

Neural Compensation for a Microcontroller Based Frequency Synthesizer-Vector Voltmeter

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Abstract—An automated neural network compensation scheme is proposed for an indigenously developed microcontroller based frequency synthesizer-vector voltmeter system, developed using direct digital synthesis and the synchronous detection technique. This compensator, when implemented online, can significantly improve the reading of an unknown voltage (both in magnitude and phase), in real-time. The neural compensator developed is trained offline on the basis of real data acquired from the system, and when this compensator is implemented online, it could outperform polynomial and fuzzy based compensators for a variety of different unknown voltages under measurement.

Index Terms—Frequency synthesizer, microcontroller, neural compensation, vector voltmeter.

I. INTRODUCTION

VECTOR voltmeters provide a convenient means of simultaneous measurement of magnitude and phase of an unknown voltage. A microcontroller based frequency synthesizer-vector voltmeter (FSVV) has been indigenously developed [1] where direct digital synthesis (DDS) is employed for the frequency synthesizer, using lookup tables, and, the vector voltmeter is designed to extract the in-phase and quadrature components of the fundamental of an unknown voltage, using synchronous detection technique. However, due to the time lag between the signal generation and detection and the phase shift during signal conditioning, the accuracy of the measured magnitude and phase of an unknown voltage can vary, with wide variations of circuit conditions/parameters and the frequency of measurement.

In this letter, we propose to develop an intelligent compensation scheme, using neural network methodologies, that can separately add, in real time, synthetic quantities of magnitude and phase, with the magnitude and phase actually measured by the vector voltmeter, so that the discrepancy between the true voltage under measurement and the final voltage displayed by the vector voltmeter is reduced. At first, a large dataset is prepared from real measurements of the FSVV instrument, under several experimental conditions, and the neural compensator is trained using the uncompensated

FSVV readings and the corresponding true voltages under measurement. Then, this neural compensator, when implemented online in real life, was found to provide better

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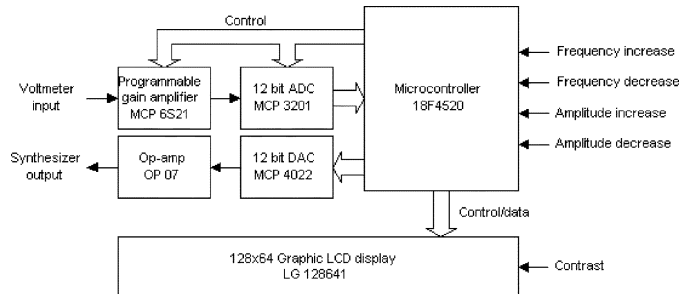


Fig. 1. Schematic block diagram of the FSVV.

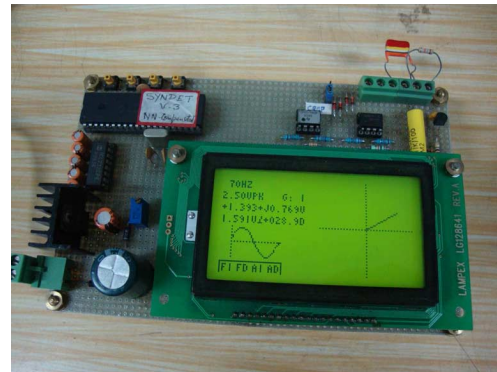


Fig. 2. Photograph of the actual system.

compensation than polynomial or fuzzy-based compensators developed for the similar situations, under a wide variety of experimental conditions.

II. THE MICROCONTROLLER BASED FSVV INSTRUMENT

Fig. 1 shows the schematic of the FSVV scheme and Fig. 2 shows the actual implementation. The system utilizes a PIC 18F4520 microcontroller, a programmable gain amplifier (MCP 6521), an MCP 3201 12-bit successive approximation type ADC, an externally connected 10-MHz quartz crystal, four TAC push switches, and a Lampex LG 128641 128 × 64 Graphic LCD Display. The frequency synthesis or signal generation scheme is developed using DDS theory, where a digital frequency control word F of $(m + p)$ bits (m : integer bits and p : fractional bits) is used to determine the ROM lookup table (LUT) address [2]. The output frequency of the synthesizer is $f = F(f_c/2^m)$, where f_c is the clock frequency.

The measurement of voltage in vector form is carried out using the synchronous detection technique, which is popularly employed to extract fundamental of an unknown signal $x(t)$, containing several harmonic components and some uncorrelated

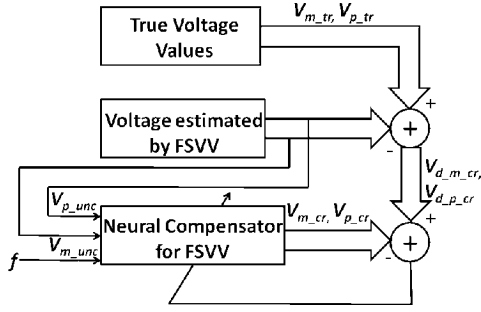


Fig. 3. The neural network compensator in training phase.

random components. The rms in-phase (I) and quadrature (Q) components of the fundamental of $x(t)$ can be estimated as

$$I = \sqrt{2} \left[\frac{1}{T} \int_0^T x(t) \sin \omega t dt \right] \quad (1)$$

$$Q = \sqrt{2} \left[\frac{1}{T} \int_0^T x(t) \cos \omega t dt \right] \quad (2)$$

where $T (= 1/f)$ is the time period of $x(t)$ and $\omega = 2\pi f$.

III. NEURAL COMPENSATION FOR FSVV SCHEME

The neural network compensator is developed to provide a three-input–two-output nonlinear function mapping:

$$[V_{m_cr}, V_{p_cr}] = F_{nn_comp}(f, V_{m_unc}, V_{p_unc}) \quad (3)$$

where f = excitation frequency, V_{m_unc} = uncompensated magnitude and V_{p_unc} = uncompensated phase determined by the vector voltmeter, V_{m_cr} = magnitude and V_{p_cr} = phase correction, to be provided by the compensator output, so that the compensated magnitude V_{m_c} and phase V_{p_c} closely approximate the true voltage under measurement V_{m_tr}/V_{p_tr} . Fig. 3 shows the development of this compensator in the training phase, on the basis of a large training dataset $\{f, V_{m_unc}, V_{p_unc} : V_{d_m_cr}, V_{d_p_cr}\}$ acquired from the experimental setup for different f and for outputs measured from different circuit configurations, e.g., R - C lead circuit, R - C lag circuit, etc., supplied by sources of different polarities, generated by the frequency synthesizer developed along with the vector voltmeter. Once trained, the vector voltmeter is implemented in real life, with the neural compensator module downloaded in the PIC18F4520 microcontroller.

IV. EXPERIMENTAL RESULTS

To make comparisons among candidate neural network methodologies that can be potentially utilized for developing the compensator, four neural network compensators, using different supervised learning methodologies were trained, namely backpropagation with Levenberg–Marquardt training (NN-LM), conjugate gradient backpropagation with Fletcher–Reeves updates (NN-CGF), scaled conjugate gradient

TABLE I
OFFLINE PERFORMANCE COMPARISON OF FOUR NEURAL COMPENSATORS

Sl. No.	Error desc.	Absolute deviation in magnitude/Phase (deg.)			
		NN-LM	NN-CGF	NN-SCG	NN-OSS
1.	Avg.	0.01/0.67	0.01/1.50	0.02/0.89	0.01/2.92
2.	Max.	0.05/3.33	0.06/4.77	0.05/3.38	0.06/9.80
3.	Std. Dev.	0.01/0.57	0.01/1.06	0.01/0.71	0.01/2.15

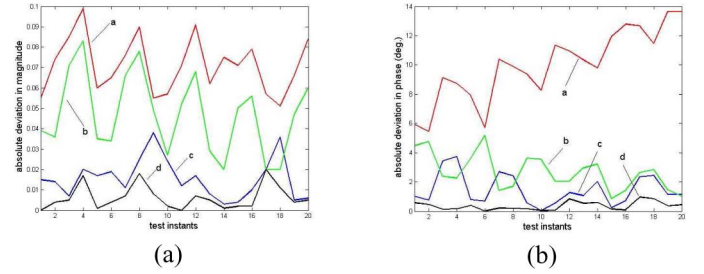


Fig. 4. Performance comparison for the (a) uncompensated, (b) polynomial, (c) fuzzy, and (d) NN-LM-compensated FSVV.

backpropagation (NN-SCG) and one step secant backpropagation (NN-OSS) [3]. Table I shows the performance results of these compensators in offline situation. It can be seen that the NN-LM compensator produced consistently the best performance and hence the FSVV was then implemented in real life situation with the NN-LM based compensator. Fig. 4 graphically shows the performance comparison of the uncompensated, polynomial-compensated [1], NN-LM compensated and a fuzzy-compensated (employing reinforcement learning algorithm) FSVV, for a variety of real life voltage measurements carried out. It can be seen that the NN-LM compensator has comfortably outperformed all the other candidate competing schemes.

V. CONCLUSION

A neural network compensator is produced for a PIC microcontroller based FSVV scheme, developed employing DDS and the synchronous detection technique. The compensator has shown excellent performance in real-life experiments in providing automated compensations for both magnitude and phase readings, and this scheme has outperformed similar compensation schemes developed using both correction polynomials and fuzzy logic.

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