Reservoir Based Learning Network for Control of Two-Area Power System with Variable Renewable Generation

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Abstract—The penetration of renewable energy sources into the electric power system is rapidly increasing. Integrating variable renewable energy sources into the transmission grid introduces challenges in real time power system operation. This causes power and frequency fluctuations and raises stability concerns. In this paper, a 200 MW photovoltaic (PV) plant is integrated into a two-area four-machine power system. In order to maintain the system frequency, a dynamic tie-line power flow control is implemented using predicted PV power as an input to the automatic generation controller in Area 1, which transfers power to Area 2 with PV generation. The prediction performances of two learning reservoir based networks, an echo state network (ESN) an extreme learning machine (ELM), are investigated for day and night time operations. The experimental study is performed using actual weather data from Clemson, SC and a real time simulation of a utility-scale PV plant integrated power system. Phasor measurement units (PMUs) are used to provide input signals to automatic generation controllers in the two area power system. Typical tie-line power flow control results based on ESN and ELM models are presented to show the impact of predicting PV power in improved automatic generation control with variable generation. ESN and ELM models provide minimal tie-line power flow deviations from reference power flows during day and night time operations, respectively.

Keywords— echo state network, extreme learning machine, phasor measurement units, PV power, prediction, renewable energy, tie-line power flow control

1. INTRODUCTION

The use of fossil fuel as an energy source introduces several environmental concerns due to greenhouse gas emissions and environmental pollution. Furthermore, the worldwide price fluctuations and uncertainty in fossil fuel has become a challenge in securing sustainable power systems. These reasons increase the requirement of clean, safe and environmental friendly power sources. Therefore the use of environmental friendly, sustainable and renewable energy sources such as photovoltaic (PV) and wind power has been increasing [1]. Renewable energy sources can be used with an alternative power or demand side management technologies to get maximum penetration of clean energy. Among the existing renewable energy sources, the use of PV plants is increasing due to the high presence of solar insolation in many places for longer periods of time and incentives from governments to encourage clean sources of energy [2].

Even though the use of renewable energy has advantages compared to use of fossil fuels, concerns still exist in the reliability and security of the power systems with high integration of PV power. The power and frequency fluctuations in systems with utility-scale MW PV plants affect the steady state and transient stability of the system due to the unpredictable variable PV generation [3]. PV power generation mainly depends on weather conditions such as solar irradiance, temperature and cloud covers. The effects of the variability and uncertainty caused by PV plants in bulk power system operation can be reduced by accurate short-term predictions of PV plant power outputs.

Artificial neural networks (ANNs) have been used widely for nonlinear prediction such as power system loads, wind power generation and PV power generation. Echo state network (ESN) and extreme learning machine (ELM) are reservoir based neural networks, which are rich in dynamics, fast and easy to develop. Therefore, these two network models are developed and compared for predicting PV plant power outputs during day and night conditions in this paper.

A two area four machine power system (Fig. 1) is considered in this study. Area 1 transfers power to Area 2 which has a 200 MW utility-scale PV plant installation. The power system with the PV plant is simulated on the real time digital simulator (RTDS). The PV plant output in the RTDS simulation is generated using actual solar irradiance and temperature data captured by the Real-Time Power and Intelligent Systems (RTPIS) Laboratory weather station at Clemson, SC. Frequency and tie-line power flow control are essential to maintain the security of the power system. In other words, fluctuations in the frequency and tie-line flow as a result of variations in the PV plant power needs to be minimized. A secondary control strategy, automatic generation control (AGC), with tie-line power flow control was implemented in Area 1 to maintain the desired system frequency and to minimize power fluctuations [4, 5]. AGC

is capable of increasing/decreasing power outputs of conventional generators (G1 and G2) in Area 1, varying the tie-line power flow to balance the PV power variability and achieve maximum penetration of PV power in Area 2. The AGC in Area 1 accomplishes the above mentioned objectives using predicted PV power reference values to control the tie-line power flow. The optimal frequency bandwidth of the AGC is determined by simulating the system with different PV power prediction time steps. Phasor measurement units (PMUs) are used to provide input signals to the automatic generation controllers in the two area power system.

The remainder of this paper is organized as follows. Section 2 describes the two-area power system with an utility-scale PV plant used in this study. The tie-line bias control with PV power prediction is described in Section 3. Section 4 describes the reservoir based learning networks used to predict PV power output. Typical results obtained are presented in Section 5. Finally, conclusions are given in the Section 6.

2. POWER SYSTEM WITH PHOTOVOLTAIC PLANT INTEGRATION

In this study, a two-area four-machine power system is considered. A 200 MW PV plant consisting of four 50 MW PV plants is integrated to Area 2 as shown in Fig. 1. The two areas are connected by two parallel transmission lines. Each area has two synchronous generators, G1 and G2 in Area 1, and G3 and G4 in Area 2, all rated at 900 MVA [5].

Four 50 MW PV plants are connected to a 230 kV utility transmission grid through a double converter and transformer stage as shown in Fig. 2. The first conversion stage is from dc to dc using a boost converter, and the second stage is from dc to ac. Maximum power point tracking (MPPT) is implemented in the first stage. In the inverter controller (second stage) design, the simple principle that active power corresponds to the phase angle difference and reactive power corresponds to the voltage magnitude difference was utilized. The inverter was bi-directional, meaning that it supplies ac power to the transmission grid and could supply instantaneous dc power to the dc bus, if necessary.

All the generators are equipped with their primary controllers, including turbine governors and automatic voltage regulators. Under normal conditions with no PV power penetration, 400MW power flow is observed from Area 1 to Area 2 [2, 5]. Seven PMUs are placed in the power system at the generator buses (1, 2, 3 and 4), ends of the tie-lines (buses 7 and 9) and the PV plant point of common coupling (bus 12) to measure the generator power outputs, area frequencies, tie-line power flow, and PV power generation respectively.

Real time weather profiles, solar irradiance and temperature, are used to simulate the PV plant generation (Fig. 2). The weather profiles are measured by the weather monitoring system at the RTPIS Laboratory, Clemson University, SC, USA. These weather parameters are passed onto the RTDS to implement a real-time simulation of the PV plant

power outputs. Corresponding PV power outputs are captured for the respective temperature and solar irradiance measurements for ESN and ELM model developments. Variations of solar irradiance and temperature during a typical day time are shown in Fig. 3 (a) and (b). The entire system used for this study including power system, PV plant that is integrated into Area 2 and PMUs are developed on a real-time platform based on the RTDS for power systems.

Fig. 1. Two-area four machine power system with a 200MW PV plant connected at bus 12 in Area 2. Each power system area is equipped with an automatic generation controller. AGC in Area 1 performs tie-line bias control and AGC in Area 2 performs frequency control.

3. TIE-LINE BIAS CONTROL USING AUTOMATIC GENERATION CONTROL (AGC)

Figure 4 (a) and (b) show the block diagrams of AGC in Area 1 and Area 2, respectively. Each AGC maintains its respective area frequency at 60Hz. In addition, Area 1 AGC regulates the tie-line power flow. Thus, the AGC in Area 1 performs tie-line bias control [2]. This is achieved by calculating area control error (ACE) as given in (1) and adjusting the power outputs of the generators in Area 1 (G1 and G2) to make ACE equal to zero. Real time PV plant generation information in Area 2 is used in the ACE calculation in Area 1. This allows for maximum utilization of the PV plant generation in Area 2 in supplying its load demand.

$$ACE = \Delta P_{tie} - \lambda_R \times \Delta f \quad (1)$$

where

- λ_R is the balancing authority's bias factor.

- ΔP_{tie} is the difference between the commanded tie-line power flow, P_{ref} , and actual tie-line power flow, P_{tie} , are shown in Fig. 4 (a).
- Δf is the difference between the Area 1 frequency, f_{PMU} , and reference frequency, f_{ref} , as shown in Fig. 4(a).

The deviation in tie-line power flow from its commanded reference value due to the response time of AGC (frequency bandwidth) is minimized by predicting the PV plant power output. The reservoir based learning networks developed to predict PV power are described in the next section. The prediction time step is synchronized with the optimal frequency bandwidth (response time) of the AGC in Area 1. An optimal prediction time step is determined to minimize the tie-line power flow deviation. Details on determining an optimal prediction time step based on a metric the authors have defined is described in Section 5.

Fig. 2. 200 MW PV plant and the RTPIS Lab (Clemson, SC) weather monitoring system.

(a)

(b)

Fig. 3. Weather profiles on August 26th, 2014 recorded at the RTPIS Lab in Clemson University, SC: (a) Solar irradiance and (b)

Temperature.

(a)

(b)

Fig. 4. (a) Block diagram of automatic generation controller in Area 1 showing measured/predicted PV power utilized as control input and (b)

Block diagram of automatic generation controller in Area 2.

4. RESERVOIR BASED LEARNING NETWORKS

ELM and ESN learning networks are chosen for PV power generation prediction since their computational requirements are less, their learning process is simple and faster, and they have the ability to learn the nonlinear behavior of PV plants connected to power systems. Temperature, solar irradiance and PV power output at current time are used as inputs for both ESN and ELM models. In rest of this section, these two learning network models are described.

4.1. Extreme Learning Machine

Extreme learning machine is a single hidden layer feedforward neural network (SFFN) whose hidden layer parameters need not to be learned. Figure 5 shows basic network architecture of ELM. In an ELM, the hidden nodes are randomly chosen and the output weights are analytically determined. Thus, the slow learning observed in feedforward neural networks such as multilayer perceptron is addressed by ELMs. ELM is extremely fast in learning the input-output mapping [6].

Fig. 5. An architecture of an ELM.

The ELM output and weight computations are explained as follows [7]. Consider n arbitrary distinct samples $(U(i), Y(i))$, where $U(i) = [U_i(1), \dots, U_K(i)]^T \in R^K$, $Y(i) = [Y_i(1), \dots, Y_L(i)]^T \in R^L$, activation function g and N number of hidden nodes. Then,

- Randomly assign input weights W_{in} and bias b , where $W_{in} = [W_{in1}, \dots, W_{inN}]^T$ and $b = [b_1, \dots, b_N]^T$
- Calculate hidden layer $H = [n \times N]$

$$H(W_{in}, b, U) = \begin{bmatrix} g(W_{in1}U(1) + b_1) & \dots & g(W_{inN}U(1) + b_N) \\ \dots & \dots & \dots \\ g(W_{in1}U(n) + b_1) & \dots & g(W_{inN}U(n) + b_N) \end{bmatrix} \quad (2)$$

- Calculate the output weights (readout weights) W_{out}

$$W_{out} = pinv(H) \times T \quad (3a)$$

$$W_{out} = [N \times L] = [W_{out1}, \dots, W_{outN}]^T \quad (3b)$$

$$T = [N \times L] = [Y_1(i)^T, \dots, Y_L(i)^T] \quad (3c)$$

where $\text{pinv}(H)$ is Moore-Penrose pseudoinverse of H , and T is the transpose of the training output matrix. Finally, output is calculated as in (4)

$$Y(i) = H \times W_{out} \quad (4)$$

4.2 Echo State Network

Echo state network is a recurrent neural network (RNN), whose training process is easier and requires less computational effort compared to traditional RNNs of similar size [8]. Fig. 6 shows basic structure of ESN.

Fig. 6. An architecture of an ESN.

ESN has a sparsely connected hidden layer which is known as reservoir. The connectivity and weights of the reservoir are randomly assigned and fixed. During learning, only the connections from the reservoir to output units (readouts) are computed [9, 10]. This makes the computation of ESN simpler and faster than RNNs. The computations in an ESN can be described as below.

Consider a discrete time ESN with K input units, N hidden layer units and L output units. Activations of inputs at time step i is $U(i) = (U_1(i), \dots, U_K(i))$, activations of hidden nodes at time step i is $X(i) = (X_1(i), \dots, X_N(i))$ and activations of outputs at time step i is $Y(i) = (Y_1(i), \dots, Y_L(i))$. The dimensions of the weight matrices are as follows

- Input weight matrix $W_{in} = [N \times K]$
- Reservoir weight matrix $W = [N \times N]$
- Feedback weight matrix $W_{fb} = [N \times L]$

- Readout weight matrix $W_{out} = [L \times (K + N + L)]$

The activation of reservoir units for $i+1^{th}$ time step is updated according to (5) [11].

$$X(i+1) = f(W_{in}U(i+1) + WX(i) + W_{fb}Y(i)) \quad (5)$$

where f is activation function for reservoir neurons.

Readout weights matrix is computed using (6).

$$(W_{out})^T = pinv(M) \times T \quad (6)$$

where M is the matrix of concatenated input/reservoir/previous target output states $(U(i), X(i), Y(i+1))$ as a row and $pinv(M)$ is the Moore-Penrose pseudoinverse of M . T is the sigmoid-inverted output $tanh^{-1}(Y(n))$ as a row. Finally, the ESN output is computed according to (7).

$$Y(i+1) = f_{out}(W_{out}(U(i+1), X(i+1), Y(i+1))) \quad (7)$$

where f_{out} is activation function for output neurons.

ESN's reservoir needs to satisfy certain conditions and these include: i) The reservoir should be rich in dynamics for the learning performance [12]; ii) The reservoir should satisfy the echo state property, that is the state of the reservoir $X(i)$ should be uniquely defined by the fading history of the input $U(i)$ [11, 13]. To ensure the echo state property, reservoir matrix should have a sparse connectivity; and iii) The reservoir size, spectral radius of the reservoir weights matrix and scaling of inputs should be carefully chosen to reach the maximum performance of the ESN [15].

5. RESULTS AND DISCUSSION

5.1 Measurement of the Effectiveness of Tie-line Power Flow Control

A metric, given in (8), is defined to measure the effectiveness of tie-line power flow control with and without prediction of PV power signals and to allow for selection of an optimal time step for predicting the PV power.

$$Metric = \frac{\sum_{i=1}^n |\Delta P_{tie}|}{\sum_{i=1}^n |P_{ref}'|} \times 100\% \quad (8)$$

where

- ΔP_{tie} is the difference between the commanded tie-line power flow, P_{ref}' , and actual tie-line power flow, P_{tie} , are shown in Fig. 4(a);

- P_{ref}' is the difference between the tie-line power flow reference with zero PV power generation in Area 2 and actual tie-line power flow, P_{tie} , are shown in Fig. 4(a); and
- n is the number of data points sampled over a given period of time.

The metric is a normalized unit less scalar value. Thus, this allows for experimentation over different time horizons. This is important as different seasons will change the duration of daylight presence, especially for places in the Northern and Southern hemispheres.

For a perfect tie-line power flow control, the ideal value of (8) is zero. To attain this ideal value or to get as close as possible, the predicted value of PV power which determines the reference power, P_{ref}' , needs to be carefully estimated. The magnitude of the predicted PV power needs to account for the anticipated time delay in generators (G1 and G2 in Area 1) attaining the desired dispatch. In other words, the anticipated time delay is the prediction time step (tp) that needs to be synchronized with the frequency bandwidth of the AGC in Area 1.

5.2 Optimal Prediction Time Step

For the power system studied in this paper (Fig. 1), the response times of the Area 1 and 2 AGCs are found to be in order of 30 to 40 seconds. Therefore, ESN/ELM models are developed to predict PV output for three different time steps in this range for this study. A second metric called the factor of reduction is defined in (9) to choose an optimal time step of three possibilities ((30s, 35s and 40s).

$$factor_of_reduction = \frac{Metric_{no_prediction}}{Metric_{tp}} \quad (9)$$

where $tp = 30, 35$ and 40 seconds.

Solar irradiance, temperature and PV plant power differ during day and night times, and as such the data poses different complexity during day and night conditions to the prediction networks. Therefore, the determination of a near-optimal prediction time step is studied for day and night conditions.

A 12-hour data for each day and night condition was captured for developing ESN and ELM models in the month of August 2014 at Clemson University. Tables I and II present the performance (based on (8) and (9)) of ESN and ELM models for the three prediction time steps using data under day and night conditions, respectively.

According to the results obtained in Tables I and II, factors of reduction greater than one are observed in all cases. Specifically, these are greater with the prediction time step of 35s for both day and night operations. It is further

observed that the ESN model outperforms the ELM model during day time operation whereas the opposite is observed during night operation. This is further investigated over longer periods of time in Section 5.3

Table I – Evaluation of ESN and ELM performance using day time data.

Time step	Metric (in (8))		Factor of reduction (in (9))	
	ESN	ELM	ESN	ELM
30	1.4961	0.8497	1.1223	1.9761
35*	0.2148	0.4982	7.8170	3.3703
40	1.3113	0.6902	1.2805	2.4327
No prediction	1.6791		1	

*Optimal prediction time step

Table II – Evaluation of ESN and ELM performance using night time data

Time step	Metric Value		Factor of reduction	
	ESN	ELM	ESN	ELM
30	0.1190	0.0344	1.3546	5.6760
35*	0.0886	0.0244	1.8194	6.6475
40	0.0923	0.0278	1.7465	5.7986
No prediction	0.1612		1	

*Optimal prediction time step

5.3 Comparison of ESN and ELM Performances under Day and Night Conditions

In order to validate the findings from Tables I and II that the ESN model performs well during day time conditions and the ELM model does during night time conditions, further studies were carried out. Results using the metric in (8), four case studies are presented in Table III. Two of the four case studies (Cases 1 and 2) are carried out during day time conditions including a sunny day and a cloudy day. The other two case studies (Cases 3 and 4) are carried out for two different nights. Again, it is observed for Cases 1 and 2, day time operation, ESN outperforms ELM, and in Cases 3 and 4, night time operation, ELM outperforms ESN.

Table III – Performance of ESN and ELM models under day and night conditions.

Reservoir Model	Case 1 – Sunny Day	Case 2 – Cloudy Day	Case 3 – Night #1	Case 4 – Night #2
ESN	0.048179	0.05838	0.015028	0.038846
ELM	0.077605	0.071144	0.012658	0.017383

The ESN model output depends on the previous states of its reservoir, but the ELM model output does not depend on its previous reservoir state. Additionally, the range of PV power output variation is large during day time (5 – 200 MW). It can be concluded that the effect of the rich dynamic reservoir of the ESN model led it to perform well compared to the feedforward nature of the ELM model.

During night time, PV power output values lies in a short range of values (1-3 MW) and fluctuates rapidly. This can be observed from Fig. 7 which represents the variation of PMU measured PV power during night time. Reservoirs of the ELM and ESN are feedforward and feedback driven respectively. This means that the ESN model is more sensitive than ELM model due to rapid input variations over time. This validates why the ESN model performance is not as good as ELM's for night conditions. In order for ESN to perform as good as ELM under such conditions, focused training is required, but this means two different ESNs will be needed, one for day time conditions and other for night time conditions. Two ESN models are essential in order to get good performance for both conditions due to their dramatic differences.

Fig. 7. Actual PV power and ELM model based predicted PV power variation during night time, recorded by the RTPIS Lab. at Clemson University, SC on November 15th, 2014.

Fig. 8 shows the variation of PV power and the corresponding tie-line power flow recorded during day time operation by the RTPIS Lab. at Clemson University, SC on August 12th, 2014. The rapid fluctuations observed in the PV plant output causes area frequencies to fluctuate rapidly as shown in Fig. 9.

(a)

(b)

Fig. 8. (a) PV power variation recorded by the RTPIS Lab. at Clemson University, SC on August 12th, 2014 and (b) the corresponding tie-line power and tie-line power reference variation.

(a)

(b)

Fig 9. Day time frequency fluctuations experienced on August 12th, 2014 (a) Area 1 frequency and (b) Area 2 frequency.

Fig. 10 shows the variation of PV power and tie-line power flow during day time operation recorded on August 22th, 2014 with the ESN model based prediction. Fig. 11 shows the corresponding variation of frequency in Area 1 and Area 2. The predicted PV power is 35s ahead (optimal time step) in this case study.

(a)

(b)

Fig 10. (a) Actual PV power and the ESN model based predicted PV power (35s ahead) variation recorded by the RTPIS Lab. at Clemson University, SC during day time on August 22th, 2014 and (b) the corresponding tie-line power and tie-line power reference variation.

(a)

(b)

Fig 11. Day time frequency fluctuations experienced on August 22nd, 2014 with PV power prediction based on an ESN model used as control input by the AGC in Area 1 (a) Area 1 frequency and (b) Area 2 frequency.

Figures 12 and 13 show the variation of tie-line power flow and area frequencies during night time operation with measured PV power and predicted PV power used as control inputs by the AGC in Area 1, respectively. The predicted PV power is based on ELM model with prediction time step of 35s.

(a)

(b)

(c)

Fig. 12. Night time variations experienced on August 7th, 2014 with measured PV power used as control inputs in AGC in Area 1 (a) Tie-line power and Tie-line power reference, (b) Area 1 frequency and (c) Area 2 frequency.

(a)

(b)

(c)

Fig.13. Night time frequency fluctuations experienced on August 27th, 2014 with PV power prediction based on an ELM model used as a control input by the AGC in Area 1 (a) Tie-line power and Tie-line power reference variation (b) Area 1 frequency and (c) Area 2 frequency.

Table IV – Area 1 and Area 2 frequencies and tie-line power flow deviations.

	Frequency Area 1		Frequency Area 2		Tie-line power deviation (MW)	
	(Hz)		(Hz)			
	Day Time	Night Time	Day Time	Night Time	Day Time	Night Time
	ESN	ELM	ESN	ELM	ESN	ELM
No prediction	59.98740	59.99998	59.99172	59.99995	8.59174	0.61555
Prediction	60.00007	60.00004	59.99999	60.00008	0.71277	0.10438

Table IV shows the mean values of Area 1 and Area 2 frequencies, and the difference between tie-line power reference and tie-line power flow of cases presented in Figs. 8 to 13.

6. CONCLUSION

Enhanced tie-line bias control in a two-area power system with large variable photovoltaic plant generation has been presented in this paper. The tie-line bias control is carried out using automatic generation with PV plant output foresight. Two learning networks are used to predict PV power outputs for three different time steps ahead. The optimal prediction time step is determined by a metric developed to evaluate the deviations of the tie-line power flow from its commanded reference value. The metric has provided insight to compare the performance of ESN and ELM model based predictions. The ESN has better performance than the ELM during day time. This is due to the existence of a rich dynamic reservoir in ESN. The ELM performs better than ESN during night time. This concludes that the ESN model is more sensitive than ELM model due to rapid input variations over time. Future work includes expanding the input parameters to reservoir learning based networks to have cloud cover and relative humidity measures and improve the prediction results. A fuzzy logic modal can be developed to identify the exact time limits of switching network models to obtain the best results. Furthermore, the proposed strategy in this paper for PV plants can be extended to other variable generation such as wind plants to improve the frequency regulation of the wind plant integrated power systems.

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8. REFERENCES

- [1] T. Alquthami, H. Ravindra, MO Faruque, M. Steurer and T. Baldwin, "Study of photovoltaic integration impact on system stability using custom model of PV arrays integrated with PSS/E," in *Noth American Power Symposium*, TX, 2010.
- [2] G. K. Venayagamoorthy, "Tie-line bias control of a power system with large PV palnts using PMU information," in *XIII Symposium of Specialists in Electric Operational and Expansion Planning*, Brazil, 2014.
- [3] S. Eftekharnejad, V. Vittal, T. Heydt, B. Keel and J. Loehr, "Impact of increased pentration of photovoltaic generation on power systems," *IEE Transactions on power systems*, vol. 28, no. 2, pp. 893-901, 2013.
- [4] H. Asano, K. Yajima, Y. Kaya, " Influence of photovoltaic power generation on required capacity for load frequency control", *IEEE Transactions on Energy Conversion*, vol. 11, no. 1, pp. 188-193, 1996.
- [5] P. Kundur, "Power system stability and control," in *McGraw-Hill*, New York, 1994.
- [6] G. Huang, Q. Zhu and C. Seiw, "Extreme learning machine: theory and applications," *Neurocomputing* , vol. 70, pp. 489-501, 2006.
- [7] S. Salcedo-Sanz, C. Casanova-Mateo, A. Pastor-Sanchez and M. Sanchez-Giron, "Daily global solar radiation prediction based on hybrid coral reefs optimization – extreme learning machine approach," in *Solar Energy*, vol.105, pp. 91-98, 2014.
- [8] G. K. Venayagamoorthy, "Online design of an echo state network based wide area monitor for a multimachine power system," *Neural Networks*, vol. 20, no. 3, pp. 404–413, 2007.
- [9] "Wikipedia-Echo stste network," [Online]. Available: http://en.wikipedia.org/wiki/Echo_state_network. [Accessed 27 08 2014].
- [10] H. Jaeger, "Short term memory in echo state networks," German National Research Institute for Computer Science, GMD-Report 152, 2002.
- [11] H. Jaeger, "The “echo state” approach to analysing and training recurrent neural networks with an Erratum note," German National Research Center for Information Technology GMD Report 148, 2001.

- [12] H. Jaeger, "A tutorial on training recurrent neural networks, covering BPPT, RTRL, EKF and the "echo state network" approach," *Fraunhofer Institute for Autonomous Intelligent Systems (AIS)*, 2013.
- [13] H. Jaeger, "Reservoir riddles: suggestions for echo state network research (extended abstract)," in *International Joint Conference on Neural Networks (IJCNN)*, Montral, Canada, July 31-August 4, 2005.
- [14] G. K. Venayagamoorthy and S. Bashyal, "Effects of spectral radius and settling time in the performance of echo state networks," *Neural Networks*, vol. 22, no. 7, pp. 861-863, 2009.

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