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Abstract- **A shunt active filter is a power electronic device used in a power system to decrease "harmonic current pollution" caused by nonlinear loads. The Echo State Network (ESN) has been widely used as an effective system identifier with much faster training speed than the other Recurrent Neural Networks (RNNs). However, only a few attempts have been made to use an ESN as a system controller. As the first attempt to use an ESN in indirect neurocontrol, this paper proposes an indirect adaptive neurocontrol scheme using two ESNs to control a shunt active filter in a multiple-reference frame. As the first step in the proposed neurocontrol scheme, an online system identifier using an ESN is implemented in the Innovative Integration M67 card consisting of the TMS320C6701 processor to identify the load harmonics in a typical electric ship power system. The shunt active filter and the ship power system are simulated using a Real-Time Digital Simulator (RTDS) system. The required computational effort and the system identification accuracy of an ESN with different dynamic reservoir size are discussed, which can provide useful information for similar applications in the future. The testing results in the real-time implementation show that the ESN is capable of providing fast and accurate system identification for the indirect neurocontrol of a shunt active filter.**

I. INTRODUCTION

Shunt active filters have been proven to be an effective tool to filter the harmonic currents injected into the power network by the wide use of power electronic devices [1]. Fig. 1 shows the structure of a shunt active filter connected to a typical electric ship power system [2]. The active filter is connected to the point of common coupling (PCC) via a three phase inductor L_f. Based on monitoring the harmonics in the three-phase load currents, i_{aL}, i_{bL}, i_{cL}, the shunt active filter injects three-phase currents, i_{af}, i_{bf}, i_{cf}, with the exact harmonics to cancel those present in i_{aL}, i_{bL}, i_{cL}. This is done by controlling the PWM inverter in an appropriate way.

The echo state network (ESN) [3] is a new type of Recurrent Neural Network (RNN), which has a much faster training speed than other types of RNNs. Because of its low training complexity, the ESN has been used for system identification purposes in applications [4,5] . However, very few attempts have been made to exploit the feasibility of using an ESN as a system closed-loop controller. In [6] and [7], a direct neurocontrol method using an ESN is applied to the traditional problem of motor speed control; however, due to its training strategy, the direct neurocontrol method can only be used over a limited operating range. In [8], a Genetic Algorithm-aided direct adaptive control method using an ESN is proposed, but the performance of the direct adaptive neurocontrol method is highly dependent on the performance of the genetic algorithm, which yields computational complexity. Compared to the many applications of using an ESN as a system identifier [4, 5, 9, 10], the feasibility of using an ESN for system control purposes still needs to be investigated.

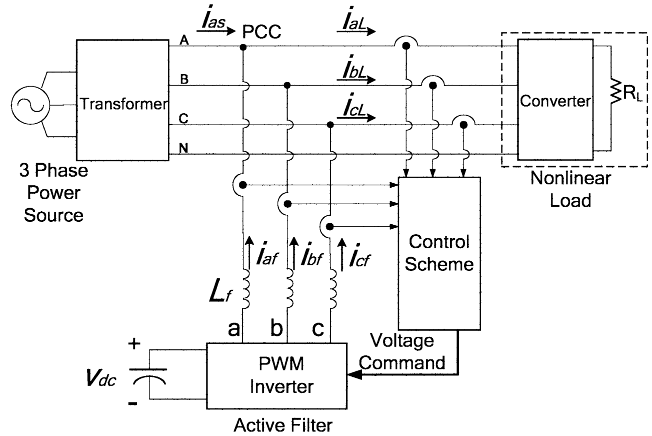

Fig.1. A shunt active filter connected to a typical shipboard power system.

As a first attempt to apply an ESN in a closed-loop control system of a shunt active filter, this paper proposes an indirect adaptive neurocontrol scheme using an ESN. The overall neurocontrol scheme using an ESN in a multiple-reference frame is shown in Section II. The online training algorithm of an ESN as a system identifier in the proposed indirect neurocontrol scheme is described in Section III. To test the feasibility of the ESN system identifier for indirect neurocontrol of a shunt active filter, the ESN system identifier is implemented in the Innovative Integration M67 card consisting of the TMS320C6701 processor to identify the load harmonics. The shipboard power system and the shunt active filter are implemented on a Real-Time Digital Simulator (RTDS) interfaced to the M67 DSP card. Section IV shows the testing results of the real-time hardware implementation. These results show that the ESN is capable of providing fast and accurate system identification for the proposed indirect neurocontrol scheme.

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II. Indirect Adaptive Neurocontrol Scheme using an Echo State Network

A. Multiple Reference Frame-Based Harmonic Extraction

Fig. 2 shows the overall scheme for the adaptive neurocontrol of a shunt active filter in the multiple-reference frame.

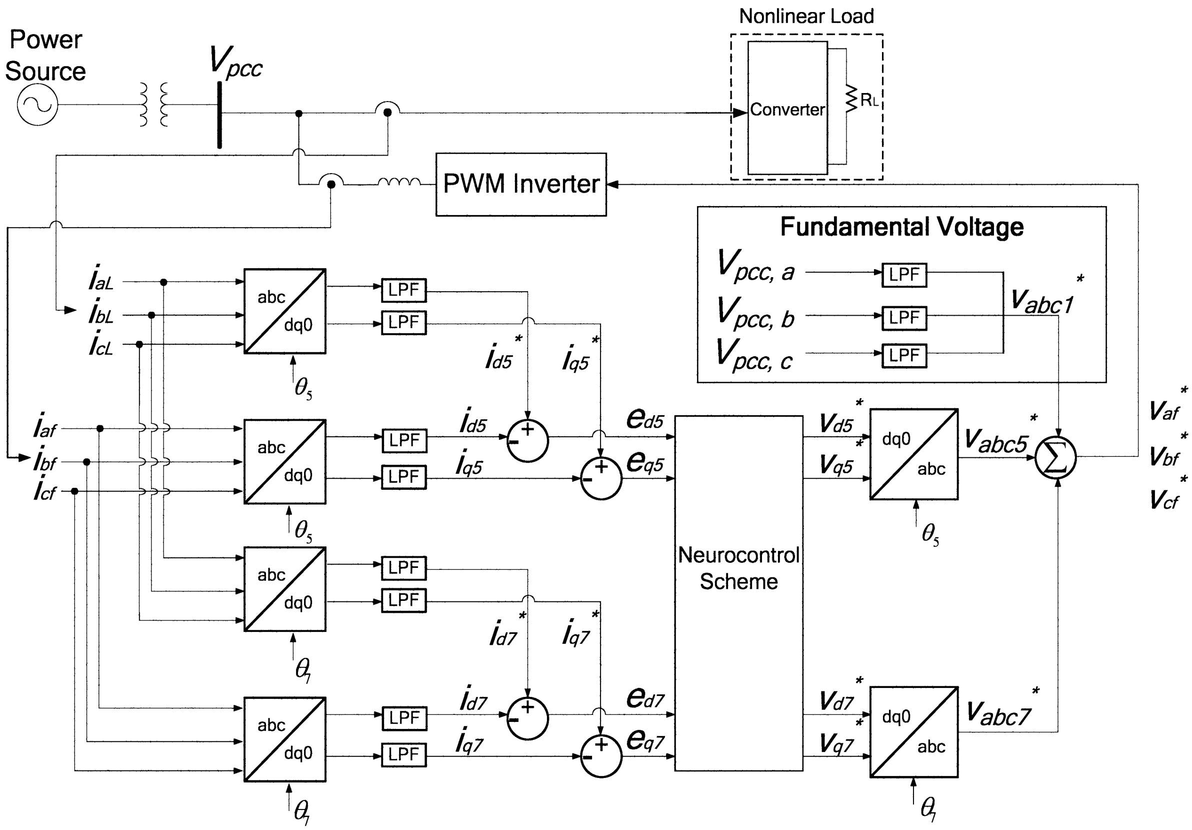


Fig. 2. Adaptive control structure for an active filter.

An AC-DC power electronic converter supplying an adjustable resistance is used as a nonlinear load, which injects current harmonics into the load currents i_{aL}, i_{bL}, i_{cL}. The 5th and 7th harmonics in the load current, which are the major current harmonics present, are extracted using multiple-reference frames. The multiple-reference frame consists of multiple *abc*-to-*dq* transforms using a transformation angle rotating at multiples of the fundamental frequency, (*e.g.* θ_5), which converts the harmonics in i_{aL}, i_{bL}, i_{cL} to dc currents i_{d5}^*, i_{q5}^* in a reference frame called the 5th harmonic reference frame (HRF). A low pass filter then extracts these dc currents by eliminating all the higher frequency components. The i_{af}, i_{bf}, i_{cf} currents are also transformed into the 5th HRF, and their d, q components i_{d5}, i_{q5} are each compared with the i_{d5}^*, i_{q5}^* respectively, to form the two errors e_{d5}, e_{q5}. The 7th harmonic currents are processed in the same way using a 7th HRF. e_{d5}, e_{q5}, e_{d7}, e_{q7} are used by the neurocontrol scheme and fed to the neurocontroller to control the voltage command of the PWM inverter. When the errors are eliminated by the neurocontroller, the shunt active filter injects exactly the correct current harmonics to cancel the current harmonics caused by the nonlinear load, and hence no current harmonics are injected to the power source.

B. Indirect Adaptive Neurocontrol using ESN

The structure of the proposed indirect adaptive ESN-based control is shown in Fig. 3. It consists of two separate ESNs, namely, one as the neuroidentifier and the other as the neurocontroller.

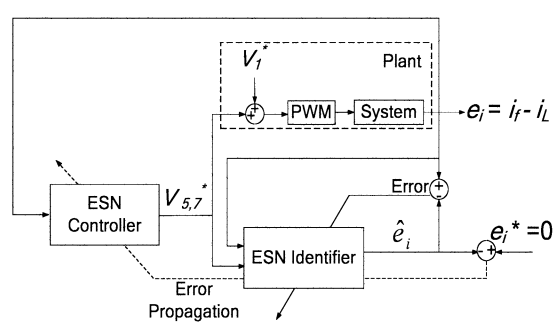


Fig. 3. Structure of the indirect adaptive ESN-based control.

The ESN based neuroidentifier is used to provide the dynamic model of the plant in an online fashion. The plant input $v = [v_{d5}^*, v_{q5}^*, v_{d7}^*, v_{q7}^*]$ and output $e_i = [e_{d5}, e_{q5}, e_{d7},$

e_{q7}] at time k are fed into the ESN identifier to estimate the plant output $\hat{e}_i = [\hat{e}_{d5}, \hat{e}_{q5}, \hat{e}_{d7}, \hat{e}_{q7}]$ at time $k+1$. The error between e and $\hat{e}$ (as defined in equation (7) in Appendix) is used to update the weights inside the ESN identifier. At each time step, the ESN based neurocontroller generates the control signals as the plant inputs in order to drive the plant output to the desired value, which is $e_i^* = [0, 0, 0, 0]$, and finally the error between $\hat{e}_i$ and e_i^* is back propagated through the ESN identifier to update the weights inside the ESN controller.

III. Online Training of the Echo State Network for System Identification

A. Structure of the ESN

The ESN [3], [11-14] is a special form of recurrent neural network proposed in recent years for modeling complex dynamic systems. A large (e.g. 100 hidden neurons) RNN is used as a "dynamic reservoir" in the hidden layer, which can be excited by suitably presented input and/or feedback of output. The architecture of the ESN used in this paper is shown in Fig. 4.

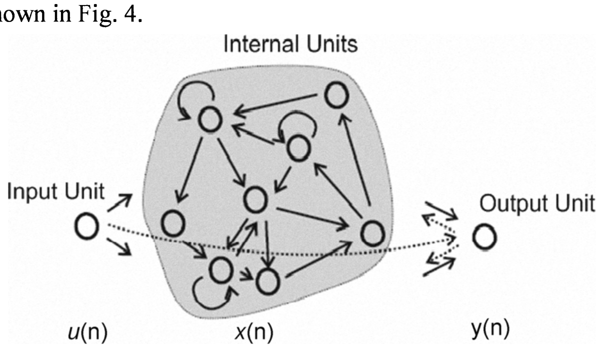


Fig. 4. ESN architecture[3].

The input weight matrix W^{in}, internal weight matrix W and output feedback matrix W^{back} do not change during the entire training process, after initially generated as shown in [4]. Only the output matrix W^{out}, is updated during online training. Therefore, maintaining the capability of modeling complex dynamic systems, the training of the ESN is much less complex compared to the other RNNs. The detailed training algorithm of the ESN is shown in the Appendix.

B. Online Training of the ESN Identifier

The ESN identifier is trained to predict the errors between the load current harmonics and the harmonics of the current injected by the shunt active filter, as shown in Fig. 3.

The training process consists of two stages [15]: in the first stage, which is called forced training, the ESN identifier is trained to track the plant dynamics when the inputs to the plant are perturbed using Pseudo Random Binary Signals (PRBS); in the second stage, which is called natural training, the ESN identifier is trained to learn the dynamics of the plant when the PRBS is removed and the system is exposed to a large disturbance such as a sudden load change. In each case the estimated output of the identifier is compared with the actual output of the plant and the resultant error vector is back-propagated through the ESN identifier to adjust its weights.

Fig. 5 shows the schematic diagram of forced training. First, the switches S_1 through S_4 are at position 1. Conventional PI controllers are used to obtain the steady-state inputs of the plant, namely, $v = [v_{d5}^*, v_{q5}^*, v_{d7}^*, v_{q7}^*]$. The steady state values are listed in Table I for a particular condition of the load.

TABLE I Steady State Values of Plant Inputs

v_{d5}^*	v_{q5}^*	v_{d7}^*	v_{q7}^*
-12.28	-1.64	9.47	-2.29

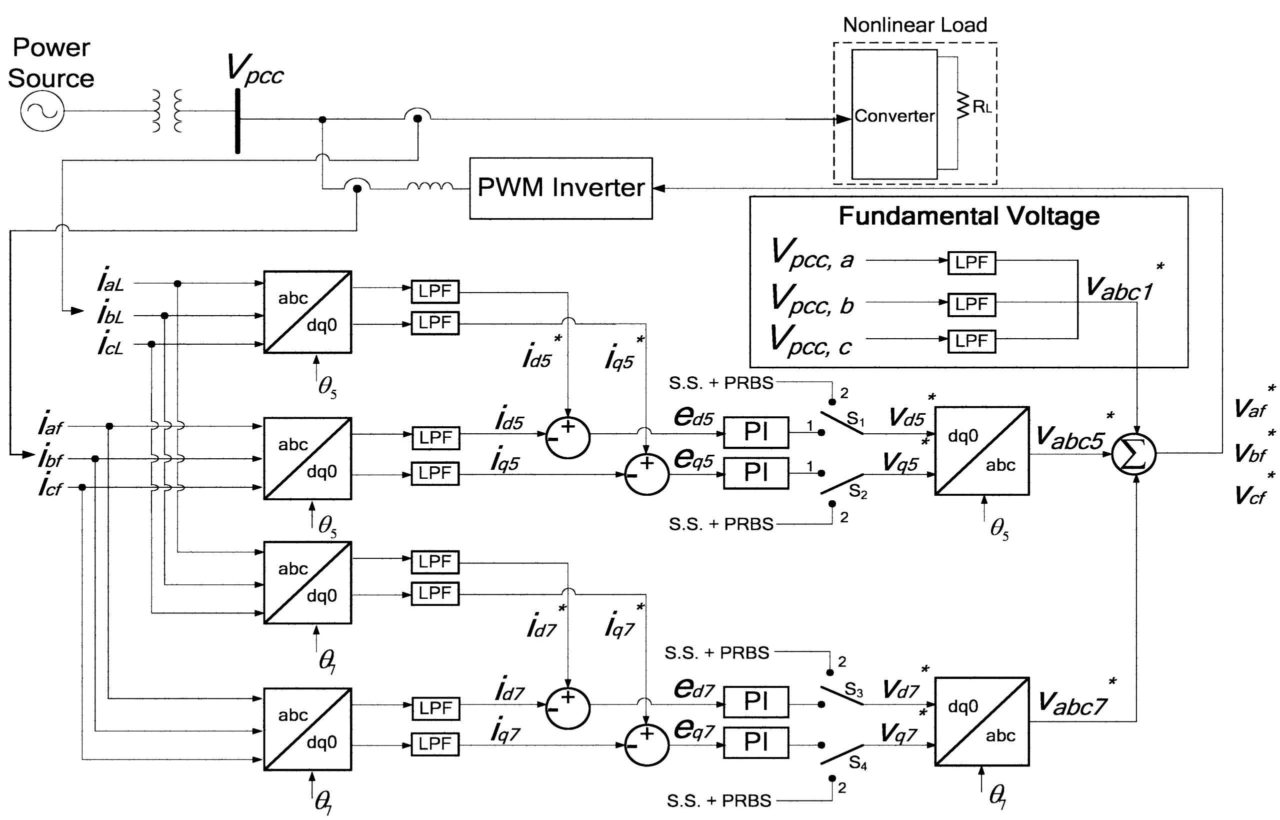


Fig. 5. Forced training of the ESN identifier.

The plant is then stopped and switches S1 to S4 are switched from position 1 to position 2. Under this condition, the previously steady inputs to the plant, [v_{d5}*, v_{q5}*, v_{d7}*, v_{q7}*], are disturbed by adding a pseudo random binary signal (PRBS) to the steady-state inputs. Each injected PRBS magnitude is limited to ± 10% of its stead-state value, and contains frequencies of 30, 60 and 90 Hz. The PRBS disturbs the system and causes small deviations of e_{d5}, e_{q5}, e_{d7} and e_{q7}, so that the ESN identifier can learn the system dynamics close to the normal operating range. Fig. 6-(a) shows the waveforms of disturbed v_{d5}*, v_{q5}*, v_{d7}* and v_{q7}*. Fig. 6-(b) shows the waveforms of the corresponding e_{d5}, e_{q5}, e_{d7} and e_{q7} caused by the disturbance. So the vector v= [v_{d5}*, v_{q5}*, v_{d7}*, v_{q7}*] which is the input to the power system, and the vector e_i= [e_{d5}, e_{q5}, e_{d7}, e_{q7}] which is the output from the power system, are used, for the training the ESN identifier.

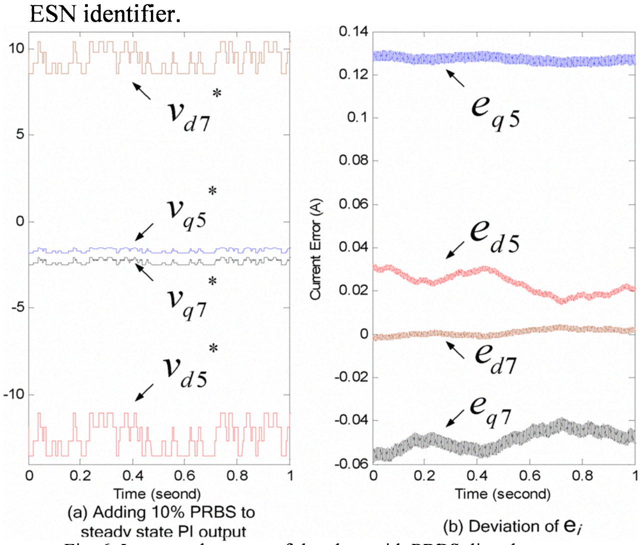
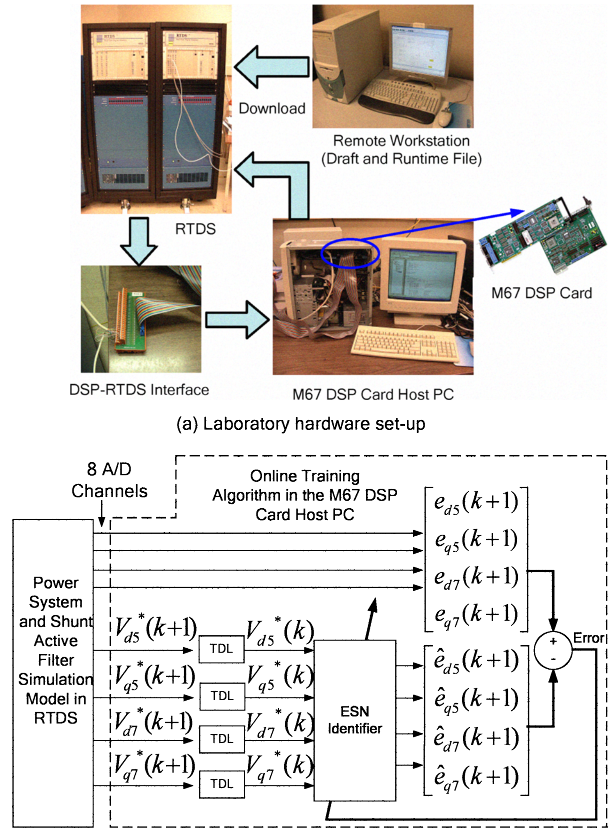


Fig. 6. Inputs and outputs of the plant with PRBS disturbance.

IV. Hardware Implementation of the ESN Identifier

A. Hardware Setup

The ESN identifier in the proposed indirect adaptive neurocontrol scheme is implemented on the Innovative Integration M67 card consisting of a TMS320C6701 DSP. The shunt active filter and the shipboard power system are simulated on a real-time digital simulator (RTDS) [16]. The connections and the flow of the data between the DSP and the RTDS are shown in Fig. 7-(a). First, the system is modeled with the simulation software RSCAD in the remote workstation, and then RTDS downloads and runs the runtime file generated by the software, finally the real time simulation values calculated by RTDS are sent to the M67 DSP card host personal computer via the DSP-RTDS interface and used for online training of the ESN identifier. Fig. 7-(b) shows the online training algorithm of the ESN identifier. At each time step, the ESN identifier predicts the outputs, which is the error vector between the harmonics of the load currents and those of the current injected by the shunt active filter, with the voltages transformed by the 5-th and 7-th reference frames as the inputs. Then, the errors between the actual values and these predicted values are calculated and used to update the weights of the ESN identifier. As the entire implementation is under real-time operation, the DSP and the RTDS can emulate the actual performance of the ESN identifier in practical applications.



(a) Laboratory hardware set-up

(b) Online training algorithm in the DSP card host PC

Fig.7. Laboratory hardware setup for the online training of the ESN identifier. TDL denotes time delay

B. Input Output Scaling

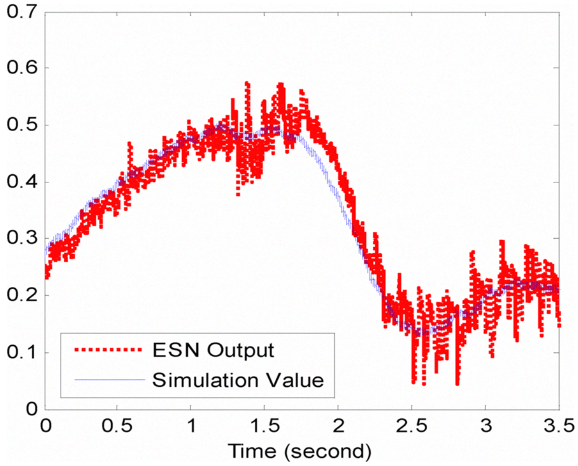
The relevant inputs and outputs of the simulated shipboard power system on the RTDS are divided by a scaling factor, because the range of the RTDS A/D channels have to be kept within [-10, 10] volts. In order to find the proper scaling factors for each channel, the simulation is run for a sufficiently long time, and the maximum absolute values of the data are used as the scaling factors for each harmonic component. The data are divided by these scaling factors before sent to the output channels of the RTDS, which are the inputs to the ESN identifier. Table II lists the scaling factors for each harmonic component.

Table II Scaling Factors of RTDS Outputs

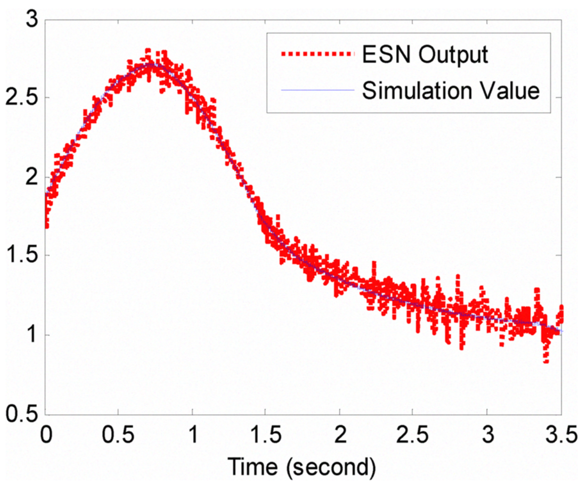
	5-d	5-q	7-d	7-q
Input v*	15	1.9	12	3
Output e_i	0.2	0.333	0.05	0.2

C. Test Results of the ESN Identifier

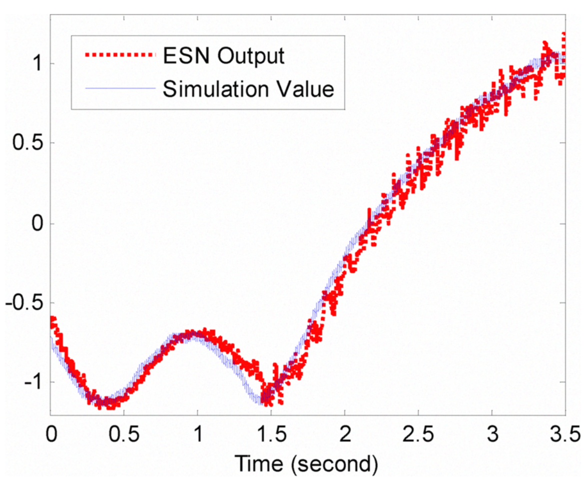
The online training results of an ESN identifier with 50 internal units is shown in Fig. 8. Figs. 8-(a), (b), (c) and (d) show the four outputs estimated by the ESN identifier and the desired values obtained from the RTDS simulation respectively.



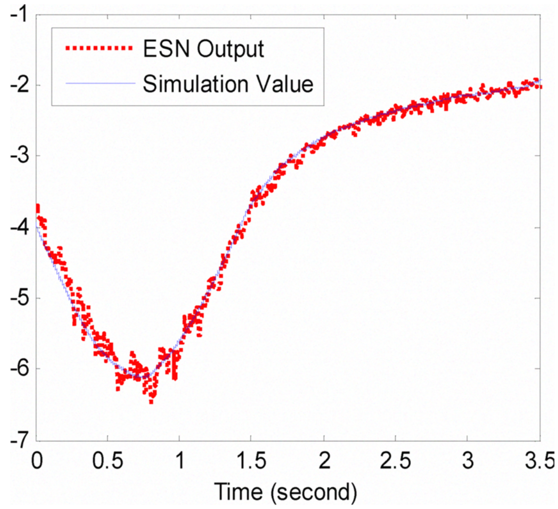
(a) ESN estimated output $\hat{e}_{d5}$ and RTDS simulation value e_{d5}.
Number of internal units=50.



(b) ESN estimated output $\hat{e}_{q5}$ and RTDS simulation value e_{q5}.
Number of internal units=50.



(c) ESN estimated output $\hat{e}_{d7}$ and RTDS simulation value e_{d7}.
Number of internal units=50.



(d) ESN estimated output $\hat{e}_{q7}$ and RTDS simulation value e_{q7}.
Number of internal units=50.

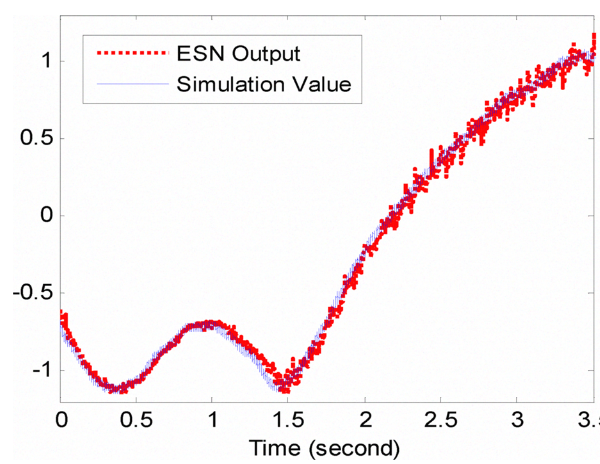
Fig.8. Online training results of the ESN identifier with 50 internal units.

Fig.8 shows that the ESN with 50 internal units is capable of providing accurate modeling of the dynamic plant. The curve of the ESN estimated output and the curve of the simulation value fit well in all four figures.

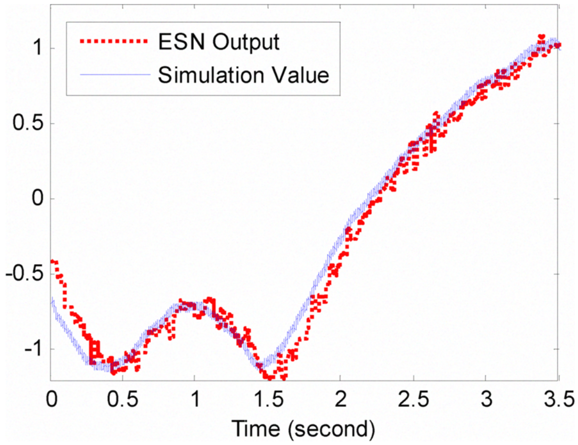
D. The Effect of the Internal Unit Size on the ESN Identifier

To evaluate the dynamic system modeling capability of the ESN with different sizes of "dynamic reservoir", two other ESNs with 20 and 100 internal units respectively are tested and compared with the ESN with 50 internal units. For convenience only one of the estimated outputs of the ESN identifier ($\hat{e}_{d7}$) and its desired output (e_{d7}, simulation output obtained from the RTDS) are shown in Figs. 9-(a) and (b) respectively. The comparison of Fig. 9 and Fig. 8-(c) shows that all three ESN identifiers are capable of providing accurate modeling of the dynamic plant. Comparisons of the other three outputs yield similar results.

However, ESN identifiers with more internal units yield better dynamic modeling capability, but also require more computational effort and start introducing a noticeable time lag, therefore making them less acceptable as a dynamic system identifier.



(a) ESN estimated output $\hat{e}_{d7}$ and RTDS simulation value e_{d7}.
Number of internal units=20



(b) ESN estimated output $\hat{e}_{d7}$ and RTDS simulation value e_{d7}.
Number of internal units=100

Fig. 9. Comparison of the ESN estimated output $\hat{e}_{d7}$ and RTDS simulation value e_{d7} using different numbers of internal units

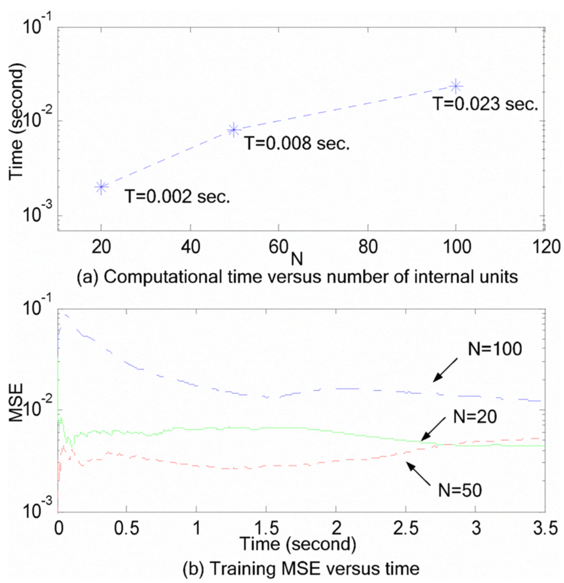


Fig. 10. Comparisons of computational efficiencies and training MSEs

Fig. 10 (a) shows the computational time required for each training step, for the three ESNs with different internal unit sizes. Recall from Fig. 4 that the internal units form a sparsely connected RNN. Therefore, as the internal unit size increases, the required computational time greatly increases, as shown in Fig. 10 (a).

As the required time for each training step increases with the number of internal units, the real-time tracking capability of the ESN identifier decreases, although the ESN with the larger number of internal units possesses better dynamic system modeling capability. The Mean Squared Errors (MSEs) (defined by equation (7) in Appendix) of the three ESN identifiers with different internal unit sizes are shown in Fig. 10 (b). The performances of the ESN identifiers with 20 and 50 internal units outweigh that of the ESN with 100 internal units. Considering the smaller computational time required, the ESN identifier with 20 internal units is preferred over the one with 50 internal units.

Therefore, for the real-time implementation of the ESN identifiers, deciding upon the number of internal units is a tradeoff between identification accuracy and required computational time, given the computational capability of the implementation hardware.

V. Conclusions

This paper proposes an indirect adaptive neurocontrol scheme which uses two Echo State Networks (ESNs) to control a shunt active filter. As the first step in the proposed neurocontrol scheme, the feasibility of the ESN identifier is evaluated in a real-time environment. The ESN identifier is implemented on an Innovative Integration M67 DSP card to identify the load harmonics. The shunt active filter and a typical shipboard power system are simulated using a real-time digital simulator system. Three ESN identifiers with different numbers of internal units are tested and evaluated, and the results could provide an empirical reference for similar applications in the future. The testing results in the real-time implementation show that the ESN is capable of providing fast and accurate system identification for the indirect neurocontrol of shunt active filter.

Appendix

The detailed steps of the online training algorithm for the ESN [4, 15] are summarized below:

1) Generate a recurrent neural network following certain rules to ensure its "echo state property"

Four weight matrices are needed. They are the input weight matrix W^{in}, internal weight matrix W, output feedback matrix W^{back} and the output weight matrix W^{out}. Once W^{in}, W and W^{back} have been generated, they will not change during the entire training process. Only the output weight matrix is updated at each time step.

The echo state property is related to the algebraic properties of the weight matrix W; however, there is no known necessary and sufficient algebraic condition which allows one to decide whether the network has the echo state property, given W^{in}, W and W^{back}. However, there are certain conditions which increase the possibility of the RNN having the echo state property. Usually W is generated by following the principles described below:

- Generate a sparse matrix W_0 and make sure the mean value of all the weights in it is about zero.
- Normalize W_0 to a matrix W_1 with unit spectral radius as:

$$W_1 = \frac{W_0}{|\lambda_{\max}|}, \tag{1}$$

where $\lambda_{\max}$ is the spectral radius of W_0.

- Scale W_1 to W, as

$$W = \alpha W_1, \tag{2}$$

where $\alpha < 1$.

2) Feed the teacher input and teacher output data (training data) to the ESN

When the training data is fed to the ESN, it will activate the dynamics within the dynamic reservoir. At each sampling step, compute the internal dynamic reservoir states according to equation (3):

$$x(n+1) = \tanh(u(n+1)W^{in} + x(n)W + y(n)W^{back}) \tag{3}$$

where u is the input vector, x is the vector of internal units and y is the output vector.

Since at sampling step $n = 0$, $x(0)$ and $y(0)$ are not defined, the following initial conditions are used:

- Initialize the network state arbitrarily, e.g. to the zero state $x(0)=0$;
- Set $y(0)=0$.

3) Compute the estimated output of the ESN

Now the output $\hat{y}(n)$ of the ESN is calculated by equation (4):

$$y(n+1) = x(n+1)W^{\text{out}}(n) \quad (4)$$

where $W^{\text{out}}(n)$ denotes the output weight matrix at time step n.

4) Update the output weights

The estimated output $\hat{y}(n+1)$ is compared with the actual output $y(n+1)$ collected from the RTDS and the error vector e_y is calculated as:

$$e_y = y(n+1) - \hat{y}(n+1) \quad (5)$$

The output weights are updated according to equation (6), as described in [15]:

$$W^{\text{out}}(n+1) = W^{\text{out}}(n) + \eta x(n+1)^{\text{T}} e_y(n+1) + \gamma x(n)^{\text{T}} e_y(n) \quad (6)$$

Where η is the learning gain and γ is the momentum gain, and each one is in the range of [0, 1], just like the parameters used in other types of neural network training schemes.

The output weights are updated such that the mean squared training error (MSE) is minimized.

$$MSE = \frac{1}{r}\sum_{n=1}^{r}(y(n) - \hat{y}(n))^2 = \frac{1}{r}\sum_{n=1}^{r}(y(n) - \sum_{i=1}^{L} W_i^{out} \cdot x(n))^2 \quad (7)$$

where r is the length of the Input/Output sequence used for training and $x(n)$ contains the states within the dynamic reservoir.

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