Enhanced Wide Area Monitoring System

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***Abstract*—This paper focuses on the design of a wide area monitoring system (WAMS) in a multimachine power system with enhanced reliability, integrity and security. A two-area four-machine power system is considered for the studies. The voltage and speed deviation information coming from the generators is used by the WAM to feed useful information to the wide area control system (WACS), which will then send control signals back to the power system. The proposed WAM uses current and past information from the generators to predict their future values. By combining features such as missing sensor fault tolerance, intrusion detection system and integrity check at the receiving end, the proposed method is more reliable and secured. The proposed EWAMS is capable of overcoming communication delays, mitigating attacks and surviving faults. Results for some modules of the system are shown in support of the proposition.**

***Index Terms*—Auto-encoder, EWAMS, MIMO, Power system, PSO, Quantum Principle, SRN, Wide Area Monitor**

I. Introduction

CONTROL of any component of an electric power system is dependent on the availability of the sensory data in timely manner. In a complex power network, the devices or sub-systems could be geographically distributed. Since different control actions have to be taken for various components, wide area monitoring and control is important for the modern power system. Since sensors associated with components could fail, or the signals coming from various distributed locations could be tampered by unwanted intruders, it is important to have a wide area monitoring (WAM) system with more reliability, integrity and security. In this paper, design of an enhanced wide area monitoring system (EWAMS) is proposed for multimachine power system.

Simultaneous recurrent neural network (SRN) and Echo State Network (ESN) based WAM has been demonstrated to be quite effective at performing predictive neuroidentification of distributed power systems for the purposes of accurate control [1]. Since different components of a power system are geographically distributed, there is communication delay between them. In a WAM, the signals that arrive from different areas have to be considered for communication delays in taking proper control decisions. In [2], a wide-area control system considering communication delays has been implemented. A recurrent neural network is used for wide-area identification in [3]. Use of adaptive critic designs (ACDs) in wide area control of a power system is studied in [4]. Use of ACDs and radial basis function networks for wide area monitoring and control is studied in [5]. SRN trained with a quantum inspired algorithm - particle swarm optimization with quantum infusion (PSO-QI) has been implemented as a WAM in [6]. Various design aspects of wide area monitoring and control systems are studied in [7].

However, to make wide area monitoring and control a feasible system to implement with real-world power systems, it needs to be realistic and have enhanced reliability, integrity, and security. Computational intelligence (CI) tools such as neural networks and swarm, evolutionary and quantum behaved algorithms provide an idealized framework with which to design powerful and effective controllers. One such system with enhanced reliability, integrity and security is presented in this paper. The main contributions of the paper are as follows:

- Proposed design of an enhanced wide area monitoring system with focus on reliability, integrity and security.
- SRN based local and wide area monitors have been implemented with a new training algorithm and two step training approach.

The remaining sections are arranged as follows: Section II describes the proposed EWAMS. The design of EWAMS is described in Section III. Section IV describes the studies carried out and results thus obtained. Conclusions are then given in Section V.

II. Enhanced Wide Area Monitoring System

Fig. 1 shows a block diagram of the proposed EWAMS applied to a two-area four-machine power grid. It uses CI techniques to more accurately predict the state of the system in advance. It consists of different components such as the missing sensor restoration (MSR) module, local area monitor (LAM) module, wide area monitor (WAM) module and the integrity check (IC) module. These modules use different technologies for reliable performance of the system.

The terminal voltage and speed deviation signals from each of the generators in the power system is received at the MSR module of the EWAMS. The MSR monitors the inputs for missing or faulty signal and triggers a CI based algorithm that restores the missing sensor input for a short period of time. This ensures reliability of the system. Since the auto-encoder used in the MSR module computes the correlation between the input signals to produce 'healthy' signal outputs, missing or 'unhealthy' inputs are immediately detected, thus also adding a level of security. The output of the MSR goes into the WAM module which predicts step-ahead values of the speed and voltage deviations of the generators. Delays over

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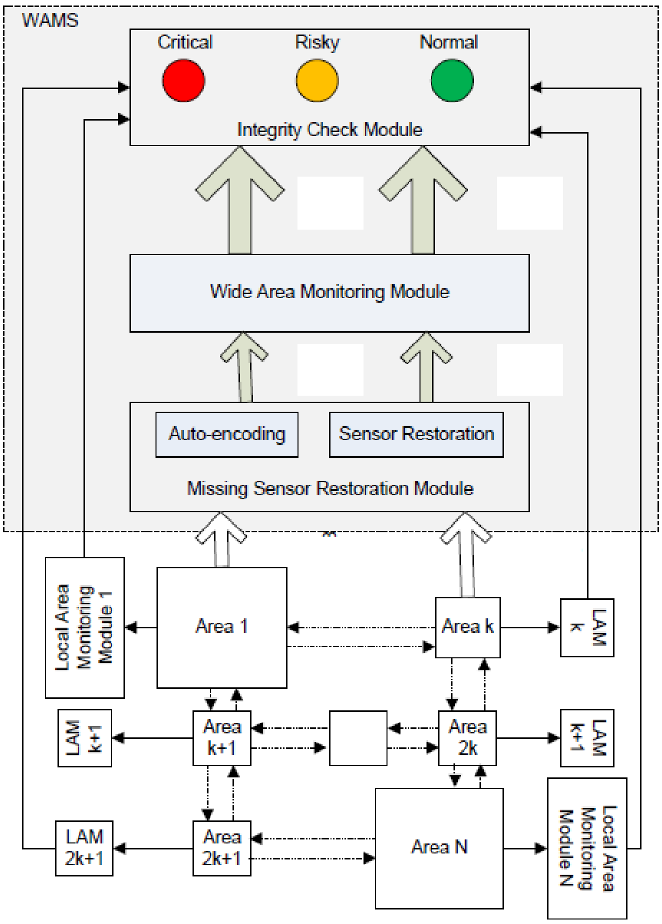

Fig. 1. Proposed design of an EWAMS.

communication channels can be overcome by these step-ahead predictions. The signal from the generators are also predicted using an LAM in each area which is assumed to have a more reliable and secured communication channel to the IC module. The output from the LAM and the WAM are then used by the IC module to compare between the predicted signals of each generator. Since the signals coming from the LAM are assumed to be more reliable, any discrepancy between the LAM and the WAM output during integrity check implies faulty or compromised signals coming from the generators. This will be treated as integrity fail and will raise different alarms. This added redundancy in the system will make it more secured and reliable. The IC module thus helps to identify the healthy, faulty or compromised state of the system. Thus by compensating for communication delays, predicting one or more steps ahead for control decision-making and with added redundancy, the EWAMS has enhanced features of reliability, integrity and security. The design of IC module, however, is not a part of this paper.

A. Reliability

A reliable system is one that functions the way its users expect it to. In this case, this means that the end result of the WAMs function should be a step-ahead prediction of the states of all generators in all areas of the multi-area system. Communication delays, congestion and security breach are some of the obstacles to reliable performance of a WAM. The MSR and the WAM modules help to ensure reliability in the EWAMS. MSR module helps by identifying the missing sensor signal and using a CI technique, such as particle swarm optimization (PSO), to restore the missing sensor. The multiple-inputs multiple-outputs (MIMO) SRN predicts future outputs of the system ahead of time. This ability of the system to predict the output well in advance makes it more reliable. Wide Area Controllers (WACs) can use this reliable information from the WAM to take proper control actions in real time.

B. Integrity

Integrity is trustworthiness. In order for a controller to make good decisions, it must have accurate, fault-free data with which to generate its choices. Real-world devices, however, are not always perfectly reliable. Sensors can malfunction, signals can become delayed due to congestion, and electromagnetic noise can cause glitches in communication. Missing-sensor fault tolerance [8] utilizes neural networks as auto-encoders to correlate interdependencies in data and detect inaccuracies in the reported data. The auto-encoder in the MSR module allows for the detection of faulty signals that is, signals that do not reflect the true state of the system and the PSO compensator uses the mutual information in the healthy signals to estimate the true value of the missing signal for brief periods, allowing for excessive lag or even sensor failure without sacrificing the integrity of the overall system. This is further enhanced by having LAMs in different areas for reporting the state of the signal through a more secured channel for the integrity check which is performed by the IC module and informed to the user in some ways.

C. Security

One of the dangers of separating monitoring and control from the system to be managed is that it becomes more vulnerable to remote interference by malicious entities. A secure system can detect such intrusions and compensate for them, not permitting them to interfere with proper function of the system as a whole and alerting human operators to the problem if such persists. The MSR module adds inherent security to the system by restoring faulty signal to real values, thus making any unhealthy or compromised signals useless. Also, the redundant information from the LAM over a secured channel provides additional security feature. The IC module uses this reliable information to alert the user about the state of the system thus making it secured.

III. DESIGN OF EWAMS

The EWAMS proposed in this paper is implemented on a multimachine power system. Different components of EWAMS are described below:

A. Multimachine Power System

The practical power system is a complex system with thousands of buses, several hundreds of generators and interactions between multiple areas with several inter-area modes of oscillations. In this study, the two-area four machine power system shown in Fig. 2 [9] is taken as the test system. The parameters of the two area system are given in [10].

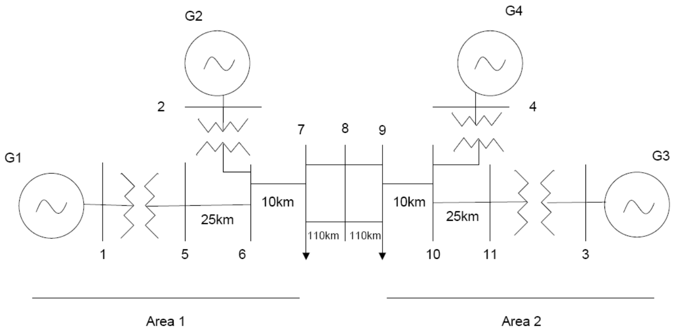

Fig. 2. Two area four machine system used in the study.

B. Missing Sensor Restoration Module

The MSR module takes the terminal voltage and speed deviations of the generators as its inputs and feeds the output, which is same as the input, to the WAM module. The MSR receives these inputs every 10 ms (100 Hz), which is possible with today's phasor measurement unit technology [10]. It is implemented by an auto-encoder and a PSO based signal restoration mechanism. The auto-encoder for the two area four machine system used in this study is realized by an MLP. When everything works properly, a trained auto-encoders outputs match its inputs. The outputs represent a re-calculation of the inputs based on the interdependencies of the signals. Thus, if one signal is reporting falsely (such as would happen if a sensor failed, but the machine it was sensing still functioned), the outputs will not match the inputs but some element of the missing sensors true behavior is still reflected in the reports of the other sensors. After it is trained, if any one of the input signals is not "healthy", there will be error on the output. So, if a faulty signal is given as input to the auto-encoder (or a sensor goes down and the signal is missing), it will identify the faulty (or missing) signal. At this point, it triggers the PSO based restoration mechanism which makes an intelligent guess of the value of the missing input signal based on the other inputs, such that the error at the output of the auto-encoder is reduced. Thus the missing or faulty signal is replaced by a true approximation of the actual signal.

C. Wide Area Monitor Module

A WAM in the EWAMS is a next state predictor. The inputs to the WAM are the current deviations in terminal voltage $Vref$ and speed $\Delta\omega$ as provided by the MSR module. The output of the WAM is a step-ahead prediction of the voltage and speed deviations. The WAM in this work is implemented by an SRN, with two sets of weights, each set of weight responsible for predicting the voltage and the speed deviations of the next sample respectively. The WAM under considerations is MIMO system and identification of such system is very difficult. Hence a two step procedure for training the MIMO SRN is implemented. In Step1, SRN is trained using a quantum inspired algorithm, particle swarm optimization with quantum infusion (PSO-QI), to obtain the input and output weights. In Step 2, the input weights obtained in Step 1 are kept fixed, and the same SRN is trained to obtain the output weights, with only one output at a time. The architecture of the implemented SRN and algorithm used to train it are described below:

1) Simultaneous Recurrent Neural Networks: Elman SRN used in this study is a three layered neural network with its feedback from the hidden layer output to the context layer inputs. It has an input layer with 8 input nodes, a hidden layer node with 15 hidden nodes and an output layer with 4 output nodes. Being an Elman network, it also has a context layer with 15 nodes whose inputs are the outputs of the corresponding hidden layer nodes.The hidden nodes have sigmoid activation function and the output nodes are linear. An Elman SRN is represented in vector notation as [11]:

$$H(t,k) = f(A*I(t,k) + B*H(t,k-1) + K) \quad (1)$$

$$O(t) = g(C*H(t,k) + K') \quad When\ k = R \quad (2)$$

where, $I = [Vref_1, Vref_2, Vref_3, Vref_4, \Delta\omega_1, \Delta\omega_2, \Delta\omega_3, \Delta\omega_4]$ is the set of inputs, H is the set of outputs from the hidden nodes and $O = [O_1, O_2, O_3, O_4] = [\Delta\hat{\omega}_1, \Delta\hat{\omega}_2, \Delta\hat{\omega}_3, \Delta\hat{\omega}_4]$ is the set of outputs. A contains weights from input layer to the hidden layer, B contains weights from context layer to the hidden layer, C contains weights from hidden layer to the output layer, k is the time index of internal recurrence, t is the time index of the input sample, R is the total number of internal recurrences, K and K' are the biases, f and g are the two activation functions. Another similar architecture is used for the voltage deviation predictions.

2) Particle Swarm Optimization with Quantum Infusion: PSO-QI is a hybrid algorithm that uses the quantum principle from quantum-behaved PSO (QPSO) to create a new offspring in PSO. After the positions and velocities of the particles are updated using standard PSO equations, a randomly chosen particle from PSO's $pbest$ (the previous particle position giving the best fitness value) population is utilized to carry out the quantum operation; and thus, create an offspring by mutating the $gbest$ (the best particle among all the particles in the swarm). The fitness of the offspring is evaluated and the offspring replaces the $gbest$ only if it has a better fitness. This ensures that the fitness of the $gbest$ is equal to or better than its fitness in the previous iteration. Thus, it is improved and pulled toward the best solution over iterations.

According to the uncertainty principle, position and velocity of a particle in quantum world cannot be determined simultaneously. Thus QPSO differs from standard PSO mainly in the fact that exact values of x and v cannot be determined. Hence the probability of finding a particle at a particular position in the quantum search space is mapped into its actual position in the solution space by a technique called "collapsing". In Quantum Delta-Potential-Well based PSO (QDPSO) [12], a delta potential well based probability density function is used to avoid explosion and help the particles converge. By using Monte Carlo Simulation [12], the position equation in QDPSO is given by (3):

$$x(k) = J(k) \pm \frac{L(k)}{2} ln(1/u) \tag{3}$$

where u is a uniform random number in the interval [0,1]. The particle's local attractor point J has coordinates given by the following equation:

$$J_d(k) = \alpha_1 P_{gd}(k) + \alpha_2 P_{id}(k) \tag{4}$$

where P_{id} is the i^{th} $pbest$ particle in d^{th} dimension and P_{gd} is d^{th} dimension of the $gbest$ particle obtained from PSO. L is the length of the potential field given by:

$$L(k) = 2\beta |J(k) - x(k)| \tag{5}$$

The parameter β is the only parameter of the algorithm. It is called the creativity coefficient and is responsible for the convergence speed of the particle.

The Mean Best Position, $mbest$, is defined as:

$$mbest(k) = \frac{1}{S}\sum_{i=0}^{S} P_i(k) = \left(\frac{1}{S}\sum_{i=0}^{S} P_{i1}(k), \ldots, \frac{1}{S}\sum_{i=0}^{S} P_{iD}(k)\right) \tag{6}$$

where S is the size of the population, D is the number of dimensions and P_i is the $pbest$ position of each particle. In QPSO, J in (5) is replaced by $mbest$ to form (7) as follows:

$$L(k) = 2\beta |mbest(k) - x(k)| \tag{7}$$

By using (4) this can also be written as follows to show the mutation on $gbest$, where the addition or subtraction is carried out with 50% probability:

$$x(k+1) = \alpha_1 P_{gd}(k) + \alpha_2 P_{id}(k) \pm \beta |mbest(k) - x(k)| ln(1/u) \tag{8}$$

In PSO-QI, the position update equation (8) has been used to mutate the $gbest$ particle obtained from PSO. The pseudocode for the PSO-QI algorithm is as follows:

Initialize position x, velocity v and let $pbest$=x
repeat
  for i = 1 to $populationsize$ **do**
    Evaluate fitness
    if fitness (i) < fitness ($pbest$) **then**
      $pbest$ = x and $gbest$ = min($pbest$)
    end if
    Update v and x using standard PSO equations
  end for
  Calculate $mbest$ using (6)
  Select a random particle r
  for d from 1 to $dimensionsize$ **do**
    $\alpha_1, \alpha_2 = rand(0, 1)$
    $J = (\alpha_1 * P_{rd} + \alpha_2 * P_{gd})/(\alpha_1 + \alpha_2)$
    $L = 2\beta * |mbest - x_{rd}|$ using (7)
    if $rand(0, 1) > 0.5$ **then**
      using (3)
      $offspring = J - \frac{L}{2} * ln(1/u)$
    else
      $offspring = J + \frac{L}{2} * ln(1/u)$
    end if
    if fitness ($offspring$)<fitness($gbest$) **then**
      $gbest = offspring$
    end if
  end for
until termination criteria is met.

D. Local Area Monitor Module

The LAM module is based on each area and takes the terminal voltage and speed deviations of the generators in that area to calculate their step-ahead predictions. It is similar to the WAM explained in the previous section in implementation and training, except that it has fewer inputs (from generators in that area). Its output goes to the WAMS through a secured communication channel for the integrity check.

E. Integrity Check Module

The IC module is basically a comparator with an intelligent algorithm as the decision maker. It compares the input from the WAM and the LAM every sample. By looking at the difference in their values in each sample and over a period of time, the intelligent algorithm makes decisions about the state of the signal. Since the information coming from the LAM is assumed to be secured and more reliable, the discrepancy identified by the IC module will be reported as errors in the signals coming from the WAM. The state of the system is thus determined as being 'normal', 'risky', or 'critical' based on the duration, amplitude and nature of discrepancy. The alarm could be visual representation in colors, or sound or other methods of communicating to the user for required action.

IV. Results and Discussions

MLP and SRN architectures are used for different modules of the EWAMS. For training these neural networks, PSO and PSO-QI algorithms have been used. These algorithms converge to a solution based on some fitness function. In this study mean squared error (MSE) between the output of the neural networks and the actual output of the generator has been used as the measure of fitness. For each generator i, MSE for Step 1 can be written as (9).

$$MSE_T = \frac{1}{4}\sum_{i=1}^{4} MSE_i \tag{9}$$

where,

$$MSE_i = \frac{1}{N}\sum_{i=1}^{N} (\Delta\omega_i(k) - \Delta\hat{\omega}_i(k)) \tag{10}$$

where $\Delta\omega$ is the actual output of the generator and $\Delta\hat{\omega}$ is the predicted output from the neural network at sample k. Eq. (10)

gives the MSE for Step 2. The neural networks are trained using the terminal voltage and speed deviations of the four generators in the two-area four-machine power grid considered in the study. The data used for the training has 1000 samples captured in 10s. A forced training is carried out in which all four generators are subjected to a PRBS excitation and their corresponding voltage and speed deviations are measured. The networks thus trained are tested on the same dataset.

A. Auto-encoder

Auto-encoder used in this study is composed of 4 MLPs, two in each area- one for the voltage and other for the speed deviation. The choice of 4 MLPs is because a MIMO MLP with large number of inputs does not perform well. The auto-encoder implementation using MLP is shown in Fig. 3. The network is trained using PSO with the fitness function given by (10). After the auto-encoder is trained, its outputs match its inputs. This is then fed to the WAM. The testing results are shown in Figs. 4 and 5. These results show that the output of the auto-encoder is able to closely match the actual values of voltage and speed deviations of the generators.

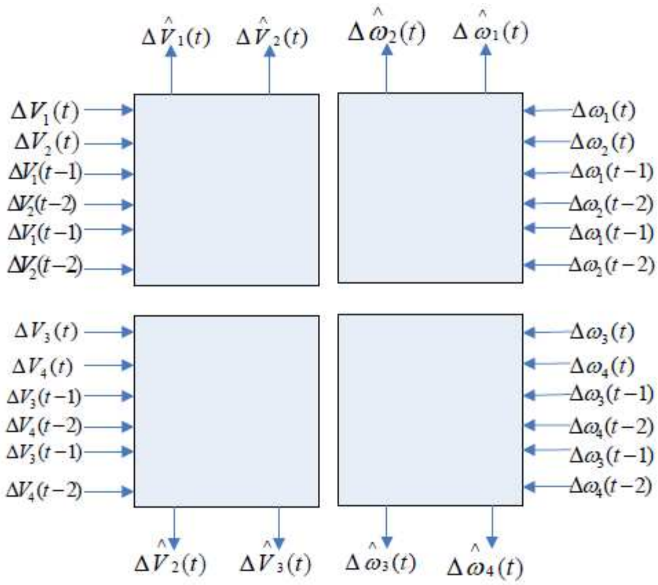

Fig. 3. Auto-encoder implementation using four MLPs.

B. WAM

WAM is implemented using SRNs. The SRN is trained using PSO-QI in two steps. The 8 inputs of the SRN are the current values of voltage and speed deviations of each generator. The 4 outputs are the one step-ahead predicted values of the voltage (or speed) deviations. Choice of this training algorithms is based on the authors' successful implementation of MIMO SRN training using this algorithm and approach in their previous work [6]. In Step 1, SRN is trained using all the inputs and outputs. In Step 2, the input weights obtained from Step 1 are kept fixed and the SRN is trained only for the output weights, one at a time for each output. The following parameters are used for PSO-QI.

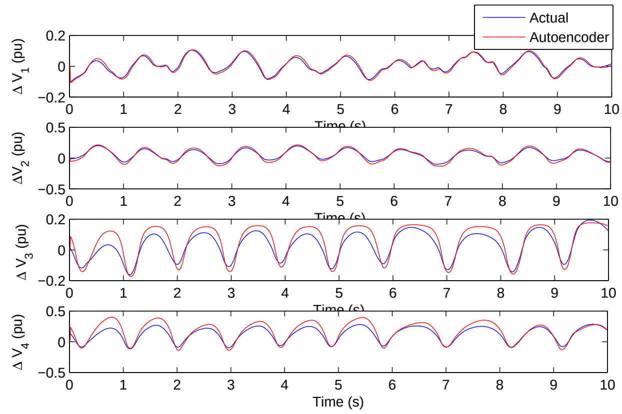

Fig. 4. Output from the auto-encoder for terminal voltage.

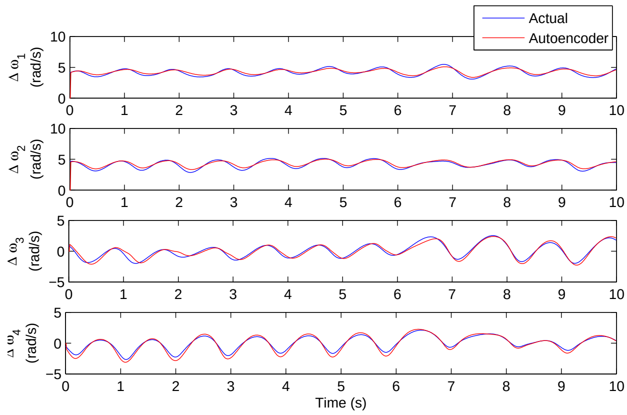

Fig. 5. Output from the auto-encoder for speed deviation.

c_1, c_2 = 2
w = linearly decreasing from 0.9 to 0.4
Population Size: 30
Number of iterations in Step 1: 100
Number of iterations in Step 2: 50
β = linearly increasing from 0.5 to 1
Dimension (D) = 405 (Step 1), 15 (Step 2)

Based on the inputs from the MSR, the WAM then computes the outputs, which are then fed to the IC module for determining the state of the system. The test results obtained for the SRN in WAM are shown in Figs. 6 and 7. The output of the WAM for the input from the MSR is shown in Figs. 8 and 9. These results show the ability of the WAM to predict the voltage and speed deviations of the generators for the input obtained from the MSR.

C. LAM

The LAM, also implemented as an Elman SRN, is local to each area. Its inputs are decided by the number of generators in that area. The structure of the SRN used in LAM is similar to that in WAM except for the number of input/output. In this study, the LAM is a 4 input and 4 output SRN with 15 hidden

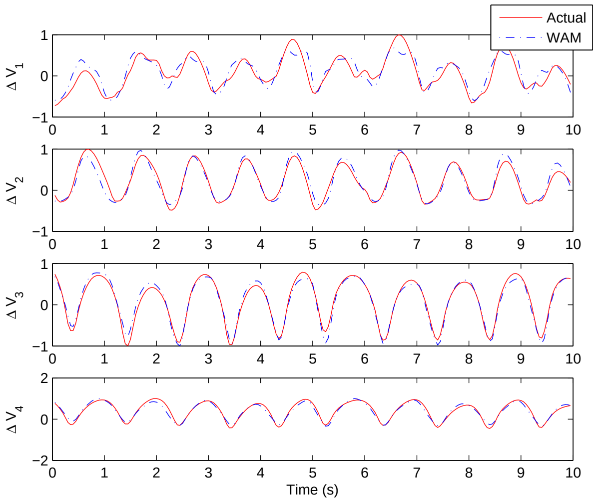

Fig. 6. Speed deviations of the four generators during testing of WAM.

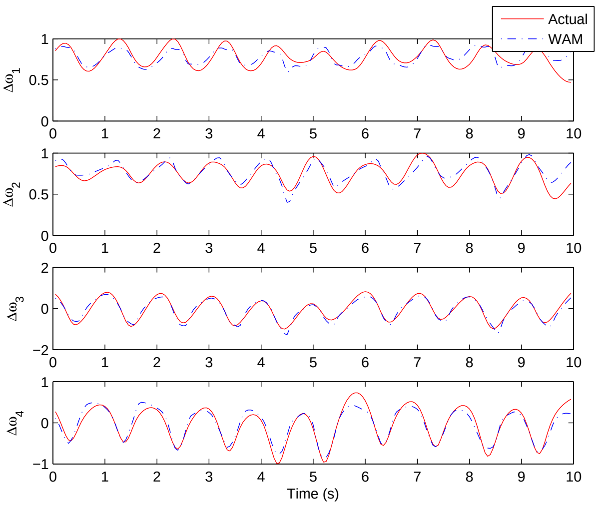

Fig. 7. Voltage deviations of the four generators during testing of WAM.

nodes. The test results obtained for the predicted values of speed and voltage deviation for Area 1 are shown in Figs. 10.

V. Conclusion

In this paper, design of an EWAMS is proposed. Some of the modules of the proposed system are implemented and shown with results. In the study, the auto-encoder is implemented by an MLP and the WAM and LAM by a MIMO SRN. The SRNs are trained using PSO-QI by using an effective two step training approach. With enhanced features of reliability, integrity and security, the proposed EWAMS will be important in the future smart grid. However, research in still in progress in this area. The implementation of PSO-based restoration mechanism in MSR and implementation of IC module is authors' work in progress and not a part of the results shown in this paper. Cellular neural networks implementation for MSR and WAM module and integration of different modules to realize the complete proposed system is a part of the authors' future work. This study is a beginner

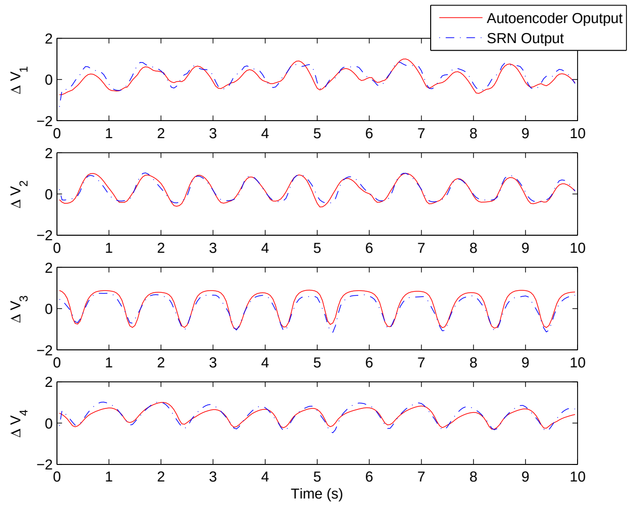

Fig. 8. Voltage deviations output from the SRN with input from the auto-encoder.

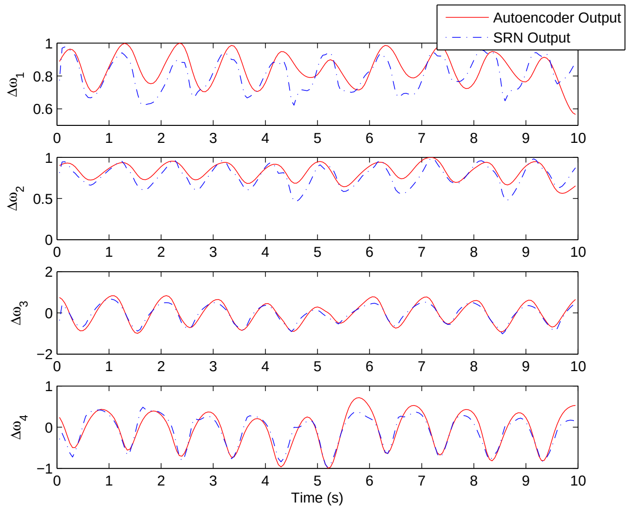

Fig. 9. Speed deviations output from the SRN with input from the auto-encoder.

level work in implementation of cyber-physical energy system and associated research. Implementation of the EWAMS on real-time hardware platform and its integration with the wide area controller will follow as other future works.

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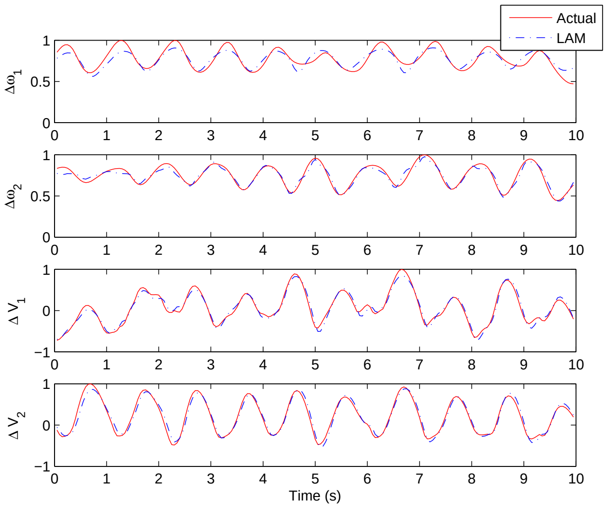

Fig. 10. Voltage and speed deviations of the generators in Area 1.

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