signal of neural network
υ	argument of the activation function
b	bias value
α	constant coefficient of the BP algorithm
γ	constant coefficient of the AI algorithm
λ	constant coefficient of the DR algorithm
η	constant coefficient of the GD algorithm

known that such an impediment has a very important effect on the results. However, the authors have proved that in most of cases adaptive neural controllers can give better results than the classical (PI) controller, which additionally requires perfect knowledge of the drive system parameters.

Control structures applied to drives with an elastic joint, presented in many papers, are mainly focused on:

- control structures with digital filters (Muszynski and Deskur, 2010),
- extended classical control methods – PI/PID or state controllers implemented with different additional feedbacks (Szabat and Orlowska-Kowalska, 2007; Harnefors et al., 2013; Thomsen et al., 2011),
- advanced control structures, such as the sliding mode control (Erenturk, 2008; Korondi et al., 1995), predictive control (Fuentes et al., 2012; Serkies and Szabat, 2013),
- control structures based on artificial intelligence: fuzzy logic, neural networks (NNs) and genetic algorithms (Orlowska-Kowalska and Szabat, 2004; Dhaouadi and Nouri, 1999; Kaminski, 2013; Lee and Blaabjerg, 2007).

Most algorithms mentioned above are fixed-gains control methods and all state variables of a two-mass system are needed for appropriate operation, not only one – easy to measure state variable (driving motor speed), as in the realization discussed in this paper.

In this paper it is assumed that the adaptive neural controller is based only on driving motor speed information. It is a case with two non-controlled directly state variables, e.g.: load side speed and shaft torque, so these signals can be treated as additional disturbances. It should be noted that the mentioned conditions are extremely difficult for the tested adaptive neural speed controllers. Such assumption is purposeful, because the features of the analyzed neural models and adaptation algorithms can be easily observed. Naturally, these controllers can be also applied in drives with a stiff mechanical connection and with different types of driving motors. Moreover, the design process is identical (parameters or equations of the motors are not needed, internal torque control loop is not taken into account during the design process of neural controllers).

Implementations of neural networks in control structures of electrical drives are widely presented in technical papers, e.g. (Bose, 2007; Maiti et al., 2012; Hao et al., 2011a, 2011b). They have also been used in two-mass systems for estimation of signals needed in control structures (Orlowska-Kowalska and Szabat, 2007; Orlowska-Kowalska and Kaminski, 2009), as well for control purposes. However, applications of neural controllers in drives with an elastic shaft are not so often described in articles. Examples of such solutions are presented in Dhaouadi and Nouri (1999) and Kaminski (2013). In most applications perceptron neural networks are used. However, other types of neural networks are also implemented, such as a radial basis neural network. The paper (Lee and Blaabjerg, 2007) presents a theoretical analysis, stability proof and simulations of a control system with a speed controller and a disturbance observer completed using radial neural networks.

Neural networks applied in adaptive control structures can be very advantageous, because there are a lot of parameters inside (e.g. weights), which can be recalculated for searching for the best working point of the control structure, and the used model can be adjusted to the object.

Analyzing the literature on the topic, it can be concluded that there is no systematic overview and comparison of neural controllers applied to electrical drives, so it will be the main goal of this study.

In this paper four neural structures implemented in a speed control loop are tested:

- Adaptive Linear Neuron and Delta Rule (Widrow and Lehr, 1995; Bechouche et al., 2012).
- Multi-Layer Perceptron (MLP) Neural Network and Backpropagation method (Bishop, 1996; Hunter et al., 2012).
- Feedforward Network and Adaptive Interaction adaptation (Brandt and Lin, 1999; Saikalis and Lin, 2001).
- Radial Basis Function Neural Network and gradient algorithm (Hao et al., 2011a, 2011b; Farrag and Putrus, 2011).

The above mentioned combinations have different topologies and algorithms used in the calculation of neural controller parameters. The first of them – ADALINE – is very basic, easy for hardware implementations, but the number of changeable parameters is small and adaptation is limited. The one which is most often presented in papers is the MLP neural network (MLP). It is usually applied in weights adaptation backpropagation algorithm. In this method output control error is propagated through the network and next updates of weights are calculated. Thus, during realization of the backpropagation method two-steps are needed for update of weights. First – processing of the input signal through the neural network structure and second – back propagation of the error. This second part of the algorithm can be troublesome for real application, especially for on-line calculation. Data processing in the whole structure of MLP requires high computational power, elementary calculations are simple, but