Expert Systems with Applications 38 (2011) 3034–3039

Contents lists available at ScienceDirect

Expert Systems with Applications

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

GA-based neural network for energy recovery system of the electric motorcycle

Chin-Hsing Cheng *, Jian-Xun Ye

Department of Electrical Engineering, Feng Chia University, No. 100, Wen Hwa Rd., Taichung 407, Taiwan

ARTICLE INFO

Keywords:
Neural network
Genetic algorithms
Energy recovery
Regenerative braking

ABSTRACT

This paper discusses a regenerative braking system for the electric motorcycle that performs regenerative energy recovery based on neural network control with a boost converter. A constant regenerative current control scheme is proposed, thereby providing improved performance and high energy recovery efficiency at minimum cost. The neural network controller is used to simulate the regenerative system in Matlab/Simulink and neural network toolbox. We can sieve out the suitable training samples to obtain good performance of the controllers, and the neural network with genetic algorithms is used to design the controller. Simulation results of neural network controller show a more steady quality and extended time of charging. The proposed scheme not only increases the traveling distance of the vehicle but also improves the performance and life-cycle of batteries, and the energy recovery of batteries becomes more stable. Therefore, the market of the electric vehicle will become more competitively.

1. Introduction

In a world where environment protection and energy conservation are growing concerns, the development of the electric motorcycle has taken on an accelerated pace with the integration of electric motor drive, electronic, and controls (Chan, 2002). Now the limitation of driving range is the key restriction for the development of the electric motorcycle. Regenerative braking allows the vehicle to use the motor as a generator every time the brakes were used, to pump the kinetic energy from braking into the battery. Thus, regenerative braking is an effective approach to extend the driving range of the electric motorcycle, at the same time it plays an important role in energy saving. Regenerative braking is a hot topic recently around the world (Cao, Bai, & Zhang, 2005).

Regenerative braking means that part of the kinetic energy of electric motorcycle can be transformed to the electric energy, which is stored in the energy cell by the boost converter circuit. The recycled energy can be utilized to accelerate the vehicle. On one hand the boost circuit works at PWM mode, which is a seriously non-linear system. On the other hand the voltage of the battery, the state of the road, and the driving range of vehicles vary largely under the presence of regenerative braking. All these lead to the invalidation of the traditional control method for regenerative braking. Various methods for retaining energy in electric vehicles have been suggested, however, the use of regenerative braking is the most attractive since it does not require the addition of extraneous equipment. Regenerative braking is accepted today as a vital part of the standard architecture for third-generation vehicles, which now includes the electronics for total energy management on board the vehicle. Various attempts to satisfy the control performance for regenerative braking have been presented in literature, such as fuzzy PID control in Paterson and Ramsay (1993), variable structure control in Chung, Lee, and Ko (1995), H_∞ control in Bai (2005) and Zhang (2004), and robust sliding model control in Ye, Bai, and Cao (2006). It should be noted, however, that a fairly concise model is usually required for the above controller design. Since the linear design model does not express the exact behavior and the unmodelled dynamics, in this paper a neural network controller is designed to guarantee the robustness for both stability and performance.

Neural networks (NNs) are a promising new generation of information processing systems that demonstrate the ability to learn from training data (Lin & Hsu, 2002). The models known as artificial neural networks (ANN), inspired from the morphology of biological neural system and organization of brain structures, attempt to emulate human-like performance (Eva, Miguel Angel, & Diego, 2007; Ghiassi, Zimbra, & Saidane, 2006; Park, El-Sharkawi, Marks, Atlas, & Damborg, 1991). One issue of great importance in the field of ANN is input data pre-processing. From simple operations, some degree of pre-processing usually speeds the training process and improves the network performance. Among the many ANN models, the multilayer perceptron (MLP) is the most widely used. Backpropagation (BP) algorithm is used to train MLP (Abdel-Aal, 2008). However, the BP networks with sigmoidal non-linearity

* Corresponding author. Tel.: +886 4 24517250x3827; fax: +886 4 24516842.
E-mail address: chcheng@fcu.edu.tw (C.-H. Cheng).

0957-4174/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2010.08.093

have many open drawbacks, such as difficulty in choosing appropriate network dimension or architecture, and the resulting local minimum. This is mostly because the translation and dilation of sigmoid function is not orthogonal, thus the correlation redundancy of these functions is large and the energy of sigmoid function is limitless, which inevitably causes slow convergence speed.

The NN is trained with an algorithm of back propagation type to adjust the connection weight parameters. However, the network weights are difficult to learn because of the structural non-linearity. Usually the local minima for neural network learning with gradient decent algorithm are inevitable in the searching for optimal weights. To obtain the optimal solution, a genetic algorithm (GA) combined with a steepest descent technique and least squares technique for optimal selection of the basis of the networks has been used (Goldberg, 1989).

This paper proposes the combination of a neural network (NN) and a genetic algorithm (GA) to develop a modeling and analysis tool to be used for energy recovery system of the electric motorcycle. Neural network models are powerful tools when modeling data sets are non-linear and highly correlated. GA is known as an efficient search algorithm. The NN with the GA chosen connections is then trained using a supervised mode of learning known as back-propagation of error (Chen, Kuo, Yan, & Lia, 2009; El-Zonkoly, 2005; Hwang, Kim, & Lee, 2008; Lin, Jan, & Shieh, 2003; Pendharkar, 2009; Tan, Lu, Loh, & Tan, 2005). Two different approaches for designing robust NN are examined. In the first approach, a GA is used to minimize the mapping error before backpropagation learning is applied. For the second approach, a GA is used to minimize the sum of second order error derivatives with respect to the NN weights.

The paper begins with modeling the mathematic model of the regenerative braking system, then focusing on the design of the neural network controller; subsequent to the simulation of the regenerative braking by Matlab/Simulink, it discusses in detail the advantage of the controller; finally the conclusion is summarized.

2. Design of GA-based neural network controller

2.1. Genetic algorithms

Genetic algorithms were introduced by Holland in the early 1970s as a special technique for function approximation. They are quite different from other more conventional optimization methods that are mainly stochastic in nature. The basic process of genetic algorithm is as follows. First, a population of chromosomes is created. Second, the chromosomes are evaluated by a defined fitness function. Third, some of the chromosomes are selected for performing genetic operations. Fourth, genetic operations of crossover and mutation are performed. The produced good offspring replace their parents in the initial population. This process repeats until a user-defined criterion is reached.

They are in the following aspects:

1. Genetic algorithm works with a coding of the parameter set, not the parameters themselves.
2. Genetic algorithm searches from a population of points, not from a single point such as conventional algorithms.
3. Genetic algorithm uses fitness function information, not derivative or other auxiliary data.
4. Genetic algorithm uses probabilistic transition rules by stochastic operands, not deterministic rules.

Genetic algorithm is proposed in this paper to find the initial value of parameters of NN, the algorithm is implemented as follows:

Step 1: Randomly generate initial population of binary chromosomes for the parameters of initial weight of NN.

Step 2: Evaluate fitness function of each chromosome in the population. The better chromosomes will return higher values in this process.

Step 3: Stop and output the optimum solutions if suitable solutions have been found or if the available computing time has expired; else proceeds.

Step 4: Generate some new chromosome (offspring) from their parents through genetic operations, which is given as follows:

a. Use roulette wheel selection to select the better chromosomes to be parent generation in the mating pool. The chromosomes with a higher fitness value have a higher probability of contributing to one or more offspring in the next generation.
b. Produce new offspring by crossing from their parent generation. The offspring are expected to be more fit than the parents.
c. Randomly choose some chromosomes from new offspring for mutation operation. This operator can create new genetic material in the population to maintain the population's diversity.

Step 5: Reserve the best chromosome of each generation. It is not guaranteed that the superior chromosome will reside in the offspring after crossover and mutation operation. As a result, reversing the elite of each generation can improve convergence speed.

Step 6: Proceed to Step 2.

2.2. Neural network controller

A neural network is a computational structure, consisting of a number of highly interconnected processing elements (or nodes), which produces a dynamic response to external input or stimuli. Neural networks were originally developed as approximations of the capabilities exhibited by biological neural systems. Much of the interest in neural networks arises from their ability to learn to recognize patterns in large data sets. This is accomplished by presenting the neural network with a series of examples of the conditions that the network is being trained to represent. The neural network then 'learns' the governing relationships in the data set by adjusting the weights between its nodes. In essence, a neural network can be viewed as a function that maps input vectors to output vectors.

The structure of neural network is shown in Fig. 1. The neural network consists of a number of nodes or neurons connected by links. The nodes are divided into several layers: the input layer, the output layer and some hidden layers in between. The nodes in the input layer take the input signal, and the nodes in the output layer provide the desired output signal. The required number of hidden layers and the number of nodes for each layer are problem-dependent. In this work, one hidden layer with three hidden units is used for neural network. In the input layer we have two nodes, each receiving an input signal from the external world. There is only one output, which gives the control signal of the controller.

It should be noted that, in the feedforward network structure, signals can only be propagated from the input layer to the hidden layers and from the hidden layers to the output node. Signal propagation between nodes within the same layer or from the input layer directly to the output layer is not permitted.

For each neuron in the input layer, the neuron output is the same as neuron input. For each neuron j in the hidden layer or the output layer, the net input is given by