NSF PROJECT ECCS#0601521:

NEURAL NETWORK FOR ESTIMATING AND COMPENSATING THE NONLINEAR CHARACTERISTICS OF NONSTATIONARY COMPLEX SYSTEMS

FOURTH AND FINAL PROGRESS REPORT: April 2010

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A. Introduction

The project commenced in May 2006 and has had a one-year no-cost extension.

The main objective of this research has been to develop a computational-intelligence-based mechanism to effectively estimate and compensate load harmonics in a non-stationary complex system - the power grid. In a power system, the current to any load can be measured and processed to extract the harmonics when the power supply voltage is sinusoidal; this is a trivial procedure. However, when the supply voltage itself is distorted, due to other nonlinear loads and saturating transformers further upstream in the power network, then the load current contains harmonics caused both by the supply (referred to as supply harmonics) and the nonlinear load (referred to as load harmonics). Simply now measuring the current waveforms of such a load, yields the combination of load harmonics and supply harmonics, and do not yield the true distortion (load harmonics only) caused by the load.

Until the start of this project there was no method of separating out the supply harmonics from the load harmonics. The project started in May, 2006 by investigating the use of neural networks and other computational intelligence algorithms to model the load and thereby separate the load harmonics from the supply harmonics as illustrated in Fig. 1 and display the information about load harmonics for use mainly by utilities concerned that a particular load may be injecting excessive amounts of harmonic currents into the power network. The next phase focused on using these estimated load harmonics in real time in a closed loop harmonic mitigation (compensation) active filter method consisting of additional hardware and neural network software in parallel with the offending load.

Most of the objectives of the project have been achieved.

A **first report** was submitted in April 2007 and it

- summarized a survey to review the drawbacks of the then recent nonlinear load harmonic estimation techniques in power systems, as well as the then existing IEEE standards for regulating the load harmonics;
- proposed the concept of "Load Modeling", which is a novel neural-network-based true harmonic detection technique to estimate how much harmonic current has been drawn from the power system. This technique requires only the voltage and current waveform measured from the PCC (Point of Common Coupling), where the load is connected;
- described a few laboratory experiments using several small power loads, both single and three phase to validate the proposed Load Modeling technique. Algorithms developed in this project gave acceptably accurate harmonic estimation results.
- investigated the performances of different types of neural networks such as the MLPN(Multi-layer Perceptron Network), the RNN(Recurrent Neural Network) and the ESN(Echo State Network) for this application.
- evaluated a simple and intuitive control scheme to improve the performance of a three-phase boost-type PWM rectifier under harmonic and unbalanced input conditions.

A **second report** was submitted in April 2008 for the period from February 2007 to February 2008, which included results centered on the following major thrusts:

- a performance comparison of three types of neural networks: MLP, RNN and ESN, with different numbers of hidden neurons, shown in detail. The training results, testing results and harmonic current prediction results were compared. The computational effort of each neural network was also discussed. It had been found that the MLP and RNN require a much larger size of training set than ESN. The RNN and ESN give more accurate load modeling results than the MLP, but require more computational effort. The choice between RNN and ESN is a tradeoff between convergence property and the necessary size of the training data. In other words, when the training data is not sufficient, which is quite possible in practice, the ESN can give better system approximation results than the MLP and RNN.
- A study on the application of an Echo State Network (ESN) for the online design of a Wide Area Monitor (WAM) for a multi-machine power system was investigated. A single ESN was used to predict the speed deviations of four generators in two different areas. The performance of this ESN WAM was evaluated for small and large disturbances on the power system. Results for an ESN based WAM and a time delayed neural network (TDNN) based WAM were presented and compared. The clear advantages of the ESN WAM were that it learned the dynamics of the power system in a shorter training time with a considerably smaller number of weights to be trained.
- To mitigate harmonic related issues in high-power adjustable speed motor drives with active filters, two or more paralleled semiconductor switching devices are generally used in each leg of the filter in order to handle the large compensation currents and provide better thermal management. In

this study, a novel topology was proposed where two active filter inverters were connected with tapped reactors to share the compensation currents. The proposed active filter topology can produce seven voltage levels, which significantly reduces the switching current ripple and the size of ripple filters.

A **third report** was submitted in April 2009 for the period March, 2008 to April 30 2009, which summarized activities and findings centered around the following thrusts:

- The proposed two ESN-based control schemes, namely the Indirect Adaptive Control and the Adaptive Critic Design-based HDP(Heuristic Dynamic Programming) Control for the active filter to compensate the load harmonics.
- Simulation models for the active filter, nonlinear load and the power system for when they are connected in the Real Time Digital Simulator (RTDS).
- An ESN used as the System Identifier in the control scheme was trained and tested online in real time on the RTDS system at Missouri University of Science and Technology in Rolla. The online training algorithm of the ESN was implemented in the Innovative Integration M67 card consisting of the TMS320C6701 processor to identify the load harmonics in a typical power system. The required computational effort and the system identification accuracy of an ESN with different dynamic reservoir size were investigated, which could provide useful information for similar applications in the future. The testing results in the real-time implementation showed that the ESN was capable of providing fast and accurate system identification for the neurocontrol of the active filter.

The active filter work continued into year four, as described below.

B. Progress during the One Year of No-Cost Extension from May 1, 2009 to April 30, 2010.

1.   Indirect Adaptive Control of an Active Filter Using Echo State Networks

1.1   Utilization of Active Filters to Address Harmonic Issues in Power System

The fact that wide use of nonlinear loads such as power electronic devices in the power grid has caused serious harmonic pollution has been recognized by utilities in recent years. One method to address this harmonic issue is to use an advanced neural network-based harmonic current prediction scheme to first estimate the true harmonic current contributed by the nonlinearity of the load, instead of the distorted power supply; then, use an active power filter to compensate the harmonic

current drawn by the nonlinear loads, leaving the source current flowing out of the PCC (Point of Common Coupling) clean and nearly purely sinusoidal [1-4]. This neural-network-based proposed harmonic detection [5-9] and compensation system is shown in Fig.1. The true harmonic detection part (shown as the "Nonlinear Load Modeling" block in Fig.1) has been thoroughly validated in three previous annual reports, so the major task during the fourth and final year of the project has been to eliminate the harmonic current caused by the nonlinear load.

As shown in the "Active Harmonic Filtering" block in Fig.1, the active filter is connected to the 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 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}[10]. This is done by controlling the PWM inverter in an appropriate way.

Typically power systems are large-scale nonlinear, non-stationary systems with varying dynamic characteristics over a wide range of operating conditions. Traditional linear controllers such as PI controllers are designed from a linearized system model with fixed parameters at a specific operating point. However, in a real power system, the active filter and the associated power network cannot be accurately modeled as a linear system with fixed and known parameters. Therefore, at other operating points or in the case of a major disturbance, a linear controller's performance degrades and may even become unstable. The drawbacks of using linear controllers to control a nonlinear system can be overcome by using neural-network-based nonlinear intelligent control techniques. Artificial neural networks (ANNs) are good at identifying nonlinear systems and avoid the need for an explicit mathematical model of the power system; such an identifier ANN can then be combined with a nonlinear intelligent neurocontroller, to provide effective control for the active filter over a wide range of operating conditions. The question then arises: which type of neural network architecture to use for the identifier? The Echo State Network [11] (ESN) is chosen.

The ESN is a new class of Recurrent Neural Network (RNN) which requires much less training effort than other types of RNN, with excellent system modeling capability [12]. Using an ESN-based current harmonic identification scheme removes the need of an explicit mathematical model of the APF and the power network.
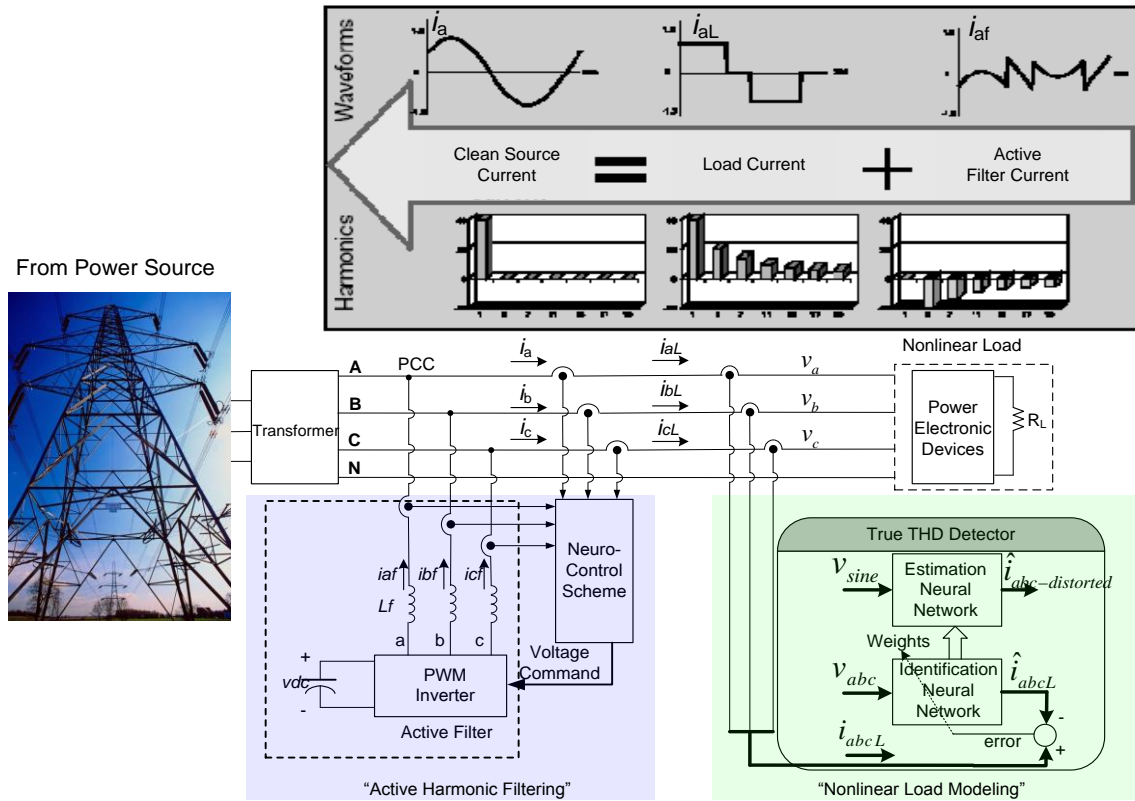
Fig.1. Neural network for estimating and compensating nonlinear load harmonic in a power system.

1.2 Multiple Reference Frame Control Scheme of the Active Filter

The overall scheme for the indirect adaptive neurocontrol of the active filter in the multiple-reference frame is shown in Fig. 2. 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 into the power source [10].
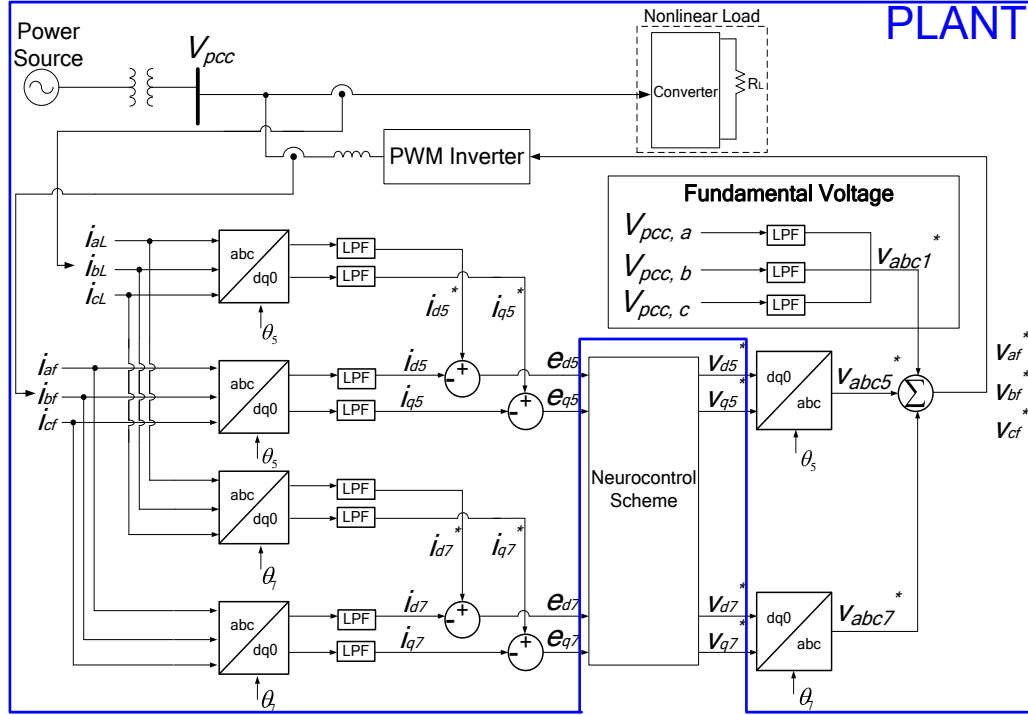

Fig. 2. Multiple-reference frame base neurocontrol scheme of the active filter.

1.3 Indirect Adaptive Control of Active Filter using Two ESNs

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. The ESN based neuroidentifier is used to provide the dynamic model of the plant in an online fashion. The plant input $v = [v_{d5}{}^*, v_{q5}{}^*, v_{d7}{}^*, v_{q7}{}^*]$, two additional signals i_{d1} and i_{q1}, which are the fundamental d-axis and q-axis load current respectively 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 $\hat{e}$ 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.
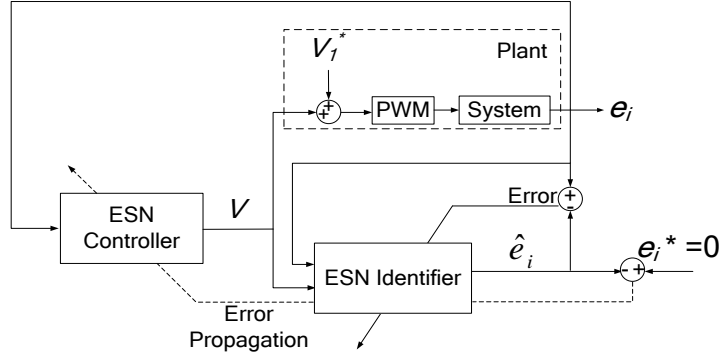
Fig. 3. Structure of the indirect adaptive ESN-based control.

1.4 Online training and Testing 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 active filter, as shown in Fig. 2.

The training process consists of two stages: 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. 4-(a) 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 plant is then stopped and switches S_1 to S_4 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 $\pm$ 10% of its steady-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.4-(b) shows the input and output vector of the ESN identifier. It should be noted that two additional signals which are the fundamental components in the load current in the d-axis and q-axis, i_{d1} and i_{q1}, are also used as inputs to the ESN identifier. They are an indication of the load change. When the load changes nonlinearly, for example, the firing angle of the load side convertor changes, i_{d1} and i_{q1} will change accordingly, so the ESN identifier can see these changes and response correctly.

(a) Forced training of the ESN identifier   (b) Input and output of the ESN identifier
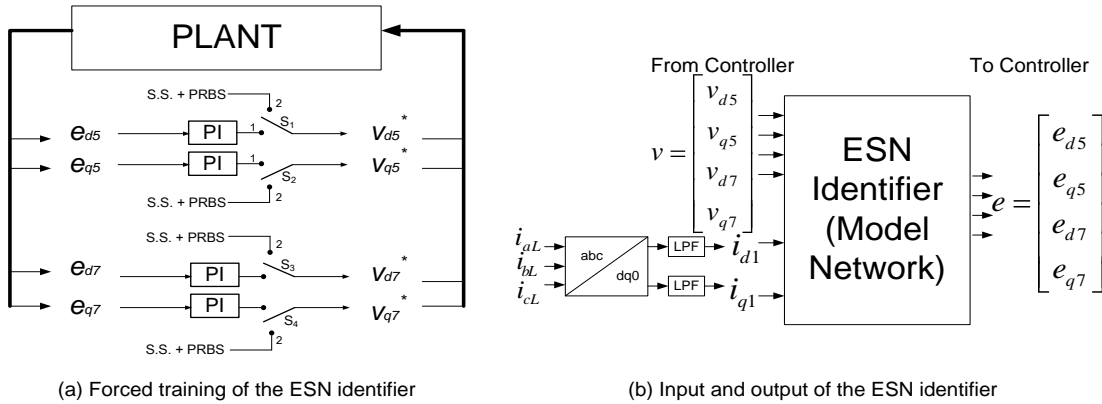
Fig.4. Online training mechanism of the ESN Identifier.

The ESN identifier is continuously trained online [13] under five different load conditions. The load change is realized by changing the firing angles of the thyristors in the load side convertor randomly among 0°, 10°, 20°, 30° and 40°. The changes of the firing angle are shown in Fig. 5-(a) and the nonlinear changes in the Phase A load current caused by the changes in the firing angle are shown in Fig. 5-(b). It can be seen clearly from Fig.6 that the load change is nonlinear.

The vector $[v_{d5}^*, v_{q5}^*, v_{d7}^*, v_{q7}^*, i_{d1}, i_{q1}]$ 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. Figure 7 shows the training and testing results of the ESN identifier. First the ESN identifier is trained online for 445 seconds and then tested for 5 seconds; during the testing, all the weights are fixed. There is a good match between the output of the ESN Identifier $\hat{e}_{d5}$, $\hat{e}_{d5}$, $\hat{e}_{d5}$ and $\hat{e}_{d5}$ and e_{d5}, e_{q5}, e_{d7} and e_{q7}, which are the actual output of the system during both the training and testing process. These results mean that the ESN identifier has successfully learned the dynamics of the system during the nonlinear load changes, so it can act as an accurate model of the system, predicting the one-step-ahead output of the PLANT when the indirect adaptive control scheme is implemented.

The important parameters used for the training and testing of the ESN identifier are listed below:
1) Load Levels: randomly chosen from Firing Angle Alpha=0°, 10°, 20°, 30° and 40°;
2) Training time for each load: 0.5 second;
3) Total Training Time: 445 seconds;
4) Testing Time: 5 seconds after the training;
5) Learning gain: 0.01;
6) Momentum gain: 0;
7) ESN Dynamic Reservoir Size: 100 internal neurons.

(a) Changes in the firing angle during the training and testing
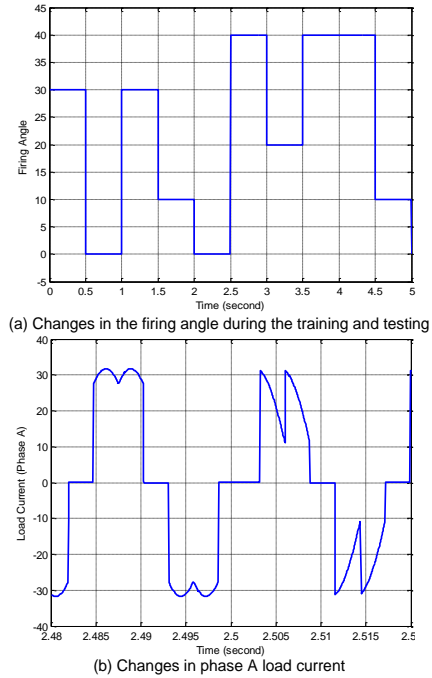
(b) Changes in phase A load current

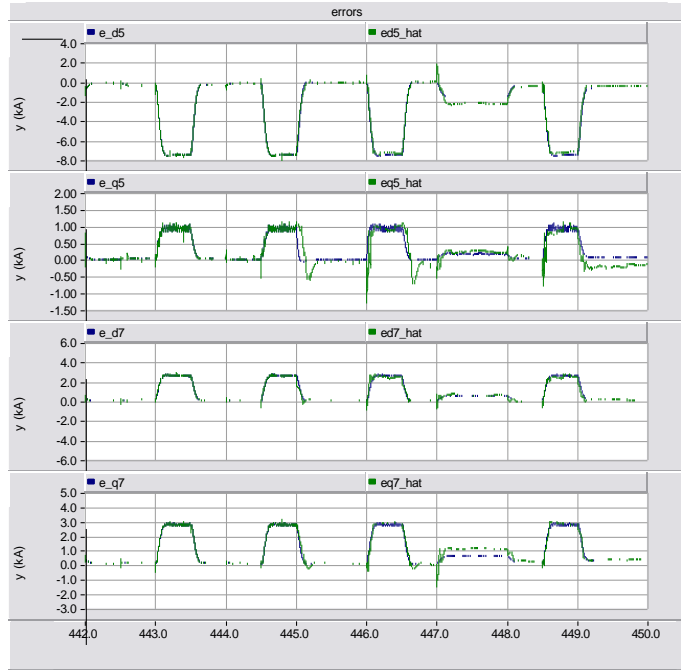Fig.5. Nonlinear load changes during training.

Fig.6. ESN Identifier training and testing results.

1.5 Control Performances of the ESN Controller

The training of the ESN controller consists of two stages: (1) offline pre-training using PI controller input and output; (2) online training. The purpose of the pre-training is to make sure that the ESN controller can at least perform like conventional PI controllers. Then the ESN identifier and controller are exposed to various load conditions during the online training process so that they can learn the system dynamics and act adaptively. The pre-training is done in MATLAB using simulation data from PSCAD. The weights obtained from the pre-training are then used as the initial weights of the ESN controller.

The control result of the proposed indirect adaptive control scheme under five different load firing angles is shown in Fig.7 when a change in firing angle occurs every 0.5 seconds. Only the waveforms of e_{d5} are plotted here, and e_{q5}, e_{d7}, e_{q7} behave in a similar manner. A comparison of the ESN controller performance and the PI controller performance is also given in Fig. 8. ESN controllers show faster damping and smaller overshoot than PI controllers. It takes less time for the ESN controller to drive e_{d5}, e_{q5}, e_{d7}, e_{q7} to zero, which is highly desirable in this active filter application.
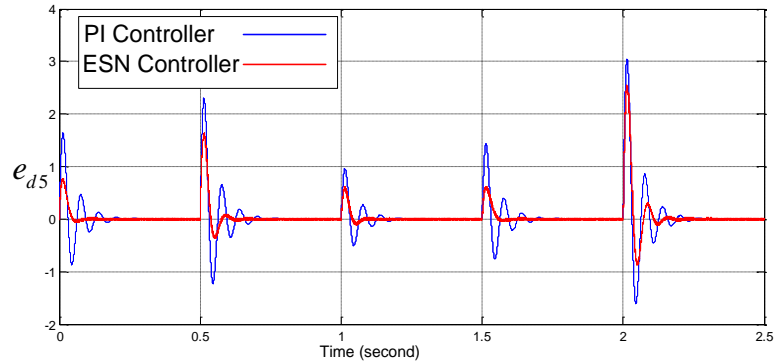
Fig.7. Comparison of ESN controller and PI controller performances.

The Phase A source currents before (Fig.8-(a)) and after (Fig.8-(b)) the harmonic compensation are shown below. The harmonic current injected by the active filter in phase A is also shown in Fig.8-(c). This figure only shows the performance of the ESN controller under one load condition. (Firing Angle=0°. 0.1 second data is plotted.)
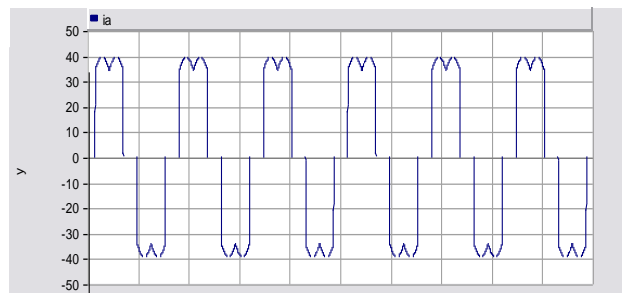
(a) Phase A source current i_a without the Active Filter
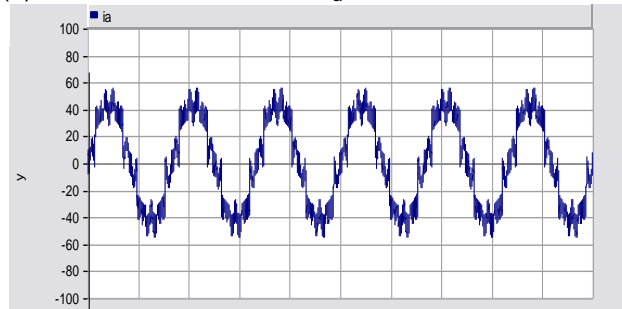
(b) Phase A source current i_a with the Active Filter
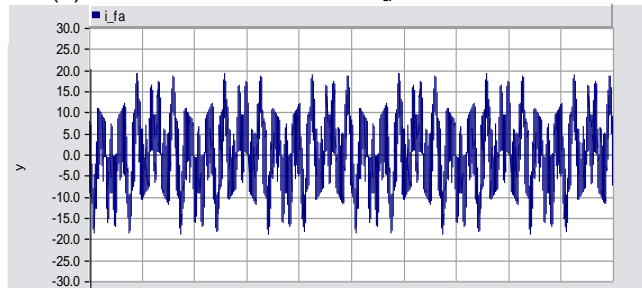
(c) Phase A current i_{fa} injected by the Active Filter

Fig.8. Source current and Active Filter injected current.

The results in Fig.8(a) and (b) show that the current waveform flowing out of the power source is nearly sinusoidal after the harmonic compensation. Also, from the comparison of performances of the proposed indirect adaptive control scheme and traditional PI controllers, is can be observed that since PI controllers are only tuned around a certain operation condition, when the load changes nonlinearly, the performances of the PI controllers degrade. The ESN controller used in the indirect adaptive control has been trained under different load conditions and actually learns the complicated system dynamics of the plant, so it gives better control results than the PI controllers.

2. ***Presentations at Conferences***

- IEEE International Joint Conference on Neural Networks (IJCNN'09), June 14-19, 2009, Atlanta, USA.
- IEEE Intelligent System Applications to Power Systems (ISAP'09), Nov. 2009, Curitiba, Brazil.

D. Summary

- A novel concept of "Load Modeling" has been proposed to provide effective, accurate true harmonic detection of the nonlinear loads in the power grid. The ability of MLPNs to learn the admittance of the customer load using actual field data and utilize a trained neural network for estimating the true harmonic distortion caused by that customer has been validated through both software simulation and laboratory experiments. The advantages of this method are that it can be implemented online without disrupting the operation of any load, since only voltages and currents need to be measured; it does not require any special instruments, and it does not need to make any assumptions about any quantities, e.g., the impedance of the source, or a sine-wave PCC voltage. Every customer has individual power meters which are already receiving the waveforms of voltage and currents, and hence, it is a feasible option to implement the scheme for each customer individually.

- Three different types of neural networks, namely, the MLP, the RNN and the ESN have been used and evaluated for this particular "Load Modeling" application. The MLP and RNN required a much larger size of training set than the ESN. The RNN and ESN gave more accurate load modeling results than the MLP, but required more computational effort. The choice between RNN and ESN is a tradeoff between convergence property and the size of necessary training data. In other words, when the training data is not sufficient, which is quite possible

in practice, the ESN can give better system approximation results than the MLP and RNN.

- A neural-network-controlled active filter has been implemented to eliminate the harmonic pollution after the harmonic current generated by the nonlinear loads in the power system was successfully determined. Since the ESN has a stronger learning ability than the MLP and easier training algorithm then the RNN, it is chosen to be the type of network that is used in the neurocontrol scheme of the active filter. The ESN identifier and ESN controller used in the indirect adaptive control scheme of the active filter are trained and tested online. The control performance of this neurocontrol scheme is compared with traditional PI controllers under five load conditions. The results show that neural-network-based intelligent control is more adaptive than traditional linear controller, especially when the operation condition of the system changes nonlinearly.

- The online training algorithm of the ESN Identifier has also been implemented in a real time, hard-ware-in-loop environment. The active filter and the power system with nonlinear loads are simulated using the Real Time Digital Simulator (RTDS). The training of the ESN Identifier is realized in a DSP board which is connected to and communicates with the RTDS. The successful real time implementation of the online training algorithm shows that the ESN has a strong potential to be used in some practical applications which require fast computational speed in the future.

- The outcomes in Year 4 of the project can be summarized as following:

  - Implemented the Indirect Adaptive Control Scheme using two ESNs for the active filter.

  - Proved the accuracy of the online training algorithm of the ESN.

  - Validated that ESNs have the ability to learn complicated power system dynamics when they are properly trained.

  - Compared the performances of the ESN controller and traditional linear PI controllers and showed that the ESN controller gives better results when the operating condition of the power system changes nonlinearly.

  - One of the major goals of this research project, which is compensating the nonlinear characteristics of non-stationary complex systems, has been successfully achieved: the nonlinear harmonic current in the power system is compensated by the current injected by the active filter using neural-network-based control schemes.

E. Overall Project Deliverables after Four Years

1. Manpower

The following PhD candidates worked on different aspects of this project at Georgia Tech:

- Joy Mazumdar, (graduated with PhD degree in August 2006. Now with Power Conversion Division, Siemens Energy and Automation, Atlanta)
- Debrup Das, PhD candidate took over from Joy Mazumdar.
- Jing Dai, PhD candidate, took over from Debrup Das.

The following students/visiting scholar worked on different aspects of this project at Missouri University of Science and Technology:

- Peng Xiao (graduated with PhD degree in September 2007)
- Shishir Bashyal (graduated with MS degree in May 2008)
- Jing Dai (Visiting Scholar from Georgia Tech from May 2008 to August 2008).

All students have learned how to
- conduct literature surveys
- develop computer code and run simulations
- prepare power point presentations and present their work to others
- write scientific papers
- collaborate with other members of the research group.

2. Follow-on Projects

The project has already generated significant knowledge, and has already resulted in several follow-on projects, including:

- How to identify resonance in the upstream supply circuitry.

3. Publications

Altogether 15 peer reviewed papers were published in international journals and conferences [1-10, 12-16].

4. Patents Filed

R. G. Harley, T. G. Habetler, Frank C. Lambert, and J. Mazumdar. "System and Method for Determining Harmonic Contributions from Non-linear Loads". Inventors: US Patent filed in August 2003. Final US patent number 7,013,227 issued on March 14, 2006.

5. Courses Taught

At Georgia Tech Dr. Harley taught a 3 credit hour one semester graduate level course on "Computational Intelligence in Electric Power" three times during the duration of this project to a total of 28 students.

At Missouri University of Science and Technology Dr. Venayagamoorthy introduced and taught a 3 credit hour one semester graduate level course on "Adaptive Critic Design" during the course of this project to over 15 students from both MST and Georgia Tech (through the distance learning platform "WebEx"). In addition, another course on Real-Time Power System Simulation (RTPSS) was introduced and taught twice by Dr. Venayagamoorthy during the duration of this project. Research from this project on active filters was introduced into the course contents of RTPSS.

6. Awards and Prizes

Dr. Harley received the following award:
- **The 2009 IEEE Richard H. Kaufmann field award with citation** *"For contributions to monitoring, control and optimization of electrical processes including electrical machines and power networks".*

Dr. Venayagamoorthy received the following awards:
- 2010 Innovation Award, Academy of Science, St. Louis, USA.
- 2010 IEEE Region 5 Outstanding Member Award.
- 2009 Missouri S&T Faculty Research Award.
- 2009 IEEE Region 5 Outstanding Educator Award Runner Up.
- Fellow of the South African Institute of Electrical Engineers - effective Feb. 18, 2009.
- Elected to Board of Governors, International Neural Network Society - 2009 to 2011.
- Fellow of the Institution of Engineering and Technology (British equivalent of the IEEE) - effective Sept. 15, 2008.
- 2008 IEEE St. Louis Outstanding Educator Award.
- 2008 Missouri S & T Faculty Excellence Award (recognizing excellence in teaching, research and service contributions to the Missouri S & T).
- IEEE PES Technical Committee Working Group Recognition Award for *Working Group on Multi-Agent Systems*, 2008

- Missouri University of Science and Technology Faculty Excellence Award (recognizing excellence in teaching, research and service contributions to the UMR).
- 2007 Missouri University of Science and Technology Commendation for Teaching Excellence.
- 2006 IEEE St. Louis Section Outstanding Section Member.
- 2006 Missouri University of Science and Technology School of Engineering Teaching Excellence Award.
- 2006 IEEE PES Walter Fee Outstanding Young Engineer.

7. *Outreaches*
- Two tutorials were presented jointly by Drs. Harley and Venayagamoorthy at international conferences and workshops [20-22].
- Several tutorials were presented by Dr. Venayagamoorthy at international conferences and workshops [17-19, 21, 23-25].
- Many invited presentations and lectures were presented by Dr. Venayagamoorthy at international conferences and universities [26-55].

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G. Publications arranged by Year

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F. Appendices
   Copies of papers