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Delayless Harmonic Filter for Single Phase Inverter Using Neural-Network

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***Abstract* — This paper presents about the feedforward neural networks for various waveform processing and delayless filtering that are applicable to power electronics. Neural-network-based processing of waves gives considerable simplification of hardware and/or software that are traditionally used for such applications. The voltage or current waveforms which have constant frequency but variable magnitudes case is investigated. The above case is mainly important for power electronics that operate on a utility system and general-purpose constant-frequency converter power supplies. In this case, the performance of neural-network-based waveform processing and delayless filtering with offline training was found to be excellent for a single phase square wave inverter operated at 50Hz.**

***Index Terms* — Neural network, delayless filtering, waveform processing.**

I. INTRODUCTION

Power electronics and variable-frequency drive systems often deal with complex voltage and current waves that are rich in harmonics. Neural-Network based waveform processing and delayless filtering has been studied for 60 Hz frequency operated inverters [1]. One of the important processing functions is predictive or delayless filtering in order to retrieve the fundamental (sine wave) component of the wave. For example, a diode or thyristor phase-controlled bridge converter, operating on a 60-Hz utility line, can generate square or six-stepped line current wave, and this waveform becomes multistepped (more than six steps) with multiple phase-shifted bridge converters on a three-phase line [2]. Similar waveforms are also generated, respectively, in the output voltage of a square-wave voltage-fed inverter with single bridge or phase-shifted multibridge configuration. The harmonic-rich line current and output voltage waves can again cause distortion in the line voltage and load current waves, respectively. It is often necessary to retrieve the fundamental component of these waves in order to calculate, for example, the displacement power factor (DPF), fundamental frequency active (P) and reactive power (Q), and energy measured by a kilowatt-hour meter. In photovoltaic and wind generation systems coupled to the grid, the distorted line voltage (due to converter harmonics) waves require delayless filtering in order to generate inverter sine reference voltage waves for controlling the line DPF to unity [3], [4]. The distorted line voltage waves also create problems in the comparator (or zero-crossing detector) which is often essential for control of the converter (e.g., cosine-wave-crossing control of a phase-controlled converter). Generally, an active or passive-type low-pass filter (LPF) with narrow bandwidth is used to filter out the harmonic components. However, an LPF causes phase lag and amplitude attenuation that vary with fundamental frequency. For a utility system, the fundamental frequency is essentially constant and, therefore, these phase and amplitude errors can be compensated without much difficulty [3]. However, for variable-frequency drive applications, the inverter usually operates in pulse width-modulation (PWM) mode with wide frequency variation generating machine voltage and current waves that is complex with harmonics. If a simple LPF with narrow bandwidth is used in these applications, the variable phase delay and amplitude attenuation for the fundamental may not be acceptable, particularly at higher fundamental frequency. The phase error is particularly harmful in a vector-controlled drive where it creates the coupling problem and, thus, deteriorates the drive performance. In the past, complex digital adaptive filters, such a finite-impulse response (FIR), infinite-impulse response (IIR), or a combination of both have been proposed [4]–[6] to obtain delayless filtering of the fundamental component.

In this paper, we propose the neural network solution for delayless filtering problems occurred in the 50 Hz operated inverters. The artificial neural network (ANN), or neural network, a generic form of artificial intelligence (AI), is recently offering a new frontier in solving many control, estimation, and diagnostic problems in power electronics and motor drives. Between the two classes of ANN, i.e., the feedforward and feedback or recurrent types, the former provides static nonlinear input–output mapping or pattern recognition property with precision interpolation capability. With appropriate training, this property permits a feedforward ANN to recognize a wave shape and retrieve the desired component of the wave. Since the shape or pattern of the wave remains constant or goes through deterministic variation, simple offline training of the network has been used in the project. The advantages of ANN processing of a wave compared to that of a digital signal processor (DSP) are obvious: it is simple and fast with a dedicated ASIC chip due to parallel processing, and the ANN has the properties of noise immunity and fault tolerance where the former is particularly important in the distorted waveform processing application. This noise immunity property also remains valid if the ANN operation is emulated by DSP. It should be mentioned here that application of an ANN for waveform processing and delayless filtering is not entirely new. The ANN, as well as fuzzy logic, have been used for estimation of rms and fundamental rms values, DPF, and PF of distorted 50-Hz line current waves [7], [8]. It has also been used successfully in a variable-frequency vector-controlled drive

[9] for feedback signal estimation of rotor flux and torque from the machine voltage and current wave signals. Recently, the ANN has also been applied in delayless filtering to generate a 50-Hz reference current wave for active filters [10] and zero-crossing detection of distorted line voltage [11] and current waves in a phase-controlled cycloconverter [12]. In this paper, ANN-based waveform processing and delayless filtering has been studied systematically for voltage waves that have constant frequency but variable magnitudes. Performance of the ANN for all the intermediate values was found to be excellent. Square-wave delayless filtering by neural network (v_a = 0.9 pu, and 0.2 pu. MSE = 9.9157e-6) is shown in the below figures.

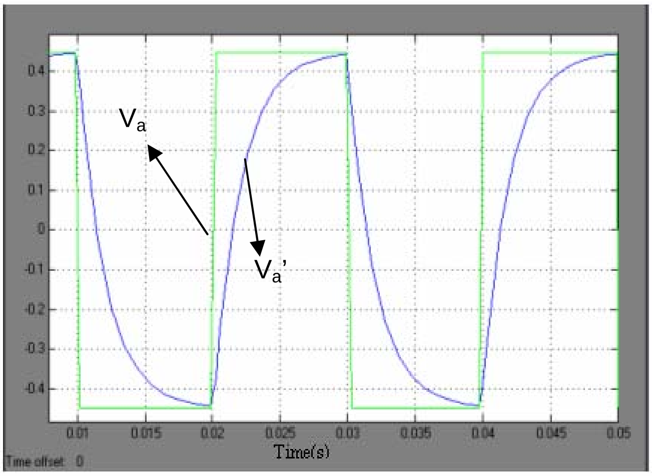
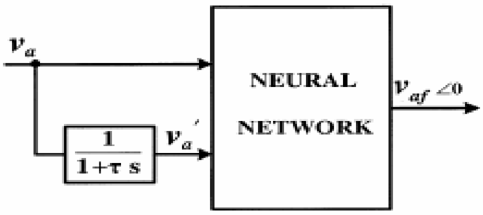


Fig. 1. (a) Input waves

Where V_a= Input square wave, V_a'= Linear wave, τ = Time constant of a low pass filter and V_{af} = output filtered wave



(2-21-1)

Fig. 1. (b) Network with I/O signals

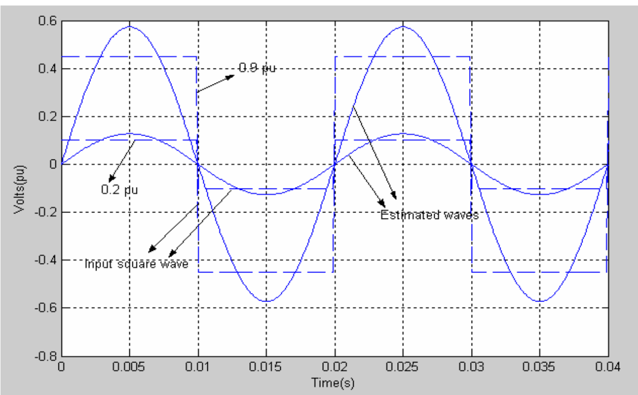


Fig. 1 (c) Output waves

II. CONSTANT-FREQUENCY VARIABLE-MAGNITUDE WAVES

The study in this section includes constant-frequency variable-magnitude single-phase wave. square waves has been studied thoroughly and discussed.

Single-Phase Square Wave

In the beginning, let us consider a simple constant frequency (50 Hz) square wave with variable magnitude, and the problem here is retrieving its fundamental component without any phase delay (delayless) with the help of the ANN. Fig. 1 shows the ANN-based generation of in-phase fundamental component where the output magnitude varies linearly with the magnitude of input square-wave. Since the square-wave amplitude is constant in the half-cycle, the ANN cannot generate a continuously variable sine wave directly from the square wave. For this reason, an auxiliary input wave is generated from the square wave through a first-order low-pass filter (LPF) shown in the figure. The LPF time constant should be large enough so that V_a' amplitude varies continuously in the half-cycle. Since the ANN requires the target or desired fundamental wave embedded in the input signal, it was retrieved by off-line FFT analysis of the input square wave. The training input data were generated from V_a and V_a' waves in the magnitude range of 0–1.0 pu with the step size of 0.1 pu and 360 data points per cycle of fundamental frequency (1 degree interval), where 1.0 pu corresponds to 0.5 (actually, $0.5V_d$ where V_d =100V) shown in Fig. 1(a). The feedforward ANN was then trained with the example data sets so that the estimated sine wave is remaining locked at 0 degree with the input square wave as shown in the figure 1(c). The MATLAB-based Neural Network Toolbox was used with Levenburg–Marquardt (L–M) based fast back propagation algorithm for the training. There is no fixed rule to determine the number of neurons in the hidden layer. In the beginning of the training, a small number of neurons are used. It is then gradually increased until satisfactory training with the desired MSE is obtained. Fig. 2(a) and 2(b) shows the Simulink blocks of the trained neural network. The network has 2, 21, and 1 neurons in the input layer; hidden layer and output layer, respectively [see Fig. 2(c)]. The training was followed by testing cycles with intermediate magnitudes of to verify the ANN training performance. The trained neural network gives excellent interpolation of magnitudes and angles. Fig. 2 summarizes the training steps of the neural network. For simplicity, only two values of (0.9 and 0.2 pu) and the corresponding outputs are shown in Fig. 1. Note that the signals may be voltage or current waves. Again, the input signals considered in the present study is square wave. Fig. 2(c) shows the ANN configuration after training with the square-wave input. Both the input signals and are normalized for ANN processing. The processed output is then converted to actual signal after denormalization. The network uses bipolar linear activation function in the input and output layers, whereas nonlinear tan-sig (or hyperbolic tan) function is used in the hidden layer. Fig. 3 shows the training MSE (mean-square error) curve which indicates that it converges to 9.9157e-006 at the end of 1224 epochs which is close to the desired goal of 1e-005.

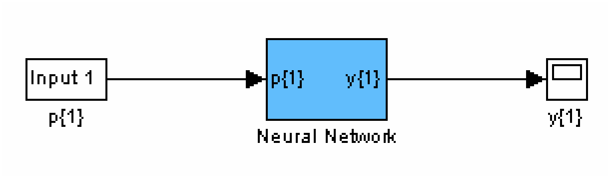


Fig. 2. (a) Simulink block of Neural network

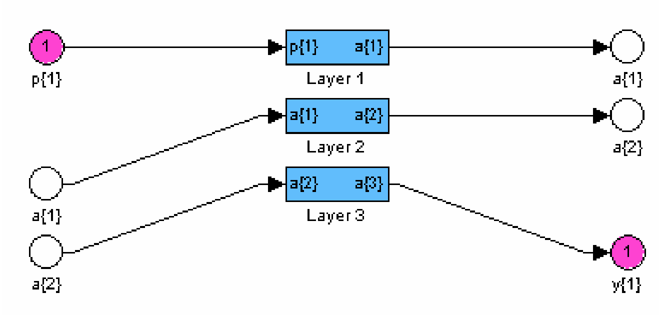


Fig. 2. (b) Simulink block of Neural network Layers

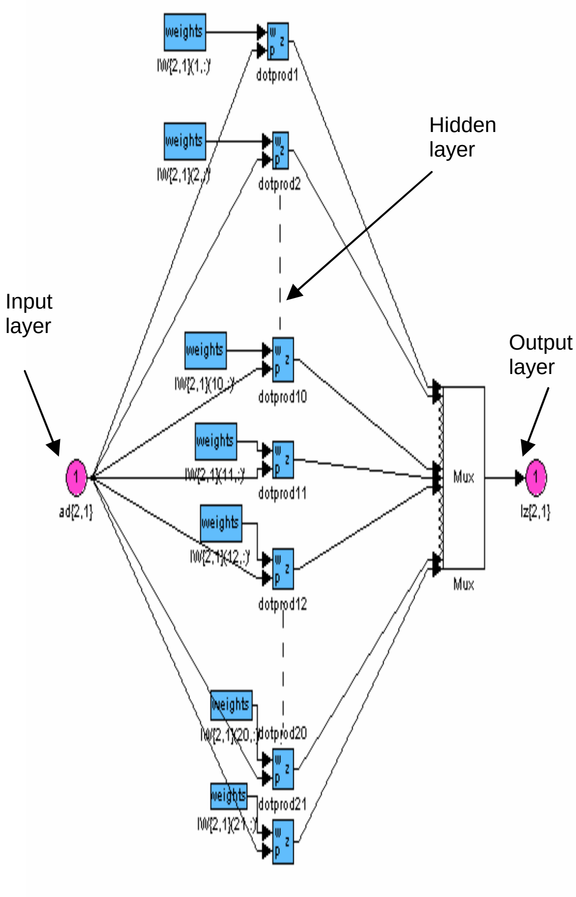


Fig. 2(c) Neural network configuration (2-21-1) for Fig. 1.

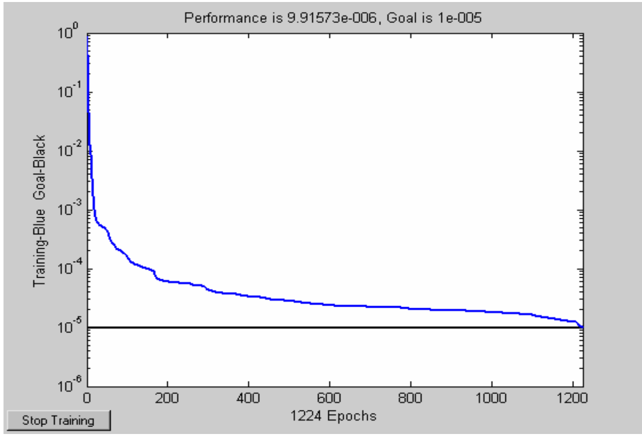


Fig. 3. Neural network configuration (2-21-1) for Fig. 1. (b) Network training MSE curve.

IV. CONCLUSION

Delayless filtering capabilities of a feedforward neural network has been systematically investigated in this paper using offline training, and performance was found to be excellent. This general wave shaping property of a neural network is also important in other areas of electrical engineering. Constant-frequency (50 Hz) single phase square wave was considered, and it was demonstrated that neural network can convert them into filtered sine waves at the synchronized phase angles, and the output magnitude linearly tracks the input magnitude. The corresponding training time is about 1 h with a Pentium 4 (2.4 GHz)-based PC. A small drift in frequency and deviation in the waveform have only negligible effect on the network performance. As a general conclusion, it can be stated that neural network has the capability of converting -phase waves of arbitrary shape into -phase waves of arbitrary shape at the same frequency with magnitude tracking (linear or nonlinear) and locked phase angles. These properties are also valid for a variable-frequency wave if the wave pattern at the network input remains the same.

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