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A B-spline network based neural controller for power electronic applications

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ABSTRACT

Conventional multi-layer feedforward ANN controllers with back-propagation training are too complex to be implemented in fast-dynamic power electric systems. This paper proposes a controller for power electric systems based on a type of on-line trained neural network called the B-spline network (BSN). Due to its linear nature and local weight updating, the BSN controller is more suitable for real-time implementation than conventional multi-layer feedforward neural controllers. Based on a frequency domain stability analysis, a design methodology for determining the two main parameters of the BSN is presented. The design procedure of the proposed BSN controller is straightforward and simple. Experimental results of UPS inverters with the proposed controller under various conditions show that the proposed controller can achieve excellent performance.

1. Introduction

Artificial Neural Network (ANN) is an interconnection of a number of artificial neurons that simulates a biological brain system. It has the ability to approximate an arbitrary function mapping and can achieve a high degree of fault tolerance [1–3]. Currently, the most popular ANN is the multi-layer feedforward ANN, which is widely used in system control. When enough number of neurons are utilized, a neural network has the ability to approximate an arbitrary function mapping. In a control application, the ANNs are trained, either off-line or on-line, so that a particular input leads to a specific target output. The current most popular training algorithm for the feedforward ANN is the back propagation (BP) [1–3], because it is stable, robust and efficient.

Power electronics is the applications of solid-state electronics for the control and conversion of electric power [4,5]. The typical power electronic circuits are dc–dc, dc–ac and dc–dc converters. In most of the power electric circuits, the solid state devices are controlled by high-frequency pulse width modulation (PWM), which is typically at frequency range from 1 kHz to 1 MHz. Therefore, normally a very fast controller is needed for power electronic circuits.

Both off-line and on-line trained ANN based controllers have been successfully applied to many industries. In off-line trained ANN, forward calculation of the ANN only involves addition, multiplication and sigmoid function mapping which can be easily implemented with a simple and low-cost analog circuit [6] or cheap micro-processors. Therefore, the computing and implementation complexity of on-line trained ANN are much higher than those of off-line trained ANNs [7]. Due to limited computing time and the need for fast controller, most ANN based controllers applied for power electric circuits are off-line trained ANNs.

For example, off-line trained ANN controllers have been used in the current control of inverters for ac motor drives [8,9]. Here, the ANN receives the phase-current errors and generates a PWM signal to drive the switches of the inverter feeding the motor. Refs. [10,11] presented an application of ANNs for the harmonic elimination of PWM inverters, where an ANN replaced a large and memory-demanding look-up table to generate the switching angles of a PWM inverter for a given modulation index.

Even though off-line trained ANNs have the advantage of ease of implementation, off-line training of an ANN requires a large number of example patterns as training data, which generally makes the design of the ANN difficult. For example, the off-line ANN applied in [6] has required hundreds of patterns according to the authors. Moreover, because the weights and the biases remain fixed during operation and are totally determined by the training data, the performance of the ANN controller is limited. Thus, in general, other than an improvement in robustness, there is no obvious advantage in replacing a conventional controller with an off-line trained ANN controller.

In on-line training, the weights and the biases of the ANN are continually adjusted during operation and hence the ANN has better adaptability to the operating conditions. The Back Propagation training algorithm used for updating the weights of the network involves a great deal of real time multiplication and division operations. If implemented in hardware, the approach results in a very complex circuit. If implemented in software, a very fast digital processor is needed since there is generally only a

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very short time within a cycle for calculating the control effort (less than 100 μS). This implementation difficulty greatly affects the use of the feedforward ANN controllers in power electric applications.

B-spline network (BSN) [12,13], which is one kind of a neural network, that utilizes piece-wise polynomial basis functions, known as B-splines or B-spline basis functions, to store information. Like other neural networks, BSN can approximate arbitrary continuous functions to any degree of accuracy as long as the network used is large enough. Unlike the global weight updating scheme used in back-propagation-based neural networks, the BSN operates with local weight updating scheme with the advantages of fast convergence speed and low computation complexity. Due to these specifications, BSN has been widely applied in modeling complex system [14], adaptive filtering [12,15], pattern reorganization [16] and controlling complex systems [17–20].

When BSN is used as a controller, the input of a BSN is simply a sequence number k to indicate the sampling interval within the current cycle. The output of a BSN is a weighted sum of all B-spline basis functions. Also, unlike the feedforward multi-layer ANNs, there is no nonlinear function to be implemented in a B-spline network, which reduces the stress of computation and implementation. These features make it more suitable than the feedforward NNs with on-line back-propagation training for providing real time, on-line solutions, as required in the present converter control.

In this paper, a feedforward learning controller based on BSN is proposed for power electric applications like UPS inverter control. Unlike the conventional multi-layer feedforward ANNs, there is no nonlinear function to be implemented in the BSN in the proposed controller, which reduces the stress of computation and implementation.

A frequency domain model of the proposed controller has been developed for stability analysis of the proposed system. The main advantage of the proposed controller is that, unlike in other ANN based schemes, the design of the proposed BSN controller is simple requiring only two parameters, the B-spline support width and the learning gain, to be determined. A third parameter, forgetting factor, introduced to increase robustness, can be easily chosen based on trial and error.

The proposed controller is applied to power converter for UPS applications. Experimental results are provided to show that the very high performance of system with the proposed controller is achieved.

2. Proposed BSN control scheme for power converters

The proposed control scheme is shown in Fig. 1 and consists of two parallel parts, viz., the B-spline controller together with reference feedforward and the feedback controller. Normally, the control target of power converters can be voltage and current based on the requirement of different applications. In the figure, the output voltage of the power converter is assumed as control target. In the z domain, the expression for the output voltage of power converter is given by

$$V_o(k) = P(z)u(k) + di(k). \tag{1}$$

Here, $P(z)$ is the discrete transfer function model of power converter with sampling period h. All cyclical disturbances that cause output voltage deviation (including distortion), such as the load current (linear and nonlinear loads) and the dead-time effect in the inverter switches, are summarized as di. The task of the BSN-based controller is to come up with suitable control input $u(k)$ such that $V_o(k)$ tracks a sinusoidal reference in the face of the disturbance inputs $di(k)$. It may be noted that the models of power converters are normally low-order linear models with disturbance.

During sampling interval k, the controller output may be written as

$$u(k) = u_{ff}(k) + u_{fb}(k) + V_{ref}(k), \tag{2}$$

where u_{ff} and u_{fb} are the outputs of the feedforward BSN controller and the feedback controller, respectively, and V_{ref} is the reference input to be tracked. The feedforward of V_{ref} is used as the major component of the control effort to achieve better tracking.

2.1. Proposed BSN controller

A BSN utilizes piece-wise polynomial basis functions, known as B-splines or B-spline basis functions, to store information. An nth-order B-spline consists of piece-wise polynomial functions of order $(n-1)$ [12–13]. The function evaluation of a B-spline is generally called the membership and is denoted μ (see Fig. 2). That part of the B-spline's input space for which μ is not to zero is called its support. Generally, the support of a basis function does not cover the whole input space and, also, the supports overlap each other. When the supports overlap each other by more than 50%, the BSN is called 'dilated' [18].

As will be shown later in Section 2, the proposed BSN controller inherently has a low-pass feature which can be used to cut off learning at high frequencies and thereby ensure error convergence. Though a BSN with dilation 1 (50% overlap) was found to be very easy to implement and analyze, such a BSN did not provide large enough attenuation to cut off the learning at high frequencies. A BSN with dilation 2 (75% overlap) was found to be capable of meeting this requirement satisfactorily. Though BSNs with higher dilations can result in even better performance, they are much more complex to implement and hence were not used.

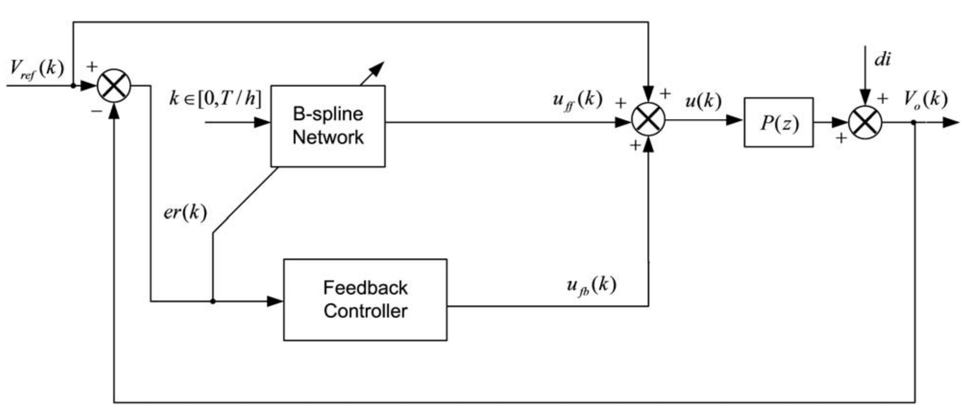

Fig. 1. Block diagram of the proposed BSN controlled power converter system.